GEOSIMULATIONS OF URBAN GROWTH, DASYMETRIC MAPPING AND POPULATION DYNAMICS IN NORTHWEST FLORIDA 1974 – 2025

by

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(Under the Direction of Fausto O. Sarmiento)

ABSTRACT

Problem: this is the first time that the SLEUTH model has been applied to Escambia, Santa Rosa and Okaloosa counties. Here, dasymetric mapping and censuses from the simulations are performed, generating three scientific questions. First, how will the Cellular Automaton (CA) model depict the different urban and other landscape changes? Second, what results will these simulations produce if dasymetric mapping and censuses from the sky are applied under past, present and future conditions? Third, using this CA model, will it be possible to replicate alternative scenarios such as smart growth and urban sprawl? The answers to these questions are the main contributions of this research to the fields of geographic techniques and demographics in space and time. **Methods:** imagery classification was applied to Landsat MSS and TM according to Anderson Level I; accuracy classification was performed comparing the classified images against sample points taken from air photos and Digital Orthoimagery Quarter Quadrangles (DOQQs); SLEUTH was implemented in a high-performance computer; dasymetric mapping using Geolytics databases developed in ArcGIS and ERDAS Imagine; and finally, census from the simulations were generated using linear regressions and the allometric growth model. **Results:** the results were graphical and statistical outputs of all methods previously mentioned plus analyses of these maps and statistics about land cover and demographics. The SLEUTH simulations produced yearly graphical and statistical results from 1975 until 2025. **Conclusions:** urban expansion principally affects agriculture, rangelands, grasslands and forests; barrenlands, especially the beaches, also suffer from development, showing unprecedented rates of urban growth. Smart growth provided an alternative strategy in which urban growth occurred in a more compact way, increasing its population density and decreasing the open space in the metro areas. Finally, the other scenario called urban sprawl simulated urban growth at a higher-rate-than normal, encouraging spontaneous and edge growth and lower population densities.

Index Words: Landsat Imagery, Cellular Automaton, SLEUTH, High Performance Computer, Dasymetric Mapping, Linear Regression, Allometric Growth Model, Smart Growth, Urban Sprawl.

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DEDICATION

To my son Alejandro.

To Cass.

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To Fausto Sarmiento for his guidance during my student years.

To Elgene Box, Marguerite Madden and Xiaobai Yao, the members of my Committee.

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CHAPTER 1

INTRODUCTION

1.1. Purpose of the Study

The main objective of this study is to analyze coastal landscapes with emphasis on the urban patterns and population changes in northwest Florida. The goal is to determine the implications that result from these processes and to suggest possible alternative scenarios to achieve better urban and regional planning. Land-cover changes associated with urban expansion in coastal areas destroy natural landscapes and biodiversity, due to demographic forces that expand cities and the agricultural frontier. Therefore, a great deal of forest, marsh and other natural areas can be lost. Also, human population growth in urban areas can increase traffic, air pollution and infrastructure problems if there are not enough economic resources or adequate planning in the cities. The following is a summary of how this dissertation is organized.

Chapter 2 shows where Escambia, Santa Rosa and Okaloosa counties are located, as well as their main physical, social and especially their demographic characteristics derived from censuses since 1970. A brief history of this region constitutes another topic of this chapter as well.

Chapter 3 is about image classification (in which multi-spectral images are converted into land-cover types). The input data are derived from Landsat satellite images: one Landsat Multi-Spectral-Scanner (MSS) image with a spatial resolution of 79 m from 1974 and three Landsat Thematic-Mapper (TM) images with spatial resolutions of 30 m from 1986, 1992 and 2001. The area of interest is separated and classified in Idrisi, an image-processing and Geographic

Information System (GIS) software package according to Anderson level I (a generic classification scheme, i.e. urban or forest). Finally, a method that tests the accuracy of the classified images against sample points was tested by selecting 1,500 ground-truth sample points from a higher-resolution image. The rest of this chapter concerns preparation of the other input layers necessary to generate the urban growth simulations.

Chapter 4 describes the implementation of the SLEUTH model (Slope, Land-cover, Excluded areas, Urban, Transportation, Hill-shaded relief), a software package from USGS (United States Geological Survey) that generates urban growth and landscape changes through time. SLEUTH uses a process called Cellular Automata (CA) that consists of thousands of micro-level pixel interactions. The model requires a high-performance computer (a computer with dozens of processors). Starting with a time series of Landsat-classified images, CA will be used to model three different scenarios into the future: normal trend, smart growth and urban sprawl.

In chapter 5, dasymetric maps are elaborated and analyzed. Dasymetry is a cartographic technique based on satellite imagery and census-block groups or tract divisions, in which more accurate maps are made because population densities are generated just inside the urbanized pixels (using medium-resolution images, as in this dissertation) or residential pixels (in high-resolution data) of every census-tract or block. Therefore, it is possible to say that this document mainly constitutes a study of demographics in space and time, enabling visualization of the demographic future with a good degree of certainty because urban expansion has been linked with population growth and population density changes. The spatial input data needed for this kind of analysis are the classified Landsat images plus the SLEUTH simulations for every five years, while the population statistics come from estimations based on Geolytics at the census-tract level and projections from the Florida Office of Demographic and Economic Research made at the county level.

Censuses from the classified and simulated images are made and analyzed in chapter 6. These censuses count urban pixels and are compared against population data derived from traditional censuses, establishing linear regressions between the number of urbanized pixels (independent variable) and the number of inhabitants (dependent variable). This technique will enhance the results of the dasymetric density mapping and SLEUTH simulations. And finally, conclusions and recommendations are made in Chapter 6.

The programs used in this research are ArcGIS (a software package for mapping and spatial analysis), ERDAS Imagine and Idrisi (Remote Sensing), USGS SLEUTH (urban growth simulation) and SPSS (software package for statistics).

1.2. Problem Rationale

According to the Online Data Repository from Project Gigalopolis, this is the first time that a SLEUTH simulation has been applied to Escambia, Santa Rosa and Okaloosa counties in Florida. This is also the first time that dasymetric densities and censuses have been performed over SLEUTH simulations, addressing three main scientific questions.

First, how will the CA model depict the different changes in urban and other landscapes in this study area? Because of the lack of a previous simulation in this region, these results should be considered for planning purposes and public policy design in these counties.

Second, what kind of results will the SLEUTH model produce if dasymetric densities and censuses are applied to these past, present and future simulations? How accurate are these results? Most researchers use this CA model just to understand urban growth and changes in the landscape. This investigation is an attempt to go beyond the traditional use of SLEUTH into a new field: demographics in space and time.

Third, using this CA model, is it possible to extrapolate the past-to-present trend into the future and also to replicate alternative scenarios such as smart growth and urban sprawl? And how will these new trends appear spatially in the landscape when demographic statistics are applied to them in the form of dasymetric densities? Finally, how well will these simulations produce population values when censuses are performed?

The answers to these questions are the main contributions of this research to the fields of geographic techniques and demographics in space and time.

CHAPTER 2

BACKGROUND AND STUDY AREA

2.1. History of Complex Systems: Cellular Automaton and Multi Agents

There are four different methods that are used to write a scientific paper: (1) Observing a phenomenon, from which processes and results can be summarized; (2) replicating processes through experimentation with different kinds of instruments and tools (this method always uses some real-physical elements of the systems); (3) mathematical formulations and equations, where the logic of processes is demonstrated through tests including numbers, letters and mathematical symbols; and, (4) using the power of computers, where the different elements of reality, with their functions and interactions are simulated, in an independent way from the objects or elements of reality. Observations and experiments are old scientific endeavors (Stevens and Lenschow 2001) and the same can be said today about mathematics, if it does not include algorithms. Nevertheless, modern simulations running on computers and made of logical and mathematical programs are able to represent the processes that generate the patterns of complex systems using spatial-temporal dimensions in a way never imagined just some decades ago.

There are many types of simulations according to the different areas of research, and inside the field of geography, models that represent dynamics of systems exist in both physical and human geography. All these advances in the representation of processes have been evolving from geometrical-mathematical models written on paper since the 19th century until now when the sophisticated simulations of systems are so complex that supercomputers and Artificial Intelligence (AI) are needed.

However, it is important to recognize that not all urban models achieve a good match with reality, because in many cases theory is too general or its application through simulations is based on constant tuning (Benenson and Torrens 2004) or modifications (intentional deformations of facts, laws, input data, etc.) in order to achieve expected results. Therefore, one of the most proved and reliable simulation methods used in Urban Geography constitutes the main focus of this research: SLEUTH (Slope, Land, Excluded, Urban, Transportation and Hill-shaded), a geosimulation based on CA and deltatrons which produces a higher degree of confidence in the results, which are compared to reality through accuracy evaluations and the Kappa index of agreement.

Most urban studies have been and still are exclusively of a theoretical nature, containing a few maps and statistical charts. According to Michael Batty: *"theory without dynamics could do little more than provide a descriptive explanation of how economic and social forces could work themselves out, given sufficient time"* (Batty 2007). But generating theory exclusively from observations through the traditional scientific method or hypothetic-deductive approach, gives us a general idea of the urban dynamics with a lack of understanding of its micro-processes. Instead, the inductive method of the SLEUTH simulation generates macro-level patterns from micro-level interactions through a positivistic approach and is based on how systems work in reality. In addition, modern simulations consider reductionism as the initial point of any research; of course some phenomena cannot be reduced to levels below the synergetic interactions. Micro-level interactions in the case of CA are pixels and in the case of multi-agents are virtual AI entities representing individuals, firms, households or cars (Benenson and Torrens 2004).

Urban geography theorists (such as William Thomas, Florian Znaniecki, Robert Park, Louis Wirth, Ernest Burgess, Everett Hughes, Robert McKenzie, Franklin Frazier, Charles Johnson, Edgar Thompson, Helen MacGill Hughes and other members of the urban sociologist school of Chicago) in the 1920's described the city as a complex urban environment: a network of cultural, ethnic and class systems. This human ecological view can be synthesized in the following sentence: *"Physical geography, natural advantages and disadvantages, including means of transportation, determine in advance the general outlines of the urban plan. As the city increases in population, the subtler influences of sympathy, rivalry, and economic necessity tend to control the distribution of population"*(Park 1925). In the same book, Burgess describes the expansion of cities as a series of concentric circles that radiate out from its central business district through time.

Nevertheless, it was not until the 1930's, when mathematical-geometrical models began to be applied into urban research, such as the Central Place Theory posited by Walter Christaller in 1933 (Lloyd and Dicken 1997). William Alonso's model (1964) extrapolated von Thunen economic assumptions from agricultural belts into cities and thus it predicted different rents, urban land-uses, and intensity of land-use (population densities and employment) as a function of distance to the central business district (CBD) of the city. This static model, moved by socio-economic forces does not offer a vision of time, growth or changes.

In 1936, mathematician Alan Turing developed the idea to create a machine based on recursion (an action dependent on previous information) and by using specifically written algorithms, he was able to represent different processes using a single machine. This early automaton device was named the “Turing Machine” and was operated by two key components: a ‘head’ that read and understood written symbols and a ‘tape’ or grid of cells that held the written symbols. The machine’s operation consisted of the head reading information from cells, and then based on that information, wrote new results or data on adjacent blank cells (Benenson and Torrens 2004). This machine was used during World War II to decipher Nazi and Japanese codes.

Given the ability of Turing’s “head” device to generate new information and store that information as memory, it later became known, more appropriately, as a processor. Using such processors, the first digital computers were built in 1946 and 1947. They were called “Colossus” and “ENIAC”, respectively (Benenson and Torrens 2004). Also during 1947, CA was first introduced by John von Neumann, a pioneer in the use of digital computers for biology. Norbert Wiener furthered this line of research when he theorized that all intelligent behavior was the result of feedback mechanisms and that it could be simulated by machines. In 1951, while working on the Manhattan Project, von Neuman and Stanislaw Ulam designed the first two-dimensional CA model (Wolfram 2002) (Benenson and Torrens 2004). Two years later, von Neumann began researching complicated CA models without the use of a computer. Also in 1953 he constructed a CA model using 29 possible colors for each cell, with rules that emulated operations of an electronic computer (Wolfram 2002). In 1955 two major advancements occurred: Enrico Fermi simulated simple nonlinear systems on a very basic computer, and scientists Newell and Simon developed *The Logic Theorist*, considered by many to be the first AI program based on a tree branching model. The latter years of the 1950’s brought about other achievements such as Gustav Hedlund’s experiment with commuting block maps and John McCarthy’s formal establishment of the field of AI. Over the decade, technological advances made it possible for computers to generate CA simulations; yet most research was directed towards differential equations. The start of the 1960's would have the effect of bringing greater attention to the use of computers for simulating space and time.

In the early 1960's, von Neuman added to his earlier work when he solved a mathematical proof for a 200,000 cell configuration that was able to reproduce itself. Edward Fredkin also simulated two-dimensional CA using computers, and noted its self-reproduction properties. Soon after, students from MIT developed more complex computer programs that were able to produce visual spatial outputs. The latter half of the decade produced research increasingly focused on CA models that showed simple behaviors of self-reproduction. The work of Hagerstrand in 1965 was a first attempt to model cities behavior using CA (Clarke and Gaydos 1998). In 1967, Stanislaw Ulam at Los Alamos began simulating systems of two-dimensional CA using single blank cells and simple growth rules that generated complicated patterns, which were relevant to the field of biology. By the end of the 1960s, the study of dynamic systems and CA was integrated (Wolfram 2002).

In the early 1970's John Conway did experiments initially by hand and later on computers with different two-dimensional CA rules in an effort to define the conditions leading to complex behavior. He succeeded when he created a CA model for biology called "The Game of Life". His research was published and popularized in *Scientific American Magazine*. This discovery was supported by discrete logistic equations and by Edward Lorenz's work on chaotic systems that led to the expansion of modeling complex behavior beyond the disciplines of physics and mathematics. In 1970, Thomas Shelling and James Sakoda independently decided to use chessboards to play flow games among cells to understand the patterns of residence segregation (Sakoda 1971; Shelling 1971). They used simple rules and assumptions; for example, they had two types of individuals (blacks and whites), which were able to migrate or to stay depending on their adjacent cells (thresholds) in nine cells representing a neighborhood. During this same time, artificial neural networks had started to be linked to two-dimensional CA models to explain complicated processes in different sciences. The first geographer to study cities as cellular spaces was Waldo Tobler. His theory was based on the idea of *"everything is related to everything else, but near things are more related than far things"* (Benenson and Torrens 2004). By the mid-1970s, Tommaso Toffoli also developed a simple two-dimensional CA model that was able to achieve stability from random initial conditions (Wolfram 2002). The end of the decade witnessed a further surge in CA research as personal computers began to be more widely available. One specific area of research focused on smart agents, or those deliberate-type agents that were able to interact in symbiotic models of the world, and in which decisions can be made via symbolic reasoning (Walker and Wooldridge 1995).

Throughout the 1960's and 1970's, geographic information systems (GIS) and CA developed in parallel with few interactions (Sui 1998). Then in the early 1980s, Stephen Wolfram after studying one and two-dimensional CA models, published his first paper "Statistical Mechanics of CA" (Wolfram 2002). Wolfram discovered that given random initial conditions, the cells could organize themselves to produce complex patterns and even fractal patterns. He identified four different classes of CA behavior (O'Sullivan 2000): stable, cyclic, chaotic and complicated patterns. His studies also revealed how the properties of CA related to hydrodynamics and thermodynamics. Yet despite this work, formal integration of GIS with CA did not occur until the late 1980s, when a collaborative effort by GIS specialists (Helen Couclelis, Robert Itami, Arnaldo Cechini, Fillipo Viola and Michael Philips) aimed to improve the analytical capabilities of GIS software package (Sui 1998). This collaboration led to the development of other joint projects linking AI and Multi Agent Systems (MAS). The last years of the 1980's witnessed further advances using CA and MAS models to better understand socioeconomic systems, making them important tools in geographical research and planning.

Early urban modeling in a GIS environment was done by White and Engelen in 1992, Batty and Longley in 1994, Wilson in 1995, and Goodchild in 1996. Advanced CA simulations for urban process modeling were developed by Hellen Couclelis and Takeyama in 1997 (Clarke and Gaydos 1998). Other researchers that developed different dynamic CA models for urban and environmental applications were Meaille and Ward in 1990, Landis in 1995, Veldkamp and Fresco in 1996, Pijanowski in 1997, Clarke and Gaydos in 1998, Wu and Webster in 1998 and 2000, Li and Yeh in 2000, Sui and Zeng in 2001, Wang and Zhang in 2001. Most of these models have been developed either as individual packages or as subcomponents linked with different GIS software package (Yang and Lo 2003).

The development and study of Complex Systems can be traced back to leading mathematicians and scientists of the twentieth century. Andrey Markov was the first mathematician to describe how discrete and stochastic processes based on probabilities that automaton cells would reach a unique equilibrium (Benenson and Torrens 2004). These rules of interaction were called Markov chains. However, further studies revealed that such Markov chains did not always reach equilibrium, but that many chains diverged and became chaotic, thus behaving similarly to open systems.

Many efforts were made to improve CA modeling capabilities, particularly in hierarchy notions, exogenous links to self-modification, inertia, utility maximization, probabilistic expressions, accessibility measures, and stochasticity (Torrens and O'Sullivan 2001). These improved models grew out of earlier game-like simulators that evolved into useful tools as pattern predictors (Yang and Lo 2003). Wolfram's discoveries in the preceding two decades constituted fundamental steps towards understanding and applying CA models to different fields of science including mathematics, physics, biology, social sciences, computer science and geography. As a result of his research and published works, systems of nonlinear differential and discrete equations have been applied to an increasingly larger number of socioeconomic systems of different scales, ranging from the whole world to specific regions, countries and even individual cities (Benenson and Torrens 2004).

Within the fields of economics, sociology and human geography, MAS have only recently been used. Some recent examples of these complex and artificially intelligent simulations are: a model predicting pedestrian movement in urban centers developed by Hacklay, O'Sullivan, Thusrstain-Godwin and Schelhorn in 2001; a simulation of citizen movements and ethnic residential segregation developed by Portugali in 2000 (O'Sullivan and Unwin 2002); and the TRANSIMS model created by Beckman in 1997 which simulated car traffic patterns in Dallas and Forth-Worth (Benenson and Torrens 2004). To serve the authors and researchers of CA and MAS research, a variety of academic journals now focus explicitly on these topics. This list includes: JASSS (*Journal of Artificial Societies and Social Simulations*), ACE (*Agent-based Computational Economics*), and the *International Journal of Geographical Information Science.*

2.2. Theory and Limitations behind Complex Systems

Through modeling is possible to explore and understand how processes operate in the real world, to predict what will happen next and to test hypotheses not just with statistical tests but through pattern measurements and analysis (O'Sullivan and Unwin 2002). However, these simulations have a constraint: the fact that they are closed models representing an open world, so it is impossible to build a system with all the elements and iterations from reality in a computer process. Nevertheless, today it is an important tool for scientific and technological research that allows us to accurately understand, represent and predict the physical world.

A main critique of these models relates to their measurement, reliability, validity and their application for solving complex, real world problems. Modern mathematical models are based on equations that originated in the 1600's. Initially, models were used as convenient calculation devices, and only later were they recognized as having a sufficiently high degree of correlation with reality to warrant their use as predictive devices (Wolfram 2002). The principle application of early models was in physics and chemistry, followed by efforts in other disciplines to use similar scientific models for analysis and prediction. The appeal of using modern scientific models is their ability to simulate and predict with a high degree of accuracy the behavior of a specific system. However, early models faced serious limitations for predicting the behavior of complex systems and the available technology could not meet the computational needs necessary to represent and model all processes within a specific system. Recent technological innovations have produced significant gains in computational power, thereby advancing the development of fractal research in the late 1960's, CA in the early 1980's and finally MAS models in the 1990's.

The concept of complexity is an emerging scientific paradigm that is based on a nonlinear view of the world (O'Sullivan and Unwin 2002). Modeling these complex systems presents challenges to researchers. The most pressing challenge is the need for computational storage and processing ability to analyze the multitude of variables in the models and to generate the possible outcomes from the interaction of those variables. The objective of these complex models is to represent the world in terms of the actual causal mechanisms that explain the intricate patterns seen in daily life.

Complex models using CA and MAS attempt to represent real processes and mechanisms that produce complicated patterns and phenomena seen in the world. Complex models constitute an improved tool for pattern measurement and hypothesis testing in the spatial sciences. Within the models spatiality is represented by grid-cells and multi-agents interact on the virtual landscape under conditions that are governed by predetermined rules. The ability of these models to make more accurate predictions about complex systems is a major advancement in the pursuit of identifying and explaining how complex processes operate in reality.

Research in urban geography had been growing rapidly during the last 40 years, where different urban phenomena have been analyzed (Benenson and Torrens 2004). Today, modern statistical and GIS software packages are able to combine quantitative and qualitative methods in ways impossible just some decades ago. Until now, most urban models had not been able to adjust well to reality, because sometimes theory was too general, mathematical and statistical methods could not explain all the complexity involved in a phenomenon, and GIS tools were unable to represent changes in time.

Therefore, the most realistic way to represent cities and their processes is through complex systems, a computer assisted method that consists of bottom-up micro level iterations of many different entities that are able to generate macro level patterns. In Geography, these systems are also called spatial models and consist of CA and Multi Agent simulations (O'Sullivan and Unwin 2002).

2.3. Cellular Automaton Models

According to Wolfram (1983): *"Cellular Automaton is a mathematical idealization of physical systems in which space and time are discrete, and physical quantities take on a finite set of discrete values. CA consists in a regular uniform array, usually infinite in extent, with a discrete variable at* *each cell. The state of a CA is completely specified by the values of the variables at each site. CA evolve in discrete time steps, with the value of a variable at one site being affected by the values of the variables at sites in its neighborhood on the previous time step. The neighborhood of a site is typically taken to be the site itself and all immediately adjacent sites. The variables at each site are updated synchronously, based on the values of the variables in their neighborhood at the preceding time step, and according to a definite set of local rules".*

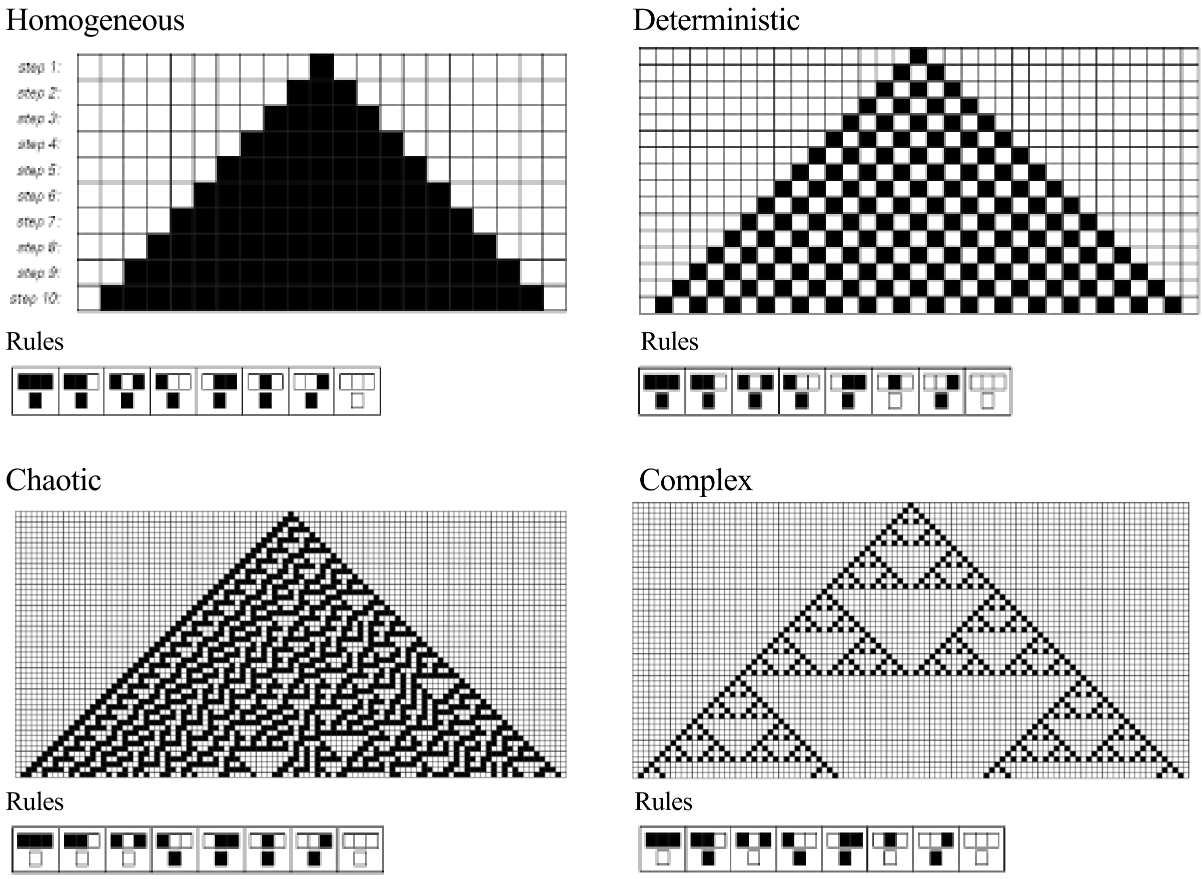
CA models begin with an array of cells that can be any value. With each sequential step, and because of specific rules, a cell will change its color depending on the outcome of the previous step and on the behavior of its surrounding cells. CA models are discrete in space, time and in their outcomes. Space is discrete because it consists of a uniform lattice of cells. Time is discrete because it makes use of different periods of time in which events can occur. Finally, the outcomes are discrete because the cells are forced to exist in a limited number of allowed states (O'Sullivan 2000).

CA models represent space and some models contain hundreds or thousands of multi agents living in these cells, generally representing land parcels. However, in economics as in other social sciences, the models do not have a spatial context, so the simulations are based on interactions among multi agents in a non-spatial context.

The basic components of CA models, whether they are 1, 2, or 3 dimensional is that they have cells and operating rules. In one-dimensional CA models the cells are of equal size and shapes (squares). In this space-time array, each cell is positioned within a neighborhood (a defined group of cells) and is related to two adjacent neighbor cells. Each cell has different states that vary in color according to the state that is represented. In the beginning CA models had just two states: 0 (dead-white) and 1 (alive-black). It was this simple alive-dead binary produced by John Conway in 1970 that became known as "The Game of Life".

CA models that present periodicity over time and therefore are statistically predictable are also totally deterministic. CA models that present non-periodicity, with unpredictable and chaotic behavior tend to develop chaotic patterns. CA models that present complex behavior do so by showing the evolution of the processes predicted at the end of “logical” patterns from the “real world”. These complex systems are able to spontaneously organize themselves. Such systems absorb the energy from their surroundings and use it to reduce their internal entropy. According to classical thermodynamics, there is no process in a closed system able to reduce the amount of entropy or to move spontaneously from a disordered state to an ordered state. Nevertheless, CA models with complex behavior are able to show order that originates from random conditions.

In the case of coastal areas, geographical constraints prevent marginal urban expansion into shoreline areas (Yang 2005). Due to the important role of physical factors that can be measured and extrapolated, a new modeling approach was needed to allow automatic processes to guide urbanization and development. Thus, CA became the modeling tool for urban geographic studies, from which demographic predictions and ecological forecasting are possible (Clarke and Gaydos 1998).



Source: Wolfram, 2002 **Figure 2.1: Different classes of One-Dimensional Cellular Automaton**

Homogeneous 1D CA: at the first step the cell in the center is black and all other cells are white. With each successive step, cells turn black whenever it or one of its neighbors was black on the previous step. Figure 2.1 shows how this leads to a simple expanding pattern uniformly filled with black cells.

Deterministic 1D CA: The rules turn a cell black if either of its neighbors was black on the previous step, or it turns a cell white if both its neighbors were white. Starting from a single black cell, this rule leads to a checkerboard pattern.

Chaotic 1D CA: The rules generate a random pattern. The CA starts from a single black cell, but the pattern produced shows almost no regularity.

Complex 1D CA: Here the rule is that a cell should be black whenever one, but not both, of its neighbors was black on the previous step. This figure starts from a single black cell that produces an overall intricate nested pattern over the course of 50 steps.

Knowing the different classes of 1-D CA models, their categories, arrangements and rules, it is possible to predict the future behavior of a process (O'Sullivan 2000). The different classes of 1-D CA models can be useful if the objective is to determine how the final patterns developed and are different from the initial conditions, transition rules and cell arrangements of the model's original state. In general, physics, mathematics, and computer science use linear (1 Dimensional) CA models. However, geography and urban modeling use higher dimensional CA to understand the different processes involved in the patterns. Typically, these fields of study use 2-D simulations, where the cells represent a grid of equal size and shape (square) spaces. In this space-time grid, each cell has a neighborhood (a defined group of proximity cells) and 4 or 8 (including diagonal cells) immediate neighbor cells. The cells can be black, white or have multiple values representing multiple states.

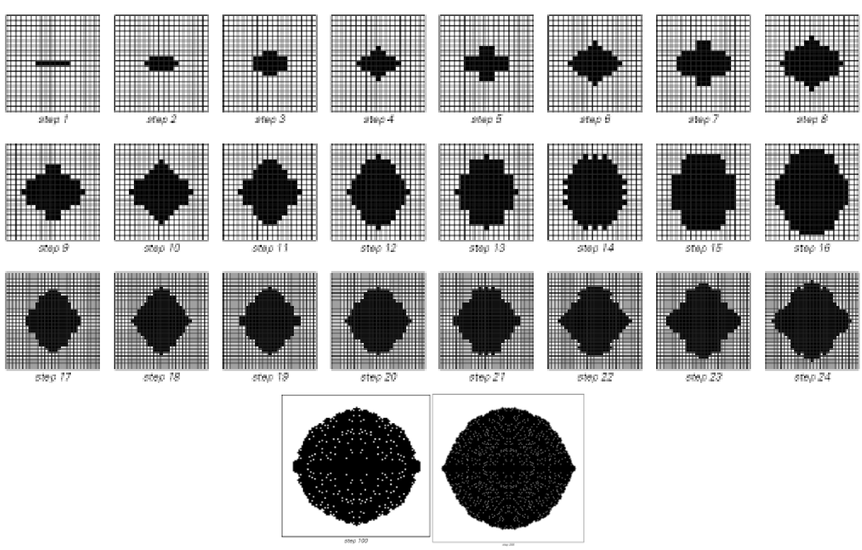


Figure 2.2: A two dimensional Cellular Automaton Source: Wolfram 2002

Figure 2.2 shows a process that yields a round shape from 200 sequential steps. The rule used here includes diagonal neighbors (8 neighbors for each cell). The rule specifies that the center should become black if either 3 or 5 of its 8 neighbors were black on the previous step or if not, the center should stay the same color (Wolfram 2002).

Three-dimensional CA have similar behavior to one or two-dimensional CA, but the number of total neighbors is larger (from 6 to 26 with the possibility to include even more) (Wolfram 2002). In 3D CA, rules depend on cells that share either a face or a corner with its neighboring cells. The rules specify that a cell should become black only when exactly two of its 26 neighbors were black on the step before. The initial condition contains a line of three black cells.

The rules that dictate how CA models grow can also be called “transition rules” because they specify how cells will be configured based on its own characteristics, those of its immediate neighbors and its neighborhood (O’Sullivan 2000).

2.4. Applications of CA in Geography

Theories of land change, such as Von Thünen’s classic “The Isolated State” where concentric zones of agricultural land-use are farther from a central market. However his theory only provides an explanation for changes in land usage, it does not explain the process itself (Walsh et al. 2004).

Technology plays a fundamental role in mapping, monitoring, and modeling land-use / land-cover dynamics across different spatial and temporal scales. Spatial technologies such as Remote Sensing, Geographic Information Systems (GIS), Global Positioning Systems (GPS), data visualizations, spatial and statistical analyses and models have been combined to understand population–environment interactions within spatial and temporal contexts.

CA models have been applied to the simulation of an impressive range of land-use dynamics, and urban growth phenomena (O'Sullivan and Torrens 2000). This modeling technique is increasingly an important tool for investigating landscape changes as well as urban/rural transitional processes.

An important issue in any two-dimensional CA model is to know what surface the different cells represent because it leads to different transition rules. In geographic applications, cells are positioned in a two-dimensional grid lattice because they originate from remote-sensed imagery and other raster sources. If the input data has a vector format, it must be converted into raster format by rasterization. Different groups of cells or regions have different cell states, depending on land values, land-covers, land-uses, population densities, etc. Nevertheless, in simple systems the cells can be classified in a binary fashion as developed or not-developed.

Modeling of complex systems with CA explains the internal processes that urban areas or landscapes undergo. CA has the capability to infuse concepts of thresholds, feedbacks, hierarchy, and complexity in the simulation of landscapes, as a consequence of scale-dependent forces and processes (O'Sullivan and Torrens 2000; Walsh et al. 2004). However, reality is based on interconnectivity, where local places are connected to each other and exist within a global context. Most urban areas do not develop as the sole result of local interactions, rather they are dependent on multiple and complex interactions that provide transport infrastructure, goods and services exchanges, and commercial networks linking different cities. Consequently, it is important to understand that the accuracy of prediction in CA simulations is just an approximation to reality. Also, the development of appropriate model structures in a landscape can be applied to other similar areas, where the only condition is the degree of homogeneity among similar landscapes.

These CA models represent landscape changes through time with a great fluidity of temporal activity in reality where the length of a time-step determines how much change may occur in a single transition. These time steps are very different depending on the application, for example geological processes have greater timescales than ecological or urban processes, and these processes generally have greater timescales than atmospheric processes.

It is also important to know if the cells have discrete or fuzzy values. Discrete cells have only a single value. Fuzzy cells are mixed cells that combine different spectral values (e.g. in residential areas, one part of the cell may be forest, while another might be grass, etc). The most complex CA models are based on multivariate fuzzy cell states, where the pixels are a combination of different categories and the rules are updated according to interrelated but distinct processes (O'Sullivan and Torrens 2000). These complex simulations help to understand how changes in transition rules affect simulated outcomes.

The complexity of CA models can also be increased by using rules where the cell is not just affected by its behavior and its immediate neighborhood, but also by cells in other distant regions. This can be achieved by using asynchronous cell updates. It is possible to develop CA simulations over irregular lattices with asymmetric cells, but these different kinds of CA modifications or dynamic complexities are more infrequently used in geographic applications (O'Sullivan and Torrens 2000).

Because of the growth in understanding of biophysical and socioeconomic processes, the availability of spatial digital data and new spatial digital technologies, geographers are able to examine the landscape at specified space-time scales: including local, regional, and global levels, by using interdisciplinary approaches and cross-cutting technologies (Walsh et al. 2004). In urban geography, the CA SLEUTH model developed by Keith Clarke is the most commonly used model to understand processes and patterns of urban growth.

Another CA geographical model was developed by Joseph Messina and Stephen Walsh in 2001 to model an area experiencing rapid change in land-use/cover due to agricultural colonization in the valleys of the Napo and Aguarico rivers of northeastern Ecuador. Since the 1970s, when government development policies distributed land parcels to immigrant families, the valley lands were deforested and transformed into extensive agricultural farms used either for subsistence agriculture or animal herding (Messina and Walsh 2001).

In 1998, Xia Li and Anthony Gar-On Yeh used CA to simulate a trend of sustainable urban development for the city of Dongguan in China's Pearl River Delta. The conversion of agricultural land into urban land in China constitutes a serious problem for urbanization because space in the eastern part of the country is severely limited and the loss of agricultural land reduces China's ability to produce food. However, this fact has not slowed the loss of eastern agriculture land to urbanization, and has resulted in highly dispersed development and migratory patterns, only worsening the problems related to sustainability (Li and Gar-On Yeh 2002). The main idea of Li's and Yeh's research was to search for better urban land-use practices to help sustain development, while minimizing the unnecessary loss of agricultural land.

Two years later these same researchers developed an Artificial Neural Network (ANN) based CA model to simulate the evolution of multiple land-uses in Dongguan. The simulation of multiple land-use changes using CA is much more difficult than the simulation of urban growth which is normally done with a binary basis (land is either assigned or not assigned to be developed). When multiple land-uses are present the transition rules become more complicated because the simulation uses a much larger set of spatial variables, factor weights and other parameters. In this research, three-layer neural networks with multiple nodes were designed to calculate multiple land-uses using a GIS software package. ANN is a group of layers and neurons, which simulate the structure of a brain.

The layers and neurons allow ANN to learn and recall information. ANN can also be constructed using back-propagation learning algorithms. The ANN-CA model in this research used multiple neurons and weights for simulating multiple land-use changes. The output layer of the network determines the transition probabilities of multiple land-uses.

Another CA model developed by Fulong Wu and Christopher J. Webster in 2000 was the simulation of artificial cities into self-organized CA models that combined classical urban economic theory with complex systems. This research replaced cell transition rules with microeconomic theory. The simulations permitted visual and economic exploration of two spatial versions of the theories of externalities and densification was based on Fuzzy cells (mixed cells that combined different spectral values) (Wu and Webster 2000).

SLEUTH models have been successfully applied in different cities by other authors. For example Keith Clarke and Leonard Gaydos in 1998 used a CA model to predict future urban transitions in the San Francisco Bay and the Washington-Baltimore corridor (Clarke and Gaydos 1998). This model was calibrated with historical data of these two metropolitan regions and used it to produce one hundred year projections of their urban growth. Yang and Lo in 2001 used a land transition model to simulate future urban growth in the Atlanta metropolitan area. The behavior rules in the model considered the spatial properties of neighboring cells, the existing urban spatial extent, transportation, and terrain slope. The difference between this CA model and other existing game-like simulators is its calibration to a time series of land-cover classified Landsat satellite images (Yang and Lo 2003). Herold et al (2002) combined remote sensing imagery, spatial metrics and CA spatial modeling to analyze and to simulate the urban growth of Santa Barbara - California between 2010 and 2030. This investigation was based on 72 years of data obtained through aerial photography and Ikonos satellite imagery that were used to model future trends of growth as well as to recreate missing historical time periods in the evolution of Santa Barbara since 1930. Spatial metrics, computed directly from thematic maps, were used to assess the impact of urban development and to analyze and verify the spatial-temporal dynamics of urban growth (Herold et al. 2003). CA model projects a spatial forecast of urban growth to the year 2030.

According to the SLEUTH Data Repository, this model has been applied successfully to the following cities: Albuquerque, NM; Alexandria, Egypt; Atlanta, GA; Austin, TX; Chaing Mai, Thailand; Chester County, Pa; Chicago, IL; Colorado Frontrange, CO; Detroit, MI; Houston, TX; Lisbon, Portugal; Mexico City, Mexico; Monterey Bay, California; New York, NY; Oahu, HI; Phoenix, AZ; Porto, Portugal; Porto Alegre, Brazil; San Antonio, TX; San Francisco, CA; San Joaquin Valley, CA; Santa Barbara, CA; Santa Monica Mountains, CA; Seattle, WA; Sioux Falls, SD; Sydney, Australia; Tampa, Florida; Tijuana, Mexico; Washington,DC/Baltimore and Yaounde, Cameroon (http://www.ncgia.ucsb.edu/projects/gig/v2/About/abApps.htm). All these urban areas are generally big cities; therefore, there are not enough SLEUTH studies about how middle and small towns grow. There are a plethora of examples of CA modeling in Geography, where researches used 3D CA models; CA based on irregular polygons instead of regular cells (Sembolini 2000), artificial neural networks, and a combination of multi-agents living in CA environments.

Table 2.1: Known SLEUTH Applications

Location	Authors
Albuquerque, NM	Hester 1999; Hester and Feller 2002
Alexandria, Egypt	Azaz 2004
Atlanta, GA	Yang and Lo 2003; Yang 2004
Austin, TX	USGS/RMMC 2004
Chester County, PA	Arthur et al. 2000; Arthur, 2001
Chicago, IL	Xian et al. 2000
Colorado Frontrange	USGS/RMMC 2004
Detroit, MI	Richards 2003
Houston, TX	Oguz et al. 2004
Lisbon, Portugal	Silva 2001; Silva and Clarke 2002
Mexico City, Mexico	UCIME 2001
Monterey Bay, California	Cogan et al. 2001
Netherlands	Tack 2000
New York, NY	Oliveri 2003; Solecki and Oliveri 2004
New York City, NY	USGS/RMMC 2004
Oahu, HI	James 2004
Phoenix, AZ	Breling-Wolf and Wu 2004
Porto, Portugal	Silva 2001; Silva and Clarke 2002
Porto Alegre, Brazil	Leao et al. 2001, 2004
San Antonio, TX	USGS/RMMC. 2004
San Francisco, CA	Clarke et al. 1997
San Joaquin Valley, CA	Dietzel and Clarke 2004a; Dietzel et al.
Santa Barbara, CA	Candau and Clarke 2000; Goldstein et al. 2000, 2004; Herold et al. 2002, 2003
Santa Monica Mountains, CA	Syphard et al. 2005
Seattle, WA	USGS/RMMC 2004
Sioux Falls, SD	Goldstein 2004a
Sydney, Australia	Liu and Phinn 2004
Tampa/S. Florida	USGS/RMMC 2004
Tijuana, Mexico	Le Page 2000
Washington, DC/Baltimore	Jantz et al. 2003
Washington/Baltimore	Acevedo 1997; Clarke et al. 1997
Yaounde, Cameroon	Sietchiping 2004

2.5. General Characteristics: Location, Climate and Population.

The study area consists of three counties located in North-West Florida: Escambia, Santa Rosa and Okaloosa; covering a combined area of more than 8,000 Km^2 with a total population of 600,000 inhabitants according to the last census of the year 2000.

Table 2.2: Main Characteristics of the Study Area

Counties	Population 2000	Area in Km^2	Land Area Km^2	Water Area Km^2	Total Density	Density in land areas
Escambia	294,410	2,268	1,716	552	129.81	171.67
Santa Rosa	117,743	3,040	2,634	406	38.73	44.70
Okaloosa	170,498	2,802	2,423	379	60.85	70.37
TOTAL	**582,651**	**8,110**	**6,772**	**1,337**	**71.84**	**86.04**

Source: U.S._Census_Bureau 2000

Figure 3: Area of Analysis in Red

A warm-temperate climate is characterized by humid and hot summers with mild winters. The average high and low temperatures in July (summer) are 33°C (91°F) and 23°C (75°F) respectively, while the corresponding averages for January (winter) are 16°C (61°F) and 4°C (40°F). Finally, precipitation is 1710 mm (67.3 inches) per year, with an increase in rain during the summer. The region constantly is affected by hurricanes: Eloise (1975), Frederic (1979), Juan (1985), Erin (1995), Opal (1995), Van (2004), and Dennis (2005).

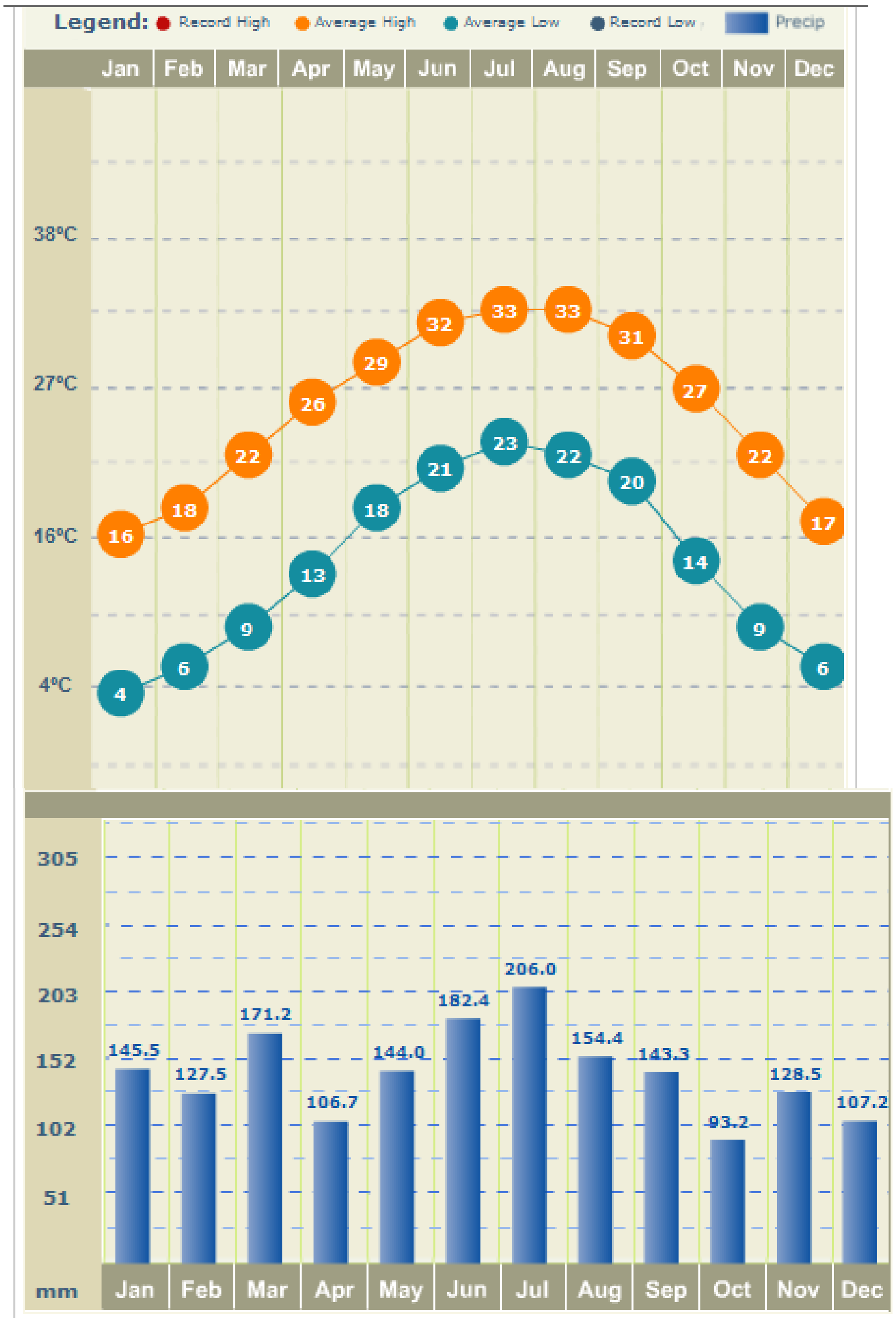


Figure 2.4: Average Temperatures and Precipitation

Note: Temperatures and Precipitation for the city of Milton, Santa Rosa county. Source: The Weather Channel

Of these three counties, Escambia has the highest population density because the city of Pensacola has a population of 56,255; however, the Pensacola Metropolitan Area (cities of

Pensacola, Ferry Pass and Brent) has a population of 412,153 (U.S._Census_Bureau 2000), being the largest metropolis in the Florida Panhandle and the largest on the Gulf Coast between Mobile and Tampa. The other main cities in this region are actually small ones such as Milton (Santa Rosa), and Fort Walton Beach or Crestview (Okaloosa).

This research will analyze urban growth and urban spatial patterns of small towns (in Escambia, Santa Rosa and Okaloosa counties) and a middle size city: Pensacola (in Escambia county). Many urban areas on the Southeast coast of the United States (especially Florida) have been growing at faster rates than other American towns because they are attractive sites for retired people, for individuals that avoid the cold winters in the north U.S. or workers who find employment in these touristy coastal areas. Pensacola represents a typical middle size urban area on the coast of Florida and the three counties selected are neither areas of highest nor lowest growth; but their population growth rates are comparable to the average growth rates of other Florida counties.

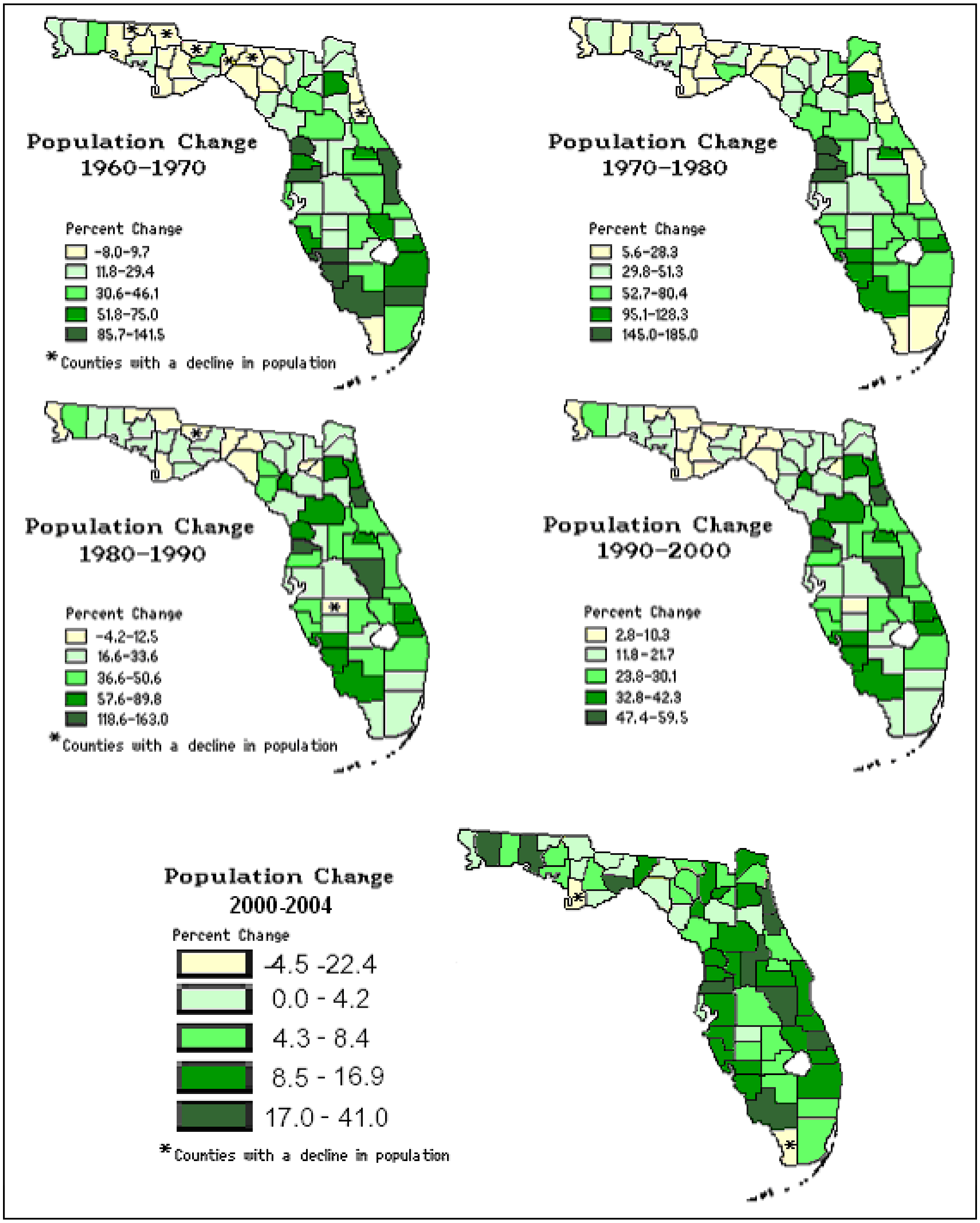


Figure 2.5: Population Growth Rates in Florida counties

Source: Florida State University 2003

Pensacola city in Escambia county and the other cities in Santa Rosa and Okaloosa counties offer good examples of how the SLEUTH model can be applied to small towns and middle size cities in coastal areas of the Southeast United Sates and especially in northwest Florida. This study also helps to identify the differences in growth patterns of middle and small size settlements in relation with big cities and metropolitan areas inside and outside the United States through a comparison of the different growth coefficients (dispersion, breed, spread, slope-resistance and road-gravity) that already exist for many cities of the world inside the SLEUTH data repository.

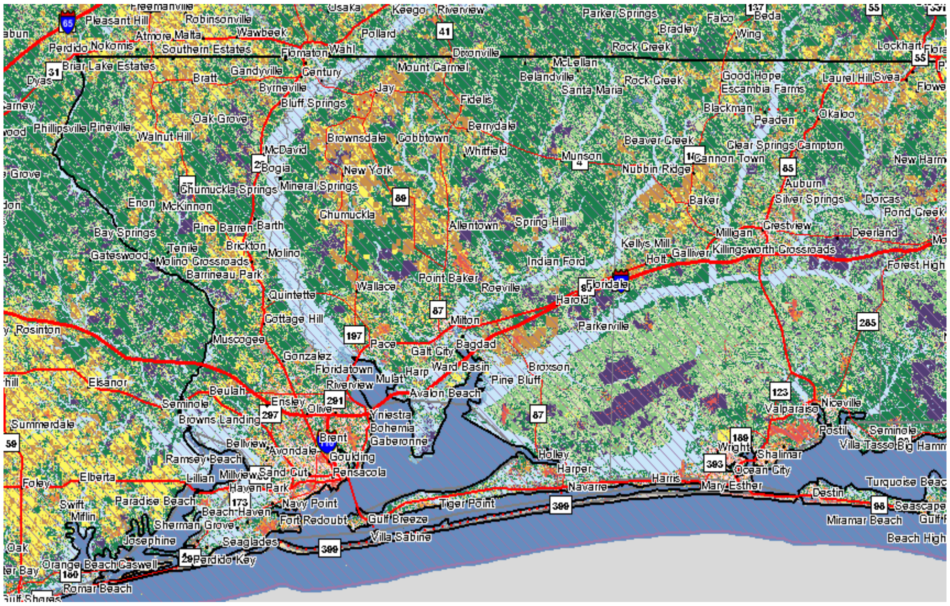
The selected area of interest has the following four corner points in UTM WGS84 Zone 16 North Coordinates:

Upper Left X: 438,000	Lower Right X: 560,010
Upper Left Y: 3,431,000	Lower Right Y: 3,347,990

According to the 1992 National Land-cover Dataset (NLCD) derived from Landsat TM imagery, and classified by EROS-USGS using Anderson level II classification scheme, the area of interest presents the following land-cover classes:

Table 2.3: Different Land-cover Classes

Land-cover Class	Color	Area in Km^2
11 Open Water		1,913.45
21 Low Intensity Residential		125.06
22 High intensity Residential		38.92
23 Commercial/Industrial/Transportation		121.76
31 Bare Rock/Sandy Clay		39.78
32 Quarries/Strip Mines/Gravel Pits		7.64
33 Transitional		500.46
41 Deciduous Forest		656.63
42 Evergreen Forest		2,873.02
43 Mixed Forest		1,311.15
71 Grasslands/Herbaceous		7.64
81 Pasture/Hay		623.63
82 Fallow		688.15
85 Urban Recreational Grasses		106.97
91 Woody Wetlands		1,038.60
92 Emergent Herbaceous Wetlands		81.34
Total Area		**10,134.20**



Source: USGS **Figure 2.6: Land-cover of the Area of Interest**

In figure 2.6 we see the names and place of the different settlements such as the main cities: Pensacola (Escambia), Milton (Santa Rosa) and Fort Walton Beach or Crestview (Okaloosa) as well as the different highways with their respective numbers.

2.6. Brief History of the Study Area

Escambia, Santa Rosa and Okaloosa counties have the oldest history in the United States (at least from the European exploration and colonization point of view) since 500 years ago, because here Spaniards found a settlement in continental North America for the first time in 1559. This region changed hands between five countries: Spain, France, Great Britain, the Confederate States, and finally became a permanent part of the United States since the Civil War, with the city of Pensacola being destroyed and re-built many times by wars.

Pensacola Bay (initially known as *Polonza*) was originally inhabited by the Panzacola Indians. Juan Ponce de León in 1513 and Don Diego Miruelo in 1516 were the first Spanish explorers in these lands (McGovern 1972). Fifteen years later (1528) Pánfilo de Nárvaez also arrived to the coasts of this Bay. The last exploration before the first settlement was carried out by Hernado de Soto in 1539. It was not until 1559 when the first European settlement in the United States was established here on Fort Pickens, Santa Rosa island by Don Tristan de Luna with approximately 1,400 persons who came from Veracruz, Mexico, and the name of the region was renamed to: “Bahía Santa María de Filipina”, but in 1561 the small town after suffering many Indian attacks was destroyed by a hurricane (Dibble and Newton 1971) and it was abandoned, with the Viceroy’s decision that northwest Florida was a dangerous place to colonize. Therefore, four years later, another location in East Florida: St. Augustine was founded instead (1565), while Pensacola was forgotten for 135 years, until in 1696 governor Andrés de Arriola resettled again, this time in the continent, in Fort Barrancas (Parks 1986) but for security and strategically reasons, soon most people went to live in the area today’s corresponding to downtown Pensacola.

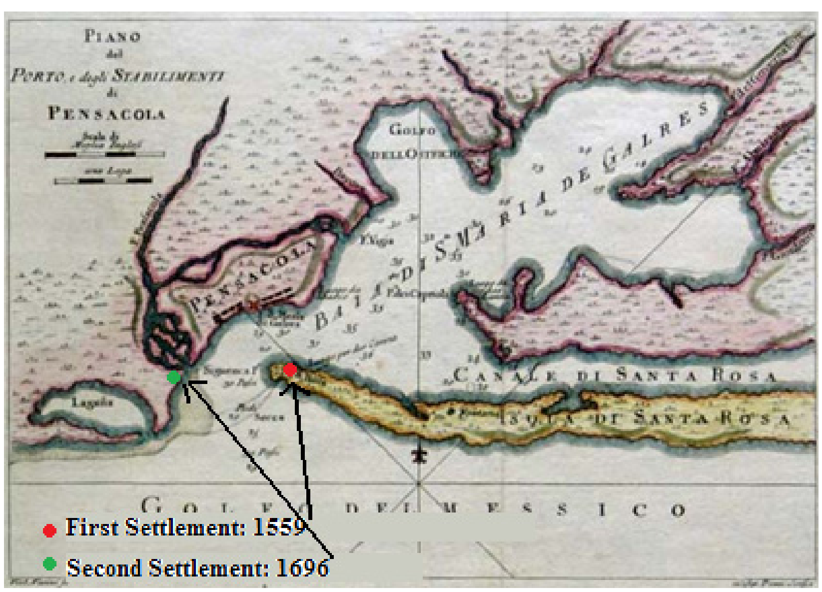


Figure 2.7: Old Map of Pensacola showing the location of the First and Second Settlement
Source: Porto and Stabilimenti 1763

In 1719, the French who were already established further west at Mobile and Biloxi, captured the settlement and controlled it for three years, until in 1722 a hurricane destroyed Pensacola and the Spanish re-captured it, founding the new town on the mainland instead of on the storm-vulnerable island (McGovern 1972). In 1757, by order of Spanish King Ferdinand VI the area was officially named "Pensacola" (Dibble and Newton 1971).

The settlement remained modest, being a strategic Spanish military port, until the end of the French and Indian War. In 1763 Pensacola was invaded by the British army, becoming the capital of British West Florida, including all the Panhandle, southwestern Alabama, Southern Mississippi, and the Florida parishes of modern Louisiana (including Baton Rouge) (McGovern 1972). The French were expelled from North America and most of Louisiana became a British colony (Parks 1986).

This period was characterized by the introduction of black slaves to work in cotton plantations (Dibble and Newton 1971). In this time Great Britain controlled all the Atlantic coast of North America, including Florida that was divided in British East Florida with its capital at Saint Augustine and British West Florida with Pensacola as its capital (Nixon 1966).

From 1775 to 1783, during the American Independence, Georgia-Alabama fought against the British Empire, but East and West Florida plus the Canadian colonies were loyal to England (Coker 1982). The Spanish were American rebels allied, and they re-captured West Florida in the Battle of Pensacola of 1781 (Nixon 1966). At the end of the war and due to the American victory, East Florida was also transferred to Spain (Parks 1986).

In 1810, American settlers in the west part of the Pearl River, declared West Florida as a new Republic, independent from Spain and this region was annexed in1812 as part of the new state of Louisiana, after the Louisiana Purchase in 1803 (Coker 1982). However, the states of Alabama and Mississippi in an attempt to avoid being trapped without ports took most of West Florida with the military aid of General Andrew Jackson, in the 1810's (McGovern 1972). He briefly returned Pensacola to Spain, but most areas further west became part of Mississippi (1817) and after Alabama (1819) (McGovern 1971). In 1819, the United States once again captured Pensacola, and in 1821 when the Adams-Onís Treaty (between Spain and the U.S.) was signed, finally Florida became part of the U.S (Procter 1978).

Pensacola was the capital of Florida until 1832, when Tallahassee became the new capital (Coker 1982). Florida officially was admitted as the 27th American state in 1845, the Panhandle and north Florida remaining the most populated parts of the state, while south Florida were having conflicts with the Seminole Indians (Parks 1986).

During the American Civil War (1861-1865), Florida became the third state to secede from the union, in 1861, and remained part of the Confederate States until a northern invasion of the Pensacola in 1862, being the city finally burned by the Yankee army (Procter 1978). Florida was readmitted to the Union in 1868 (Pearce 2000).

Since then and until now, this region had been losing importance in the Florida context, because of the enormous population growth in South, East and Central Florida, where Miami, Tampa, Orlando and Jacksonville have become the new metropolitan and most important urban areas.

CHAPTER 3

DATA AND METHODS

3.1. Image Classification

Earth surface features can be interpreted using satellite imagery. They are commonly categorized as being either land-cover or land-use. It is important to identify differences between surface cover (e.g. grassland or shrub) and land-use activity (e.g. pasture). Cultural and economic activities such as farming, mining, and railroads are examples of land-use.

The goal of a thematic mapping project is to obtain each individual land-cover from remote sensor data as accurately as possible. To produce the most accurate map, it is necessary to utilize methods based on digital image analysis and to compare against the ground-truth data (in this case USGS air photos and Digital Orthoimagery Quarter Quadrangles (DOQQs) will be used as sources of ground-truth).

The classification process involves the methods of land-cover mapping (through supervised classification), and accuracy evaluation using error matrices and Kappa coefficients. These methods are applied on the images using IDRISI software package.

As mentioned before, the land-cover data is classified from Landsat MSS and TM images in their respective land-cover datasets using supervised classification (training areas with polygons and the maximum likelihood classifier); these results are compared with the random samples obtained from USGS air photos and DOQQs, assuming that these images represent the ground-truth. In this way, is possible to derive accuracy tests through error matrices and Kappa indices of agreement.

Each of the bands in an image has different pixel values (digital numbers or variations in the tones of gray), but in order to have a better visual understanding of the land-cover, it is possible to combine three different bands using blue, green and red colors to produce a true or a false color composite display.

The time series imagery that is used in this research comes from two different satellites using two different instruments: Landsat 1 with its MSS instrument and Landsat 5 with its TM instrument, consequently their spatial and spectral resolution as well as their size (in number of pixels and megabytes) will be different for the MSS 1974 image in relation with the other TM images

Table 3.1: Specific Characteristics of the Landsat Images Acquired

Characteristics	Image from 1974	Image from 1986	Image from 1992	Image from 2001
Satellite	Landsat 1	Landsat 5	Landsat 5	Landsat 5
Instrument	Multi Spectral Scanner MSS	Thematic Mapper TM	Thematic Mapper TM	Thematic Mapper TM
Scene ID	LM1021039007429790	LT5020039008620010	LT5020039009210510	LT5020039000119310
Path	021	020	020	020
Row	039	039	039	039
Acquisition Date	24 Oct 1974	19 Jul 1986	14 Apr 1992	12 Jul 2001
Volume	1 of 1	1 of 1	1 of 1	1 of 1
Correction Level	Precision	Precision	Precision	Precision
Unit Number	00001	00002	00003	00004
Rows	3631	6958	7013	7073
Columns	3938	7479	7479	7507
Format	NLAPS	NLAPS	NLAPS	NLAPS
Order Number	0110506020010	0110506020010	0110506020010	0110506020010
Band 1 (Blue)	---	0.45μm – 0.52μm	0.45μm – 0.52μm	0.45μm – 0.52μm
Band 2 (Green)	0.50μm – 0.60μm	0.52μm – 0.60μm	0.52μm – 0.60μm	0.52μm – 0.60μm
Band 3 (Red)	0.60μm – 0.70μm	0.63μm – 0.69μm	0.63μm – 0.69μm	0.63μm – 0.69μm
Band 4 (Near IR)	0.70μm – 0.80μm	0.76μm – 0.90μm	0.76μm – 0.90μm	0.76μm – 0.90μm
Band 5 (Mid IR)	0.80μm – 1.10μm	1.55μm – 1.75μm	1.55μm – 1.75μm	1.55μm – 1.75μm
Band 6 (Ther IR)	---	10.4μm – 12.5μm	10.4μm – 12.5μm	10.4μm – 12.5μm
Band 7 (Mid IR)	---	2.08μm – 2.35μm	2.08μm – 2.35μm	2.08μm – 2.35μm
Spatial Resolution	79 m	30 m	30 m	30 m

* Landsat TM 4-5 Thermal-IR band has a resolution of 120m
Source: Metadata from original Landsat Images (NASA and USGS)

MSS 1974, TM 1986, TM 1992 and TM 2001

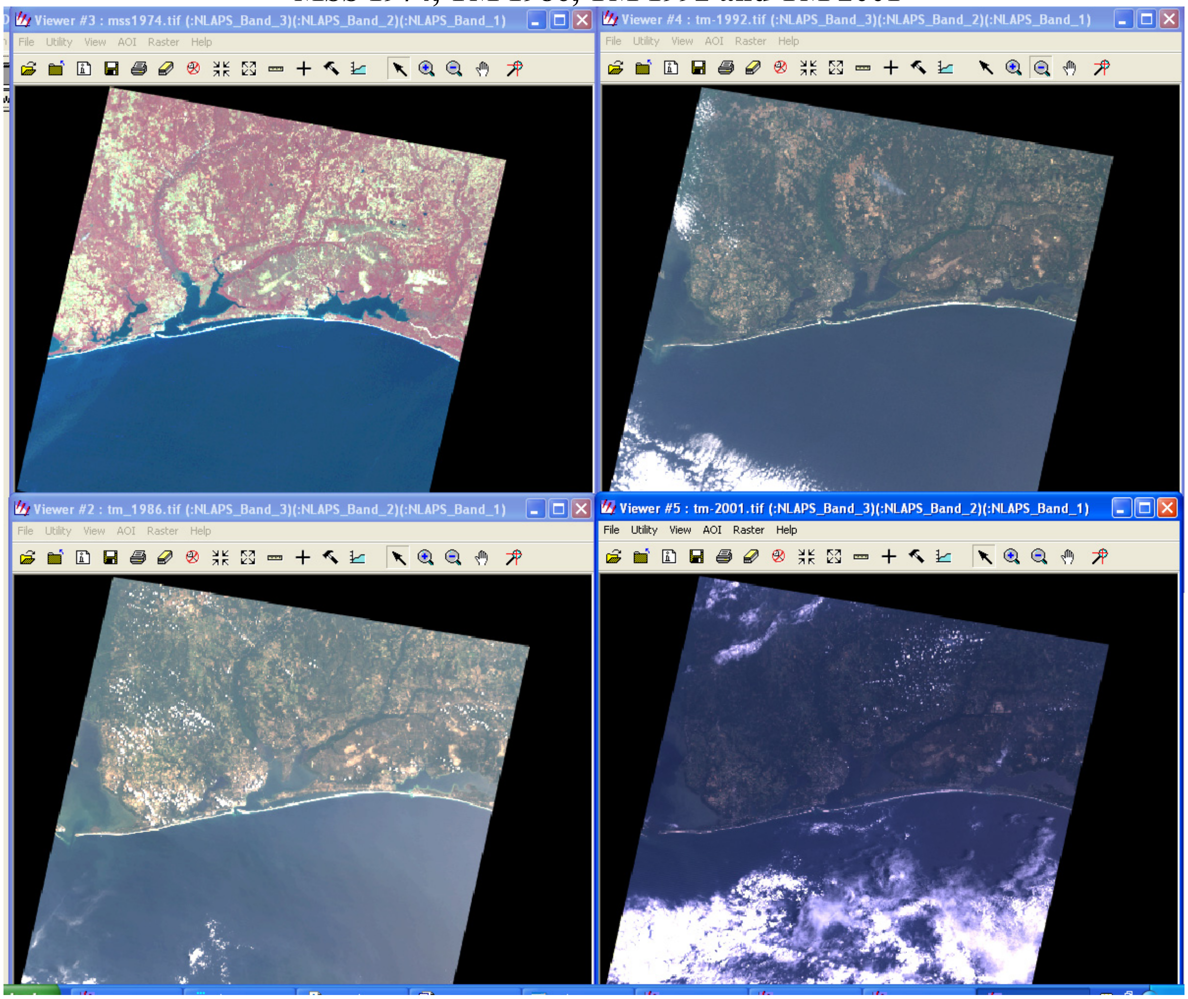


Figure 3.1: Landsat Images in TIF format

The upper left image is the Landsat MSS 1974.tif
The lower left image is the Landsat TM 1986.tif
The upper right image is the Landsat TM 1992.tif
The lower right image is the Landsat TM 2001.tif
Bands 1 (green), 2 (red) and 3 (infrared) appears in the MSS image.
Bands 1 (blue) 2 and 3 (red) appears in the TM images.

From these Landsat images, just the area of interest corresponding to Escambia, Santa Rosa and Okaloosa counties was used in this study. Therefore, using ERDAS Imagine, the original areas (180 x 180 Km) of 32,400 Km^2 are reduced to 4068 x 2768 pixels (122,04 x 83.84 Km) or 10231.83 Km^2 where the three counties of interest are located plus water areas and small amounts of land surrounding these counties in Florida and Alabama.

MSS 1974, TM 1986, TM 1992 and TM 2001

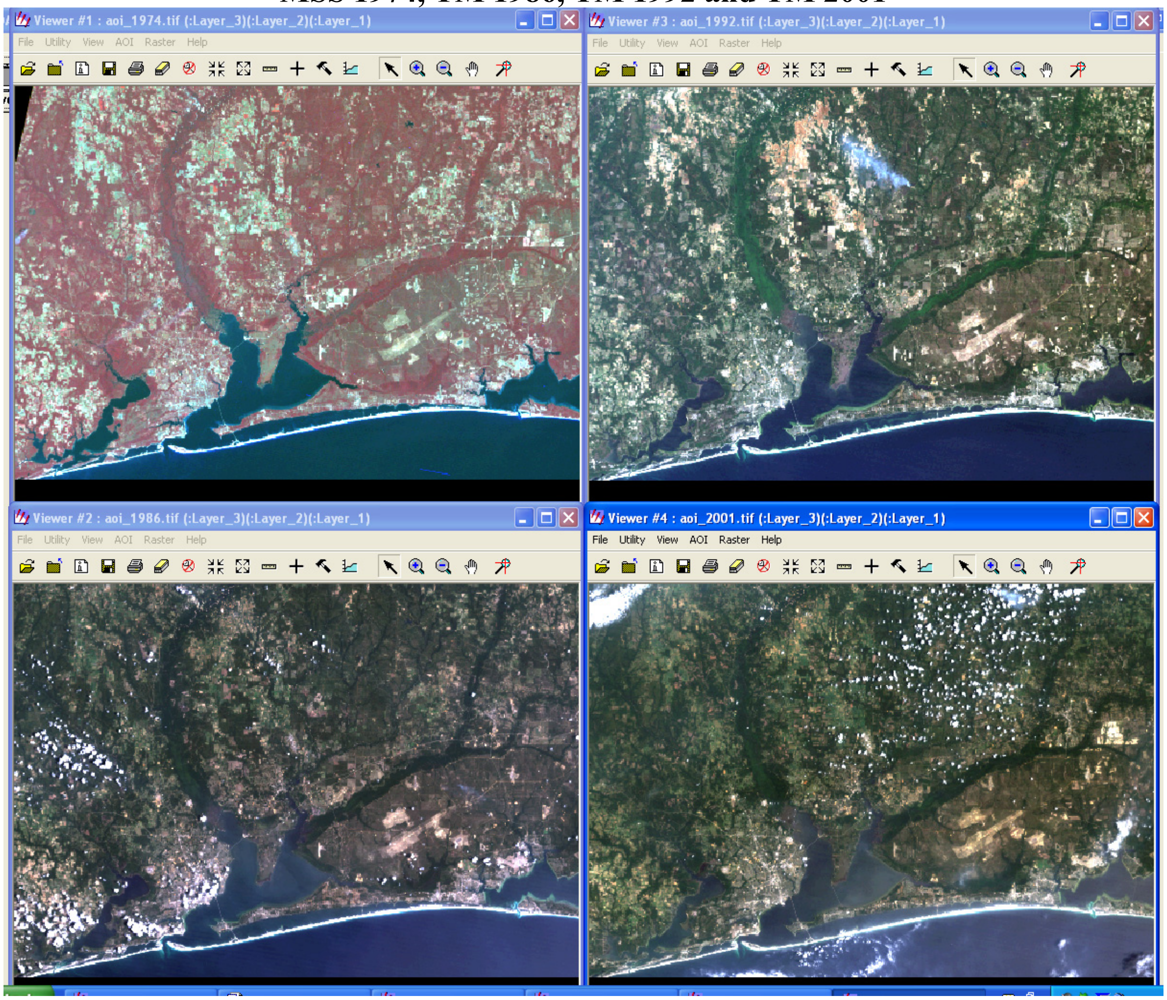


Figure 3.2: Areas of Interest from Landsat images in TIF format

Upper left image: AOI of the Landsat MSS 1974.tif Upper right image: AOI of the Landsat TM 1992.tif
Lower left image: AOI of the Landsat TM 1986.tif Lower right image: AOI of the Landsat TM 2001.tif
Bands 1 (green), 2 (red) and 3 (infrared) appears in the MSS image.
Bands 1 (blue) 2 and 3 (red) appears in the TM images.
Note: All these AOIs from different years correspond to the same area, they have the same resolution (30 meters) and the same number of pixels: 4068 pixels * 2768 pixels = 11'260,224 pixels

Image classification can be unsupervised, semi-supervised or supervised to derive land-cover classes through the use of image classifiers. The extraction of information from remotely sensed digital data can use different algorithms (cluster-busting, sub-pixel processing, fuzzy logic, fractals, etc.) and the software package is able to partition effectively multispectral feature space into a number of different homogeneous and mutually exclusive categories with their own mean vectors and associated statistics. The result is a matrix of different clusters that are then labeled by an analyst into information classes.

The classification is implemented based on Anderson’s Level 1 classification scheme (in other cases, the classification scheme is determined in relation with the objectives of the project; however, a classification scheme has to be hierarchical, mutually exclusive and totally exhaustive).

First, as a prerequisite to perform supervised classifications using Idrisi, it is necessary to select different training polygons from the area of interest of the multiband (multispectral) satellite images for every land-cover class. The analyst must zoom in many times to select just the pixels that correspond to a specific class (especially in the case of urban areas, which are often a mixture of developed lands with trees and grass). In this case the following six classes were determined: urban, agriculture-pastures, forests, water, wetlands and barrenlands. To yield accurate results, training polygons need to be representative and complete (Lillesand and Kieffer 2000), gathering pixels with different spectral characteristics that in reality will represent just one type of land-cover (water has different colors, according to sediments, algae, etc; forests constitute all kinds of trees, agriculture-pastures can contain crops of different kinds that have different spectral signatures). Through the collection of these polygons, the algorithms have a statistical data base from which to select new areas that resemble or are close in spectral values to the selected polygons and will classify the whole satellite image in the assigned land-cover classes.

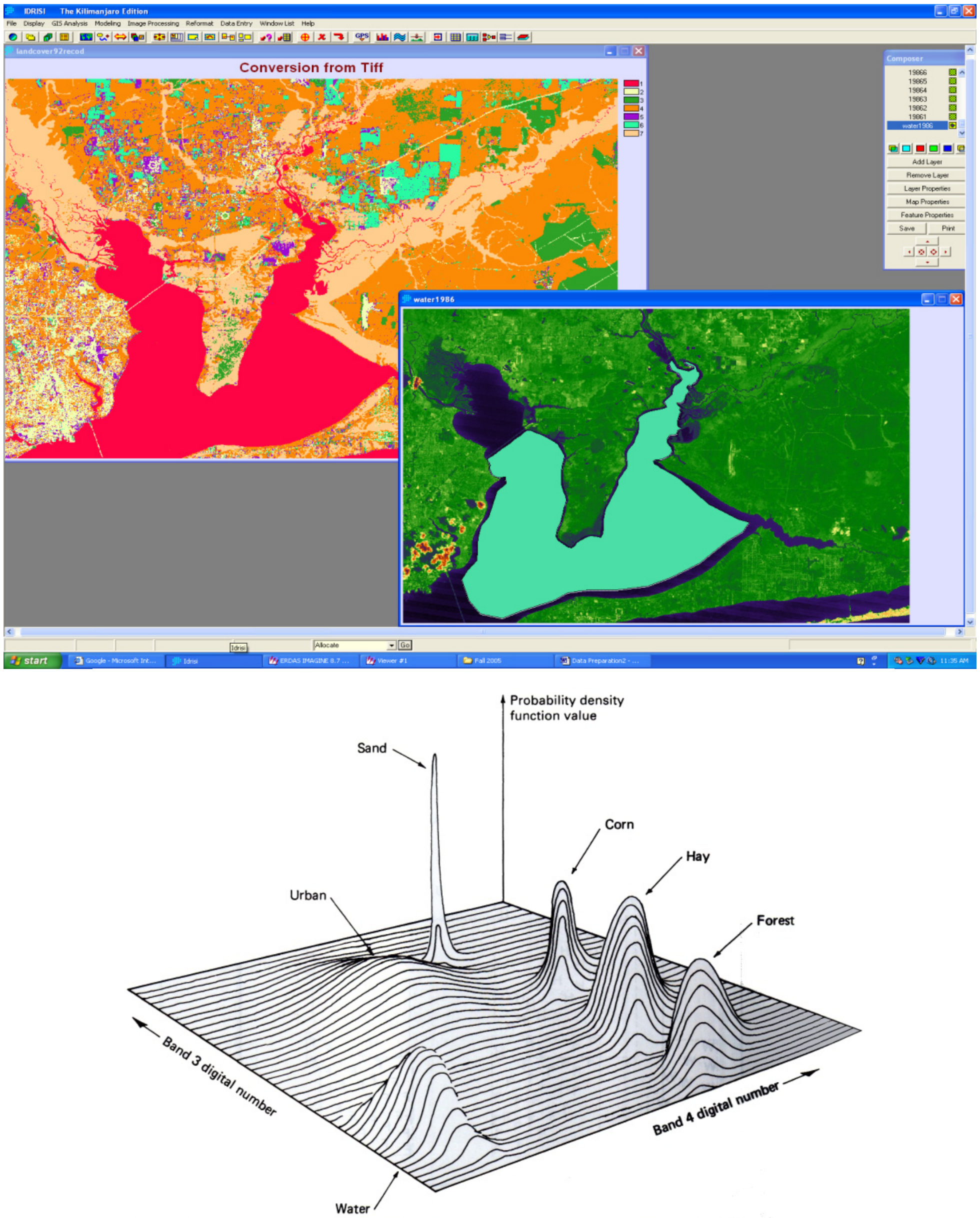


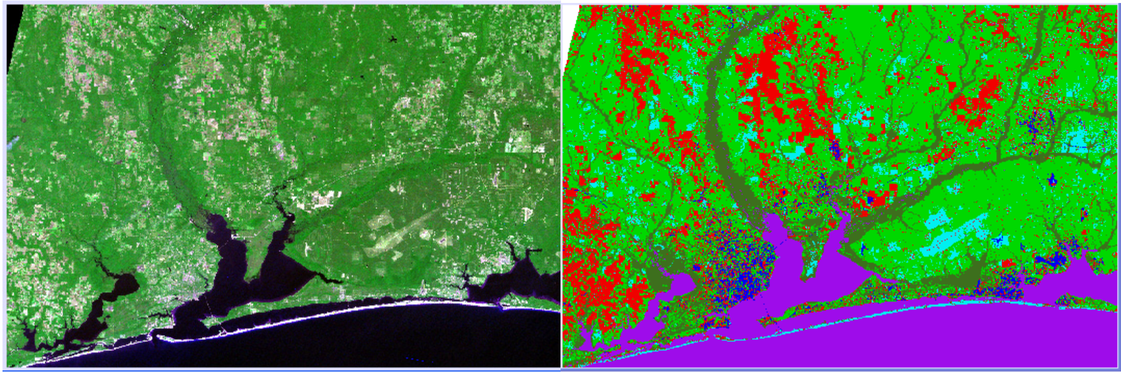
Figure 3.3: Polygon's Training for Supervised Classification Probability and Density Functions of the Gaussian Maximum Likelihood Classifier
Source: Lillesand and Kieffer 2000

After these polygons are selected, the classification algorithm is run: the Gaussian maximum likelihood classifier, which assigns equal probabilities to each class. In the supervised image classification, this classifier uses a probability density function over the means of the selected areas (training polygons) and covariance matrices from the spectral signature file to determine the categories where each one of the pixels belong to (Lillesand and Kieffer 2000). The raster layer output is a classified image in which each cell has been assigned to a spectral class related to a specific land-cover type on the ground.

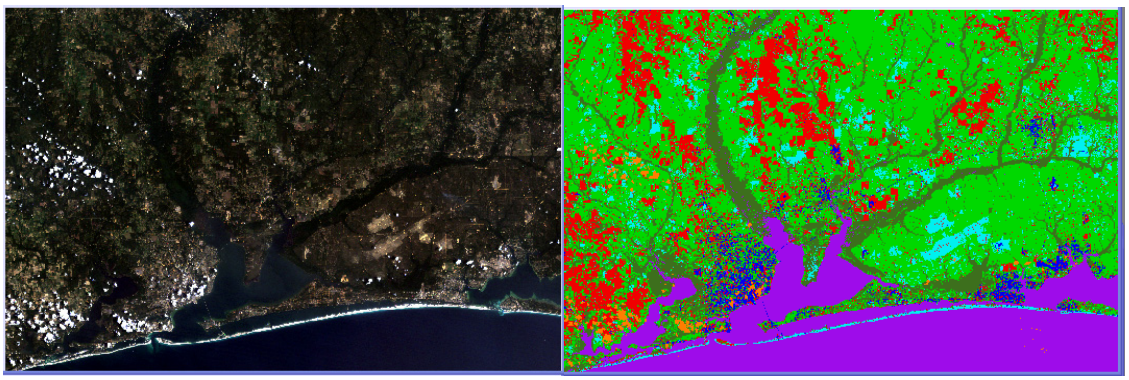
It is also important to consider that the size of the images, the spatial resolution, the land-cover classes and the color palette used in the classified images need to be exactly the same ones (it was necessary to diminish the spatial resolution for the 1974 Landsat MSS image from 79 m to 30 m) to generate the SLEUTH model using a high-performance computer.

The images that resulted from these classification processes show that most land-cover types (especially water) rarely changed over time, whereas urban lands were more dynamic, expanding continuously since 1974, affecting forests, agriculture-pastures and especially barrenlands because there was a trend of expansion into the beaches of this region. Similarly, wetlands are hardly affected by urban expansion because of protection laws and county regulations. A statistical analysis of this situation can be found at the end of the next section: editing images.

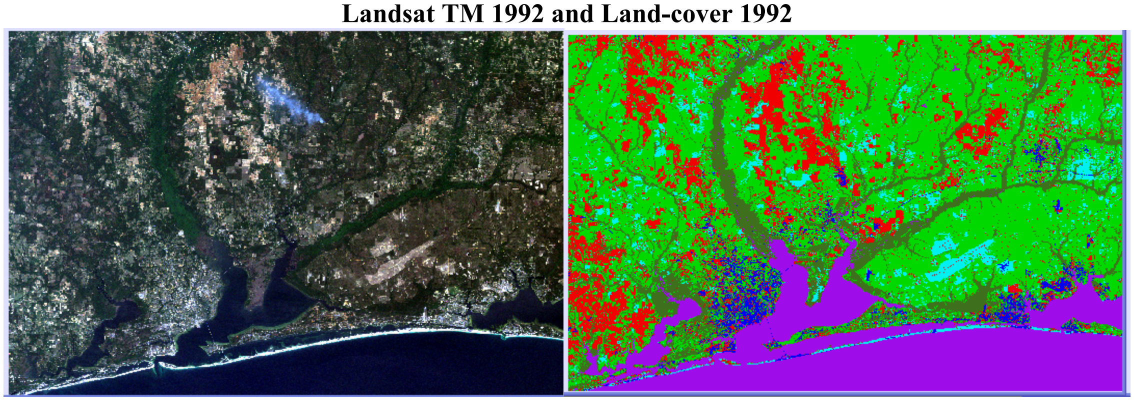
Landsat MSS 1974 and Land-cover 1974



Landsat TM 1986 and Land-cover 1986



Landsat TM 1992 and Land-cover 1992



Landsat TM 2001 and Land-cover 2001

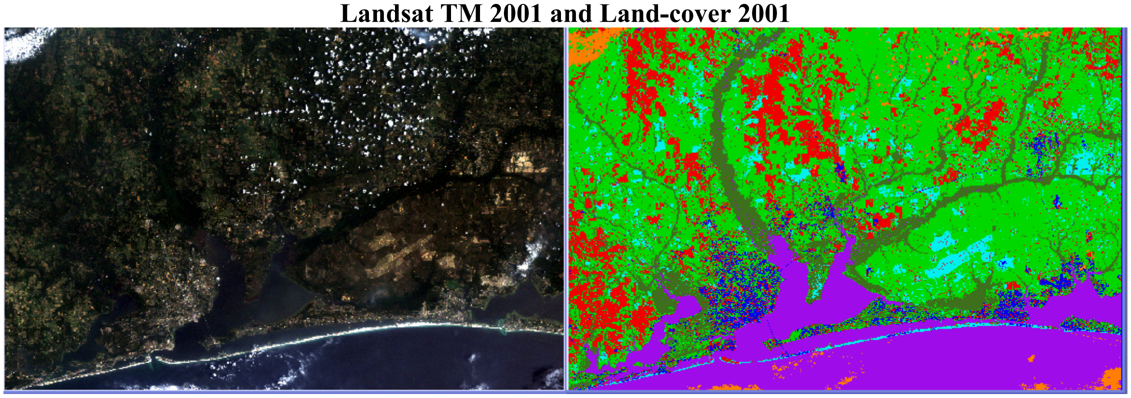


Figure 3.4: Satellite and Classified Images (Anderson Level I)

3.2. Editing Images

The classification of the Landsat images into thematic maps or land-cover datasets needs to be edited, because urban areas contain highways, airports, railroads and bridges and for dasymetric densities purposes is very important to isolated the infrastructure that will not become populated.

Therefore, using Adobe Photoshop bridges were transformed manually into water, highways and railroads into grasslands and airports into barrenlands. Also, some areas from the classified Landsat 1986 and 2001 did present significant areas with clouds. These cloudy areas were replaced with the correspondent clean areas from the land-cover 1992, using the mosaic technique from ERDAS Imagine. This process was done in order to erase these clouds because the SLEUTH model does not have this category and because it constitutes an obstacle for the dasymetric process. Finally, the land-cover from 1974 is missing a small portion of triangular shape at its left upper corner; this whole area was transferred from the 1986 classified image using ERDAS Imagine as well.

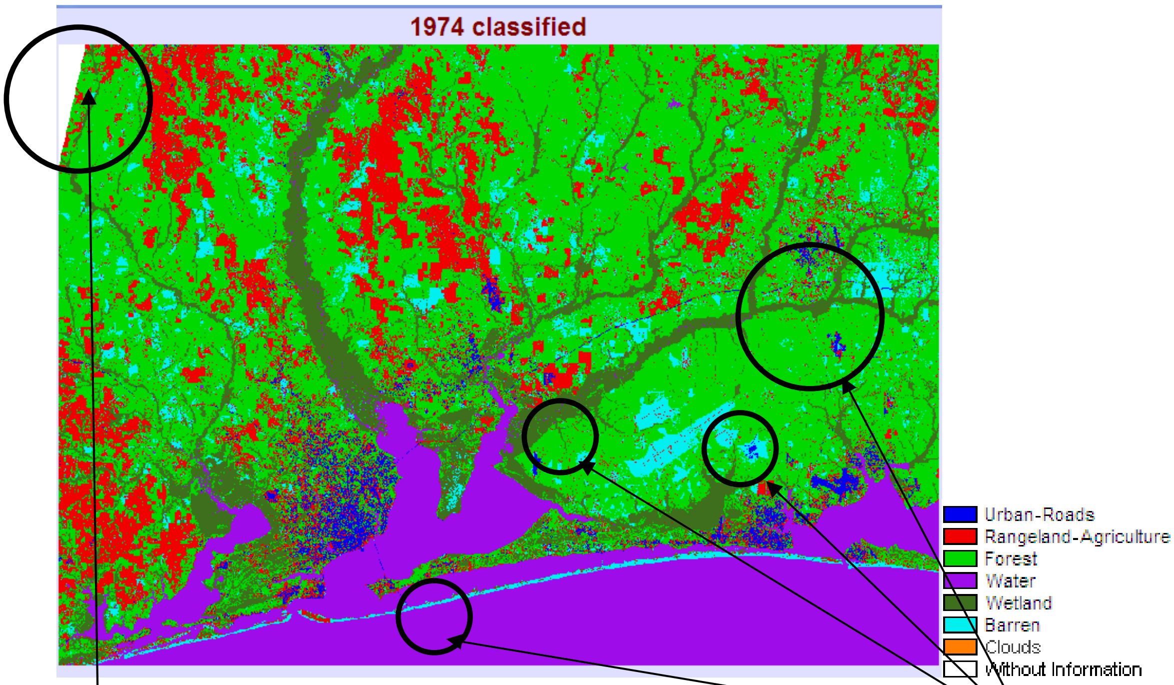


Figure 3.5: Problems found in Land-cover 1974

There is an area in the upper left corner that is outside the satellite image

There are highways, airports and bridges that need to be changed from urban into rangeland (for highways), water (for bridges) and barrenland (for airports) because when dasymetric mapping will be applied, all these pixels that appear here as urban areas cannot become populated

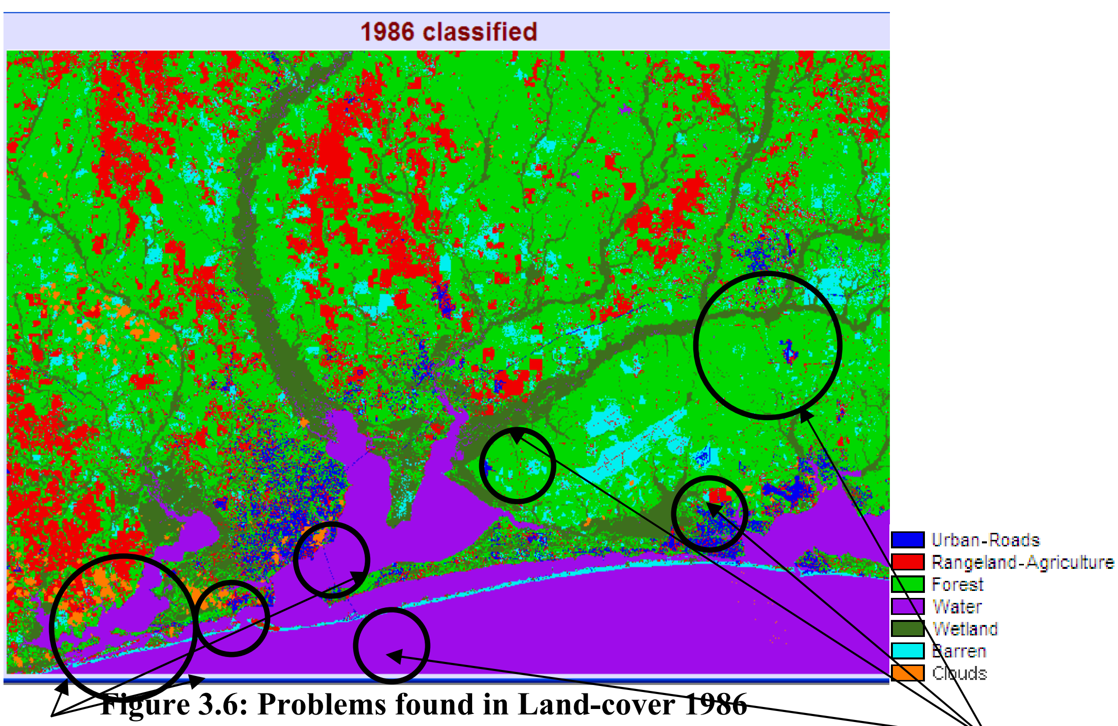


Figure 3.6: Problems found in Land-cover 1986

There are some cloud areas in the image

There are highways, airports and bridges that need to be changed from urban into rangeland (for highways), water (for bridges) and barrenland (for airports) because when dasymetric mapping will be applied, all these pixels that appear here as urban areas cannot become populated

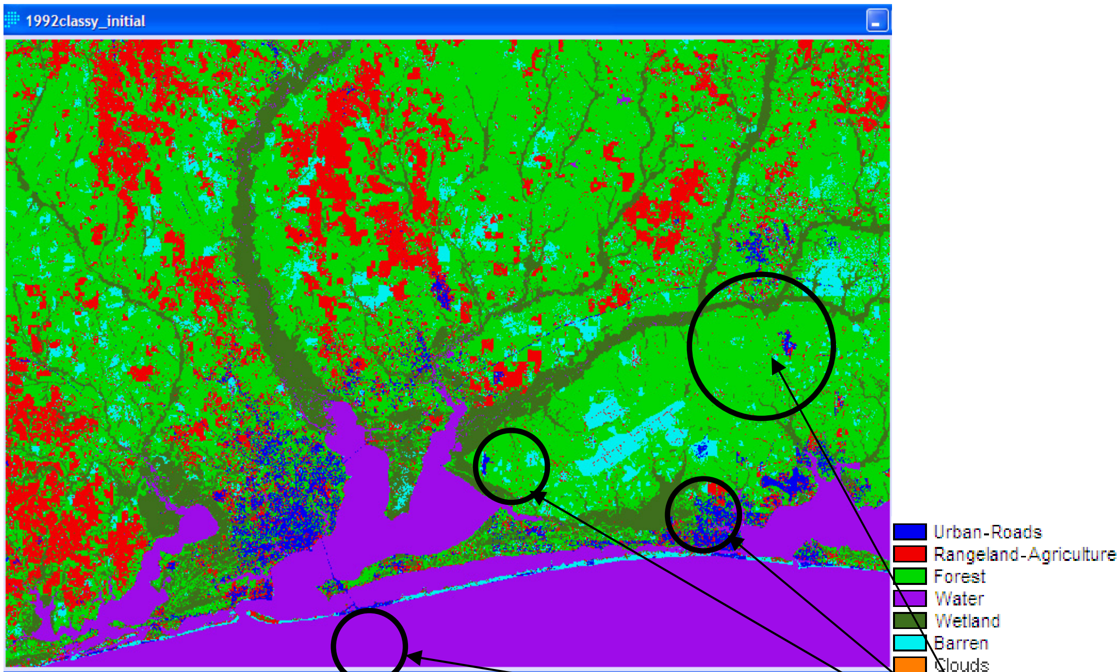


Figure 3.7: Problems found in Land-cover 1992

There are highways, airports and bridges that need to be changed from urban into rangeland (for highways), water (for bridges) and barrenland (for airports) because when dasymetric mapping will be applied, all these pixels that appear here as urban areas cannot become populated

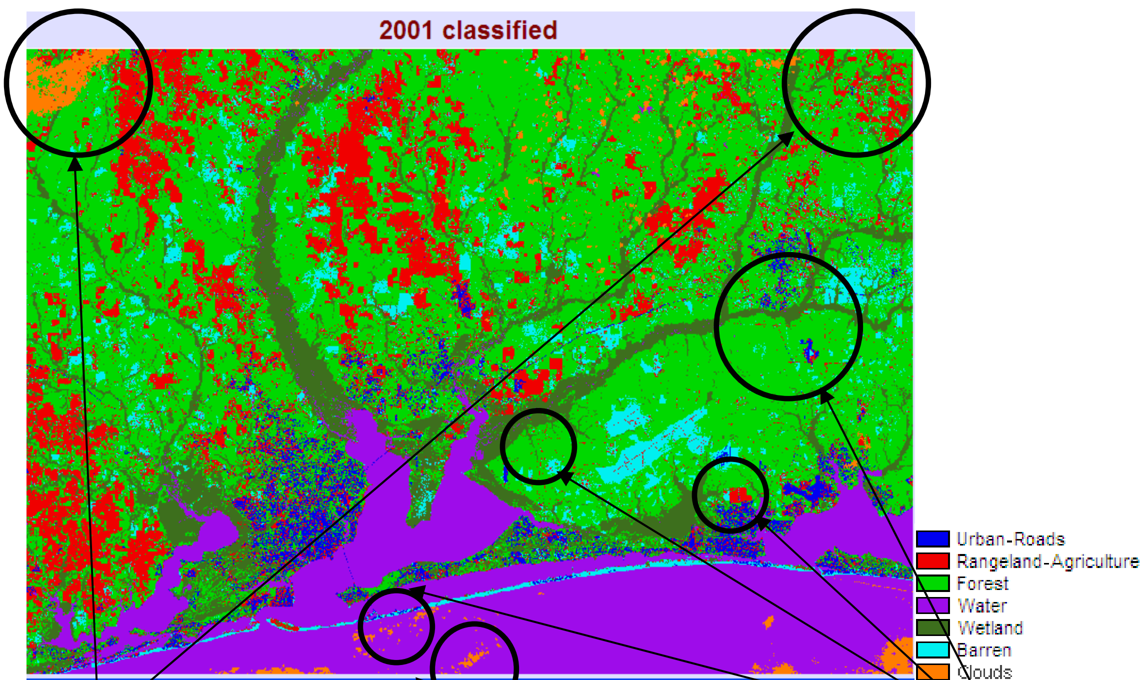


Figure 3.8: Problems found in Land-cover 2001

There are some cloud areas in the image

There are highways, airports and bridges that need to be changed from urban into rangeland (for highways), water (for bridges) and barrenland (for airports) because when dasymetric mapping will be applied, all these pixels that appear here as urban areas cannot become populated

After the problems were detected, it was necessary to begin the editing process. As mentioned, the Land-cover from 1974 has a triangular area that was not classified in the upper left corner because this region did not exist in the original Landsat 1974 image. This area containing 66,625 pixels (0.5917% of the total surface) was replaced with its corresponded land-cover from 1986 (but with a rectangular shape) using ERDAS Imagine software package. The rectangular area that was replaced is located in the following UTM WGS84 zone 16 north coordinates (see figure 3.9)

Upper Left X: 438,000	Lower Right X: 441,706
Upper Left Y: 3,431,000	Lower Right Y: 3,415,056

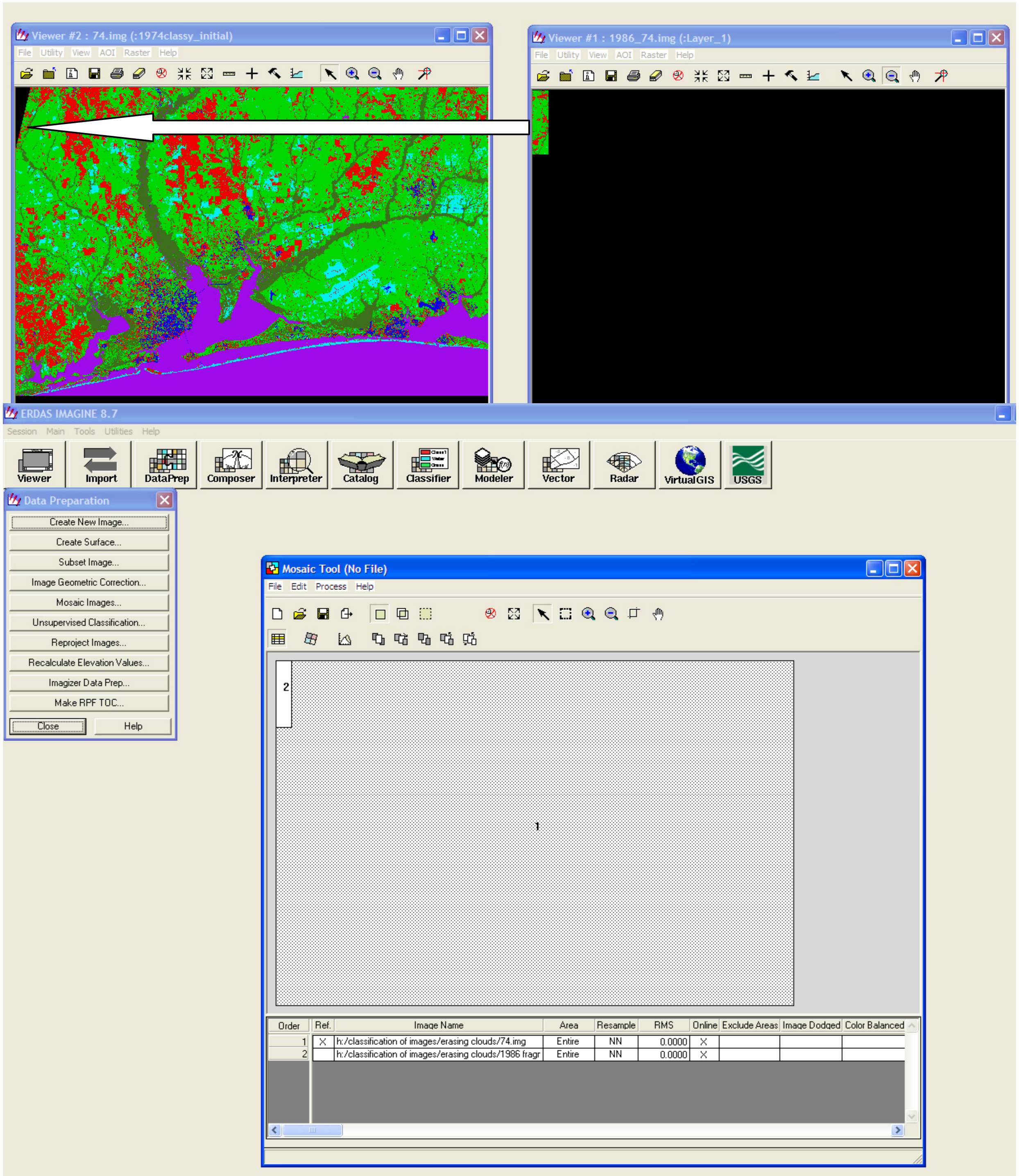


Figure 3.9: Replaced Area in the Land-cover 1974 using the Mosaic Technique

Note: This triangular area (in black) from land-cover 1974 was replaced with the rectangular area from land-cover 1986 using ERDAS Imagine software package. 66,625 pixels from 1986 (0.5917% of the total surface) are transferred from 1986 into 1974.

The next step editing the land-cover images is to remove the clouds from the land-covers 1986 and 2001 using as a template the areas from land-cover 1992, which is a totally clean image and the closest in time to both of them. In order to do this procedure, is necessary first to locate the clouds and to register its coordinates (UTM WGS84 zone 16 north) in rectangular areas that will be substituted with the clean areas from land-cover 1992.

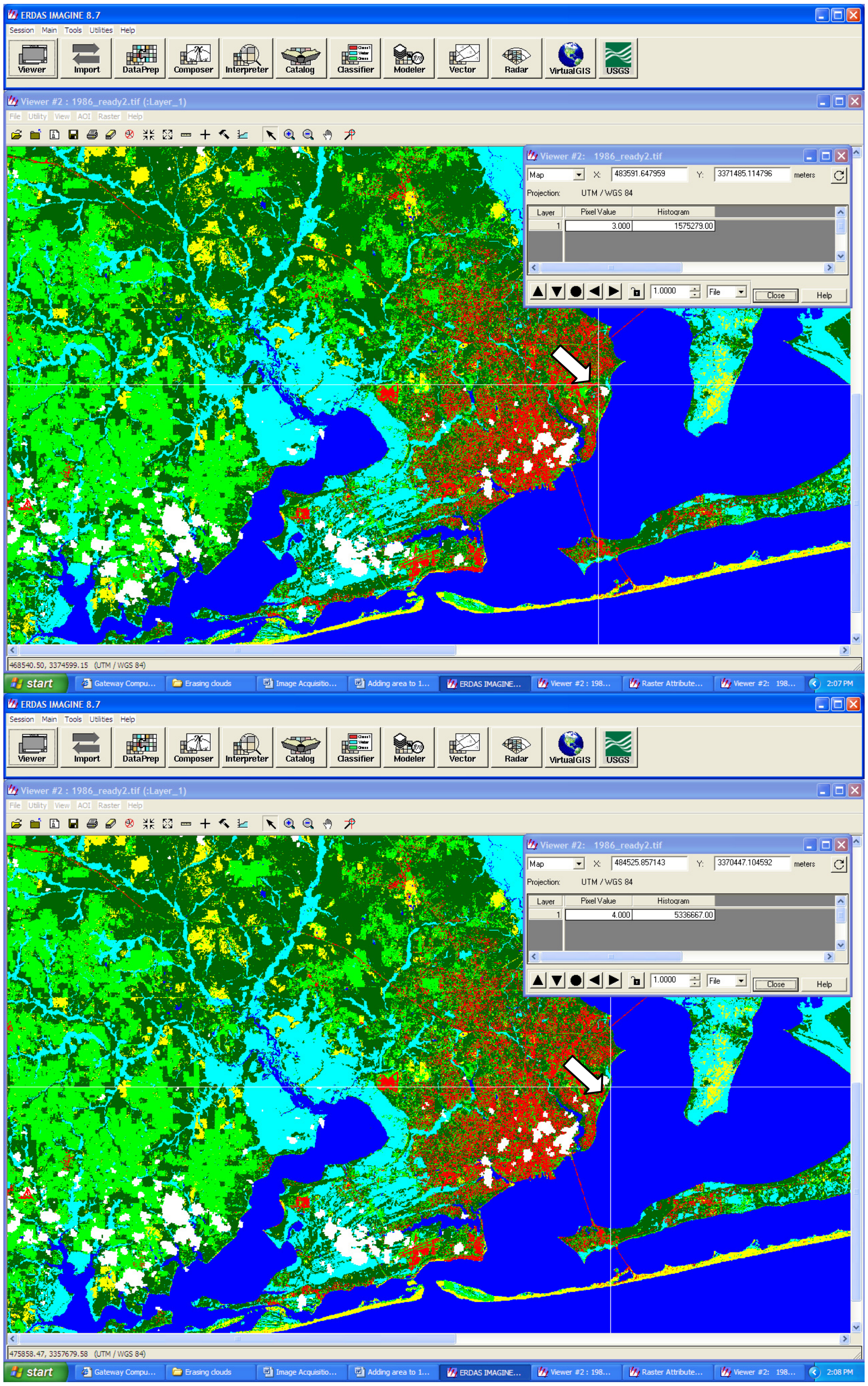


Figure 3.10: Collecting Cloudy Areas from Land-cover 1986

Note: Cloudy Area # 15 (in white color) is shown in this example

In this way, all the different coordinates that enclose the areas with clouds and its shadows in the Land-cover 1986 are chosen, as is shown in table A-I.1 in appendix I (page 331).

After determining 52 cloudy areas (in UTM WGS84 coordinates) from the Land-cover 1986, these areas will be replaced by new 52 clean areas from the Land-cover 1992 using the Mosaic function from ERDAS Imagine.

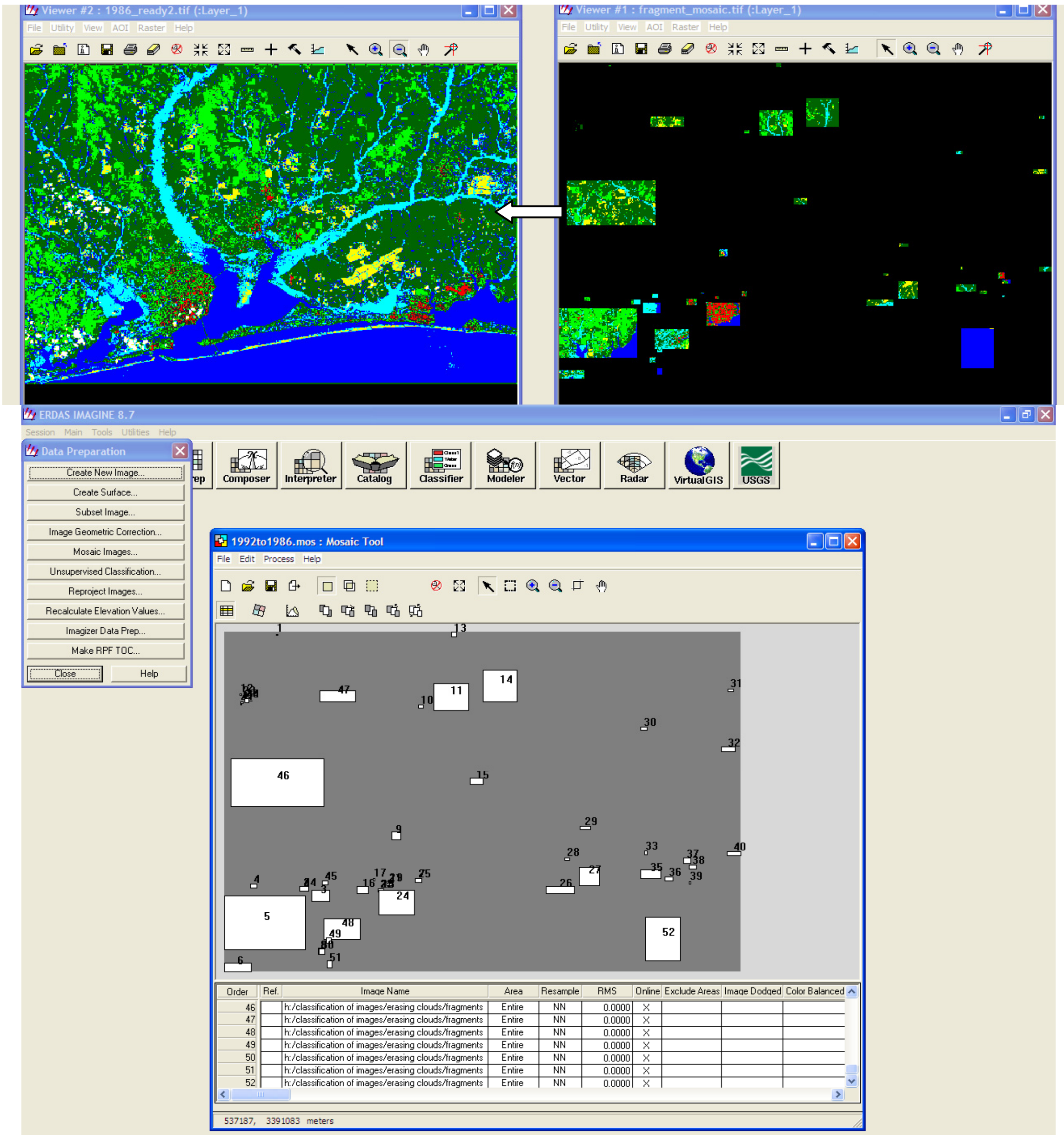


Figure 3.11: Mosaic of Land-cover 1992 showing 52 areas that will replace cloudy areas in the Land-cover 1986

Note: These 52 clean rectangular areas from Land-cover 1992 replace 52 cloudy rectangular areas from Land-cover 1986 using ERDAS Imagine software package. Upper Left Image shows Land-cover 1986. Upper Right Image shows small clean areas from the Land-cover 1992 image. 1'040,244 pixels from 1986 (9.2382% of the total surface) are transferred from 1992 into 1986.

After the 52 areas were transfer, it was determined that 1'040,244 pixels from 1986 (9.2382% of the total surface) had been transfer from Land Cove r 1992 into Land-cover 1986.

Following the process it was necessary to remove clouds from Land-cover 2001 using the same template from Land-cover 1992. Therefore, it was necessary to locate the clouds and to register its coordinates (UTM WGS84 Zone 16 North) in rectangular areas that will be substituted with the clean areas from Land-cover 1992.

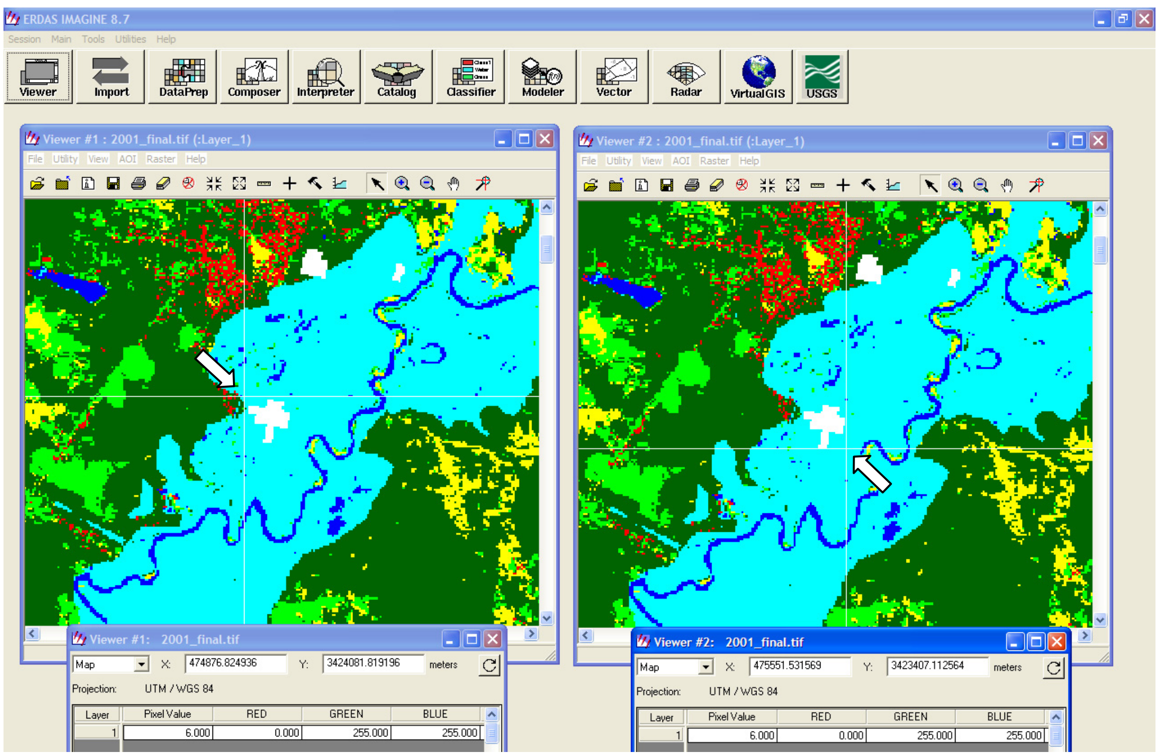


Figure 3.12: Collecting Cloudy Areas from Land-cover 2001

Note: Cloudy Area #7 is shown in this example.

All the different coordinates (the 4 corners) that enclose the 68 areas with clouds and its shadows in the Land-cover 2001 are chosen, as is shown in the table A-I.2 in appendix I (page 332).

After the 68 cloudy areas had been determined (in UTM WGS84 coordinates) from Land-cover 2001, these areas will be replaced by new 68 clean areas from the land-cover 1992 using the mosaic function from ERDAS Imagine.

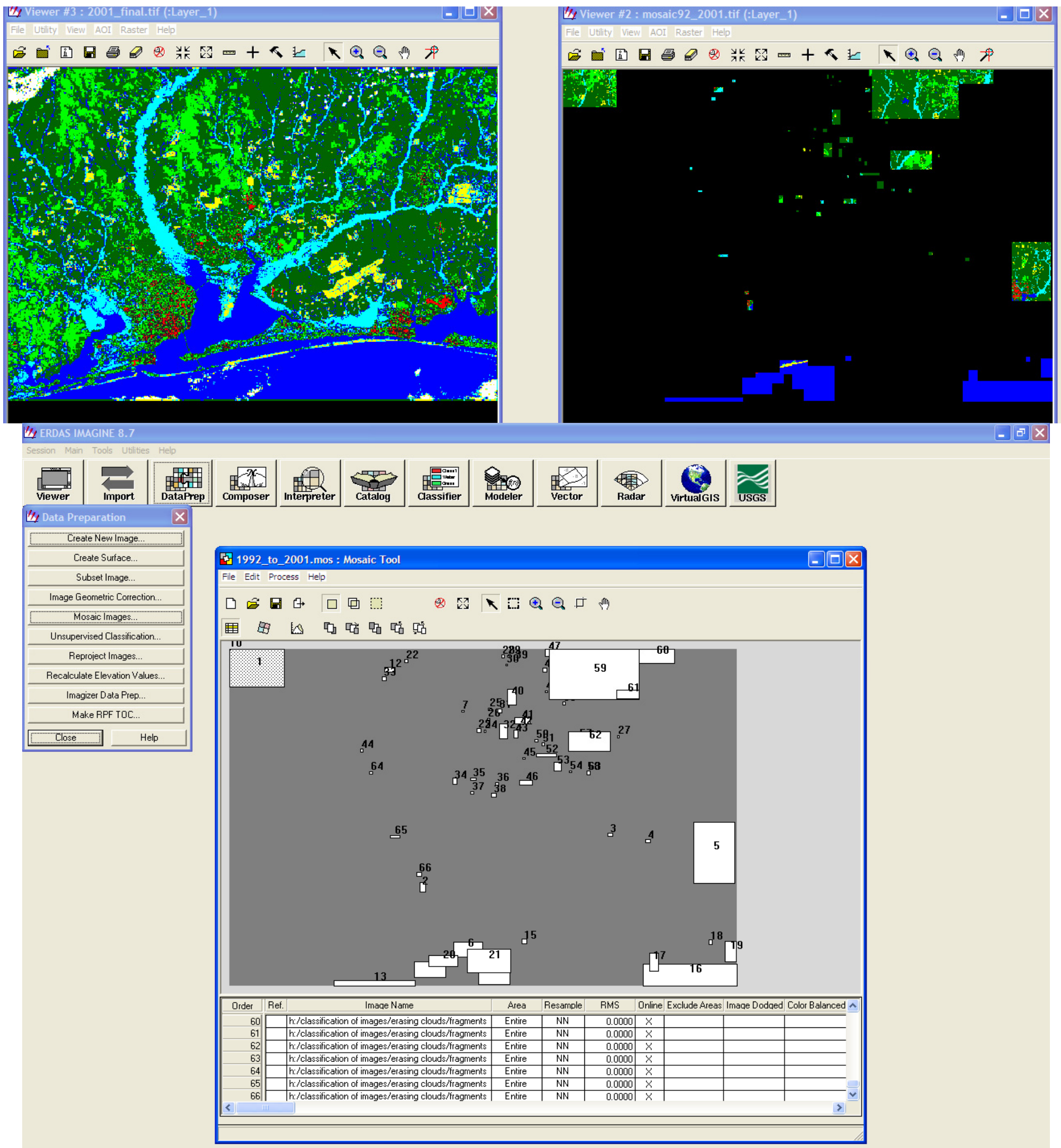


Figure 3.13: Mosaic of Land-cover 1992 showing 52 areas that will replace cloudy areas in the Land-cover 2001

Note: These 68 clean rectangular areas from Land-cover 1992 replace 68 cloudy rectangular areas from Land-cover 2001 using ERDAS Imagine software package. Upper Left Image shows Land-cover 2001. Upper Right Image shows small clean areas from the Land-cover 1992 image. 1’100,143 pixels from 1986 (9.7717% of the total surface) are transferred from 1992 into 2001.

After the 68 areas were transferred, it was possible to determine that 1'100,143 pixels from 1986 (9.7717% of the total surface) had been transfer from land cover 2001 into land-cover 1986.

As mentioned before, the highways, airports, railroads and bridges need to be erased for dasymetric densities, in order to isolate infrastructure that will not become populated. This process is done using Adobe Photoshop. In this way, bridges are manually transformed into water (sea, rivers or lakes), highways and railroads into grasslands and airports into barrenlands. In the case of the intra-urban streets, industrial parks, commercial areas and parking lots, they could not be distinguished from the residential areas, therefore all of them will be considered as urban areas and therefore will become populated to obtain dasymetric densities.

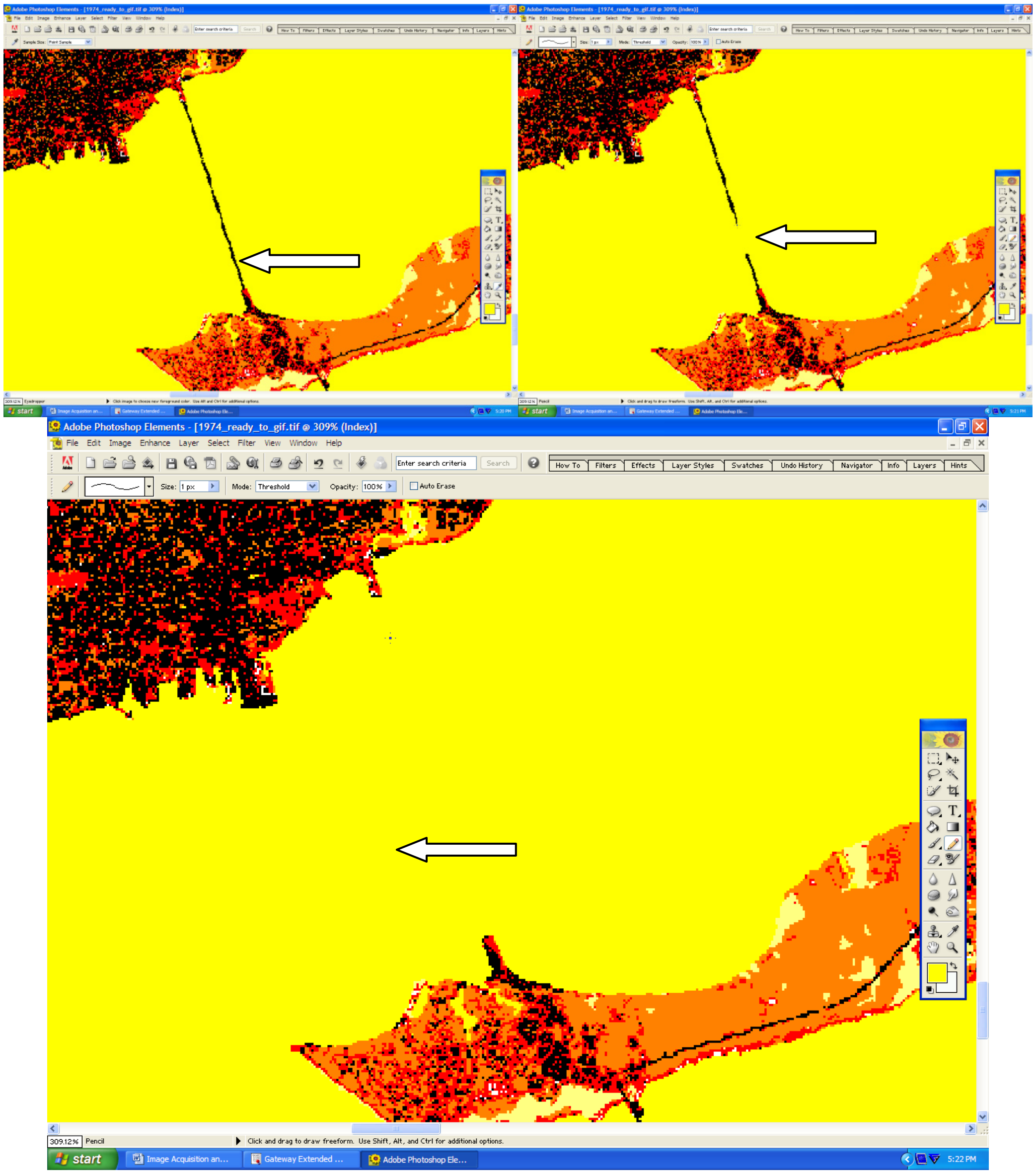


Figure 3.14: Bridges are transformed into water (sea, rivers or lakes) using Photoshop
Note: all bridges were erased in all 4 images

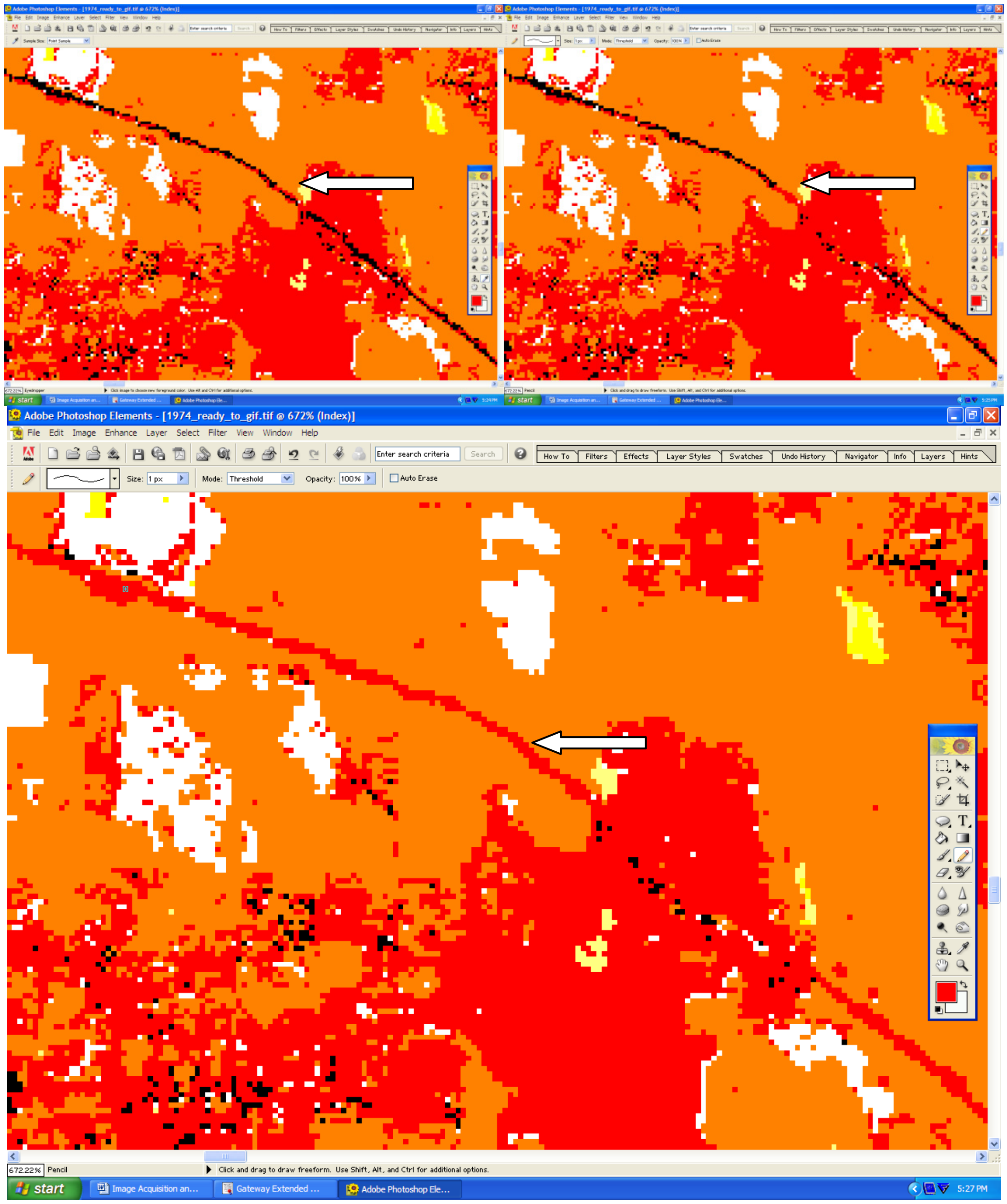


Figure 3.15: Highways are transformed into grasslands using Adobe Photoshop

Note: all highways were erased in all 4 images

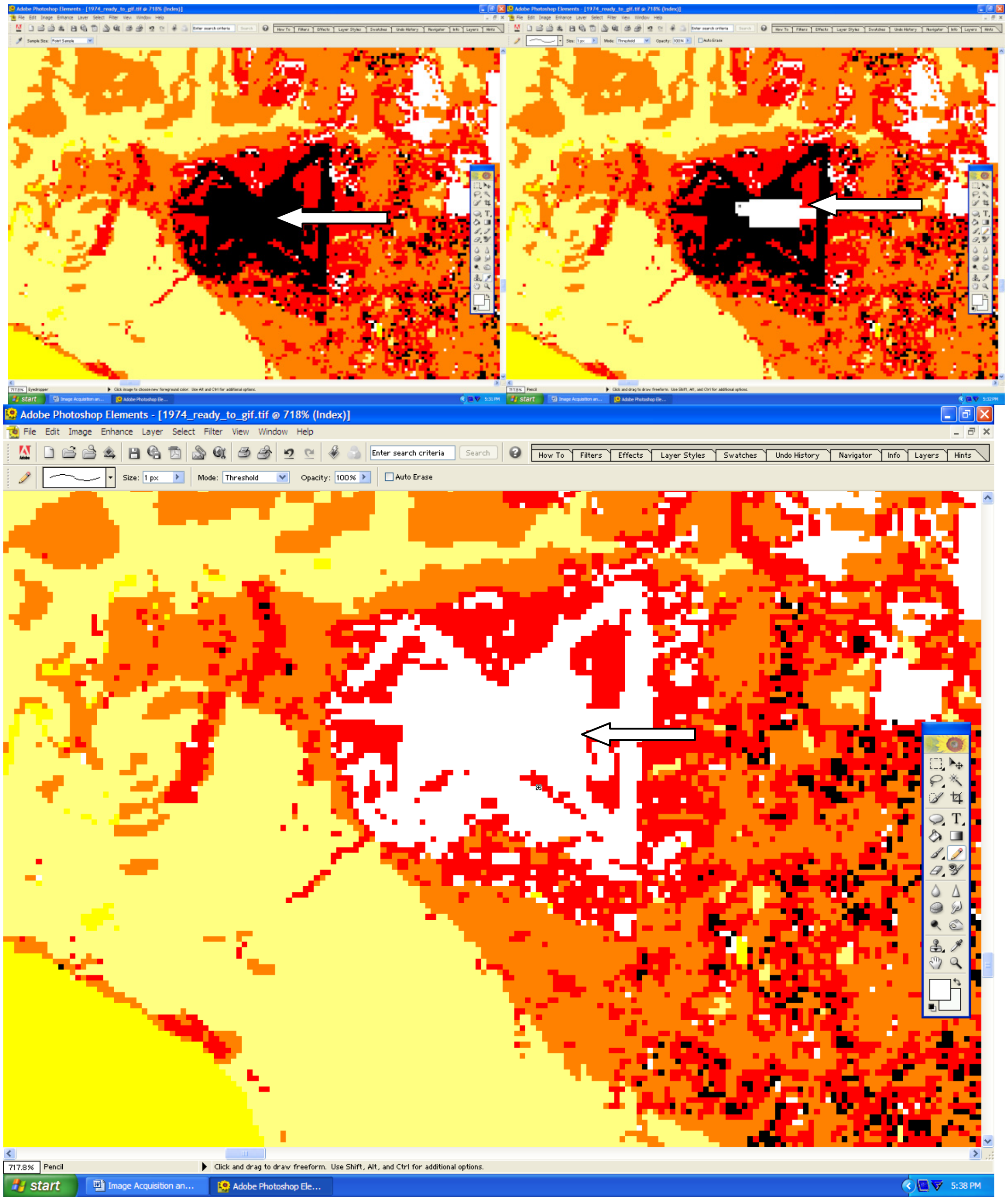


Figure 3.16: Airports are transformed into barrenlands using Adobe Photoshop
Note: all airports were erased in all 4 images

After the editing the images is done, in ERDAS Imagine all spatial statics are obtained to determine how the different landscapes had been changing since 1974 until 2001 counting the number of pixels that every one of the land-covers have in every one of the 4 time series classified Landsat images.

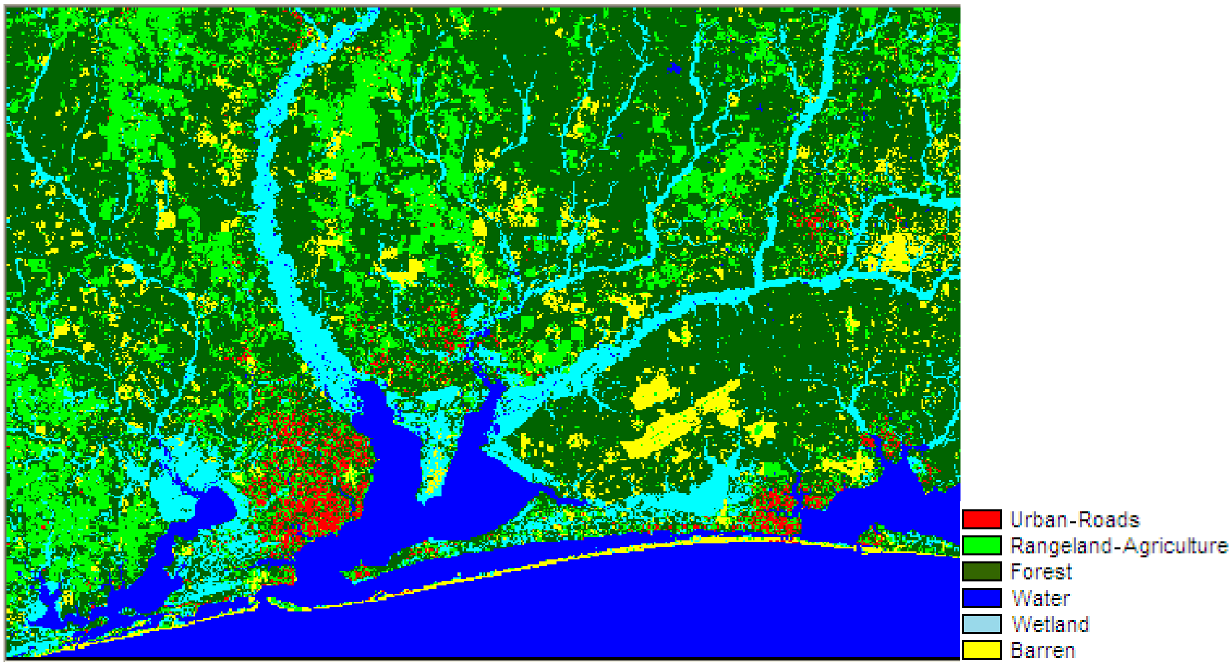


Figure 3.17: Land-cover 1974 after Editing

Note: Land-cover 1974 contains 65,844 pixels from 1986 (0.5847% of the total surface)

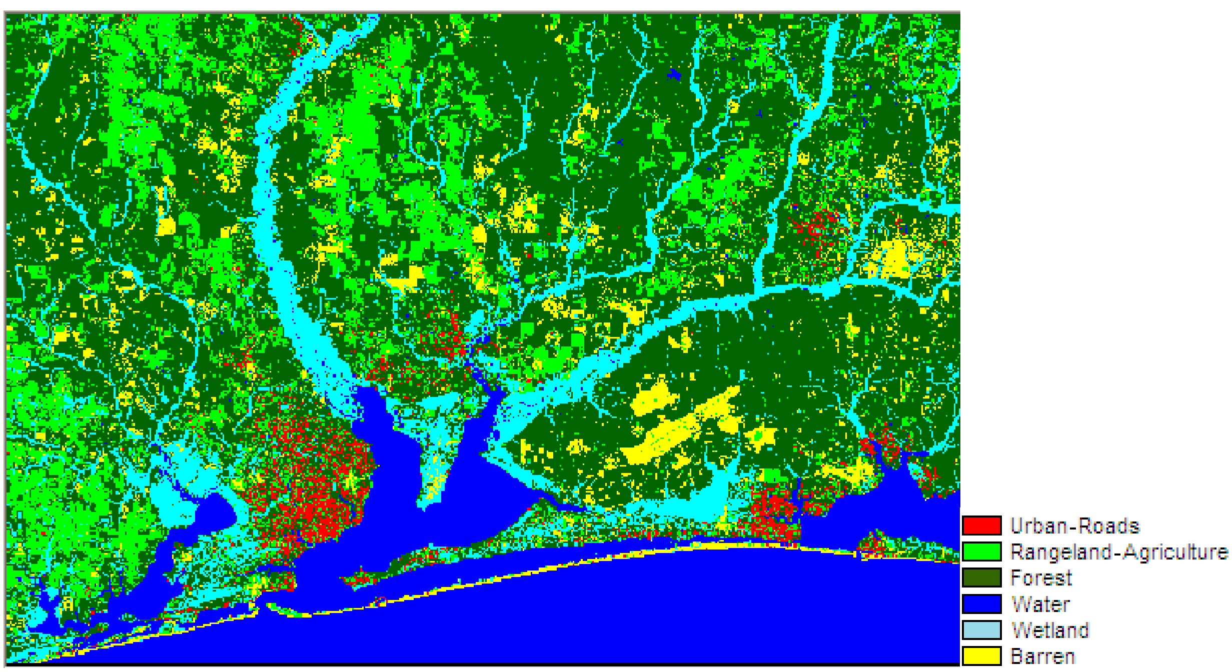


Figure 3.18: Land-cover 1986 after Editing

Note: Land-cover 1986 contains 1’040,244 pixels from 1986 (9.2382% of the total surface)

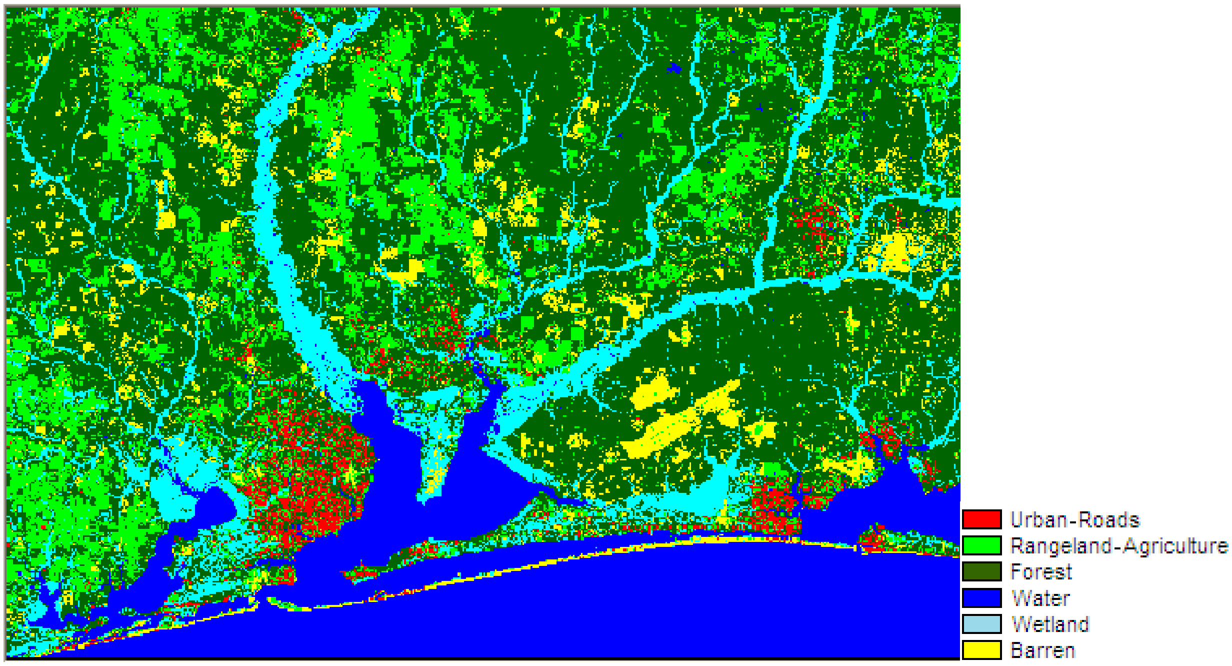


Figure 3.19: Land-cover 1992 after Editing

Note: All pixels correspond to Land-cover 1992.

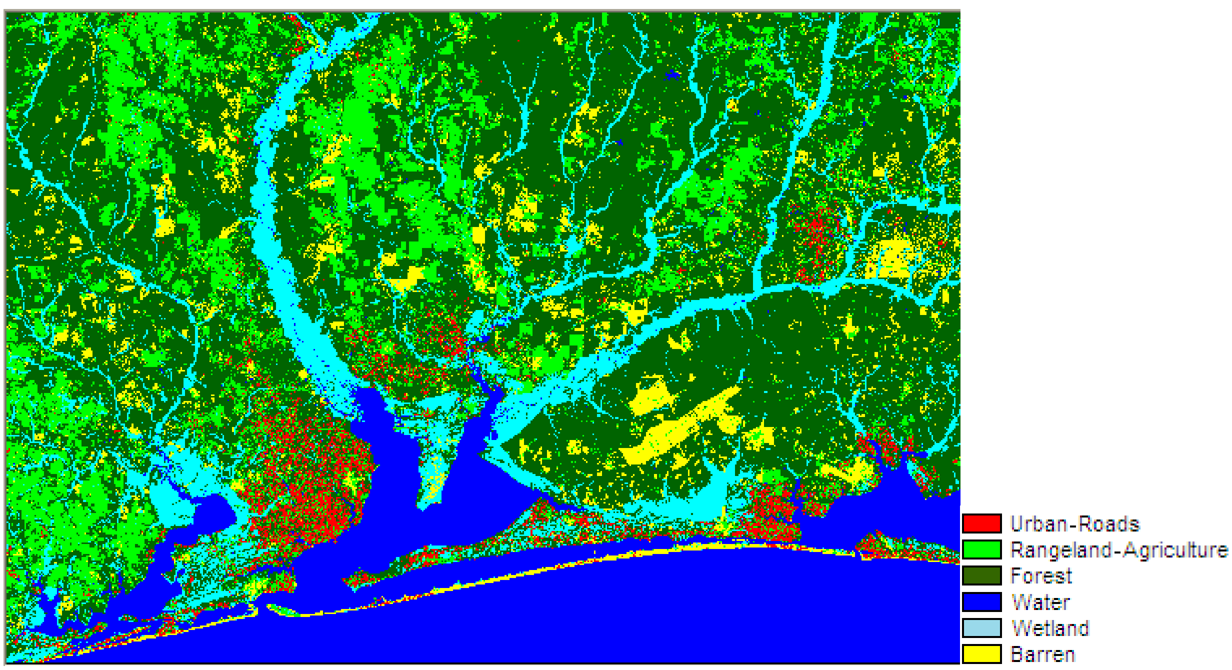


Figure 3.20: Land-cover 2001 after Editing

Note: Land-cover 2001 contains 1’100,143 pixels from 1986 (9.7717% of the total surface)

It is necessary to mention that these land-cover images are ready to be used in the SLEUTH model. Five tables are built to show the different land-cover statistics through time using surface in number of pixels, surface in Km^2, total changes in area, surface in percentages and yearly percentage of change in the land-cover maps.

Table 3.2: Surface in number of Pixels of the Land-Cover Maps

Land-cover	Area in 1974	Area in 1986	Area in 1992	Area in 2001
Urban-Roads	175,007	224,348	252,277	301,581
Rangeland-Agriculture	1,656,455	1,609,530	1,605,214	1,596,778
Forests	5,396,171	5,378,834	5,378,834	5,344,673
Water	2,126,910	2,126,923	2,126,929	2,126,788
Wetland	1,245,202	1,244,897	1,244,707	1,242,690
Barren-lands	660,479	659,502	652,263	647,714
Total Area in Pixels	**11’260,224**	**11’260,224**	**11’260,224**	**11’260,224**

Table 3.3: Surface in Km^2 of the Land-Cover Maps

Land-cover	Area in 1974	Area in 1986	Area in 1992	Area in 2001
Urban-Roads	157.51	201.91	227.05	271.42
Rangeland-Agriculture	1,490.81	1,448.58	1,444.69	1,437.10
Forests	4,856.55	4,855.52	4,840.95	4,810.21
Water	1,914.22	1,914.23	1,914.24	1,914.11
Wetland	1,120.68	1,120.41	1,120.24	1,118.42
Barren-lands	594.43	593.55	587.04	582.94
Total Area in Km^2	**10,134.20**	**10,134.20**	**10,134.20**	**10,134.20**

Table 3.4: Total Changes in Area (Km2) in the Land-Cover Maps

Land-cover	1974 - 1986	1986 - 1992	1992 - 2001
Urban-Roads	44.40	25.14	44.37
Rangeland-Agriculture	-42.23	-3.89	-7.59
Forests	-1.03	-14.57	-30.74
Water	0.01	0.01	-0.13
Wetland	-0.27	-0.17	-1.82
Barren-lands	-0.88	-6.51	-4.10

Table 3.5: Surface in Percentages (%) of the Land-Cover Maps

Land-cover	**Area in 1974**	**Area in 1986**	**Area in 1992**	**Area in 2001**
Urban-Roads	1.55%	1.99%	2.24%	2.68%
Rangeland-Agriculture	14.71%	14.29%	14.26%	14.18%
Forests	47.92%	47.91%	47.77%	47.47%
Water	18.89%	18.89%	18.89%	18.89%
Wetland	11.06%	11.06%	11.05%	11.04%
Barren-lands	5.87%	5.86%	5.79%	5.75%
Total Percentage	**100.00%**	**100.00%**	**100.00%**	**100.00%**

Table 3.6: Yearly Percentage (%) of Change in the Land-Cover Maps

Land-cover	**1974 - 1986**	**1986 - 1992**	**1992 - 2001**
Urban-Roads	2.09%	1.97%	2.00%
Rangeland-Agriculture	-0.24%	-0.04%	-0.06%
Forests	-0.03%	0.00%	-0.07%
Water	0.00%	0.00%	0.00%
Wetland	0.00%	0.00%	-0.02%
Barren-lands	-0.01%	-0.18%	-0.08%

Most changes through time happen in the urban-roads land-cover type, because in 1974 this type constituted just 1.55% of the total surface and in 2001 it went up to 2.68%, growing yearly from a minimum of 1.97% (between 1986-1992) and a maximum of 2.09% (between 1974-1986). In the last period the yearly growth rate was 2.00% (1992-2001). In 1974 urban-roads had a surface of 157.51 Km^2 and in 2001 the area was 271.42 Km^2, a total expansion of 113.91 Km^2 more.

Rangeland, agriculture and grasslands decreased from 14.71% of the total surface in 1974 to 14.18% in 2001. The yearly rates of decrease were -0.24 % in the period 1974-1986, -0.04% between 1986 and 1992 and -0.06% in the last stage 1992-2001. In absolute terms, this land-cover went down from 1,490.81 Km^2 in 1974 to 1,437.10 in 2001, a total loss of 53.71 Km^2, especially in the period 1974-1986, when -42.23 Km^2 were transformed into urban areas. Also this period contains the greatest amount of time (12 years).

Forest areas also decreased from 47.92 % of the total surface in 1974 to 47.47% in 2001. The yearly rates of decrease were -0.03% between 1974 and 1986, 0.00% in the period 1986-1992 and just -0.06% in the last stage 1992-2001. In square kilometers, this land-cover went down from 4,856.55 Km2 in 1974 to 4,810.21 Km^2 in 2001, a total loss of 46.34 Km^2, particularly in the period 1992-2001 (9 years), when -30.74 Km^2 were transformed most into urban areas.

The Barren lands also suffered a small decreased, representing 5.87% of the total surface in 1974 whereas in 2001 they became 5.75%. The yearly rates of decrease were -0.01% in the period 1974- 1986, -0.18% between 1986 and 1992 and -0.08% in the last stage 1992-2001. In absolute terms, this land-cover went down from 594.43 Km2 in 1974 to 582.94 Km^2 in 2001, a total reduction of 11.49 Km^2, especially in two periods: between 1986 and 1992 and in the period 1992-2001 when -6.51 Km^2 and 4.10Km^2 became new urban areas. It is important to indicate that there has been a strong attraction in the last years for urban development in the islands, especially inside Santa Rosa island, where numerous protected areas exist.

Because wetlands constitute protected areas and it is not possible to urbanize in water, these two land-covers had been maintained with almost the same surface during this 27 years. In 1974, wetlands constitute 11.06% of the total surface (1,120.68 Km^2) and in 2001 this percentage was almost the same: 11.04% or 1,118.42 Km^2. In the case of the water land-cover (lakes, rivers and sea), in 1974 it constitutes 18.89% of the total area of the region and 1,914.22 Km^2 and in 2001 it was basically the same: 18.89% or 1,914.11 Km^2, in other words there have been no change.

3.3. Accuracy Evaluation

The sample points (in a random way according to where features are easily identified in the high-resolution images) taken from air photos and DOQQs from the USGS (representing ground-truth) are compared against the classified image in a error matrix in order to show the accuracy of the classified images (through the maximum likelihood classifier method) in relation to the ground-truth (USGS raster datasets). Just in the case of the Land-cover image 1992, this thematic map will be compared against random sample points from a previously classified land-cover made by USGS called National Land-cover Data (NLCD) for the year 1992.

As a broad guideline, it has been suggested that at least 50 samples points of each land-cover category be included in the error matrix. And if the area is too large or there are more than 12 land-cover categories, the minimum number of samples should be 75 or 100 points per category (Congalton and Green 1999).

In this specific case, accuracy classification is performed selecting 250 random points per land-cover (a total of 1,500 random ground-truth sample points from higher-resolution imagery). In order to test the accuracy classification of Land-cover 1974, 125 USGS black and white aerial photos taken in 1976 at scale 1:80,000 were used. To test the accuracy classification of Land-cover 1986, 90 Color Infrared National High Altitude Photography from 1986 were used. Land-cover 1992 was compared against 1,500 random points obtained from USGS National Land-cover Data (NLCD) for the year 1992 with a spatial resolution of 30m and previously tested by USGS for accuracy above 85%. And finally to test the accuracy of the Land-cover 2001, 75 DOQQs (color infra-red) at 3.75 min from January 1999 were used.

Table 3.7: Land-cover compared against Higher-resolution Imagery to test Classification Accuracy

Land-cover	Higher-resolution Imagery
Land-cover 1974	125 USGS black and white aerial photos taken in 1976 at scale 1:80,000
Land-cover 1986	90 Color Infrared National High Altitude Photography from 1986
Land-cover 1992	1,500 random points obtained from USGS National Land-cover Data (NLCD) for the year 1992 with a spatial resolution of 30m
Land-cover 2001	75 Digital Orthoimagery Quarter Quadrangles (DOQQs) (color infra-red) at 3.75 min from January 1999

All these higher-resolution imagery were obtained from USGS web page using Earth Explorer search. The only exception was the USGS National Land-cover Data (NLCD) from the year 1992 that was downloaded from the USGS NLCD web page.

Using ERDAS Imagine software package, two windows were opened: one for the geo-referenced satellite image (upper left) and other one for the classified satellite image or land-cover (upper right). The coordinates (UTM WGS 84) were taken from every one of the sample points. Additionally, a third window shows the different higher-resolution photos or USGS NLCD 1992 to provide a better view of the landscape and to facilitate the selection of sample points (lower left). Because of the higher-resolution photograph, it was possible to have the confidence that every random point in the real world (higher-resolution photography) represents the desire sample of a specific land-cover. In this way, knowing the coordinates (UTM WGS 84) of every one of the 250 random points per land-cover (1,500 points totally), it was possible to select them using ArcMap. In the lower right window is possible to visualize the selected land-cover points with a radius increased in ArcMap.

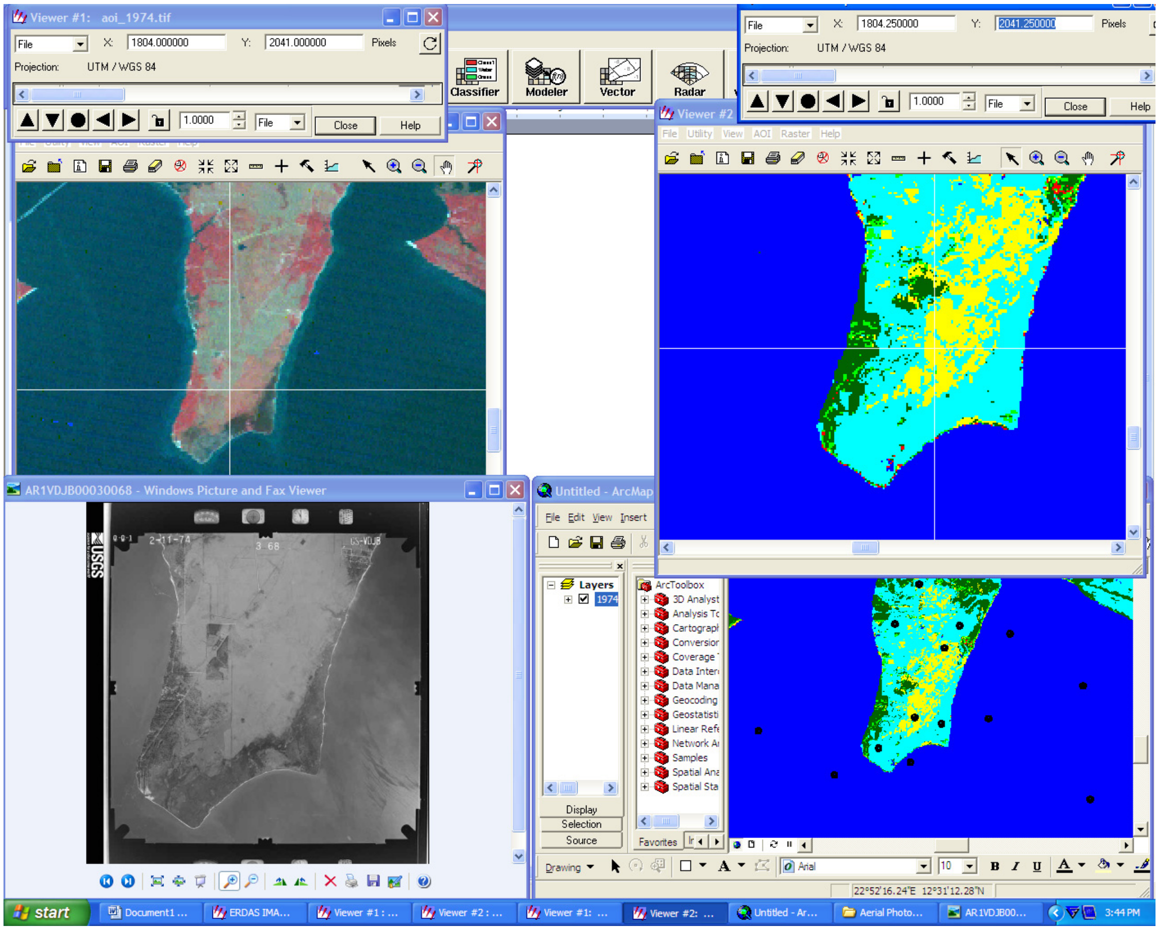


Figure 3.21: Selecting Random Sample Points for Accuracy Evaluation

Notes: This is an example of how points were selected for the year 1974.
Georeferenced satellite image in ERDAS Imagine (upper left).
Classified satellite image or land-cover in ERDAS Imagine (upper right).
Higher-resolution photo (lower left).
Selected land-cover points with a radius increased (lower right) in ArcMap.

After the coordinates of 1,500 points had been selected (250 per land-cover category) in the higher-resolution imagery or from USGS NLCD 1992, and transferred all these point coordinates into Arc Map, the resulting image looks almost entire black with few color pixels (just 1,500 from a total of 11,260,224), representing the six land-covers (urban, agriculture-rangeland, forest, water, wetland and barrenland) used in this research.

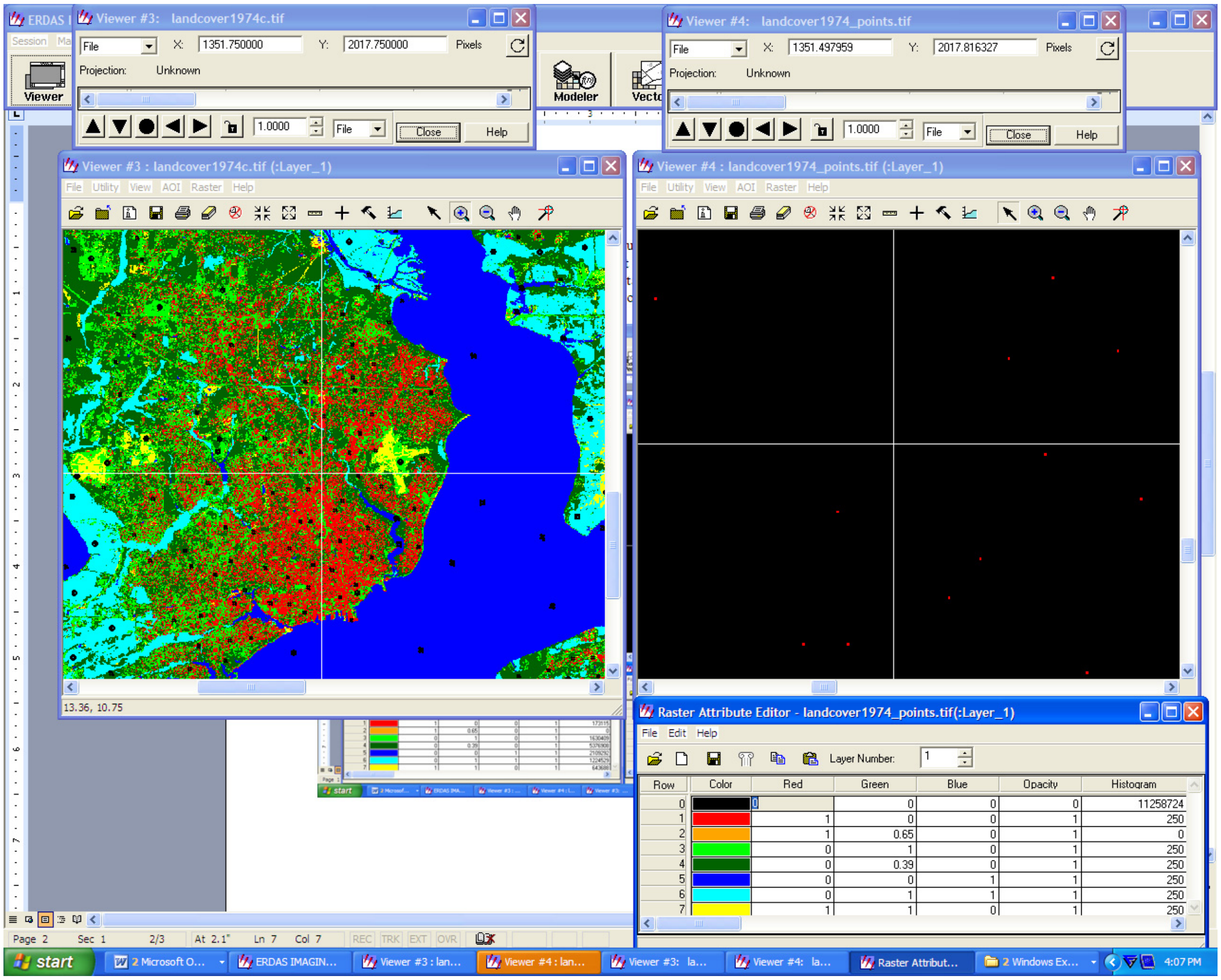


Figure 3.22: Random Points used as a sample (ground-truth) to Test Classification Accuracy

Note: Upper left window contains randomly selected black dots representing different land-cover classes. Upper right window contains the resulting image which looks almost entire black but in reality it contains very small selected pixels, each one with their own color representing their respective land-cover. The Attribute window (lower right) indicates that 1,500 sample points (250 per category) were taken from the image to test classification accuracy.

Assessing the accuracy of classification in digital images is a very important process because the results indicate the quality of the different satellite images and the ability of the classifier algorithm to meet some minimum threshold accuracy (at least 85%) to be used after for different kinds of applications at the local, regional and continental scales.

Accuracy results are computed through weighting cell percentages by the proportion of each land-cover within a given region. Accuracy results are reported using several definitions of agreement between the map and primary or alternate reference sample points. A direct comparison at each pixel of the classified image with the corresponding labeled points from USGS photos (pixel-to-pixel comparison) is the best protocol for defining agreement. It reflects a "conservative bias" (Verbyla and Hammond 1995) due to the confounding of true classification error with errors attributable to miss-registration.

The producer's and user's accuracy is an indication of the accuracy of the individual classes. The producer's accuracy relates to the probability that a reference sample (photo-interpreted land-cover class in this project) will be correctly mapped and measures the errors of omission (1 - producer's accuracy). In contrast, the reliability of the classes being accurately classified is measured by the user's accuracy. The user's accuracy indicates the probability that a sample from land-cover map actually matches what it is from the reference data (photo-interpreted land-cover class in this project) and measures the error of commission (1 - user's accuracy). From the overall accuracy of an image assessed, it is possible to determine also the margin of error (1 - overall's accuracy) per image.

The Overall Accuracy or Percentage of Agreement is computed by dividing the total correct (sum of the major diagonal) by the total number of pixels of the error matrix. The producer's accuracy is obtained dividing the number of correct pixels in a specific category by the total number of pixels in the column Total and measures the probability of a reference pixel being correctly classified (it is a measure of omission error). The user's accuracy is obtained dividing the number of correct pixels in a specific category by the total number of pixels in the row Total and measures the probability of a pixel classified represents that category in the ground (it is a measure of commission error). A comparison of the different percentages of errors and the different producer's and user's accuracies in the error matrices will determine which categories had been classified better and which categories had been classified worst by the algorithm classifier.

Because the percentage of agreement does not take into account the proportion of agreement between data sets that is due to chance, it tends to overestimate classification accuracy. Therefore, it is necessary to calculate also the Kappa index, which is a multivariate technique that measures the proportion of agreement after chance agreement is removed from consideration (Lillesand and Kieffer 2000). The formula to obtain the Kappa index is:

$$K = \frac{N\sum^{r} x_{ii} - \sum^{r}(x_i \times x_{+i})}{N^2 - \sum^{r}(x_i \times x_{+i})}$$

Where:

K = Kappa index

r = number of rows in the error matrix

$x_{i\,i}$= the number of observations in row i and column i (on the major diagonal)

x_i = total of observations in row i (shown as marginal total to right of the matrix)

$x_{+\,i}$= total of observations in column i (shown as marginal total at bottom of the matrix)

N = total number of observations included in matrix

Some programs are able to calculate Kappa coefficient of agreement (Congalton 1991) and automatically are computed from the error matrix. Also, it is possible to compare Kappa indices for each class or category within the image. This categorical comparison is very useful because it is possible to determine in which categories the Gaussian maximum likelihood classifier is having more problems of classification. The idea is to calibrate the algorithm to achieve better classifications. It is also important to indicate that the levels of accuracy with Kappa indexes in general are smaller than using normal percentages of agreements.

The error matrices and the Kappa index of agreement produced in Idrisi between the 1,500 random sample points (ground-truth) and the classified land-covers show levels of agreement above the necessary 85%. For example, the overall Kappa index of agreement varies between a minimum of 87.00% for land-cover 1976 and a maximum of 90.24% for land-cover 2001. For land-covers 1986 and 1992 the Kappa values were 88.24% and 89.52% respectively.

Table 3.8: Error Matrix and Kappa Indexes of POINTS74 (columns: truth) against LANDCOVER74 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**205**	3	7	1	4	8	228	10.09%
3	22	**225**	13	2	4	4	270	16.67%
4	9	11	**224**	0	6	6	256	12.50%
5	4	1	0	**245**	1	9	260	05.77%
6	3	4	3	2	**231**	7	250	07.60%
7	7	6	3	0	4	**216**	236	08.47%
Total	250	250	250	250	250	250	**1500**	
Error O	18.00%	10.00%	10.40%	2.00%	7.60%	13.60%		10.27%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.29% (8.98% - 11.56%)
95% Confidence Interval = +/- 1.54% (8.73% - 11.80%)
99% Confidence Interval = +/- 2.02% (8.24% - 12.29%)

KAPPA INDEX OF AGREEMENT (KIA)

Using LANDCOVER74 as the reference image

Category	KIA
1	87.89%
3	80.00%
4	85.00%
5	93.08%
6	90.88%
7	89.83%

Using POINTS74 as the reference image

Category	KIA
1	78.77%
3	87.80%
4	87.46%
5	97.58%
6	90.88%
7	83.86%

Overall Kappa = 87.00%

Table 3.9: Error Matrix and Kappa Indexes of POINTS86 (columns: truth) against LANDCOVER86 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**217**	5	3	2	3	4	234	7.26%
3	16	**222**	15	2	4	5	264	15.91%
4	7	15	**220**	0	8	6	256	14.06%
5	4	0	3	**243**	1	8	259	6.18%
6	2	3	6	3	**230**	6	250	8.00%
7	4	5	3	0	4	**221**	237	6.75%
Total	250	250	250	250	250	250	**1500**	
Error O	13.20%	11.20%	12.00%	2.80%	8.00%	11.60%		9.80%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.26% (8.54% - 11.06%)
95% Confidence Interval = +/- 1.50% (8.30% - 11.30%)
99% Confidence Interval = +/- 1.98% (7.82% - 11.78%)

KAPPA INDEX OF AGREEMENT (KIA)

Using LANDCOVER86 as the reference image

Category	KIA
1	91.28%
3	80.91%
4	83.12%
5	92.59%
6	90.40%
7	91.90%

Using POINTS86 as the reference image

Category	KIA
1	84.36%
3	86.41%
4	85.53%
5	96.62%
6	90.40%
7	86.22%

Overall Kappa = 88.24%

Table 3.10: Error Matrix and Kappa Indexes of POINTS92 (columns: truth) against LANDCOVER92 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**207**	8	10	1	6	6	238	13.03%
3	16	**234**	3	0	3	6	262	10.69%
4	11	5	**226**	2	5	5	254	11.02%
5	1	1	2	**246**	1	8	259	5.02%
6	4	1	6	1	**234**	3	249	6.02%
7	11	1	3	0	1	**222**	238	6.72%
Total	250	250	250	250	250	250	**1500**	
Error O	17.20%	6.40%	9.60%	1.60%	6.40%	11.20%		0.0873%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.20% (753% - 9.93%)
95% Confidence Interval = +/- 1.43% (730% – 10.16%)
99% Confidence Interval = +/- 1.88% (685% – 10.61%)

KAPPA INDEX OF AGREEMENT (KIA)

Using LANDCOVER92 as the reference image

Category	KIA
1	84.37%
3	87.18%
4	86.77%
5	93.98%
6	92.77%
7	91.93%

Using POINTS92 as the reference image

Category	KIA
1	79.56%
3	92.25%
4	88.44%
5	98.07%
6	92.33%
7	86.69%

Overall Kappa = 89.52%

Table 3.11: Error Matrix and Kappa Indexes of POINTS01 (columns: truth) against LANCOVER01 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**220**	3	3	1	3	3	233	0.0558
3	17	**229**	13	3	1	4	267	0.1423
4	5	8	**228**	0	6	7	254	0.1024
5	3	1	1	**245**	1	8	259	0.0541
6	1	5	3	1	**234**	6	250	0.0640
7	4	4	2	0	5	**222**	237	0.0633
Total	250	250	250	250	250	250	**1500**	
Error O	0.1200	0.0840	0.0880	0.0200	0.0640	0.1120		0.0813

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission (expressed as percentages)
ErrorC = Errors of Commission (expressed as percentages)
90% Confidence Interval = +/- 0.0116 (0.0697 - 0.0929)
95% Confidence Interval = +/- 0.0138 (0.0675 - 0.0952)
99% Confidence Interval = +/- 0.0182 (0.0631 - 0.0995)

KAPPA INDEX OF AGREEMENT (KIA)

Using LANDCOVER01 as the reference image

Category	KIA
1	0.9330
3	0.8292
4	0.8772
5	0.9351
6	0.9232
7	0.9241

Using POINTS01 as the reference image

Category	KIA
1	0.8579
3	0.8978
4	0.8941
5	0.9758
6	0.9232
7	0.8670

Overall Kappa = 0.9024

Analyzing these error matrices and Kappa indexes is possible to determine the categories with the lowest classification accuracy as well as the categories with the highest accuracy. When errors are equal or above the threshold of 15.00%, they are represented in red color. The same red color is applied when there are 15 or more mismatches among pixels (see inside error matrices). But if there are almost no errors, equal or below the threshold of 5.00%, they are represented in blue color. The same blue color is applied when there are 5 or less mismatches among pixels inside the error matrices. Black color represents errors with values between 5.00% and 15.00% or between 5 and 15 mismatches among pixels. Finally all the data with bold black color represent in the main diagonals of the error matrices show the level of accuracy among categories. Overall Kappa also is shown in bold black color.

It is also important to remember the numbers applied to each category: 1=urban; 3=agriculture-rangeland; 4=forests; 5=water; 6=wetlands and 7=barrenlands.

In all error matrices, most errors occur between categories urban (1) and agriculture-rangeland (3): 22 errors in land-cover 1974, 16 errors in land-cover 1986, 16 errors in land-cover 1992 and 17 errors in Land-cover 2001. Also, analyzing the accuracy of Land-cover 1986, 15 errors occurred between categories agriculture-rangeland (3) and forests (4). It is possible that all these errors were made selecting the polygons for urban development in suburbs and residential areas, because using 30m ($900m^2$) resolution Landsat images makes difficult to differentiate small houses (less than $300m^2$) from its surroundings, generally yards, grasses and trees. The same mistake in the selection of the urban areas can explain the confusion in the classifier algorithm between agriculture-rangeland and forests in land-cover 1986.

The producer's accuracy in category urban (1) demonstrate errors of omission (1 - producer's accuracy) higher than 15.00% for two land-covers: 18.00% in land-cover 1974 and 17.20% in Land-cover 1992. All other categories present errors of omission below the threshold of 15.00%.

The user's accuracy in category agriculture-rangeland (3) indicates errors of commission (1 - user's accuracy) higher than 15.00% for two land-covers: 16.67% in land-cover 1974 and 15.91% in land-cover 1992, whereas all other categories present errors of omission below the threshold of 15.00%. The reason for these errors of omission and commission were explained two paragraphs before.

Using land-covers as the reference image, Kappa indexes of agreement were low for the categories 3=agriculture-rangeland (80.00% and 80.91%) and 4=forests (85.00% and 83.12%) for the years 1974 and 1986 respectively.

And using the random sample points as the reference image, Kappa indexes of agreement were low especially for categories 1=urban for the years 1974 (78.77%), 1986 (84.36%) and 1992 (79.56%). This is due to the conflicts identifying at 30m resolution single residential houses from their yards, which are considered part of agriculture-rangeland or forest lands. Another low Kappa index using the random sample points as the reference image occur with category 7=barrenlands in the year 1974, which presents the value of 83.86%. The reason is a slightly confusion of the classifier algorithm between barrenlands with several other land-covers.

All other categories in the error matrices present less than 15 errors per each 250 points. In a similar way, most Kappa indexes of agreement show values above the threshold of 85.00%, being necessary to say that the highest accuracies in the classification of the satellite images exist in category 5=water, where few mismatches among pixels in reality exist, presenting errors of omission of just 2.00%, 2.80%, 1.60% and 2.00% for land-covers 1974, 1986, 1992 and 2001. In a similar way, for Kappa index of agreement in the category 5=water using points as the reference image, the percentages of match are almost perfect: 97.58% for the year 1974, 96.62% for the year 1986, 98.07% for the year 1992 and 97.58% for the year 2001. The reason for this great accuracy has to be with the fact that water absorbs all energy in the near IR and mid IR, reflecting almost no energy at all and consequently appears totally dark in these wavelengths (Lillesand and Kieffer 2000), therefore, it is much easy that the classifier algorithm will separate with a high degree of accuracy this land-cover from the rest of the landscape.

3.4. Slope and Hill-shaded Relief

In order to generate slopes and hill-shaded relief is necessary to have a Digital Elevation Model (DEM), which was obtained from the following EROS Data Center web page at 30 m resolution: http://seamless.usgs.gov/website/seamless/viewer.php

Using Seamless, first an area of interest was selected to download the DEM in ArcGRID format. After, this DEM was changed into a new extension (TIFF) and projection: UTM WGS84 Zone 16 North using ERDAS Imagine software package because it needs to match exactly the classified Land-covers previously derived from the Landsat satellite images.

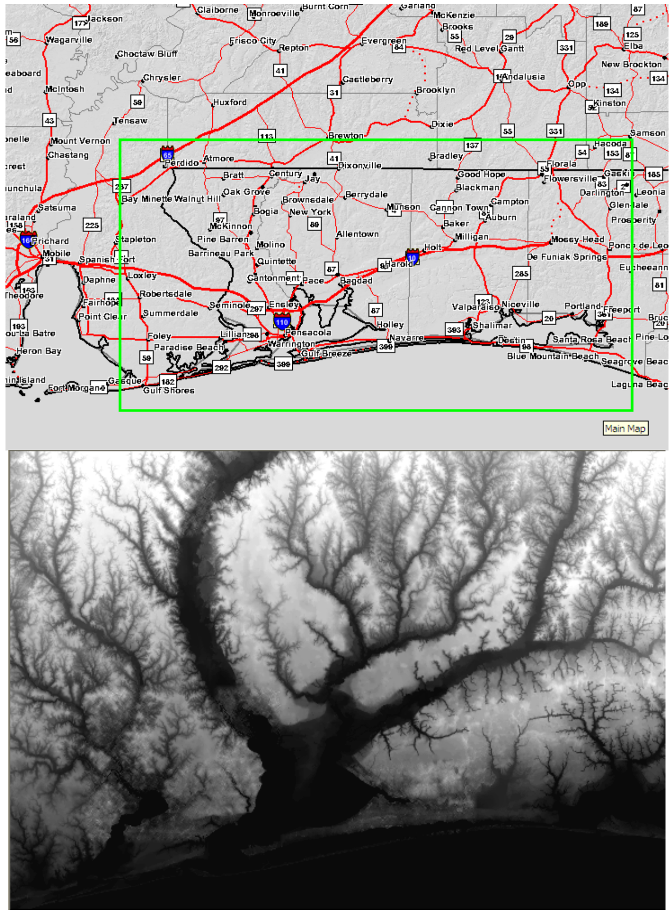


Figure 3.23: Selecting DEM from EROS DATA Center

Note: First Image shows the area of interest from Seamless. Second Image shows the DEM at 30m resolution

Also in Erdas Imagine, this TIFF DEM was converted into slope (in percentage) and hillshaded-relief. After, the slope was recoded with new values from 0 to 100% (all values higher than 100% were reclassified into 100). In this new image, all slopes with more than 20% inclination are considered as critical slopes and consequently they are unable to become urbanized. From the total surface of land of 8,219.97 Km^2 (9,133,301 pixels) just 17.50 Km^2 (19,440 pixels) correspond to critical slopes or 0.2129% of the surface. The rest of the landscape is water: 1,914.23 Km^2 or 2,126,923 pixels.

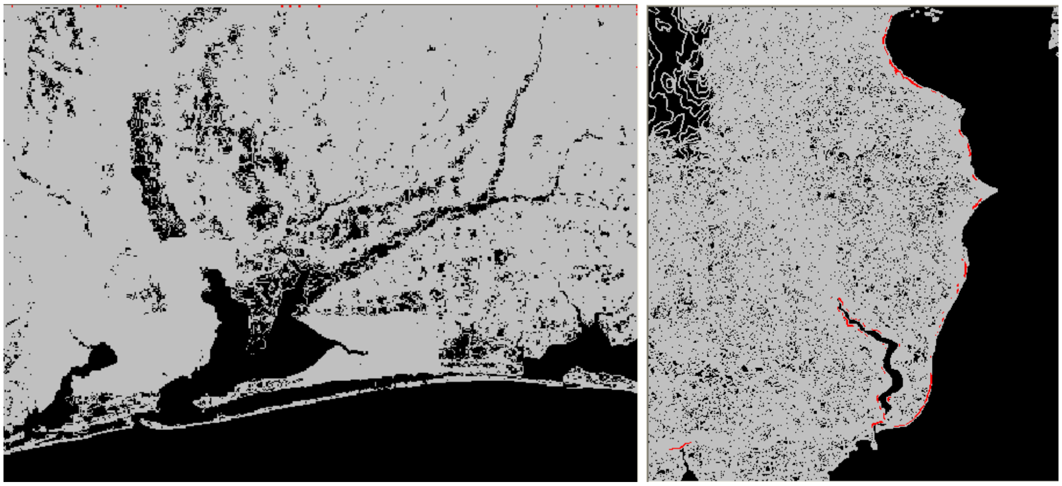


Figure 3.24: Critical Slopes (more than 20% inclination) in the Landscape

Note: Slopes lower than 20% correspond to gray areas. 8,202.47 Km^2 or 80.94% of the area of interest
Slopes higher than 20% are shown in red color. 17.50 Km^2 or 0.17% of the area of interest
Water areas are indicated in black color. 1,914.23 Km^2 or 18.89% of the area of interest

In conclusion, most of the area is flat with very few slopes were urbanization cannot be developed. Finally, This TIFF image of slopes is transformed into GIF (8 bits) extension using Adobe Photoshop.

Using this same DEM, it was possible to extract the Hillshaded-relief as well in TIFF extension at 32 bits through ERDAS Imagine software package. This image was then reduced to 8 bits using a function of this same software package called Histogram Equalization.

After the Hillshaded-relief was derived from the DEM, a water mask is added. It is necessary to indicate that water has almost been unchanged among different years. This mask was created in ERDAS Imagine as well, separating the category water from the other land-covers in the Land-cover 1992 through the method of recoding. Here, all values were reclassified to zero (0) while water was reclassified from 5 into 1.

Later, using the Modeler function from Erdas Imagine, the original Hillshaded-relief plus the water mask were added together in just one layer and finally all these three layers were transformed from TIFF into GIF extension in Adobe Photoshop.

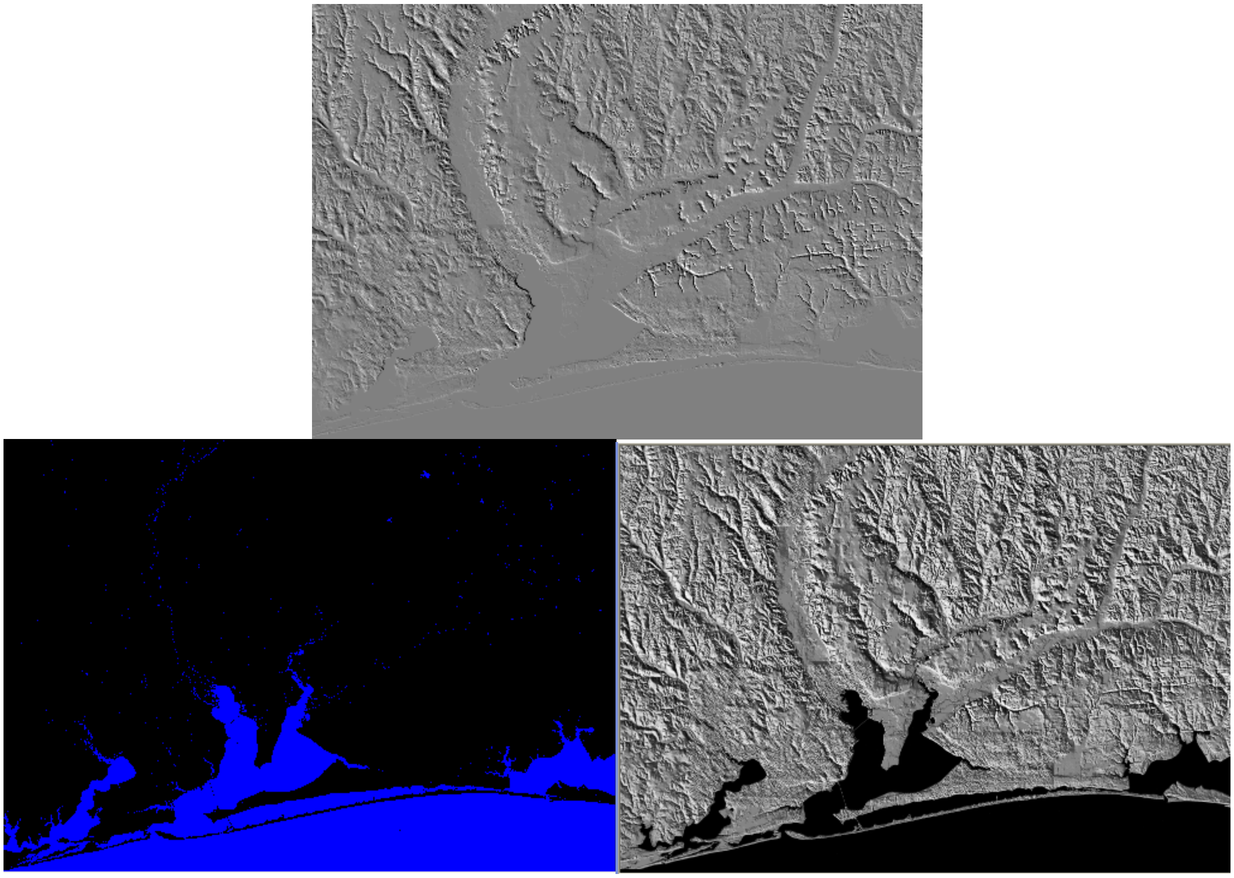


Figure 3.25: Hillshaded-relief, Water Mask and both layers combined

3.5. Excluded Areas

Excluded areas constitute zones where urban growth or development could not occur such as water, wetlands, military bases, indigenous reservations, national parks and urban parks. Because environmental protection is an important concern for future urban development in these three counties, the conservation of wetlands, small streams and some beaches is a main priority for the local governments, for the State of Florida and for the Federal Government. A summary of all excluded natural areas for these three counties is presented in the following map and table.

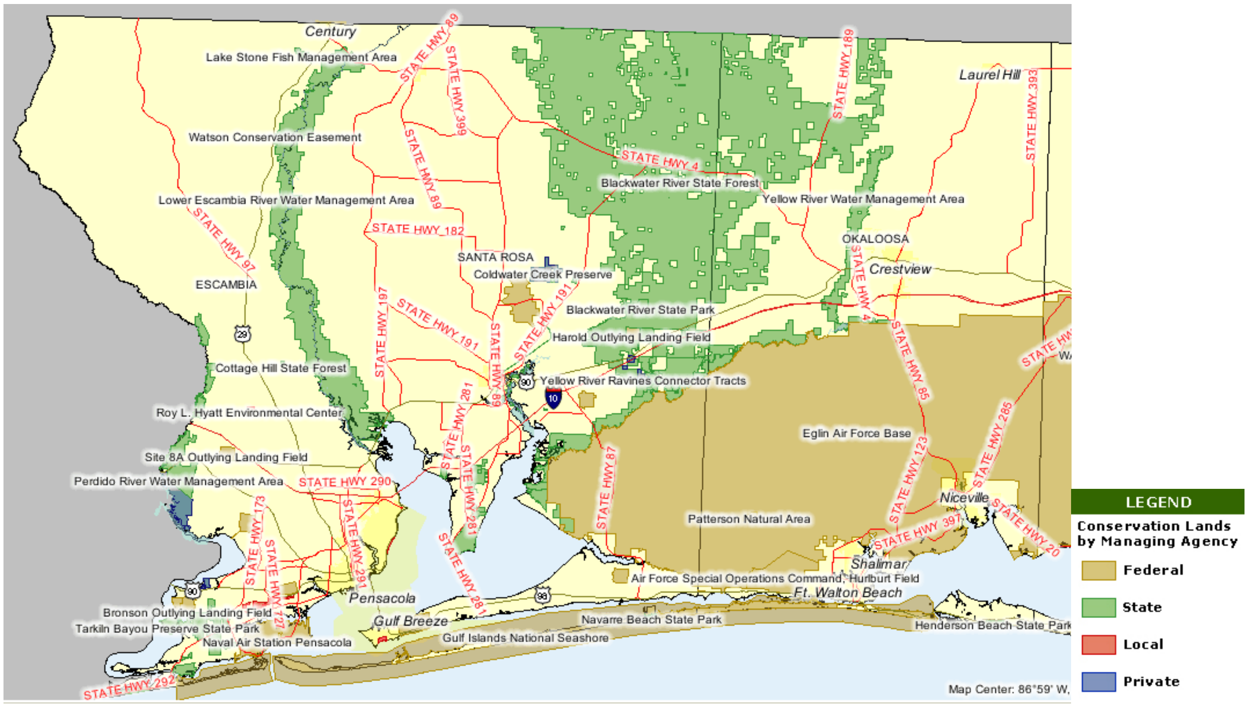


Figure 3.26: Protected Natural Areas in Escambia, Santa Rosa and Okaloosa counties
Source: Source: Florida Department of Environmental Protection

Table 3.12: Protected Natural Areas In Escambia, Santa Rosa and Okaloosa

Counties	Escambia	Santa Rosa	Okaloosa
Natural areas in Acres	43,410	239,700	314,760
Natural areas in Km^2	173.64	958.80	1,259.04
% of Territory	10.12%	36.40%	51.96%

Sources: Main and Allen 2005

The most important protected natural area in this region is the Eglin Air Force Base Wildlife Management Area, located in Santa Rosa and Okaloosa counties with a surface of approximately 460,000 acres (1,840 Km^2) and contains some of the most biologically significant public land in the United States with more than 90 rare or imperiled species, The base manages approximately 320,000 acres (1,280 Km^2) with a leaf pine sand-hill ecosystem, the largest property of this habitat under single ownership (Main and Allen 2005).

Another important natural area is Blackwater River State Park, located also in the border between Santa Rosa and Okaloosa counties, and includes one of the purest sand bottom rivers in the world as well as various pine and hardwood forests. The other natural parks are less important, especially because of their sizes.

Escambia River Wildlife Management Area has 34,000 acres (136 Km^2) buffering the Escambia River and is a locally known for its freshwater fish. There are other smaller protected natural areas in the region such as Navarre Beach State Park in Santa Rosa island, and in the sea surrounding this island and Perdido key there is part of the Gulf Islands Natural Seashore. Finally, Perdido Water Management Area and the Yellow River Water Management Area should be included in this list.

In order to delineate this GIS layer of excluded areas, a shapefile containing all protected areas (national parks and military bases) was downloaded from the web link of Southwest Florida Water Management District: http://www.swfwmd.state.fl.us/data/gis/layer_library/index.php?category=land_resources

Later, from this shapefile, just the areas concerned with Escambia, Santa Rosa and Okaloosa were selected using ArcMap.

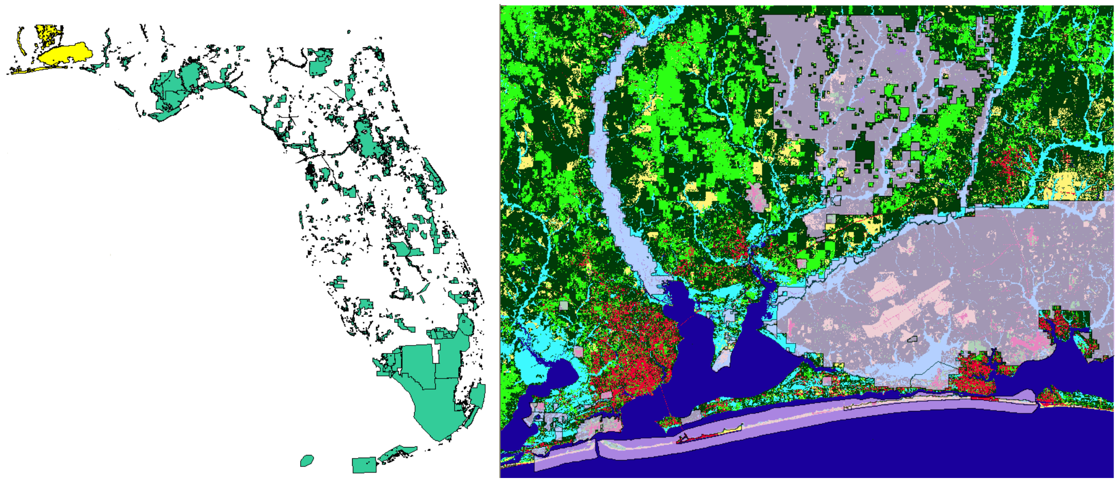


Figure 3.27: Selection of Protected Areas (National Parks and Military Bases) in ArcMap
Notes: Left Image contains all protected areas in the State of Florida
Right Image shows the protected areas (50% transparency) in Escambia, Okaloosa and Santa Rosa counties

Using this same software package (ArcMap), the shapefile was rasterized into GRID extension using a pixel size of 30 meters in order to homogenize the spatial resolution with the Land-covers. After, the rasterized image in ERDAS Imagine is modified to the new projection UTM WGS84 Zone 16 North and to the correct coordinates of the Area of Interest. Finally, the image is transformed from 32 into 8 bits depth and from GRID into TIFF through the function Histogram Equalization. Finally, this dataset is recoded assigning the value of 100 to excluded areas while the rest of areas have a value of 0.

But this dataset from Southwest Florida Water Management District does not take to account other wetlands and water itself (ocean, rivers and creeks), which also constitute excluded areas. Therefore, it is necessary to derive from the Land-cover 1992 these two categories as well. The main watersheds in these three counties are the ones which correspond to the most important rivers: Perdido, Conecuh (also called Escambia), Blackwater and Yellow rivers, existing as well some minor rivers and creeks in the area of Choctawhatchee bay (Okaloosa county).

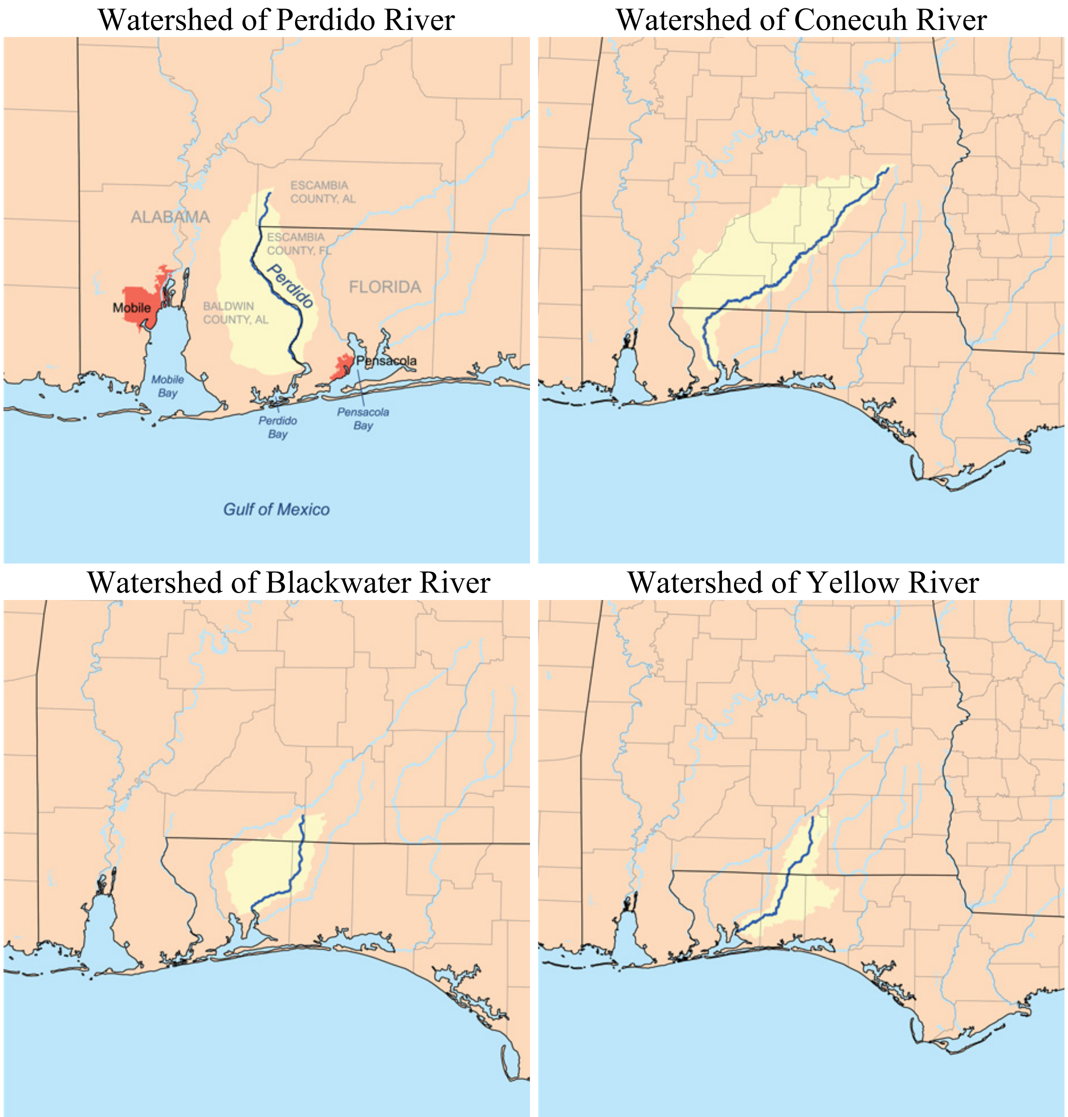


Figure 3.28: Main watersheds with its rivers

Note: There are some minor rivers and creeks in the area of Choctawhatchee bay (Okaloosa county)
Source: Musser

The **Perdido River** is a river of Alabama and Florida, with approximately 60 miles (100 Km) long. The river forms part of the boundary between the two states and drains into the Gulf of Mexico. The **Conecuh River** is a 231 mile (372 Km) long river in Alabama and Florida, here it changes the name into Escambia river, flowing 54 miles along the border between Escambia and Santa Rosa Counties into Escambia Bay which constitutes part of the Great Pensacola Bay. The

Blackwater River has its origin in Alabama, but most of its 58 mile (93 Km) length is in Florida, flowing south towards Blackwater Bay, part of Pensacola Bay. Finally, the **Yellow River** is a river which runs through Florida and Alabama, finishing also in Blackwater Bay. Finally, as it was mentioned before, there are some minor rivers and creeks in the area of Choctawhatchee bay (Fernald and Prudum 1998).

The wetland areas or swamps are associated with river floodplains, being highly productive habitats because floods deposit large amounts of sediments (nutrient rich) that support diverse plant communities, such as trees that produce nuts and fruits (mast), providing consequently important food resources for wildlife. These swamps are also critical for migratory wildlife such as songbirds, waterfowl, etc. and a protected habitat for the black bear (Nelson 1995).

Using the function reclassification or recoding from Erdas Imagine, from Land-cover 1992, two landscapes were selected: water (containing bays, ocean, rivers and creeks) and wetlands, which were separated from the rest of the image and after assigned a value of 100, while the rest of land-covers adopted the value of zero (0).

Finally, both excluded areas: the protected areas: natural parks, reservations and military bases plus the layer of water-wetlands were combined in just one layer through the Modeler function in ERDAS Imagine. This combination was easily generated because both layers have the same values: 100 for protected areas and zero (0) for areas where urban growth can occur. Nevertheless, the resulting image was recoded because some zones were both: national park, reservations or military bases as well as water-wetlands, consequently generating values of 200, which necessary need to be reclassified into values of 100. At the end, using Adobe Photoshop the final layer was transformed from 8 bits TIFF into GIF extension.

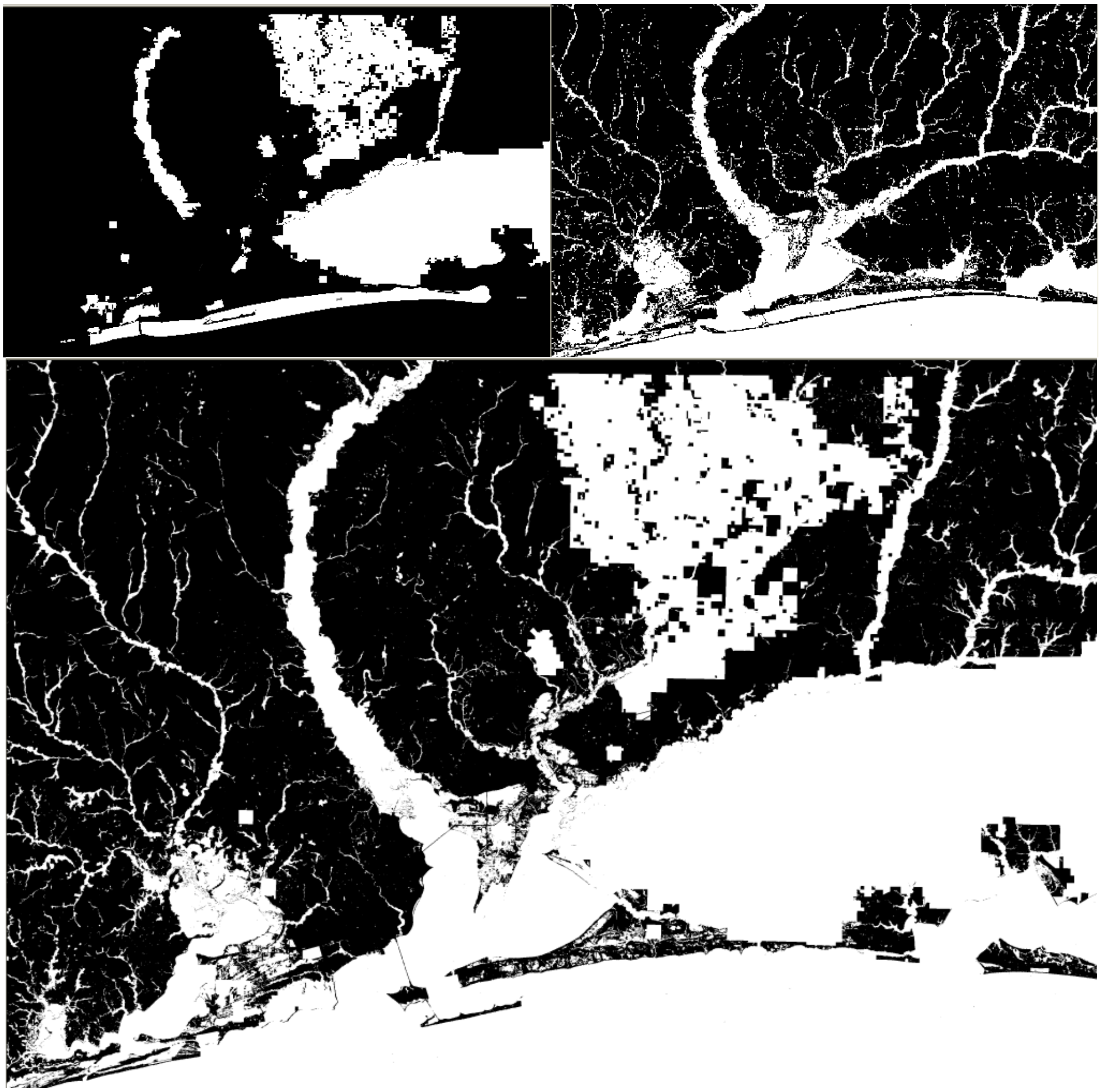


Figure 3.29: All Excluded Areas: National Parks, Military Bases, Reservations, Water and Wetlands

Notes: Excluded Areas are shown in white color (value=100). Other areas appear in black color (value=0)
Upper Left Image: National parks, Reservations and Military Bases.
Upper Right Image: Water and Wetlands
Lower Image: All Excluded Areas

Analyzing the image with all excluded areas, from a total surface of 10,134.20 Km^2 (11,260,224 pixels), 5,094.72 Km^2 or 5,660,802 pixels constitute unprotected areas or zones where urban development can occur (50.27% of total surface). In the other hand, 5,039.48 Km^2

or 5,599,422 pixels correspond to excluded areas (national parks, urban parks, indigenous reservations, wetlands and water), in percentage these protected areas represent 49.73% of total surface of the region of analysis.

3.6. Urban Areas

In all the counties of the different states of this country exists incorporated and unincorporated cities and towns which constitute Census Designated Places (CDP). According to the definition of the United States Census Bureau, incorporated urban areas or municipalities are managed by a type of governmental unit (a mayor and a city council) under state law as a city or town, having legally prescribed limits, powers, and functions (Cromley 2007).

Instead, the unincorporated urban areas (townships, counties or parishes) are also called census-designated places and according to law, they are lands that are not a part of any municipality (city or town), lacking their own government. Therefore, usually they are not subject to be taxed by a city government, being administered by default as a part of larger territorial divisions such as a county, or the state itself. In Escambia, Santa Rosa and Okaloosa counties, the following table and map shows the different incorporate and unincorporate urban areas (Cromley 2007).

Table 3.13: Incorporate and Unincorporate Urban Areas

Escambia		Santa Rosa		Okaloosa	
Incorporate	**Unincorporate**	**Incorporate**	**Unincorporate**	**Incorporate**	**Unincorporate**
Town of Century	Bellview	City of Gulf Breeze	Bagdad	Town of Cinco Bayou	Eglin AFB
City of Pensacola	Beulah	Town of Jay	Navarre	City of Crestview	Lake Lorraine
	Brent	City of Milton	Navarre Beach	City of Destin	Ocean City
	Cantonment		Pace	City of Fort Walton Beach	Wright
	Ensley			City of Laurel Hill	Baker
	Ferry Pass			City of Mary Esther	Holt
	Gonzalez			City of Niceville	Milligan
	Goulding			Town of Shalimar	
	Innerarity Point			City of Valparaiso	
	McDavid				
	Molino				
	Myrtle Grove				
	Perdido Key				
	Walnut Hill				
	Warrington				
	West Pensacola				
	Beulah				
	Barrineau Park				

Source: City of Wonders 2005

Figure 3.30: Incorporate and Unicorporate Areas in Escambia, Santa Rosa and Okaloosa
Source: MapQuest 2007

For this research, it is necessary to isolate just urban areas (incorporate and unicorporate) from each one of the four Land-covers. This urban layer is created in ERDAS Imagine, separating the category 1: urban from the rest of the landscape through the method of recoding. Here, urban pixels were reclassified from 1 into 256, whereas all other land-cover values were reclassified to zero (0).

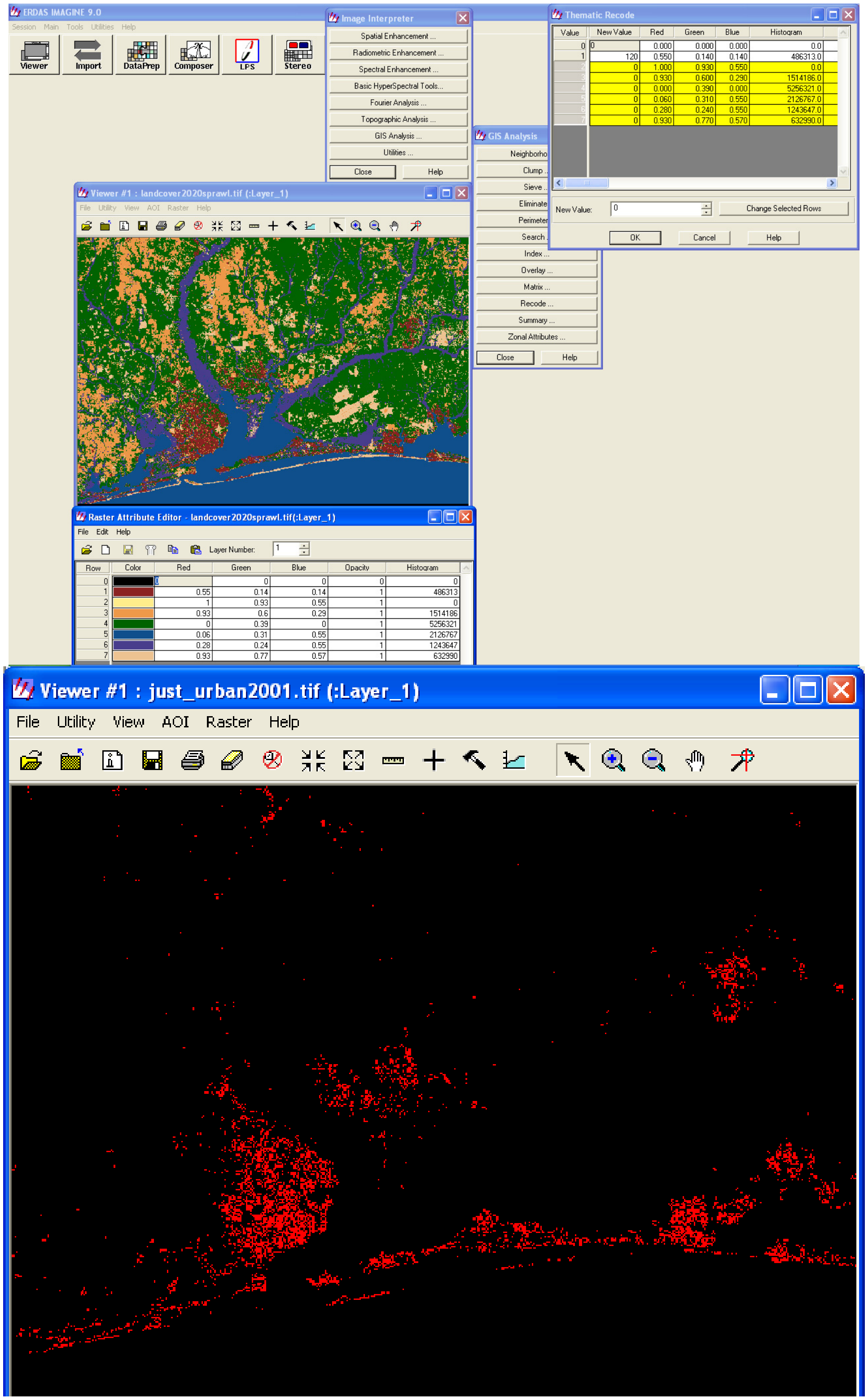


Figure 3.31: Reclassification (Recoding) of Land-cover images just in Urban Areas

Notes: New Urban Areas value = 256 (before Urban = 1)
All other areas = 0 (before Agriculture-Rangeland=3, Forests=4, Water=5 Wetlands=6 and Barrenlands=7)

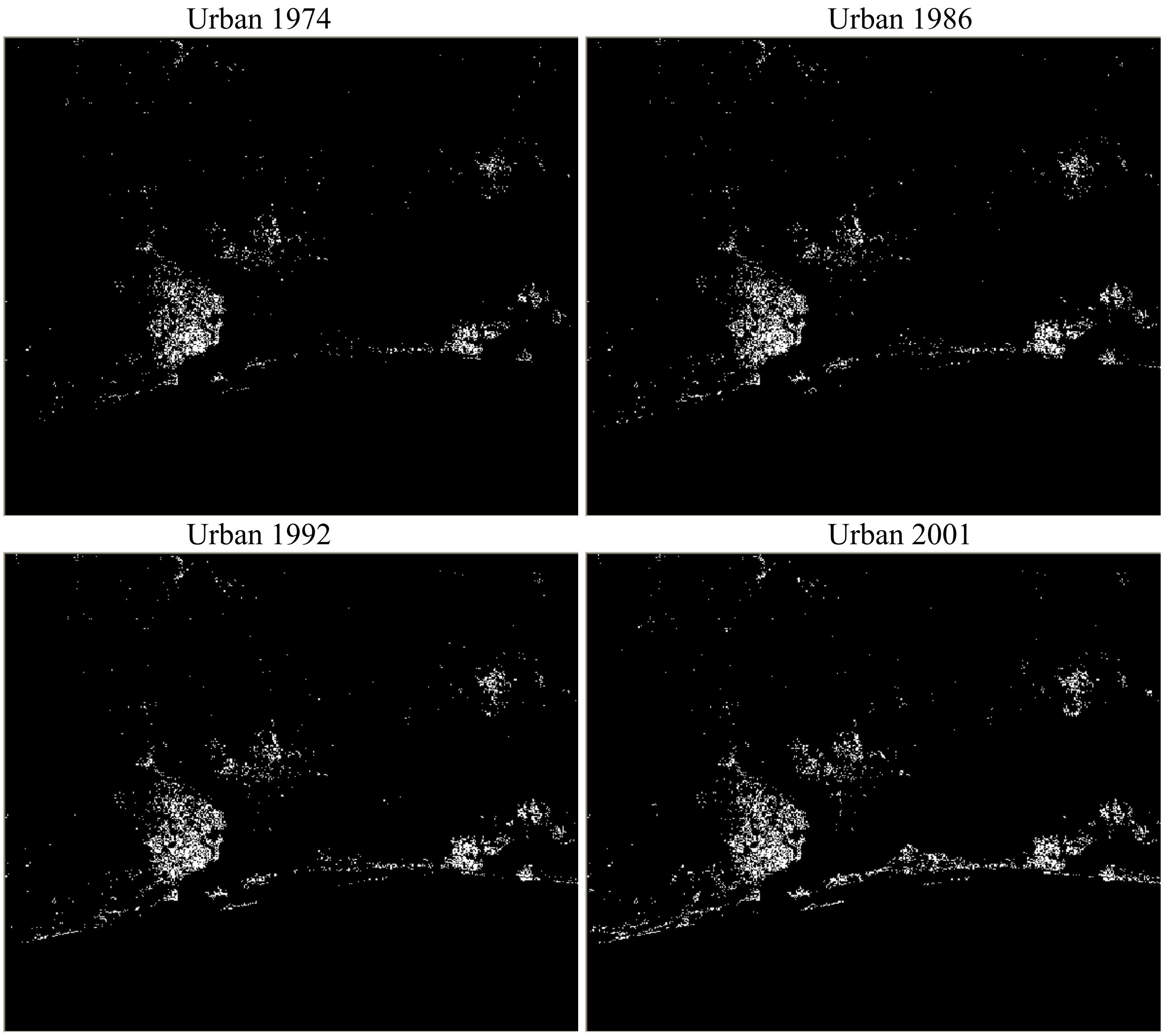


Figure 3.32: Urban Land-covers

All these urban layers contain statistics as well (the sums of the different pixels), the same ones that are described in the following tables:

Table 3.14: Surface in number of Pixels of the Urban Areas

Land-cover	Area in 1974	Area in 1986	Area in 1992	Area in 2001
Urban	175,007	224,348	252,277	301,581
Other Categories	11,085,217	11,035,876	11,007,947	10,958,643
Total Area in Pixels	**11,260,224**	**11,260,224**	**11,260,224**	**11,260,224**

Table 3.15: Surface in Km^2 of the Urban Areas

Land-cover	Area in 1974	Area in 1986	Area in 1992	Area in 2001
Urban	157.51	201.91	227.05	271.42
Other Categories	9,976.69	9,932.29	9,907.15	9,862.78
Total Area in Km^2	**10,134.20**	**10,134.20**	**10,134.20**	**10,134.20**

Table 3.16: Total Changes in Area (Km2) in the Urban Category

Land-cover	1974 - 1986	1986 - 1992	1992 - 2001
Urban	44.40	25.14	44.37
Other Categories	-44.40	-25.14	-44.37

Table 3.17: Surface in Percentages (%) of the Urban Areas

Land-cover	Area in 1974	Area in 1986	Area in 1992	Area in 2001
Urban	1.55%	1.99%	2.24%	2.68%
Other Categories	98.45%	98.01%	97.76%	97.32%
Total Percentage	**100.00%**	**100.00%**	**100.00%**	**100.00%**

Table 3.18: Yearly Percentage (%) of Change in the Urban Areas

Land-cover	1974 - 1986	1986 - 1992	1992 - 2001
Urban	2.09%	1.97%	2.00%
Other Categories	-0.04%	-0.04%	-0.05%

Analyzing these tables, most changes through time happen in the urban category, because in 1974 this landscape constituted just 1.55% of the total surface and in 2001 it went up to 2.67843%, growing yearly from a minimum of 1.97% (between 1986-1992) and a maximum of 2.09% (between 1974-1986). In the last period the yearly growth rate was 2.00% (1992-2001). In 1974 urban-roads had a surface of 157.51 Km^2 and in 2001 the area was 271.42 Km^2, a total expansion of 113.91 Km^2 more.

All the other categories together decreased from 98.45% of the total surface in 1974 to 97.33% in 2001. The yearly rates of decrease were -0.04% in the period 1974-1986, -0.04% between 1986 and 1992 and -0.05% in the last stage 1992-2001. In absolute terms, these areas went down from 9,976.69 Km^2 in 1974 to 9,862.78 Km^2 in 2001, a total loss of 113.91 Km^2, especially in the periods 1974-1986 (12 years) and 1992-2001 (9 years) when -44.40 Km^2 and -44.37 Km^2 respectively were transformed into urban areas.

3.7. Transportation

The transportation layer was generated using the three local GIS datasets of the counties of Escambia, Santa Rosa and Okaloosa for smaller streets plus the information from the Florida Department of Transportation for main highways (see figure 3.33)..

In the case of the local transportation layer (shapefiles) of each county, the projection was changed from NAD 1983 HARN to WGS 84 Zone 16 North using ArcMap software package (Florida Department of Transportation 2005).

Figure 3.33: Local transportation datasets for Escambia, Santa Rosa and Okaloosa
Note: Left image shows transportation layer of Escambia county
Center image correspond to transportation layer of Santa Rosa county
Right image indicates the transportation layer of Okaloosa county

Then, all three shapefiles were rasterized (GRID extension) in ESRI ArcMap and later these images were exported as GRID 32 bits. In ERDAS Imagine, these layers are transformed from GRID into TIFF and the number of bits is reduced from 32 into 8 using Histogram Equalization. Finally, all values of the streets were recoded with the new value of 25 in every one of these three datasets, whereas the rest of areas in each image have the assigned value of zero (0).

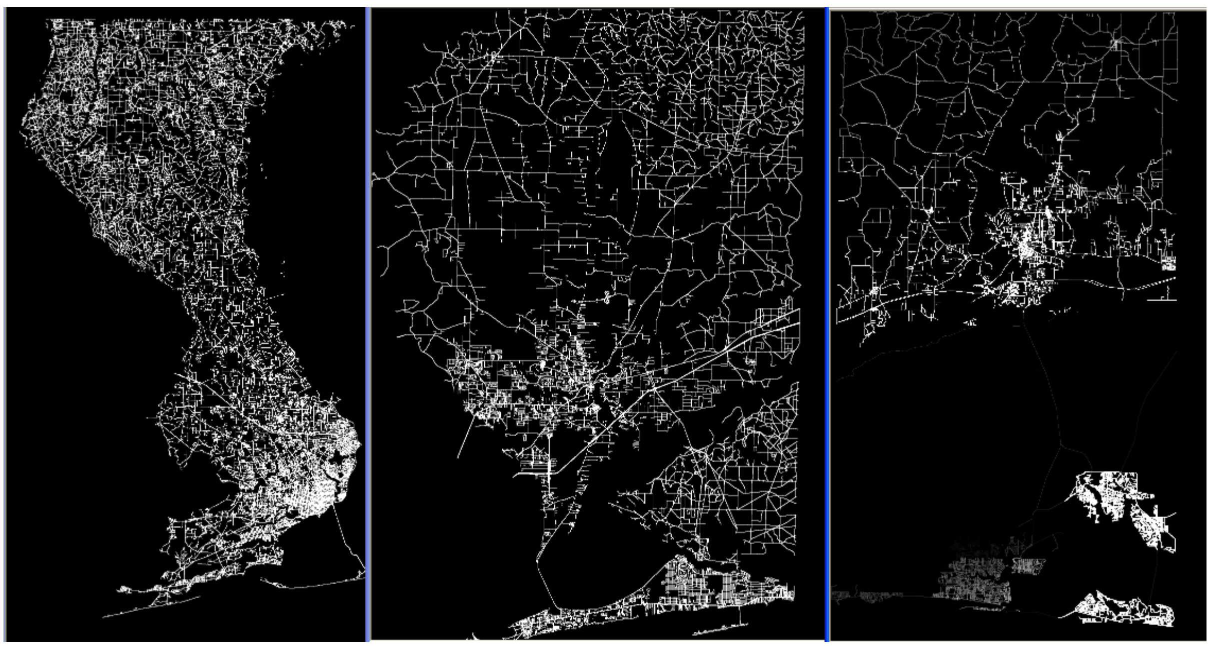


Figure 3.34: High Density Roads in Raster (TIFF) Format

Note: Left image shows transportation layer of Escambia county
Center image correspond to transportation layer of Santa Rosa county
Right image indicates the transportation layer of Okaloosa county

Also, the information from the Florida Department of Transportation was used for the main highways. This dataset with just highways and main roads was downloaded in shapefile format from the following web page:

http://www.dot.state.fl.us/planning/statistics/GIS/#roaddata

The main roads and highways (shapefiles) from just the three counties of interest: Escambia, Santa Rosa and Okaloosa were selected from all the State of Florida and transformed into a new shapefile layer using ESRI ArcMap.

Figure 3.35: Selection of Roads and Highways for Escambia, Santa Rosa and Okaloosa

After, the new transportation layer corresponding to these counties is changed its projection from UTM NAD1983 Zone 17 North (because most of the State of Florida corresponds to this zone) into UTM WGS 84 Zone 16 North.

With this new projection, is also necessary to create a buffer. Therefore, using ArcMap again, a buffer of 30 meters is created along the main roads and highways for the area of interest. The final result is that the main system of transportation has 60 meters width. In reality the width is less, but it is important to remember that the minimum pixel resolution possible is 30m.

The next step is to give a new value to these roads according to its importance and to the instructions obtained from Project Gigalopolis webpage. Therefore, using ArcMap and a hardcopy of the 2004 Rand McNally Atlas of the United Sates, all main roads and highways were selected and classify according to the following criteria established in table 3.19.

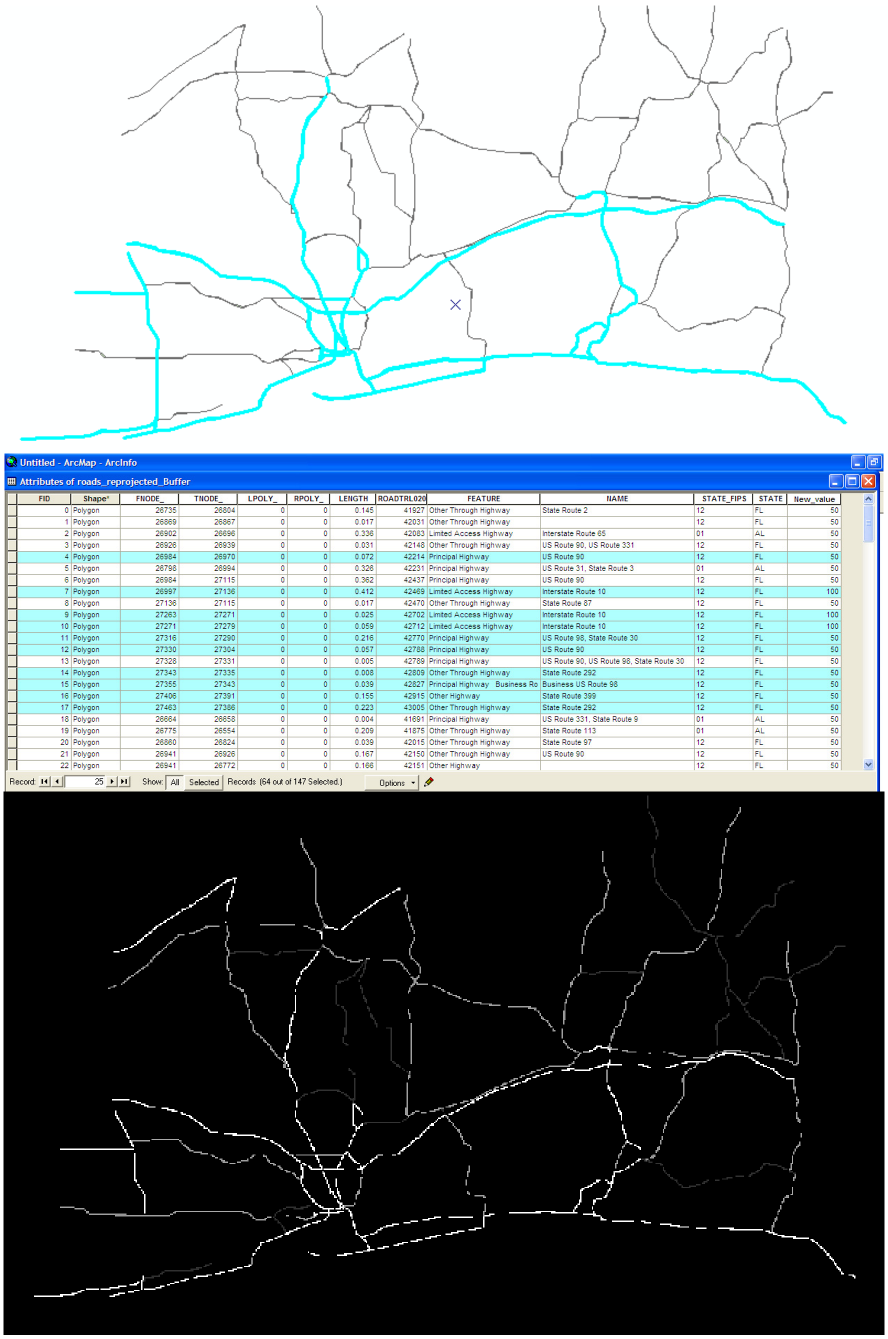
Table 3.19: Values applied to Main Roads and Highways according to their Importance

Route Type from U.S. McNally Atlas	Examples in the area	New Value
Free limited access highway	Interstates 10 and 110	100
Toll limited access highway	Toll bridges	100
Other multilane highway	Highways 29, 98, 85	100
Other through highway	Routes 182, 191, 197, 393	75
Other road	Smaller routes and streets that appear in this dataset from Florida Dep. of Transportation	50
Unpaved rote		50
Scenic route		50

Source: (Rand Mc Nally 2004).
Note 1: All routes, regardless of their importance in Santa Rosa island or near from the beach were assigned a value of 100 in order to simulate the fast growing urbanization of the beaches.
Note 2: It is important to remember that all small streets were recoded before with the value of 25.

Every main road and highway was selected looking first in the hardcopy Rand McNally Atlas of the United Sates and after selecting it from the Florida Department of Transportation geographical database. Finally different values were assigned according to the importance of every road or highway.

The resulting digital map in vector format (shapefile) is rasterized and converted consequently in TIFF format using ESRI ArcMap. Finally this dataset is exported into ERDAS Imagine where the area of interest was defined with precision through Image Subset using the same four corners (in UTM WGS 84 Zone 16 North) that were established before for the area of interest of the satellite images.


Untitled - ArcMap - ArcInfo

Attributes of roads_reprojected_Buffer

FID	Shape*	FNODE_	TNODE_	LPOLY_	RPOLY_	LENGTH	ROADTRL020	FEATURE	NAME	STATE_FIPS	STATE	New_value
0	Polygon	26735	26804	0	0	0.145	41927	Other Through Highway	State Route 2	12	FL	50
1	Polygon	26869	26867	0	0	0.017	42031	Other Through Highway		12	FL	50
2	Polygon	26902	26696	0	0	0.336	42083	Limited Access Highway	Interstate Route 65	01	AL	50
3	Polygon	26926	26939	0	0	0.031	42148	Other Through Highway	US Route 90, US Route 331	12	FL	50
4	Polygon	26984	26970	0	0	0.072	42214	Principal Highway	US Route 90	12	FL	50
5	Polygon	26798	26994	0	0	0.326	42231	Principal Highway	US Route 31, State Route 3	01	AL	50
6	Polygon	26984	27115	0	0	0.362	42437	Principal Highway	US Route 90	12	FL	50
7	Polygon	26997	27136	0	0	0.412	42469	Limited Access Highway	Interstate Route 10	12	FL	100
8	Polygon	27136	27115	0	0	0.017	42470	Other Through Highway	State Route 87	12	FL	50
9	Polygon	27263	27271	0	0	0.025	42702	Limited Access Highway	Interstate Route 10	12	FL	100
10	Polygon	27271	27279	0	0	0.059	42712	Limited Access Highway	Interstate Route 10	12	FL	100
11	Polygon	27316	27290	0	0	0.216	42770	Principal Highway	US Route 98, State Route 30	12	FL	50
12	Polygon	27330	27304	0	0	0.057	42788	Principal Highway	US Route 90	12	FL	50
13	Polygon	27328	27331	0	0	0.005	42789	Principal Highway	US Route 90, US Route 98, State Route 30	12	FL	50
14	Polygon	27343	27335	0	0	0.008	42809	Other Through Highway	State Route 292	12	FL	50
15	Polygon	27355	27343	0	0	0.039	42827	Principal Highway Business Ro	Business US Route 98	12	FL	50
16	Polygon	27406	27391	0	0	0.155	42915	Other Highway	State Route 399	12	FL	50
17	Polygon	27463	27386	0	0	0.223	43005	Other Through Highway	State Route 292	12	FL	50
18	Polygon	26664	26658	0	0	0.004	41691	Principal Highway	US Route 331, State Route 9	01	AL	50
19	Polygon	26775	26554	0	0	0.209	41875	Other Through Highway	State Route 113	01	AL	50
20	Polygon	26860	26824	0	0	0.039	42015	Other Through Highway	State Route 97	12	FL	50
21	Polygon	26941	26926	0	0	0.167	42150	Other Through Highway	US Route 90	12	FL	50
22	Polygon	26941	26772	0	0	0.166	42151	Other Highway		12	FL	50

Record: 25 Show: All Selected Records (64 out of 147 Selected.) Options

Figure 3.36: Selection of Main Roads and Highways and their assignation of Values

Notes: Upper image (Map) shows the selection of different main roads and highways in ArcMap. Middle image (table) depicts the assignation of values according to the importance of every road or highway. Lower image: Main Highways and Roads in ERDAS Imagine.

The layer of main roads and highways needs to be combined with the three datasets of normal streets that correspond to Escambia, Santa Rosa and Okaloosa counties. This process is done through the function Modeler of ERDAS Imagine where all roads from all four layers were added together in a sum. Because at the end some roads had values above 100, it was necessary to recode (reclassify) the image again assigning the values of table 3.19 to main highways and roads while normal streets maintain the value of 25. Finally, this transportation layer was transformed into an 8 bits GIF image using Adobe Photoshop.

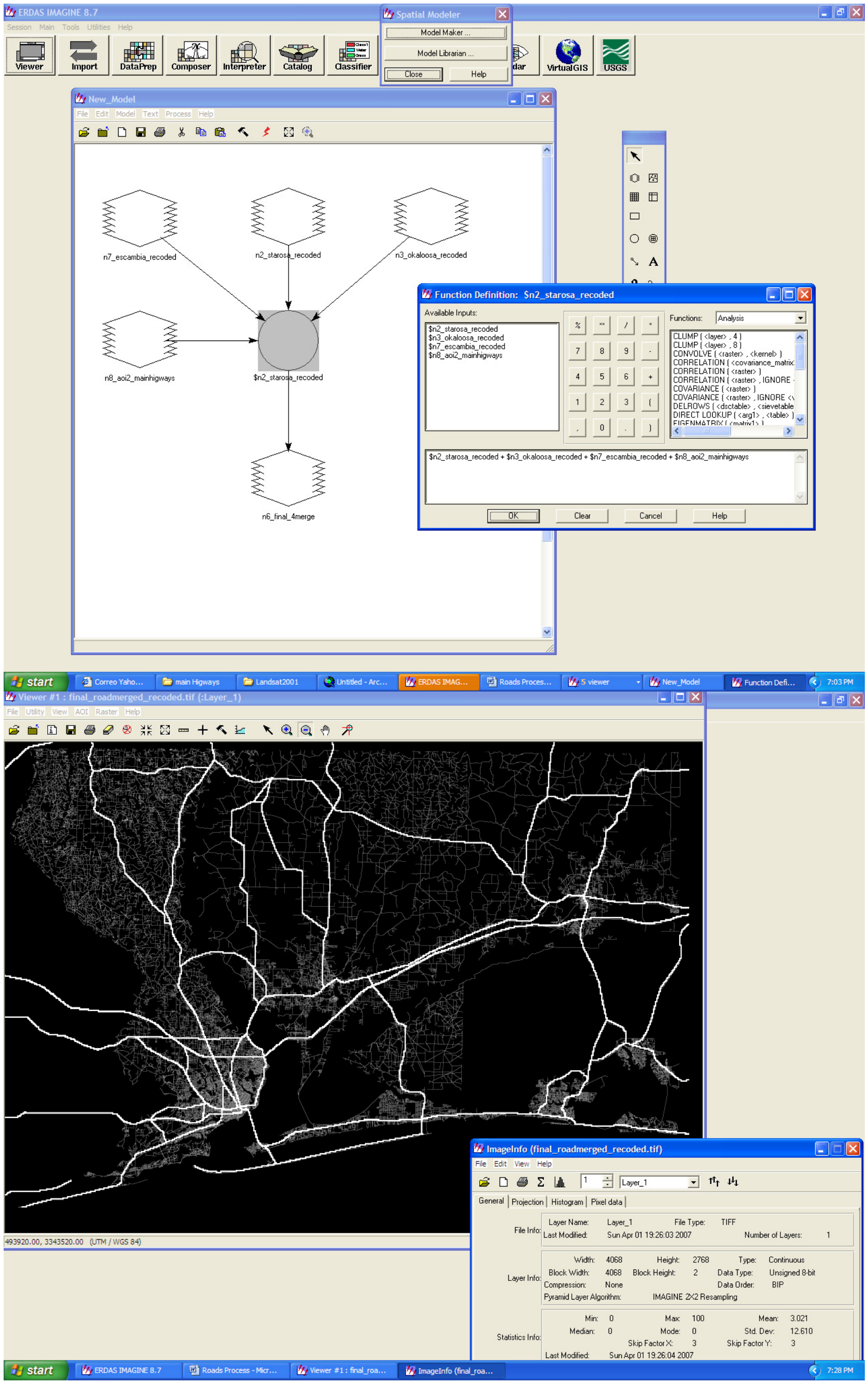


Figure 3.37: Model of fusion of the four Transportation Datasets and Final Transportation Layer after Recoding

CHAPTER 4

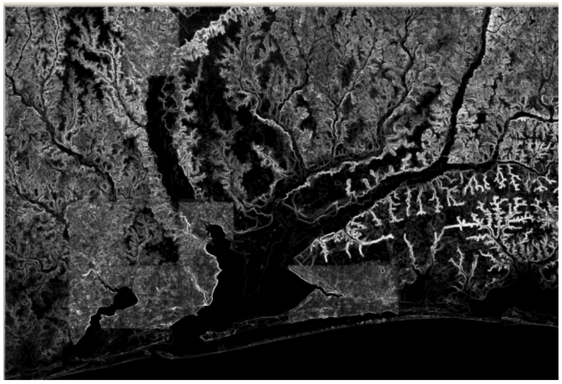
SLEUTH SIMULATIONS

4.1. SLEUTH Model

Keith Clarke and co-authors developed a diffusion CA model of urban development with Deltatrons for land change cover in the mid-1990s. The first simulations were performed on imagery of Santa Barbara, California, but today their model has been applied to other urban areas of the United States, as well as to cities elsewhere in the world, through a project called Gigalopolis (http://www.ncgia.ucsb.edu/projects/gig/project_gig.htm). The goal of Clarke and colleagues is to build a general, standardized tool for medium and high-resolution simulations of urban growth. This CA model was called SLEUTH as an acronym for Slope, Land-cover, Exclusion, Urban, Transportation, and Hillshaded-relief.

The urban areas inside this CA model have a behavior similar to a living organism, where each cell acts independently of the others, and patterns emerge during growth as the organism learns more about its environment (Clarke and Gaydos 1998). The rules are applied to a cell at a time and the whole grid is updated as annual iterations are completed. Potential cells for urbanization are selected at random through Monte Carlo runs and the growth rules evaluate the properties of the cell and its neighbors in relation to slope, distance to roads and its own characteristics (e.g. if the cell is urban or not). The decision to urbanize is based on weighted probabilities that encourage or inhibit growth. The input requirements for SLEUTH are six layers: slope, land-cover, areas excluded from use, existing urbanized areas, transportation networks, and hill-shaded relief.

1 Slope layer derived from DEM

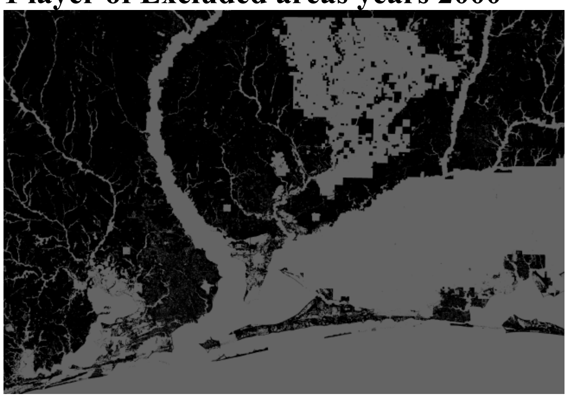


% slope equation: Pixel value range: 0 – 100

4 Land-cover layers from 74, 86, 92 & 01

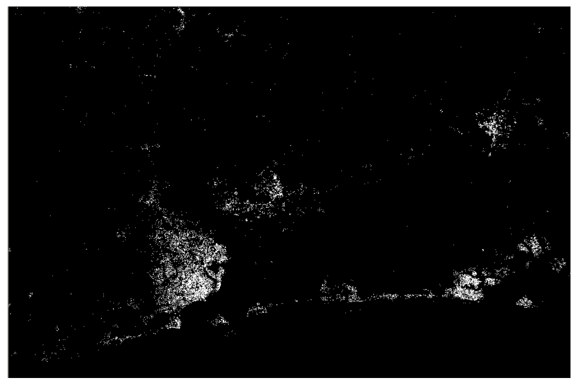
Pixel value range: 0 – 255

1 layer of Excluded areas years 2000



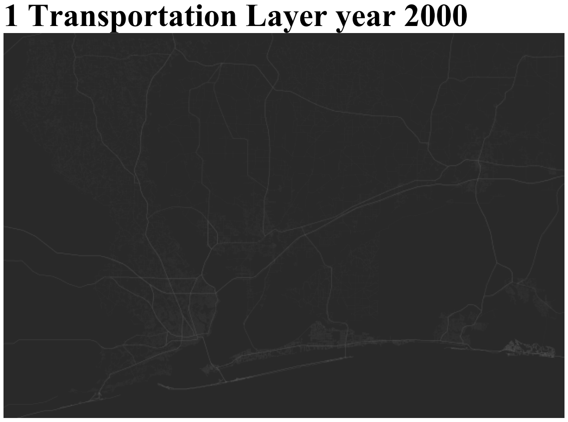
Pixel value range: 0 - 255 (values>100=100)

4 Urban Areas layers for 74, 86, 92 & 01



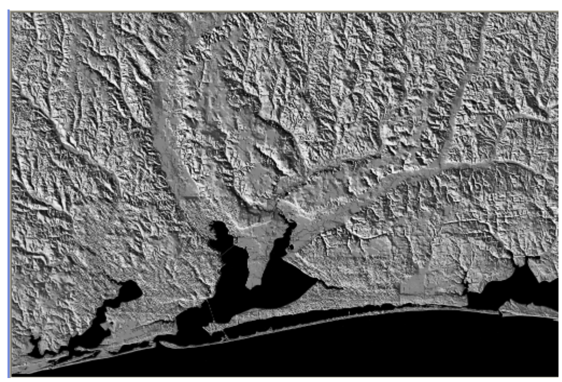
Pixel value range: 0= nonurban; 256 = urban

1 Transportation Layer year 2000



Pixel value range: binary: 0 = non-road, 0 < n < 256 = road

1 Hillshaded-relief layer derived from DEM



Derived from DEM

Figure 4.1: Input layers (8 bits GIF images) for SLEUTH model with a resolution of 30m

The behavior of the system is controlled by the following five coefficients, which affect the acceptance level of randomly drawn numbers (Clarke and Gaydos 1998):

a) A *dispersion coefficient* affects urbanization through <u>spontaneous</u> and <u>road-influenced</u> growth. The *dispersion coefficient* controls the likelihood that any pixel can be randomly selected for possible urban development, determining in this way the dispersiveness of the model.

b) A *breed coefficient* affects urbanization through <u>new spreading center</u> and <u>road-influenced</u> growth. The *breed coefficient* determines the probabilities that isolated pixels will be urbanized beginning their own growth cycles.

c) A *spread coefficient* affects urbanization through <u>edge</u> growth. In <u>edge growth</u>, the *spread coefficient* determines the probability that from a spreading center, a pixel will be randomly selected to become urban, generating a process of outward expansion at the edges of existing urbanized clusters.

d) A *slope-resistance coefficient* affects all types of urban growth: <u>spontaneous,</u> <u>new spreading center,</u> <u>edge</u> and <u>road-influenced</u> growth (Clarke 1999), generating urban limitations to steeper or critical slopes, while making flat areas suitable for urbanization.

e) A *road-gravity coefficient* affects urbanization through <u>road-influenced</u> growth (Clarke et al., Project Gigalopolis), determining the distances and possibilities of urbanization in cells along the roads according to the pixels-roads distances and the dimensions of the image.

Also, four types of growth listed below are possible in the model:

Spontaneous Growth: Outside of the boundaries of a group of urbanized pixels, new randomly chosen cells are able to become urbanized anywhere on the landscape if they fall in a suitable location according to the slope values: if the slope is 0%, the probabilities for a cell to become spontaneous urban is high, but if the slope is 21% or higher, the probabilities for a cell to become spontaneous urbanized is zero (Clarke and Gaydos 1998; Benenson and Torrens 2004)

New Spreading Center Growth: When cells have two or more non-urbanized cells within a 3x3 Moore neighborhood and the slope is low, new pixels can become randomly urbanized.. This group of cells then has a fixed probability to become a new spreading center.

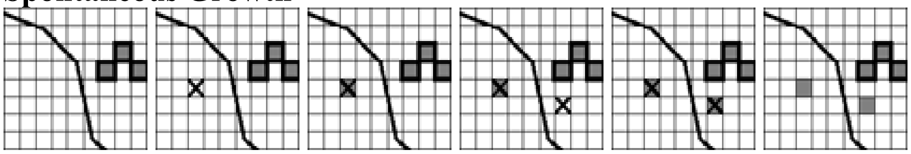
Edge Growth: This type of growth is the most common type of development and occurs at the edges of already urbanized clusters where according to the limitation of the slopes, new cells have a fixed probability of becoming urbanized in a process of expansion of developed cells spreading outward if they have three or more urbanized neighbors within the 3x3 Moore neighborhood.

Road-influenced Growth: Because urbanization processes tend to follow lines of transportation, randomly chosen cells are developed along the transportation network.

- Select a cell close to the road to generate a new spreading center
- Simulate transport of the spreading center along the road
- Anchor spreading center at destination

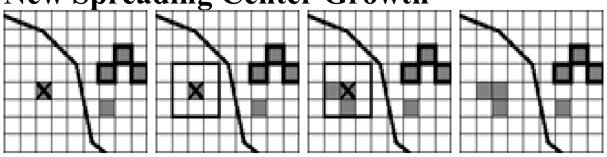
The model works using input data in three different spatial resolution GIF formats with a radiometric resolution of 8 bits. The calibration process requires brute force Monte Carlo runs and it is done in three steps. The first step is to calibrate the simulation using a coarse spatial resolution data (coarse calibration). After the five coefficients are obtained, they will be used to recalibrate, but this time using medium spatial resolution data (fine calibration). From this process, again new coefficients are obtained and used for the final calibration that works with higher spatial resolution data. After these three calibrations are done, the final results (dispersion, breed, spread, slope and road-gravity coefficients) are used in the prediction stage to simulate changes in the landscape until a determined year (in this case, year 2025).

Spontaneous Growth



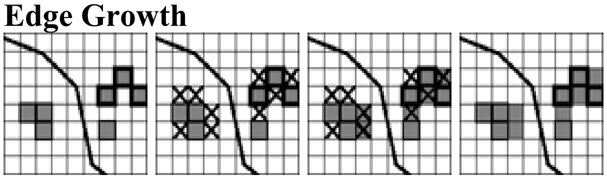
Spontaneous growth is a function of dispersion coefficient and slope-resistance coefficient

New Spreading Center Growth



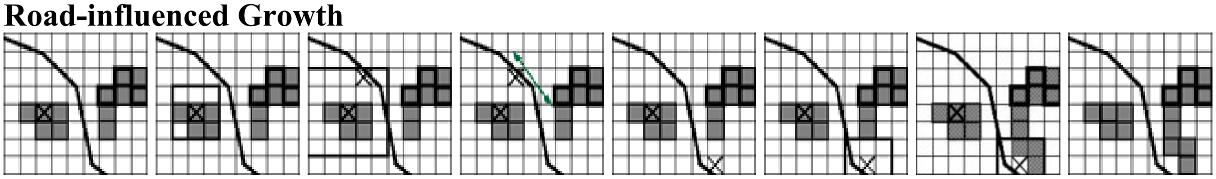
New spreading center growth is a function of spontaneous growth, breed coefficient and slope-resistance

Edge Growth



Edge growth is a function of spread coefficient and slope-resistance

Road-influenced Growth



Road-influenced growth is a function of breed coefficient, road-gravity coefficient, slope-resistance and dispersion coefficient. Source: Clarke 1999

Figure 4.2: Different types of Urban Growth inside SLEUTH

The behavior rules of the SLEUTH model at each iteration (T1 to T0) are based on the four types of growth (spontaneous, spreading center, organic and road-influenced) plus the deltatron processes, providing continuous feedback.

Deltatrons are semi-independent agents with their own life cycles able to store a pixel's information (in a delta space) about the different types of land-cover transitions and their respective aging processes (in the case of urban cells) in order to bring new changes in the landscape. Deltatron dynamics are based on a transition matrix where urbanization drives new changes in the landscape based on the pixel's average slope information and the different land-cover structure or classes. At each iteration, deltatrons become older and older by one unit of time (generally one year) until they reach a predetermined threshold age, at which time they die, generating new spaces to seed again new deltatrons (Benenson and Torrens 2004).

The landscape patterns are generated because the selected land-cover type invades and diffuses from its edges into other land-cover types. The visible landscape changes are based on lagged spatial autocorrelation.

4.2. Deltatron Dynamics

Deltatron dynamics generate land-cover changes through two continuous phases. To generate the changes, first a pixel (i, j) is selected randomly (pixels in urban and excluded areas will not be selected). After, two land-cover classes are selected randomly (e.g. yellow and green). From these two choices, the system finds the land-cover class whose average slope is most similar to the current pixel slope (e.g. 2.00%). In this example we suppose that the yellow class has an average slope of 1.20% and thus, this is the most similar value with the pixel' slope (i, j=2%). In order to create the changes, the system has to obtain information from a Transition Probability Matrix (where different transition probabilities values exist among the different land-covers). In this case, the transition probability between an orange pixel that wants to become yellow has a value of 0.05. This transition probability value (0.05) will be checked against the maximum transition probability threshold (e.g. P=0.05), and if it is greater, that pixel will fail to change and a new random site will be selected. But, if the transition probability value between the two classes is smaller than P, the landscape modification is implemented (Candau and Clarke 2000). In this example the values are the same (0.05) and the pixel (i, j) will change its class. This single change then spreads randomly to its neighbor cells forming a new land-cover cluster (in reality because many pixels are selected randomly, also many new land transitions are formed). All these new land-cover transformations also constitute a new landscape where urban cells are constantly growing in a continuous process. At the time where these clusters of land transition have occurred, deltatrons are born with a value of one (this indicates its lifecycle age) in a Delta Space (a grid space that mirrors the data dimensions exactly) existing separately from the virtual landscape (Dietzel and Clarke 2004).

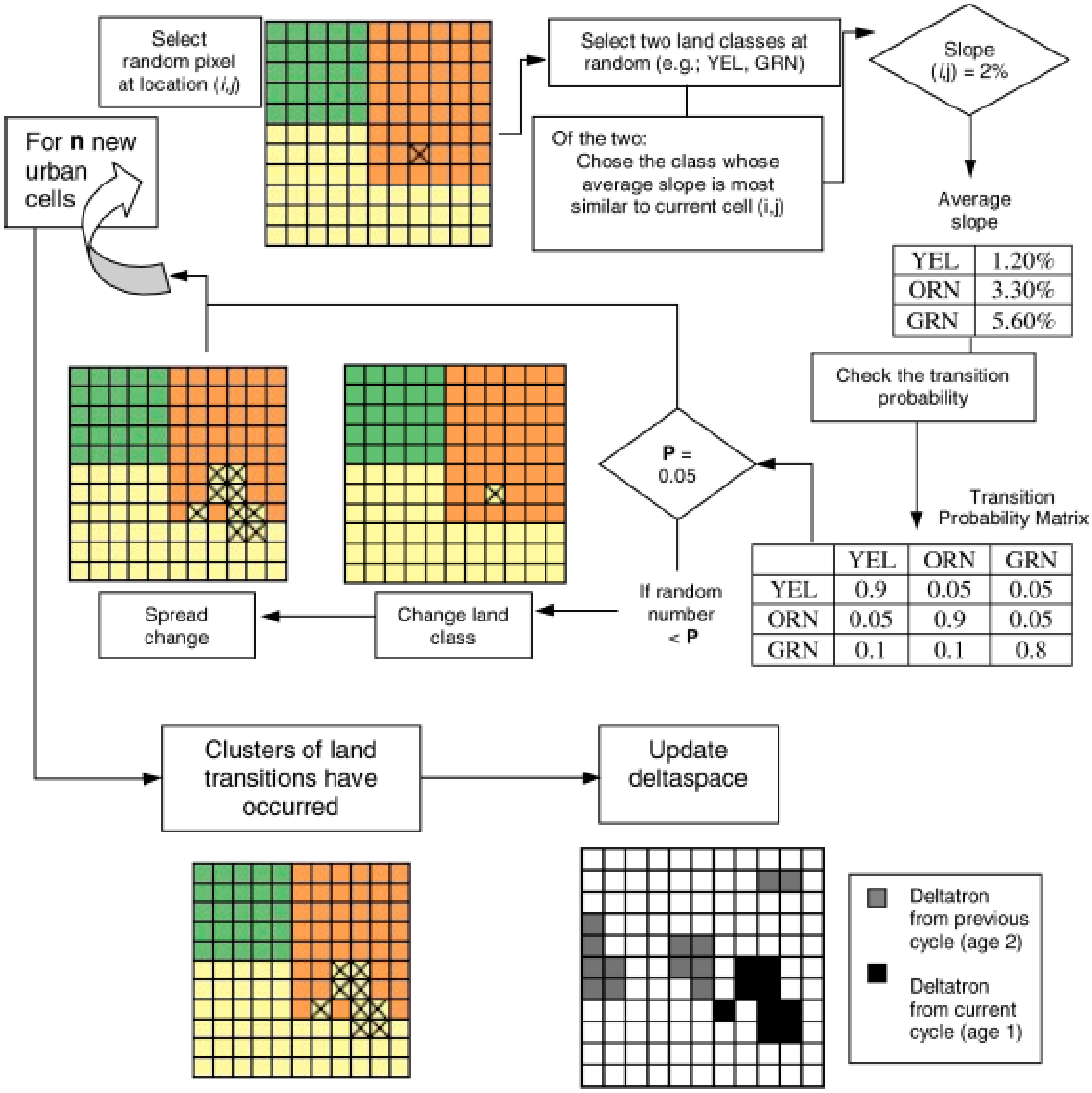
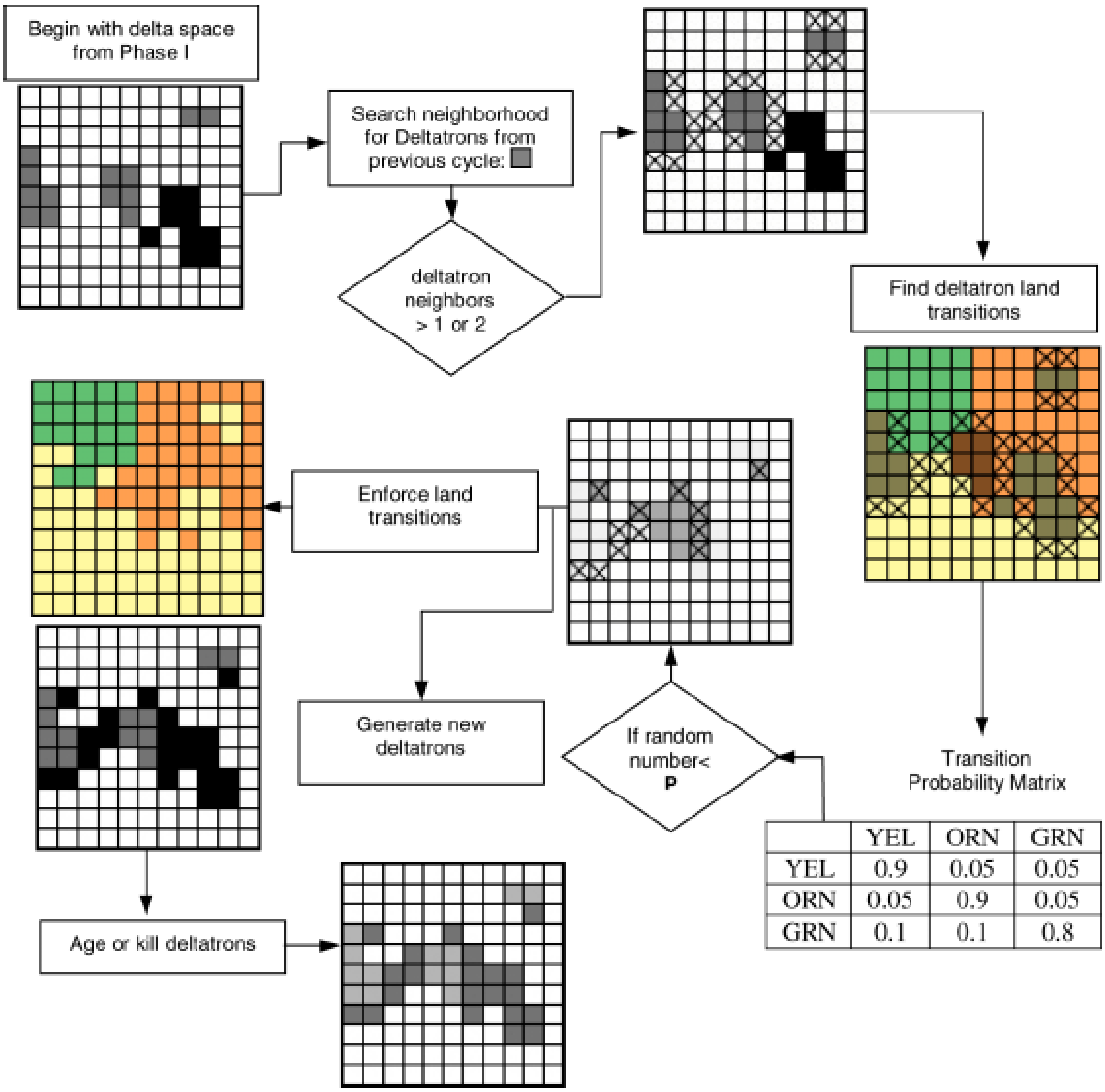


Figure 4.3: Phase I of Deltatron Dynamics

Note: The virtual landscape is in colors while Delta Space is represented with black and white.
Source: Dietzel and Clarke 2004

The deltatrons for the previous phase with an age=2 now try to initiate changes of the new land type being introduced into their neighborhood through a process based upon standard CA rules (very similar to the edge growth) (Candau et al. 2000). Different cells (pixels that are not deltatrons yet) are randomly selected when they have one or two deltatron neighbors with ages=2. Then, another test is performed in order to find the deltatron land transition probabilities. This test is performed using the same Transition Probability Matrix from phase I, where transition probabilities between different land-cover types are compared against a maximum transition probability threshold (P). Here, all values greater than P will fail to success, while all values smaller than P will generate new deltatrons (age=1) in the Delta Space (Candau and Clarke 2000). These deltatrons will enforce land transitions as well as they will generate new deltatrons, until over time they will age, decay and eventually die or be killed (at the threshold age=3) by the system (disappearing from the Delta Space cells), becoming new Delta pixels available for possible “new born” deltatrons in a continuous life cycle.



	YEL	ORN	GRN
YEL	0.9	0.05	0.05
ORN	0.05	0.9	0.05
GRN	0.1	0.1	0.8

Aging Deltatrons

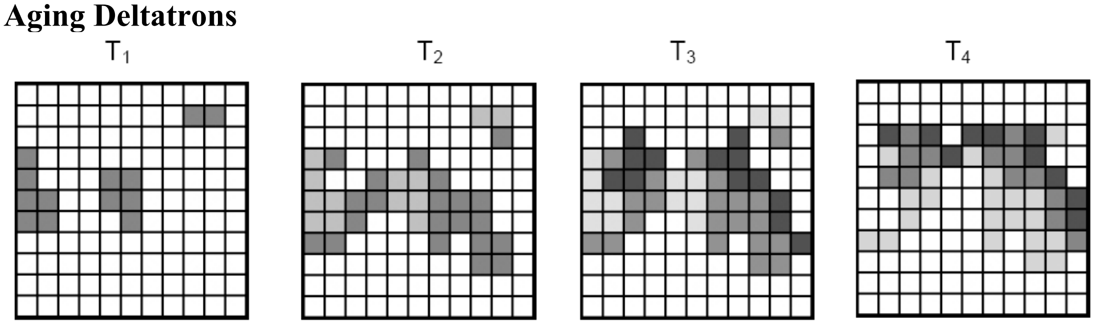


Figure 4.4: Phase II of Deltatron Dynamics

Note: The virtual landscape is in colors while Delta Space is represented with black and white.
Sources: Candau and Clarke 2000; Dietzel and Clarke 2004

4.3. Characteristics of a High-performance computer

Parallel computing consists of simultaneous use of many central processing units (CPUs) to perform a task as soon as possible (Openshaw and Abrahart 1999). Parallel processing is used in many disciplines, and the main applications in geomatics are related with spatial data mining and simulations, both of these techniques are used in the research through SLEUTH.

The first performed simulations were made by the US military for nuclear bomb design in National Laboratories and by the National Security Agency (NSA) for encryption and decryption (Openshaw and Abrahart 1999). Nevertheless, after the end of the Cold War (1989), the supercomputer market emerged for different scientific studies at the University level. In geography, Openshaw in 1995 was one of the first scientists in propose and use high-performance computer s in spatial data mining.

It is necessary to indicate the differences that exist between a high-performance computer with dozens of processors and a supercomputer with hundreds of processors. Of course, many times supercomputers are used for many research teams which not necessarily are using all processors, but just some of them in every one of their projects.

Always parallel processing uses a Master processor, which takes care of the distribution of tasks to the different slave processors as well as the recollection of results from the slaves before compiling them. A connection to the high-performance or supercomputer is possible using network protocols like Secure Shell (SHH) or File Transfer Protocol (SFTP). A network protocol enables the connection, communication and data transfer between two computers.

Generally, when multiple processors are used, the speed is measured in teraflops (a trillion floating point operations per second). For example, the fastest computer in the world (until June 2007), the IBM Blue Gene/L was able to reach a maximum of 360 teraflops per second.

In this specific research, two high-performance computer s at University of Georgia (UGA) were used to generate the SLEUTH simulations. Both of them use Red Hat Linux as the Operator System. One of them uses 120 Nodes each with two cores (1 processor per core). The other one uses 39 nodes with four cores each (2 processors per core), and SLEUTH tasks were assigned to both of them according to the traffic (which processors were free at that moment) at the RCC (Research Center for Computing in UGA).

The communication between the laptop computer of the author of this research and the high-performance computer was made via a Secure Shell (SHH) network protocol used to connect the local personal computer (PC) to the remote high-performance computer through a secure channel for tasks assignment; and, a Secure File Transfer Protocol (SFTP) used to transfer files (file allocation and data input) from the local PC computer to the remote high-performance computer over the Internet. Also, SLEUTH is able to run in parallel if its software package configuration is modified. But, because I could not modify this software package, I decided to play the role of the Master processor and tasks were manually sent to the different processors. In the case of an automated parallel processing, a Message Passing Interface (MPI) is the language used for message-passing on a parallel computer between the Master processor and its slaves. See tables A-III.1 to table A-II.2 and figures A-III.1 to A-III.2 in appendix III (pages 341 and 342).

Table 1: UGA - RCC High-performance computer: Rackable Linux Cluster of Opterons (rcluster)

Processor: AMD Dual processor Single core Opteron 248	Processor: AMD Dual processor Dual core Opteron 275
Number of computing cores: 2 (1 core per processor)	Number of computing cores: 4 (2 core per processor)
Number of Processors per node: 2	Number of Processors per node: 2
CPU Speed: 2.2GHZ	CPU Speed: 2.2GHz
Hyper-transport bus technology: 800 Mhz bandwidth per processor	Hyper-transport bus technology: 1000 MHz bandwidth per processor
RAM Memory per Processor: 4GB	RAM Memory per Processor: 8GB
L-2 CPU Cache size: 1 Mb	L-2 CPU Cache size: 2x1 Mb
Number of Nodes: 120	Number of Nodes: 39
Operating system: Red Hat Linux	Operating system: Red Hat Linux

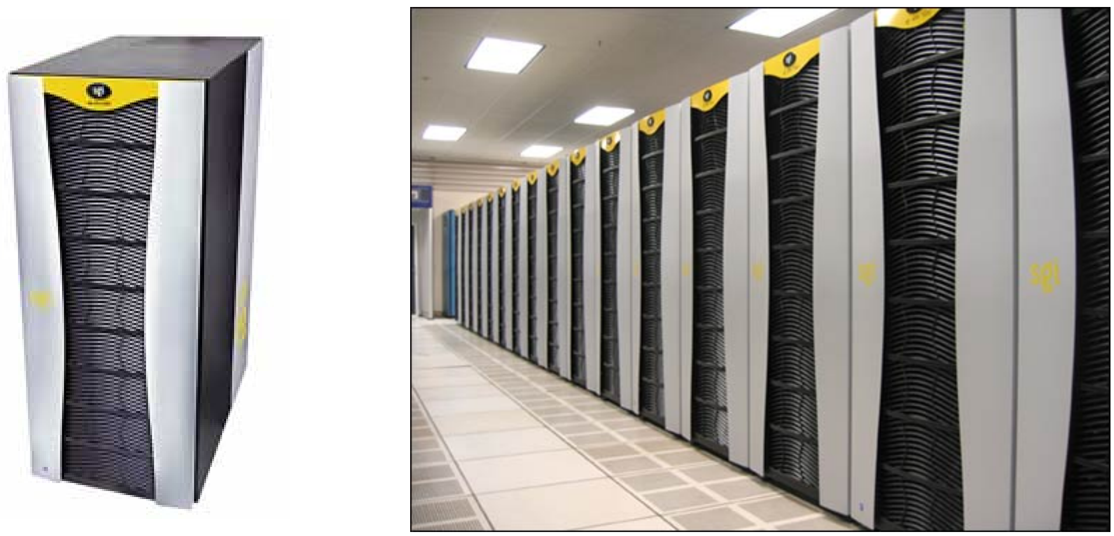


Figure 4.5: a High-performance computer (left) vs. a Supercomputer (right)

Note: A High-performance computer is made by dozens clusters of processors, while a supercomputer is made by hundreds or thousands of these clusters.

4.4. SLEUTH Model Implementation

As mentioned before, the SLEUTH model (including CA and deltatrons dynamics) was applied in the LINUX cluster high-performance computer. The procedures for the implementation of these simulations consist of four major components: (1) preparation of input layers, (2) calibrations (data mining), (3) simulations, and (4) model output.

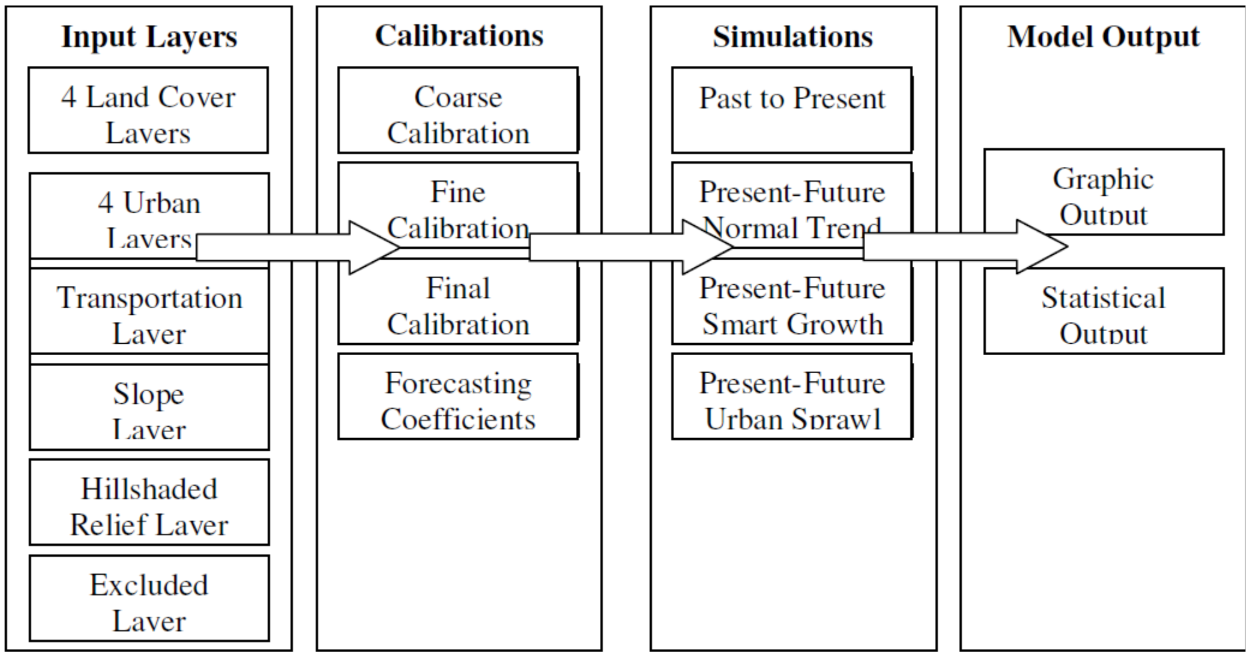


Figure 4.6: Input, Calibrations, Simulations and Output

In order to run the model, six types of GIF layers were assembled: slope, 4 Land-covers (1974, 1986, 1992 and 2001), excluded areas, 4 urban areas (1974, 1986, 1992 and 2001), transportation and hillshaded-relief. The accuracy of the land-cover and urban layers exceeded the minimum requirement of 85% according to Anderson level I classification (Anderson, Hardy et al. 1976).

To run the model, all the layers were standardized in terms of data format (GIF 8bits), resolution (30 meters per pixels), and dimensions (4068 pixels × 2768 pixels).

The objective behind the calibrations of the model is to determine the best fit values between the land-cover trend and the simulation from past (since 1974) to present (2001) for the five growth coefficients (road-gravity, spontaneous, breed, edge-growth and slope-resistance growth). These calibrations consist on statistic metrics (measures) of historical fit such as Lee and Salee Index and Product.

The Lee and Salee index consist on a shape's measurement of spatial fit between the urban simulation growth and the known urban extent for the control years. And the Product index is the multiplication of all other spatial metrics according to Project Gigalopolis information. (http://www.ncgia.ucsb.edu/projects/gig/v2/About/dtDtControlDefine.htm).

The calibration of the model is the phase that demands the highest possible and available computer power in a triple stage calibration at a resolution of 30 meters per pixel using 11,260,224 pixels per image (4068 × 2768 pixels). Therefore, the number of random samples in all calibrations and simulations were maintained at 1% of the value of all pixels: 112,602.

The first stage also called coarse calibration, and 7,776 simulations were run using 36 processors simultaneously to find the first and second highest Lee & Salee indexes (64.98 and 64.98) from the control_stats.log file following the instructions from Project Gigalopolis web page. Because the number of all possible combinations for every one of the 5 coefficients involved varies from 0 to 100 (100^5), the goal of this calibration is to diminish the range of possibilities that each control coefficient can adopt. Therefore, for each coefficient, the values were: star: 1 (initiates the first simulation) step: 20 (increases from 1 to 20, 40, 60, 80 and 100), stop: 100 and Monte Carlo=5; resulting in 7,776 simulations ran in 36 processors simultaneously in a total time of 27 hours 13 minutes and 45.59 seconds. All these simulations are performed through brute force Monte Carlo runs, a computational algorithm which relies on random sampling to compute the results, converting the whole system from deterministic into stochastic.

After, the second phase is called fine calibration, and 10,125 simulations were run using 45 processors simultaneously to find the highest Product (18.84) from the control_stats.log file. The highest product was chosen in this case because some years before Lo and Yang (2003) also used a similar index conformed of the weighted sums of all the statistical measures. Here, based on the highest Lee and Salee indexes from coarse calibration, Monte Carlo iterations were increased to 8 and the coefficients used the following values: diffusion (start: 1, step 5, stop: 20); breed (start: 1, step 5, stop:40); spread (start: 1, step: 5, stop: 20); slope (start: 80, step: 5, stop:100); and, road-gravity (start: 20, step: 10, stop:100). The total time involved in this stage was 39 hours 28 minutes and 07.05 seconds.

The last stage is the final calibration, and here as well the Highest Product (0.18.46) from the control_stats.log file was chosen among 5,184 simulations using 36 processors simultaneously. In this case, the Monte Carlo iterations were increased to 10 and based on the Highest Product from the fine calibration, the coefficients were assigned the following values: diffusion (start: 10, step 2, stop:20); breed (start: 40, step: 2, stop: 50); spread (start: 5, step: 1, stop: 10); slope (start: 90, step: 2, stop: 100); and, road-gravity (start: 70, step: 10, stop:100). The maximum time in this phase was 31hours 39 minutes and 11.70 seconds.

With these results, finally the highest pop-area value (265,579.37) from the avg.log file was chosen among 7 simulations made in just one processor to derive the best forecasting coefficients. To generate these numbers, Monte Carlo was elevated to its maximum: 100 and the coefficients were assigned the following input values: diffusion (start: 10, step 1, stop: 10); breed (start: 40, step: 1, stop: 40); spread (start: 5, step: 1, stop: 5); slope (start: 100, step: 1, stop:100); and, road-gravity (start: 70, step: 5, stop:100). The best fit values founded between the land-cover transition and the simulations were: diffusion: 13%; spread: 6%; breed: 52%; slope-resistance: 60%; and road-gravity: 89%; and the time involved was 14 hours, 29 minutes and 28.30 seconds.

In total, 23,092 simulations ran to determine the best formula which yields the simulation that best matches the land-cover map transition from 1974 to 2001. It is very important to notice that all these 23,092 simulations were developed in just 112 hours 49 minutes and 32.64 seconds involving a total of 118 processors. A few years before, in order to simulate the growth of the city of Atlanta, Yang and Lo using a Sun Ultra Model 1 workstation, with 143Mhz CPU and 64Mb RAM, expended a total of 21,422 hours and 29 minutes in 4,269 calibrations to find the best formula that shows this land-cover transition using a resolution of 240 meters. In other words, they expended approximately 190 times more time using just one processor at a time working with a resolution 8 times greater than the simulations made in this research paper (Yang and Lo 2003). See tables A-II.1 to A-II.9 in appendix II (pages 333 to 340).

RESULTS FROM FINAL CALIBRATION

THAT WILL BE APPLIED FOR DERVE FORECASTING COEFFICIENTS

The Highest Product (0.18457) from the control_stats.log file is being chosen among 5,184 simulations made in final calibration.

Table 4.2: Control Stats file for sub_Cal 1a

Runs	Product	Compare	Pop	Edges	Clusters	Cluster Size	Lee & Salee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch
20, 21, 22, 23	18.46	85.00	100.00	86.30	58.78	96.43	59.52	84.16	100.00	94.75	95.60	100.00	97.83

Diff	Brd	Sprd	Slp	RG
10	40	5	100	70-80-90-100

Note: Product index consists on all other metrics multiplied together.

DERVE FORECASTING COEFFICIENTS

Table 4.3: Scenario used in the High-performance computer for Derive Forecasting Coefficients

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	10 – 1 – 10			40 – 1 – 40			5 – 1 – 5			100 – 1 – 100			70 – 5 – 100		
Total # of simulations	7														

Table 4.4: Derive Forecasting Coefficients: 1 sub-scenarios with Monte Carlo = 100

Name of Calibration	Processor-node	# of Simulations	Time
sub_derVe.sh	C1-10	7	14h 29’ 28.30’’

Note: Results were computed using http://www.csgnetwork.com/timescalc.html

RESULTS PRODUCED AFTER DERVING FORECASTING COEFFICIENTS

The highest pop-area value (265,579.37) from the avg.log file is being chosen among 7 simulations made to derive forecasting coefficients.

Table 4.5: Avg.log file for sub_Derive

run	year	index	sng	sdg	sdc	og	rt	pop	area	edges	clusters	xmean	ymean
3	2001	3	119.65	96.59	0.00	3571.23	57..41	265579.37	265579.37	170123.01	25749.32	1919.69	1839.99
rad	**slope**	**cl_size**	**Diffus**	**spread**	**breed**	**slp_res**	**rd_grav**	**%urban**	**%road**	**grw_rate**	**leesalee**	**grw_pix**	
290.75	1.67	10.00	12.95	6.47	51.78	59.81	89.02	16.34	0.00	1.46	0.47	3867.29	

After these calibrations were run and the formula (based on SLEUTH coefficients) that best matches the land-cover transition was found (diffusion: 13%; spread: 6%; breed: 52%; slope-resistance: 60%; and road-gravity: 89%); two simulations maintaining this founded formula (test and land test) were run from past to present (1,974 - 2,001). In the SLEUTH simulations the most influential coefficient was road-gravity (89%). After comes slope (60%) and breed (52%). diffusion (13%) and spread (6%) are the coefficients that influence the less. The past to the present (1974–2001) simulations serves both as a visual verification for the accuracy of the different model calibrations and shows the historical perception of land-cover and urban development changes. To minimize the uncertainty, Monte Carlo iterations were setup at a 100 level.

After, this formula that predicted the pattern of growth seen in Escambia, Santa Rosa, and Okaloosa counties from year 1974 to 2001 was then used to predict urban growth and other land-cover changes from 2001 through 2025. Therefore, 3 other simulations were applied from present into the future (year 2,001 to 2,025). These present-future simulations were based on 3 different scenarios: a Normal Trend transition (from 1974 to 2025), maintaining the coefficients founded in the past-present calibrations (diffusion: 13%; breed: 52%; spread: 6%; slope-resistance: 60%; and road-gravity: 89%), plus two other scenarios developed for comparison and contrast with normal growth, were parameters were modified to further predict the growth of Escambia, Santa Rosa, and Okaloosa counties under conditions of both urban sprawl and smart growth patterns. This simulation was completed after 2 hours 38 minutes and 49.94 seconds.

In the case of smart growth and urban sprawl, the three coefficients that affect the most: road-gravity (89%), slope (60%) and breed (52%) were maintained with the same values and in both cases Monte Carlo=100. Nevertheless, for smart growth (from 2001 to 2025), diffusion and spread coefficients were reduced by 50%, whereas the others coefficients maintained their original values as was mentioned before (diffusion: 6%; breed: 52%; spread: 3%; slope-resistance: 60%; and road-gravity: 89%). This simulation was completed in 2 hours 23 minutes and 48.82 seconds. And for a higher rate of urban sprawl (from 2001 to 2025), diffusion and spread coefficients are increased by 50%, whereas the others coefficients were preserved as their original values (diffusion: 20%; breed: 52%; spread: 9%; slope-resistance: 60%; and road-gravity: 89%) with Monte Carlo=100. This simulation ran for 2 hours 29 minutes and 36.50 seconds.

TEST

Table 4.6: NORMAL TRENDS for Scenario's Coefficients from 1974 to 2001

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	13 – 1 – 13			52 – 1 – 52			6 – 1 – 6			60 – 1 – 60			89 – 1 – 89		
Total # of simulations			1												

LAND TEST

Table 4.7: NORMAL TRENDS Scenario's Coefficients from 1974 to 2001

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	13 – 1 – 13			52 – 1 – 52			6 – 1 – 6			60 – 1 – 60			89 – 1 – 89		
Total # of simulations			1												

1st PROJECTION from 2001 to 2025

Table 4.8: NORMAL TRENDS Scenario's Coefficients

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	13 – 1 – 13			52 – 1 – 52			6 – 1 – 6			60 – 1 – 60			89 – 1 – 89		
Total # of simulations			1												

2nd PROJECTION: SMART GROWTH from 2001 to 2025

Table 4.9: SMART GROWTH: (Diff: 13-7=6); Brd=52; (Sprd: 6-3=3); Slp=60 & RG=89

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	6 – 1 – 6			52 – 1 – 52			3 – 1 – 3			60 – 1 – 60			89 – 1 – 89		
Total # of simulations			1												

Note: For smart growth, diffusion and spread coefficients are reduced in 50% each one, whereas the other coefficients maintain their original values.

3rd PROJECTION: URBAN SPRAWL from 2001 to 2025

Table 4.10: URBAN SPRAWL: (Diff: 13+7=20); Brd=52; (Sprd: 6+3=9); Slp=60 & RG=89

MC = 100	Coefficient Settings (Values)														
	Diff			Brd			Sprd			Slp			RG		
Subsets	start	step	stop	start	step	stop	start	step	stop	start	step	stop	start	step	stop
sub_derVe.sh	20 – 1 – 20			52 – 1 – 52			9 – 1 – 9			60 – 1 – 60			89 – 1 – 89		
Total # of simulations			1												

Note: For urban sprawl, diffusion and spread coefficients are increased in 50% each one, whereas the other coefficients maintain their original values.

SUMMARY OF FINAL RESULTS

Table 4.11: Test, Land Test and Predictions: 5 sub-scenarios with Monte Carlo = 100

Name of Calibration	Processor-node	# of Simulations	Time
sub_test	C2-10	1	2h 04’ 21.93’’
sub_landtest	C2-09	1	2h 05’ 49.93’’
sub_predict1	C3-01	1	2h 38’ 49.94’’
sub_predict2	C3-31	1	2h 23’ 48.82’’
sub_predict3	C1-18	1	2h 29’ 36.50’’
TOTAL		**5**	**Max. Time: 2h 38’ 49.94’’**

Note: Results were computed using http://www.csgnetwork.com/timescalc.html

SUMMARY OF PROCEDURES

Table 4.12: SPATIAL DATA MINING

CALIBRATIONS	NUMBER OF SIMULATIONS	# OF PROCESSORS INVOLVED	MAXIMUM TIMES
Coarse Calibration	7,776	36	27h 13’ 45.59’’
Fine Calibration	10,125	45	39h 28’ 07.05’’
Final Calibration	5,184	36	31h 39’ 11.70’’
Derive Coefficients	7	1	14h 29’ 28.30’’
TOTAL	**23,092**	**118**	**112h 49’ 32.64’’**

Note: All 23,092 simulations were made in approximately 4 days 17 hours running the UGA-RCC High-performance computer .

Table 4.13: SIMULATIONS

SIMULATIONS	NUMBER OF SIMULATIONS	# OF PROCESSORS INVOLVED	MAXIMUM TIME
Test, Land Test, Predictions 1, 2 and 3	**5**	**5**	**2h 38’ 49.94’’**

Note: All 5 simulations were made in approximately 2 and 1/2 hours running the UGA-RCC High-performance computer .

4.5. Smart Growth and Urban Sprawl

Smart Growth “*refers to development principles and planning practices that create more efficient land-use and transport patterns”* (Litman 2007). In other words, is a theory of urban planning which considers that cities should growth in a compact way avoiding urban sprawl.

Consequently, it tries to achieve a sense of community through walkable, mixed used (residential-commercial) neighborhoods.

This urban planning model began in the early 1970s with Architects Peter Calthorpe and Andrés Duany, who promoted the idea of urban villages that relied on walking (healthier pedestrian-based lifestyle that can reduce emissions and pollution, saving money on fuel and maintenance), bicycling and public transportation instead of private automobiles (Frumkin 2002). For support of this theory, government expenses in highway and road building plus long distances utility networks (electricity, water and sewage) should be considered in the true cost of sprawl because the cost of basic infrastructure is higher per parcel in sprawl neighborhoods than in compact ones.

Smart growth uses gentrification or regeneration to revitalize neglected down-towns or centers. With people working and shopping near their homes, costs of transportation and utility infrastructure are drastically reduced (Lee 2005).

Environmental groups and some professional organizations promote smart growth with its green belt boundaries where development is prohibited. The goal is to provide fresh air and clean water and include parks and recreation areas inside compact, livable urban neighborhoods where historic preservation is an important issue and socioeconomic segregation will diminish. Here, urban sprawl is drastically reduced through strategies of redevelopment based on zoning policies and laws implemented by local governments where residential and services-commerce (the highest percentage of GDP and jobs) grow together in a compact mixed-use manner called transit-oriented development (TOD) in order to maximize access to public transport (buses and trains) while new development is restricted to specific areas (Schlossberg and Brown 2004). Consequently, parking lot area decreases, there are more townhouses, condominiums, and apartments, less space for private yards, increasing size of buildings and increasing population densities.

The first urban growth boundary used to limit the growth of a city was imposed in Fayette County, Kentucky in 1958. Fifteen years later, the state of Oregon in 1973 created a law limiting the surface that cities can occupy, through boundaries that protect wild areas and farm lands around urbanized areas. Therefore, Portland is a leader in smart growth development (Jönson and Tengström 2006). After these laws were enacted, urban population density had slightly increasing since the 1970s. Nevertheless, because of population pressure, boundaries had been constantly modified and expanded. Another example is San Francisco Bay, where urban boundaries have also been adopted (Cervero 2001).

In the specific case of Florida, in 1972 a series of statutes were enacted in order to regulate developments of importance and imposed state growth priorities on local planning. These State plans have environmental, economic, and social components. In 1985, a Growth Management Act stipulates that *"public facilities and services needed to support development shall be available concurrent with the impacts of such development"* (Nicholas and Steiner 2001).

Smart growth has been criticized by the National Motorists Association, because they are against some components of smart growth, especially the ones concerned with reduction of automobile ownership. The Cato Institute believes that smart growth greatly increased land values, becoming more difficult for families to afford houses. Finally, Wendell Cox and Joshua Utt argue that these strategies intensify problems instead of solving them. They claim that after 50 years of urban decentralization, the lowest municipal government expenditures per capita are in the lower-density areas of the cities (Cox and Utt 2004).

Urban Sprawl is a 20th century phenomenon that consists on the spreading of a city and its suburbs over rural land at the fringe of an urban area. The neighborhoods in a sprawl city contain generally many single-family homes separated by big lawns from each other (as opposed to apartments) and have automobiles to commute to work (a situation known as automobile dependency where walking and other transportation methods are impractical; therefore, few sidewalks exist), generating extended cities with low population densities.

In the past, local governments used to build continuous streets in a given location in a way that the towns were able to expand without any kinds of interruption plus the fact that the lots of land where houses or other buildings were constructed had small sizes. In a sprawl situation, the developers by law need to use a certain percentage of the land for public use (roads, green areas and parks), consequently buying cheaper land, where the profit margins are higher (Gordon and Richardson 2000).

One of the characteristics of urban sprawl is single-use zoning, where residential, commercial and industrial areas use large tracts of lands and are separated from one another. Consequently, from the places where people live, they need to commute far distances to work, shop, and recreate, requiring automobiles as well as extra land for parking lots. Another characteristic of sprawl is leap-frog development, where one subdivision is separated by large green belts from another one, they offer few streets to enter and exit the neighborhood and numerous curved roads and cul-de-sac (Song and Knaap 2004).

This landscape is also characterized by strip and shopping malls, where retail stores (with many chains) are located together in big buildings (one or two floors) sharing a common spacious parking lot for the vehicles. Generally these malls are located near important highways or avenues(Cox and Utt 2004).

The United States is the country where cities have the lowest population densities covering largest areas of the landscape, especially in the suburbs due to urban sprawl. Following this trend are the Canadian and Australian cities and in a smaller manner the new European' cities suburbs (Cox 2008). Even some urban areas in the U.S. and other developed countries have expanded geographically while maintaining or losing population. At the same time, numerous urban cores have been constantly diminishing their population densities due to population losses.

Urban sprawl also has been criticized by the American Institute of Architects, the Sierra Club, the San Francisco Bay Area's Greenbelt Alliance and other environmental organizations because they associate sprawl with a number of negative environmental impacts such as the dependence on the automobile due to the enormous distances and consequent emissions, pollution, fossil fuel dependency (the most polluted air today is on the highways). For example, in a report titled "*The Dark Side of the American Dream: The Costs and Consequences of Suburban Sprawl"*, the Sierra Club ranked U.S. metropolitan areas according to their sprawl degrees (Ewing, Pendall et al. 2002). Public health concerns also exist such as car accidents, injuries (risks of dying are greater on highways) and lack of physical activity and exercise, which together with an unhealthy diet generate obesity, diabetes and heart related problems (Frumkin 2002). Opponents of urban sprawl talk about the decrease of social interactions among persons, because face-to-face contact becomes more limited. Another concern about urban sprawl is the decrease of farmland and wild areas which become transformed into new residential neighborhoods during urban expansion. Infrastructure costs are lower in compact areas whereas in urban sprawl costs of infrastructure are greater due to greater distances between buildings.

In response to these critiques, Peter Gordon, Wendell Cox, and other planners and consultants have analyzed the pros and cons of urban sprawl and smart growth. They have concluded that urban sprawl accompanies more affordable real estate, more green space, less traffic, less concerns about spreading disease in crowded conditions (Cox and Pavletich 2008) and temperatures more consistent with natural conditions.

The larger amount of land and lower population density seen in urban sprawl results in more affordable houses, especially compared with compact cities where land is limited and real estate prices are constantly increasing. Unlimited areas and lower density also causes less traffic and more green spaces. Finally, the phenomenon of "urban heat island" (Lo et al. 1997) which results from high concentrations of buildings and concrete and less green space, results in hotter cities. This phenomenon happens much less in urban sprawl than in compact cities. Urban sprawl not only increases green space, but increases the amount of privately owned green space.

Supporters of urban sprawl claim that the use of cars for commuting is much more convenient than using public transportation. Individuals can go and come as they please, regulate music and temperature, stop for food or restroom at will plus commuting times can be many times lower. While compact cities have more face-to-face communication, urban sprawl residents still communicate with their neighbors. However, a good amount of their social interactions may have shifted toward cell-phone communications (Tertoolen et al. 1998). Finally, air quality increases in areas with lower population densities and bigger green areas.

The SLEUTH simulations produce yearly graphical and statistical results since 1975 until 2025 based on the number of pixels that every year change within the different land-cover types generating in this way the continuous evolution of the landscape. It is also necessary to mention that SLEUTH produced two kinds of simulations: simulations of changes in the landscape and simulations of types of urban growth.

4.6. SLEUTH: Simulations of Changes in the Landscape

From past to present (1974-2001) one scenario called normal trend was generated through SLEUTH, whereas from present to future (2001-2025), three possible urban growth scenarios were simulated for Escambia, Santa Rosa and Okaloosa counties. The normal trend scenario assumes that the current growth trend would continue after 2001 for 24 years more until 2025; therefore, the same initial conditions used for the past to the present simulation were maintained (diffusion: 13%; spread: 6%; breed: 52%; slope-resistance: 60%; and road-gravity: 89%). According to the results for the normal trend, the simulation indicates that most of the urban growth is based on three types of coefficients: road-gravity (89%), slope-resistance (60%) and breed (52%) and consequently two types of growth are the most important ones: new spreading center and road-influenced growth. Nevertheless, because of the existence of so many urban clusters in the simulations, edge growth (based on spread coefficient) together with road-influenced accounts for the higher number of new urbanized pixels. In reality, the normal trend simulation constitutes the benchmark for comparison with the other two scenarios: smart growth and urban sprawl. At the beginning according to the classified image from 1974, urban areas constitute 157.51 Km^2 and looking at the classified image 2001 these areas growth to 271.42 Km^2, having a net increment in urban land between 1974 and 2001 of 113.91 Km^2 according to the classified images. Nevertheless, the normal trend shows that for the simulation 2001 these areas will growth to 269.46 Km^2 and the net increment in urban land in 27 years was 111.95 Km^2. Using the projections of this same normal trend, these areas will be 388.32 Km^2 in 2025, representing an increase of 116.9 Km^2. Because of this strong growth, urban land areas would occupy about 3.8318% of the total landscape by 2025 in relation with just 1.5542% in 1974 and 2.6783% in 2001.

The second scenario, smart growth provides an alternative growth strategy in which urban areas grow in a more compact way, consequently increasing its population density and decreasing the vegetated area and open space in metro areas. This trend is achieved reducing diffusion coefficient from 13 into 6 as well as spread coefficient from 6 to 3, while maintained the other coefficients without changes. Under this scenario, the projected urban area for year 2025 would be 290.03 Km^2 and the total increase from 2001 to 2025 will be just 18.61 Km^2 in 24 years, occupying 2.7437% of the entire surface.

The last scenario embodies a super sprawl growth strategy, which requires the increase in growth rate of diffusion (from 13 to 20) and spread coefficients (from 6 to 9), whereas the other coefficients did not have any changes. This scenario simulates the spatial consequences of urban growth at a higher rate than normal encouraging spontaneous and edge growth, so development in isolated areas as well as around existing urban clusters will occur. All these will happen while maintaining the same demographic projections, consequently population densities will decrease as well as the urban areas will tend to be more diffused than normal. This design is based on the finding that the low-density urban use (mainly residential) tends to develop away from existing large urban facilities (Yang and Lo 2003). Under this scenario, the projected urban land for 2025 would be 449.51 Km^2, which implies a net increase in urban land of 178.09 Km^2 since 2001 (271.42 Km^2), occupying 4.4356% of the entire modeled area for year 2025. See figures A-III.3 to A-III.30 in appendix III (pages 343 to 356).

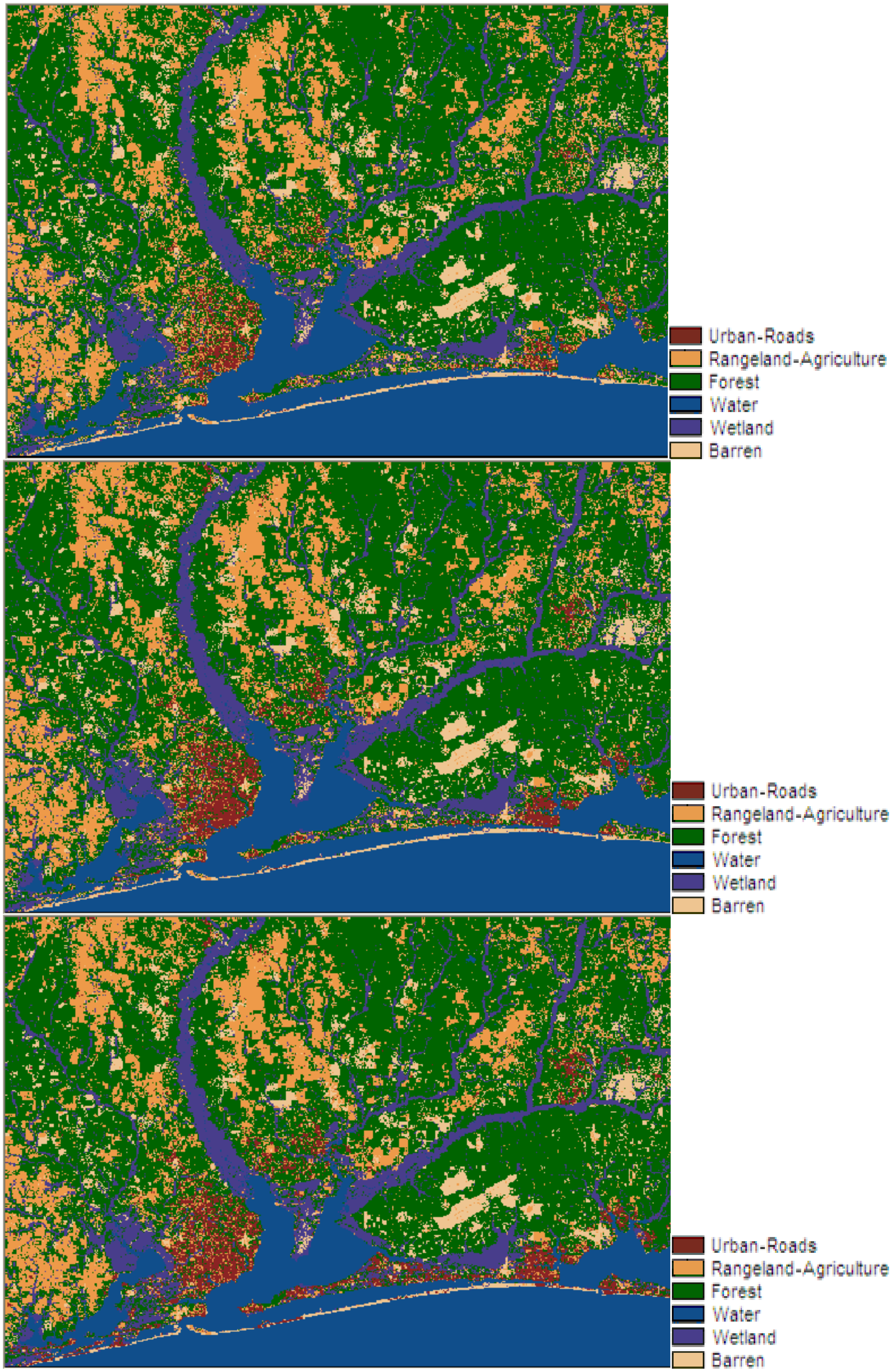


Figure 4.7: Examples of SLEUTH simulations for years 1975, 2001 and 2025

Table 4.14: Historical Land-cover of Escambia, Santa Rosa and Okaloosa (# pixels)

	LAND-COVER TYPES						
YEARS	Urban	Agriculture Pastures	Forests	Water	Wetlands	Barren Lands	TOTAL
Real 1974	**175,007**	**1,656,455**	**5,396,171**	**2,126,910**	**1'245,202**	**660,479**	**11,260,224**
Sim 1975	178,472	1,654,639	5,394,724	2,126,895	1,245,244	660,250	11,260,224
Sim 1980	198,782	1,644,113	5,386,179	2,126,889	1,245,307	658,954	11,260,224
Sim 1985	220,071	1,633,359	5,377,059	2,126,887	1,245,322	657,526	11,260,224
Real 1986	**224,348**	**1,609,530**	**5,395,024**	**2,126,923**	**1,244,897**	**659,502**	**11,260,224**
Sim 1986	224,426	1,631,136	5,375,215	2,126,886	1,245,330	657,231	11,260,224
Sim 1990	242,173	1,622,241	5,367,545	2,126,884	1,245,421	655,960	11,260,224
Real 1992	**252,277**	**1,605,214**	**5,378,834**	**2,126,929**	**1,244,707**	**652,263**	**11,260,224**
Sim 1992	252,270	1,617,188	5,363,212	2,126,885	1,245,407	655,262	11,260,224
Sim 1995	267,716	1,609,668	5,356,217	2,126,882	1,245,460	654,281	11,260,224
Sim 2000	293,982	1,597,106	5,344,425	2,126,880	1,245,516	652,315	11,260,224
Real 2001	**301,581**	**1,596,778**	**5,344,673**	**2,126,788**	**1,242,690**	**647,714**	**11,260,224**
Sim 2001	299,401	1,594,524	5,341,907	2,126,884	1,245,506	652,002	11,260,224

Table 4.15: Projections of Land-cover of Escambia, Sta. Rosa & Okaloosa (# pixels)

	LAND-COVER TYPES						
YEARS	Urban	Agriculture Pastures	Forests	Water	Wetlands	Barren Lands	TOTAL
Smart Growth 2005	308,944	1,594,309	5,340,479	2,126,767	1,242,753	646,972	11,260,224
Normal Trend 2005	**321,703**	**1,590,163**	**5,333,094**	**2,126,767**	**1,242,818**	**645,679**	**11,260,224**
Urban Sprawl 2005	333,035	1,586,712	5,326,296	2,126,767	1,242,964	644,450	11,260,224
Smart Growth 2010	312,307	1,593,143	5,338,576	2,126,769	1,242,733	646,696	11,260,224
Normal Trend 2010	**347,582**	**1,581,839**	**5,318,004**	**2,126,768**	**1,242,949**	**643,082**	**11,260,224**
Urban Sprawl 2010	372,639	1,574,676	5,302,472	2,126,768	1,243,305	640,364	11,260,224
Smart Growth 2015	315,647	1,592,030	5,336,686	2,126,768	1,242,725	646,368	11,260,224
Normal Trend 2015	**373,495**	**1,574,373**	**5,302,089**	**2,126,764**	**1,243,066**	**640,437**	**11,260,224**
Urban Sprawl 2015	414,228	1,562,535	5,276,896	2,126,766	1,243,346	636,453	11,260,224
Smart Growth 2020	318,967	1,590,872	5,334,860	2,126,766	1,242,743	646,016	11,260,224
Normal Trend 2020	**401,690**	**1,566,113**	**5,284,800**	**2,126,764**	**1,243,177**	**637,680**	**11,260,224**
Urban Sprawl 2020	455,327	1,551,214	5,250,970	2,126,761	1,243,463	632,489	11,260,224
Smart Growth 2025	322,258	1,589,897	5,332,869	2,126,765	1,242,758	645,677	11,260,224
Normal Trend 2025	**431,468**	**1,558,081**	**5,265,757**	**2,126,760**	**1,243,343**	**634,815**	**11,260,224**
Urban Sprawl 2025	499,457	1,539,250	5,222,562	2,126,760	1,243,523	628,672	11,260,224

Table 4.16: Historical Land-cover of Escambia, Santa Rosa and Okaloosa (in Km2)

YEARS	LAND-COVER TYPES Urban	Agriculture Pastures	Forests	Water	Wetlands	Barren Lands	TOTAL
Real 1974	**157.51**	**1,490.81**	**4,856.55**	**1,914.22**	**1,120.68**	**594.43**	**10,134.20**
Sim 1975	160.62	1,489.18	4,855.25	1,914.21	1,120.72	594.23	10,134.20
Sim 1980	178.90	1,479.70	4,847.56	1,914.20	1,120.78	593.06	10,134.20
Sim 1985	198.06	1,470.02	4,839.35	1,914.20	1,120.79	591.77	10,134.20
Real 1986	**201.91**	**1,448.58**	**4,855.52**	**1,914.23**	**1,120.41**	**593.55**	**10,134.20**
Sim 1986	201.98	1,468.02	4,837.69	1,914.20	1,120.80	591.51	10,134.20
Sim 1990	217.96	1,460.02	4,830.79	1,914.20	1,120.88	590.36	10,134.20
Real 1992	**227.05**	**1,444.69**	**4,840.95**	**1,914.24**	**1,120.24**	**587.04**	**10,134.20**
Sim 1992	227.04	1,455.47	4,826.89	1,914.20	1,120.87	589.74	10,134.20
Sim 1995	240.94	1,448.70	4,820.60	1,914.19	1,120.91	588.85	10,134.20
Sim 2000	264.58	1,437.40	4,809.98	1,914.19	1,120.96	587.08	10,134.20
Real 2001	**271.42**	**1,437.10**	**4,810.21**	**1,914.11**	**1,118.42**	**582.94**	**10,134.20**
Sim 2001	269.46	1,435.07	4,807.72	1,914.20	1,120.96	586.80	10,134.20

Table 4.17: Land-cover Projections of Escambia, Sta. Rosa & Okaloosa (in Km2)

YEARS	LAND-COVER TYPES Urban	Agriculture Pastures	Forests	Water	Wetlands	Barren Lands	TOTAL
Smart Growth 2005	278.05	1,434.88	4,806.43	1,914.09	1,118.48	582.27	10,134.20
Normal Trend 2005	**289.53**	**1,431.15**	**4,799.78**	**1,914.09**	**1,118.54**	**581.11**	**10,134.20**
Urban Sprawl 2005	299.73	1,428.04	4,793.67	1,914.09	1,118.67	580.01	10,134.20
Smart Growth 2010	281.08	1,433.83	4,804.72	1,914.09	1,118.46	582.03	10,134.20
Normal Trend 2010	**312.82**	**1,423.66**	**4,786.20**	**1,914.09**	**1,118.65**	**578.77**	**10,134.20**
Urban Sprawl 2010	335.38	1,417.21	4,772.22	1,914.09	1,118.97	576.33	10,134.20
Smart Growth 2015	284.08	1,432.83	4,803.02	1,914.09	1,118.45	581.73	10,134.20
Normal Trend 2015	**336.15**	**1,416.94**	**4,771.88**	**1,914.09**	**1,118.76**	**576.39**	**10,134.20**
Urban Sprawl 2015	372.81	1,406.28	4,749.21	1,914.09	1,119.01	572.81	10,134.20
Smart Growth 2020	287.07	1,431.78	4,801.37	1,914.09	1,118.47	581.41	10,134.20
Normal Trend 2020	**361.52**	**1,409.50**	**4,756.32**	**1,914.09**	**1,118.86**	**573.91**	**10,134.20**
Urban Sprawl 2020	409.79	1,396.09	4,725.87	1,914.08	1,119.12	569.24	10,134.20
Smart Growth 2025	290.03	1,430.91	4,799.58	1,914.09	1,118.48	581.11	10,134.20
Normal Trend 2025	**388.32**	**1,402.27**	**4,739.18**	**1,914.08**	**1,119.01**	**571.33**	**10,134.20**
Urban Sprawl 2025	449.51	1,385.33	4,700.31	1,914.08	1,119.17	565.80	10,134.20

Table 4.18: Historical Land-cover of Escambia, Sta. Rosa and Okaloosa (Area %)

	LAND-COVER TYPES						
YEARS	**Urban**	**Agriculture Pastures**	**Forests**	**Water**	**Wetlands**	**Barren Lands**	**TOTAL**
Real 1974	**1.55**	**14.71**	**47.92**	**18.89**	**11.06**	**5.87**	**100.00**
Sim 1975	1.59	14.69	47.91	18.89	11.06	5.86	100.00
Sim 1980	1.77	14.60	47.83	18.89	11.06	5.85	100.00
Sim 1985	1.95	14.51	47.75	18.89	11.06	5.84	100.00
Real 1986	**1.99**	**14.29**	**47.91**	**18.89**	**11.06**	**5.86**	**100.00**
Sim 1986	1.99	14.49	47.74	18.89	11.06	5.84	100.00
Sim 1990	2.15	14.41	47.67	18.89	11.06	5.83	100.00
Real 1992	**2.24**	**14.26**	**47.77**	**18.89**	**11.05**	**5.79**	**100.00**
Sim 1992	2.24	14.36	47.63	18.89	11.06	5.82	100.00
Sim 1995	2.38	14.30	47.57	18.89	11.06	5.81	100.00
Sim 2000	2.61	14.18	47.46	18.89	11.06	5.79	100.00
Real 2001	**2.68**	**14.18**	**47.47**	**18.89**	**11.04**	**5.75**	**100.00**
Sim 2001	2.66	14.16	47.44	18.89	11.06	5.79	100.00

Table 4.19: Land-cover Projections of Escambia, Sta. Rosa and Okaloosa (Area %)

	LAND-COVER TYPES						
YEARS	**Urban**	**Agriculture Pastures**	**Forests**	**Water**	**Wetlands**	**Barren Lands**	**TOTAL**
Smart Growth 2005	2.74	14.16	47.43	18.89	11.04	5.75	100.00
Normal Trend 2005	**2.86**	**14.12**	**47.36**	**18.89**	**11.04**	**5.73**	**100.00**
Urban Sprawl 2005	2.96	14.09	47.30	18.89	11.04	5.72	100.00
Smart Growth 2010	2.77	14.15	47.41	18.89	11.04	5.74	100.00
Normal Trend 2010	**3.09**	**14.05**	**47.23**	**18.89**	**11.04**	**5.71**	**100.00**
Urban Sprawl 2010	3.31	13.98	47.09	18.89	11.04	5.69	100.00
Smart Growth 2015	2.80	14.14	47.39	18.89	11.04	5.74	100.00
Normal Trend 2015	**3.32**	**13.98**	**47.09**	**18.89**	**11.04**	**5.69**	**100.00**
Urban Sprawl 2015	3.68	13.88	46.86	18.89	11.04	5.65	100.00
Smart Growth 2020	2.83	14.13	47.38	18.89	11.04	5.74	100.00
Normal Trend 2020	**3.57**	**13.91**	**46.93**	**18.89**	**11.04**	**5.66**	**100.00**
Urban Sprawl 2020	4.04	13.78	46.63	18.89	11.04	5.62	100.00
Smart Growth 2025	2.86	14.12	47.36	18.89	11.04	5.73	100.00
Normal Trend 2025	**3.83**	**13.84**	**46.76**	**18.89**	**11.04**	**5.64**	**100.00**
Urban Sprawl 2025	4.44	13.67	46.38	18.89	11.04	5.58	100.00

As mentioned in chapter 3, in the case of rangeland, agriculture and grasslands from past to present (1974-2001) decrease of this category was from 14.71% of the total surface in 1974 to 14.18% in 2001 according to the classified Land-cover. The yearly rates of decrease were -0.24% in the period 1974-1986, -0.04% between 1986 and 1992 and -0.06% in the last stage 1992-2001. In surface, this land-cover went down from 1,490.81 Km^2 in 1974 to 1,437.10 in 2001, a total loss of 53.71 Km^2, especially in the period 1974-1986, when -42.23 Km^2 were transformed into urban areas. Also this period contains the greatest amount of time (12 years).

According to the simulated Land-cover (normal trend), the category rangelands, agriculture and grasslands decreased from 1,490.81 Km^2 (1,656,455 pixels) in 1974 (classified land-cover) to 1,435.07 Km^2 (1,594,524 pixels) according to the simulation of the year 2001. The total decrease in 27 years was -55.74 Km^2 or -61,931 pixels. Therefore in 1974 the percentage of this land-cover in the landscape was 14.71% and in the simulation of 2025 this value had diminished to 14.16% of the landscape.

Looking into the future and according to the normal trend simulation, the category rangelands, agriculture and grasslands will decrease from 1,437.10 Km^2 (1,596,778 pixels) in 2001 (classified land-cover) to 1,402.27 Km^2 (1,558,081 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -34.83 Km^2 or -38,697 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 14.18% and in the simulation of 2025 this value will diminished to 13.84% of the landscape.

According to the smart growth simulation, the category rangelands, agriculture and grasslands will decrease from 1,437.10 Km^2 (1,596,778 pixels) in 2001 (classified land-cover) to just 1,430.91 Km^2 (1,589,897 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be just -6.19 Km^2 or -6,881 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 14.18% and in the simulation of 2025 this value will slightly diminished to 14.12% of the landscape. The reason why this land-cover changes so little is because of the strong constrains that are applied to the urban growth using the smart growth simulations.

Using the urban sprawl simulation, rangelands, agriculture and grasslands will decrease from 1,437.10 Km^2 (1,596,778 pixels) in 2001 (classified land-cover) to 1,385.33 Km^2 (1,539,250 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -51.77

Km^2 or -57,528 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 14.18% and in the simulation of 2025 this value will diminished to 13.67**%** of the landscape. The reason why the changes in this category are higher using the urban sprawl simulation is due to the lack of constrains to urban growth.

When forest areas are being analyzed according to the classified land-cover trend from past to present (1974-2001) decreased from 47.92% of the total surface in 1974 to 47.47% in 2001 n the way how it was mentioned before in chapter 3. The yearly rates of decrease were -0.0268% between 1974 and 1986, -0.05% in the period 1986-1992 and -0.06% in the last stage 1992-2001. This land-cover went down from 4,856.55 Km^2 in 1974 to 4,810.21 Km^2 in 2001, a total loss of 46.34 Km^2, particularly in the period 1992-2001 (9 years), when -30.74 Km^2 were transformed most into urban areas.

According to the simulated land-cover (normal trend), the category forests decreased from 4,856.55 Km^2 (5,396,171 pixels) in 1974 (classified land-cover) to 4,807.72 Km^2 (5,341,907 pixels) according to the simulation of the year 2001. The total decrease in 27 years was -48.83 Km^2 or -54,264 pixels. Therefore in 1974 the percentage of this land-cover in the landscape was 47.92% and in the simulation of 2001 this value had diminished to 47.44% of the landscape.

Looking into the future and according to the normal trend simulation, the category forests will decrease from 4,810.21 Km^2 (5,344,673 pixels) in 2001 (classified land-cover) to 4,739.18 Km^2 (5,265,757 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -71.03 Km^2 or -78,916 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 47.47% and in the simulation of 2025 this value will diminished to 46.76% of the landscape.

According to the smart growth simulation, the category forests will decrease from 4,810.21 Km^2 (5,344,673 pixels) in 2001 (classified land-cover) to just 4,799.58 Km^2 (5,332,869 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be just -10.63 Km^2 or -11,804 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 47.47% and in the simulation of 2025 this value will slightly diminished to 47.36% of the landscape. The reason why this land-cover changes so little is because of the strong constrains that are applied to the urban growth using the smart growth simulations.

And using the urban sprawl simulation, forests will decrease from 4,810.21 Km^2 (5,344,673 pixels) in 2001 (classified land-cover) to 4,700.31 Km^2 (5,222,562 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -109.90 Km^2 or -122,111 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 47.47% and in the simulation of 2025 this value will diminished to 46.38% of the landscape. The reason why the changes in this category are higher using the urban sprawl simulation is due to the lack of constrains to urban growth.

Analyzing barrenlands inside the classified land-cover trend, from past to present (1974-2001) suffered a small decreased, representing 5.87% of the total surface in 1974 whereas in 2001 they become 5.75% as it was mentioned in chapter 3. The yearly rates of decrease were -0.01 % in the period 1974- 1986, -0.1838% between 1986 and 1992 and -0.08% in the last stage 1992-2001. In absolute terms, this land-cover went down from 594.43 Km2 in 1974 to 582.94 Km^2 in 2001, a total reduction of 11.49 Km^2, especially in two periods: between 1986 and 1992 and in the period 1992-2001 when -6.51 Km^2 and 4.10 Km^2 becoming new urban areas. It is important to indicate that there has been a strong attraction in recent years for urban development in the islands, especially inside Santa Rosa island, where numerous protected areas also exist.

According to the simulated Land-cover (normal trend), the category barrenlands decreased from 594.43 Km^2 (660,479 pixels) in 1974 (classified land-cover) to 586.80 Km^2 (652,002 pixels) according to the simulation of the year 2001. The total decrease in 27 years was -7.63 Km^2 or -8,477 pixels. Therefore in 1974 the percentage of this land-cover in the landscape was 5.87% and in the simulation of 2001 this value had diminished to 5.79% of the landscape.

Looking into the future and according to the normal trend simulation, the category barrenland will decrease from 582.94 Km^2 (647,714 pixels) in 2001 (classified land-cover) to 571.33 Km^2 (634,815 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -11.61 Km^2 or -12,899 pixels. Therefore, in 2001 the percentage of this land-cover in the landscape was 5.75% and in the simulation of 2025 this value will diminished to 5.64% of the landscape.

According to the smart growth simulation, the category barrenlands will decrease from 582.94 Km^2 (647,714 pixels) in 2001 (classified land-cover) to just 581.11 Km^2 (645,677 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be just -1.83 Km^2 or -2,037 pixels. Therefore in 2001 the percentage of this land-cover in the landscape was 5.75% and in the simulation of 2025 this value will slightly diminished to 5.73% of the landscape. The reason why this land-cover changes so little is because of the strong constrains that are applied to urban growth using the smart growth simulations.

Using the urban sprawl simulation, barrenlands will decrease from 582.94 Km^2 (647,714 pixels) in 2001 (classified land-cover) to 565.80 Km^2 (628,672 pixels) according to the simulation of the year 2025. The total decrease in 24 years will be -17.14 Km^2 or -19,042 pixels. Therefore, in 2001 the percentage of this land-cover in the landscape was 5.75% and in the simulation of 2025 this value will diminished to 5.58% of the landscape. The reason why changes in this category are higher using urban sprawl simulation is due to the lack of constrains to urban growth.

Because wetlands constitute protected areas and water is unable to be urbanized, these two land-covers have been maintained with the same surface from 1974 to 2001 (27 years). For example, in 1974, wetlands constitute 1,120.68 Km^2 or 11.06% of the total surface and in 2001 this percentage was almost the same: 1,118.42 Km^2 or 11.04% of this area. In the case of the water land-cover (lakes, rivers and sea), in 1974 it constitutes 1,914.22 Km^2 or 18.89% of the total area of the region and in 2001 it was basically the same: 1,914.11 Km^2 or 18.89%; in other words, there had been basically no change.

According to the simulated land-cover (normal trend), the category wetlands slightly went up from 1,120.68 Km^2 (1,245,202 pixels) in 1974 (classified land-cover) to 1,120.96 Km^2 (1,245,506 pixels) according to the simulation of the year 2001. The total increase in 27 years was just +0.28 Km^2 or +304 pixels. Therefore in 1974 the percentage of this land-cover in the landscape was 11.06% and in the simulation of 2001 this value was almost maintain in 11.06% of the landscape. It is necessary to indicate that the deltatrons were affecting this category during all simulations and scenarios; this is the reason why looking at the classified images, wetlands are slightly decreasing from 1,120.68Km^2 (11.06% of the landscape) in 1974 towards 1,118.42 Km^2 (11.04%) in 2001; but contrary always according to the simulation trends, wetlands are able to show small gains in the landscape. And the reason why deltatrons propagate small increments in wetlands is because the system finds the land-cover class whose average slope is most similar to the urban class slope.

Looking into the future, the category wetland will slightly increase from 1,118.42 Km^2 in 2001 (classified land-cover) to 1,119.01 Km^2 in 2025 according to the normal trend projection;

to 1,118.48 Km2 in 2025 according to the smart growth projection and to 1,119.17 Km^2 in 2025 according to the urban sprawl projection. The total increase in 27 years will be between +0.0611 Km^2 in the case of smart growth; +0.06 Km^2 in the case of the normal trend projection and +0.75 Km^2 in the case of urban sprawl. In other words, there will be almost no change in category wetlands according to the SLEUTH simulations because wetlands are protected land-covers. Therefore, in 2001 the percentage of this land-cover in the landscape was 11.04% and in the simulations of 2025 this value will slightly increase between 11.04% (smart growth projection) and 11.04% (urban sprawl projection) or 11.04% in the case of the normal trend projection.

In the case of water, according to the normal trend simulations, this category slightly went up from 1,914.22 Km^2 (2,126,910 pixels) in 1974 (classified land-cover) to 1,914.20 Km^2 (2,126,884 pixels) according to the simulation of the year 2001, becoming a land-cover without changes in 27 years. Therefore in 1974 the percentage of this land-cover in the landscape was 18.89% and in the simulation of 2001 this value was 18.89% in reality the same.

Looking into the future, the land-cover water will not present changes regardless of the projection (normal trend, smart growth and urban sprawl) because deltatrons do not work on the water mask of the hill-shaded relief that was created beforehand for SLEUTH simulations. This is the same reason why this category almost did not change between 1974 and 2001 with the exceptions of vey small changes that are produced because of small variations in the classification of the Landsat images. Consequently from 2001 until 2025 the areas with water will correspond to 1,914.09 Km^2 (2,126,767 pixels) or 18.89% of the area of research in all three projections already mentioned.

The main conclusions from the simulations, their statistics and analyses are that urban expansion principally affects the category agriculture, rangelands and grasslands, in second place forests are diminished by urban expansion and finally the category barrenlands suffer also development, especially the areas of the beaches, which presented an unprecedented urban growth unable to be match by the SLEUTH simulation from 1974 to 2001 because only one formula (parameters calibration) was used for all 3 counties and census-tracts regardless of the differences at the micro level. On the other hand, wetlands are basically not affected by the urban expansion because they constitute protected areas and water cover (lakes, rivers and sea) is not affected at all.

Finally, the land-cover maps simulated by SLEUTH generally show small gradual yearly changes, which are difficult to visualize at the regional or county level, but easier to notice zooming in at the city or census-tract level. Therefore, changes are not obvious year-to-year instead they become evident though land-covers comparisons at least every five years.

4.7. SLEUTH: Simulations of Types of Urban Growth

In order to define which types of urban growth predominates, the next step is to analyze the four images about urban areas (1974, 1986, 1992 and 2001) that were isolated from the landscape beforehand and which constitute part of the input data required to build up the SLEUTH model together with the SLEUTH results about urban growth types that are also produced in the simulations. For the four classified land-covers, urban areas were reclassified from 1 into 100 while agriculture-rangelands (3), forests (4), water (5), wetlands (6), and barrenlands (7) were reclassified all of them into zero (0). Finally, in the case of the simulations, urban areas were also reclassified from 1 into 100 while the other land-covers mentioned before adopted the value of zero as well. In the case of the urban SLEUTH simulations, besides showing the original urban areas at the beginning of the simulations from past to present (in 1974) and from present into the future (in 2001), additionally the 4 types of urban growth: edge, road growth, spread and breed growth also are produced graphically and statistically. For a better understanding of the urban dynamics, in the case of edge and road growth, both were reclassified together with the new value of 150 because they are part of the urban expansion inside and in the periphery of the cities. On the other hand, spread and breed growth were also reclassified together with the new value of 200 because both of them constitute the generation of urban pixels in rural areas.

It is necessary to indicate that these urbanization processes, which produce the expansion of cities are associated with internal growth (births – deaths) and migration flows from other areas of the United Sates (especially North-South flows) to towns along the beach, generating a high levels of urbanization along the coast line of North-West Florida. See figures A-III.31 to A-III.58 in appendix III (pages 357 to 370).

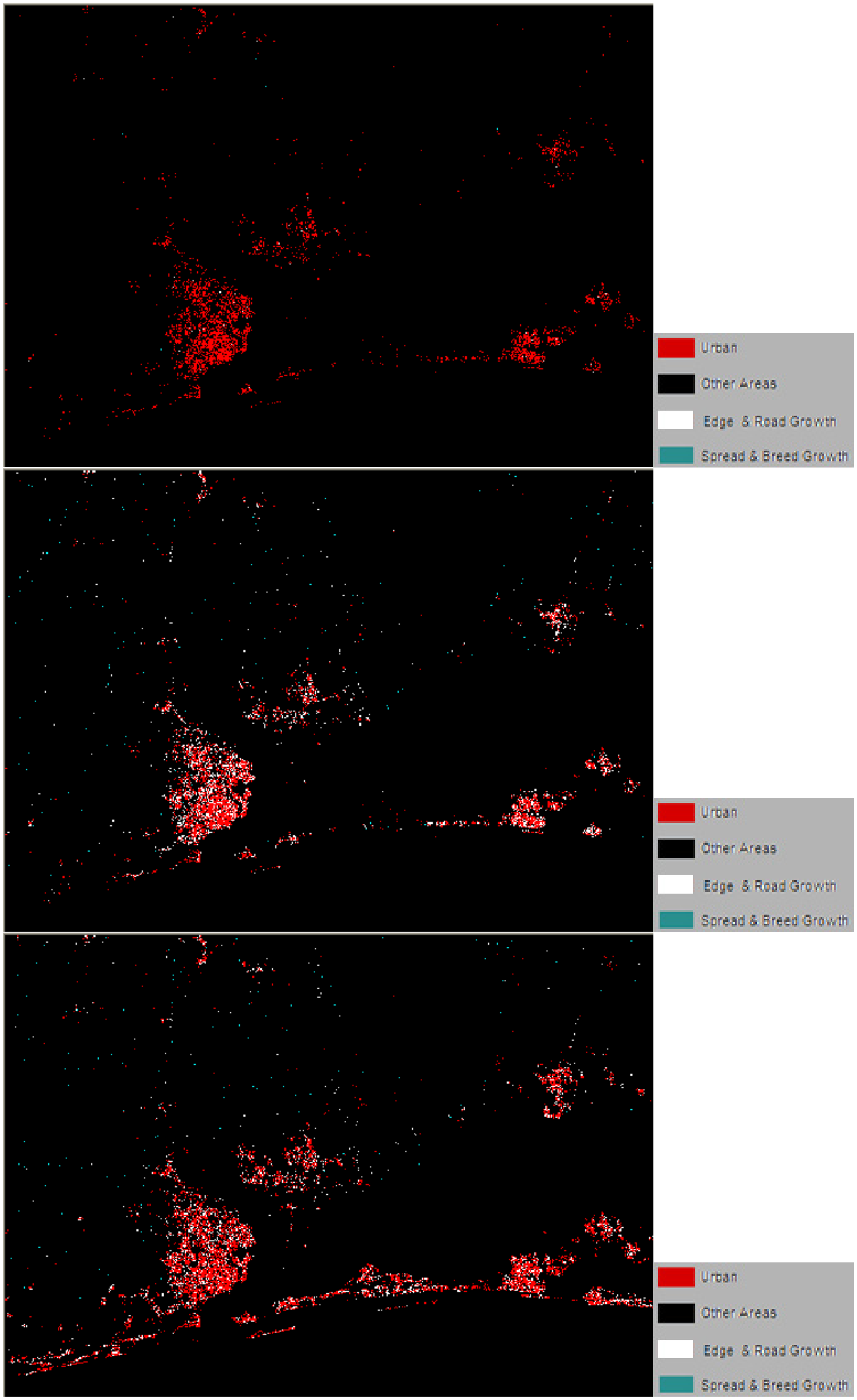


Figure 4.8: Examples of Urban SLEUTH Simulation for years 1975, 2001 and 2025

Table 4.20: Historical Urban Cover of Escambia, Sta. Rosa and Okaloosa (# pixels)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 1974**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Real 1974	**175,007**	**---**	**---**	**175,007**
Sim 1975	175,007	3,071	277	178,355
Sim 1980	175,007	21,931	1,707	198,645
Sim 1985	175,007	41,682	3,261	219,950
Real 1986	**224,348**	**---**	**---**	**224,348**
Sim 1986	175,007	45,654	3,600	224,261
Sim 1990	175,007	61,981	4,900	241,888
Real 1992	**252,277**	**---**	**---**	**252,277**
Sim 1992	175,007	71,422	5,663	252,092
Sim 1995	175,007	85,673	6,788	267,468
Sim 2000	175,007	110,230	8,872	294,109
Real 2001	**301,581**	**---**	**---**	**301,581**
Sim 2001	175,007	115,153	9,293	299,453

Table 4.21: Urban Cover Projections of Escambia, Sta. Rosa and Okaloosa (# pixels)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 2001**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Smart 2005	301,581	4,874	184	306,639
Normal 2005	**301,581**	**18,834**	**1,014**	**321,429**
Sprawl 2005	301,581	29,310	1,637	332,528
Smart 2010	301,581	8,302	201	310,084
Normal 2010	**301,581**	**43,450**	**2,446**	**347,477**
Sprawl 2010	301,581	66,808	3,950	372,339
Smart 2015	301,581	11,707	230	313,518
Normal 2015	**301,581**	**67,923**	**3,995**	**373,499**
Sprawl 2015	301,581	105,906	6,530	414,017
Smart 2020	301,581	15,011	243	316,835
Normal 2020	**301,581**	**94,527**	**5,637**	**401,745**
Sprawl 2020	301,581	144,858	9,293	455,732
Smart 2025	301,581	18,173	266	320,020
Normal 2025	**301,581**	**122,071**	**7,526**	**431,178**
Sprawl 2025	301,581	186,027	12,350	499,958

Table 4.22: Historical Urban Cover of Escambia, Sta. Rosa and Okaloosa (in Km^2)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 1974**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Real 1974	**157.51**	**---**	**---**	**157.51**
Sim 1975	157.51	2.76	0.25	160.52
Sim 1980	157.51	19.74	1.54	178.78
Sim 1985	157.51	37.51	2.93	197.96
Real 1986	**201.91**	**---**	**---**	**201.91**
Sim 1986	157.51	41.09	3.24	201.83
Sim 1990	157.51	55.78	4.41	217.70
Real 1992	**227.05**	**---**	**---**	**227.05**
Sim 1992	157.51	64.28	5.10	226.88
Sim 1995	157.51	77.11	6.11	240.72
Sim 2000	157.51	99.21	7.98	264.70
Real 2001	**271.42**	**---**	**---**	**271.42**
Sim 2001	157.51	103.64	8.36	269.51

Table 4.23: Urban Cover Projections of Escambia, Sta. Rosa and Okaloosa (in Km^2)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 2001**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Smart 2005	271.42	4.39	0.17	275.98
Normal 2005	**271.42**	**16.95**	**0.91**	**289.29**
Sprawl 2005	271.42	26.38	1.47	299.28
Smart 2010	271.42	7.47	0.18	279.08
Normal 2010	**271.42**	**39.11**	**2.20**	**312.73**
Sprawl 2010	271.42	60.13	3.56	335.11
Smart 2015	271.42	10.54	0.21	282.17
Normal 2015	**271.42**	**61.13**	**3.60**	**336.15**
Sprawl 2015	271.42	95.32	5.88	372.62
Smart 2020	271.42	13.51	0.22	285.15
Normal 2020	**271.42**	**85.07**	**5.07**	**361.57**
Sprawl 2020	271.42	130.37	8.36	410.16
Smart 2025	271.42	16.36	0.24	288.02
Normal 2025	**271.42**	**109.86**	**6.77**	**388.06**
Sprawl 2025	271.42	167.42	11.12	449.96

Table 4.24: Historical Urban Cover of Escambia, Sta. Rosa and Okaloosa (in %)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 1974**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Real 1974	**100.00**	**---**	**---**	**100.00**
Sim 1975	98.12	1.72	0.16	100.00
Sim 1980	88.10	11.04	0.86	100.00
Sim 1985	79.57	18.95	1.48	100.00
Real 1986	**100.00**	**---**	**---**	**100.00**
Sim 1986	78.04	20.36	1.61	100.00
Sim 1990	72.35	25.62	2.03	100.00
Real 1992	**100.00**	**---**	**---**	**100.00**
Sim 1992	69.42	28.33	2.25	100.00
Sim 1995	65.43	32.03	2.54	100.00
Sim 2000	59.50	37.48	3.02	100.00
Real 2001	**100.00**	**---**	**---**	**100.00**
Sim 2001	58.44	38.45	3.10	100.00

Table 4.25: Urban Cover Projections of Escambia, Sta. Rosa and Okaloosa (in %)

	LAND-COVER TYPES			
YEARS	**Initial Urban Areas in 2001**	**Edge and Road Growth**	**Spread and Breed Growth**	**TOTAL URBAN**
Smart 2005	98.35	1.59	0.06	100.00
Normal 2005	**93.83**	**5.86**	**0.32**	**100.00**
Sprawl 2005	90.69	8.81	0.49	100.00
Smart 2010	97.26	2.68	0.06	100.00
Normal 2010	**86.79**	**12.50**	**0.70**	**100.00**
Sprawl 2010	81.00	17.94	1.06	100.00
Smart 2015	96.19	3.73	0.07	100.00
Normal 2015	**80.74**	**18.19**	**1.07**	**100.00**
Sprawl 2015	72.84	25.58	1.58	100.00
Smart 2020	95.19	4.74	0.08	100.00
Normal 2020	**75.07**	**23.53**	**1.40**	**100.00**
Sprawl 2020	66.18	31.79	2.04	100.00
Smart 2025	94.24	5.68	0.08	100.00
Normal 2025	**69.94**	**28.31**	**1.75**	**100.00**
Sprawl 2025	60.32	37.21	2.47	100.00

Analyzing these figures and tables, in the year 1974 (classified land-cover) urban areas constituted 157.51 Km^2 (175,007 pixels) and every year these values went up achieving urban areas for the simulation of the year 2001 the value of 269.51 Km^2 (299,453 pixels). This growth was generated predominantly because of the edge and road-influenced growth, increasing the number of urban pixels in 115,153 (103.64 Km^2), especially inside and in the periphery of the cities as well as along the major roads and highways, while the spread and breed growth constituted just 8.36 Km^2 of new urban growth (9,293 pixels) that was generated in the rural areas of this region of analysis. For the simulation of 2001, 58.44% where constituted by initial urban pixels from 1974, 38.45% of the pixel was produced by edge and road-influenced growth and just 3.10% was the product of spread and breed growth.

Looking into the future, and according to the normal trend simulations, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and every 5 years of simulation, these values went up achieving urban areas for the simulation of the year 2025 the value of 388.06 Km^2 (431,178 pixels). This growth was generated predominantly because of the edge and road-influenced growth, increasing the number of urban pixels in 122,071 (109.86 Km^2), especially inside and in the periphery of the cities as well as along the major roads and highways, while the spread and breed growth constituted just 6.77 Km^2 of new urban growth (7,526 pixels) that was generated in the rural areas of this region of analysis. For the simulation of 2025 (normal trend), 69.94% where constituted by initial urban pixels from 1974, 28.3110% of the pixel was produced by edge and road-influenced growth and just 1.75% was the product of spread and breed growth.

In the case of the smart growth projections, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and every 5 years of simulation, these values went up achieving urban areas for the simulation of the year 2025 the value of 288.02 Km^2 (320,020 pixels). This growth was generated predominantly because of the edge and road-influenced growth, increasing the number of urban pixels in 18,173 (16.36 Km^2), especially inside and in the periphery of the cities as well as along the major roads and highways, while the spread and breed growth constituted just 0.24 Km^2 of new urban growth (266 pixels) that was generated in the rural areas of this region of analysis. For the simulation of 2025 (smart growth), 94.24% where constituted by initial urban pixels from 1974, 5.6787% of the pixel was produced by Edge and road-influenced growth and just 0.08% was the product of spread and breed growth. The reason why this land-cover changes so little is because of the strong constrains that are applied to the urban growth using the smart growth simulations.

Analyzing the urban sprawl simulation, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and every 5 years of simulation, these values went up achieving urban areas for the simulation of the year 2025 the value of 449.96 Km^2 (499,958 pixels). This growth was generated predominantly because of the edge and road-influenced growth, increasing the number of urban pixels in 186,027 (167.42 Km^2), especially inside and in the periphery of the cities as well as along the major roads and highways, while the spread and breed growth constituted just 11.12 Km^2 of new urban growth (12,350 pixels) that was generated in the rural areas of this region of analysis. For the simulation of 2025 (urban sprawl), 60.32% where constituted by initial urban pixels from 1974, 37.21% of the pixel was produced by Edge and road-influenced growth and just 2.47% was the product of spread and breed growth. The reason why changes in this category are higher using the urban sprawl simulation the lack of constrains to urban growth.

The growth in urban land as projected under these three different scenarios would slowly change more and more of the spatial form in the cities of these three counties with numerous edge cities developed throughout new areas. These changes using all three different scenarios are not really of any drastic magnitude at least until 2025; nevertheless, they should be highlighted for local or regional planning considerations.

Finally, the images produced every single year were later organized every five years in Power Point. Using this software package, different animation movies were created showing the progressive landscape changes (due to deltatrons) and urban expansion (due to the CA rules) in the form of normal growth from 1974 to 2001 (past to present) and later in 3 different scenarios from present to future simulations (2001 to 2025): normal growth, smart growth and urban sprawl. In addition to map outputs, additional cartographic elements such as title, legend and north arrow were also included. The yearly changes can be barely perceived from the animation's visual outputs because of its high-resolution and consequently small size of every one of its 11,260,224 pixels. By evaluating these animations carefully, it is found that by approximately the year 2025, a small metropolitan area would begin to emerge in the city of Pensacola plus its suburbs. The historical urban development direction in Pensacola city was towards north and west. This is related to the fact that the southern and eastern parts are surrounded by water. With these results, it is expected that all these simulations could aid in the understanding of urban coastal dynamics of middle size cities and their surroundings.

In order to find the accuracy of the SLEUTH simulations it was necessary to compare them first against the same 1,500 random sample points (ground-truth) used in Chapter 3 to assess the accuracy of the classified land-cover images; and, finally these simulations were compared against the classified land-cover images (ground-truth).

4.8. Accuracy Evaluations of SLEUTH Simulations against Random Sample Points

Because the first SLEUTH simulation begins in 1975, it was possible to assess just the SLEUTH simulations of years 1986, 1992 and 2001 against the 1,500 random sample points, obtaining results above the necessary 85% minimum threshold of agreement. These error matrices and Kappa index of agreement were generated in Idrisi Andes and the Kappa results vary between a minimum of 87.84% for the simulation 1986 and a maximum of 89.44% for the simulation 1992. For the simulation 2001, the Kappa value was 88.00%.

Table 4.26: Error Matrix and Kappa Indexes of POINTS86 (columns: truth) against SIM1986 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**213**	5	5	2	4	3	232	8.19%
3	19	**223**	15	2	3	6	268	16.79%
4	8	14	**218**	0	8	6	254	14.17%
5	4	0	3	**243**	1	8	259	6.18%
6	2	3	6	3	**230**	6	250	8.00%
7	4	5	3	0	4	**221**	237	6.75%
Total	250	250	250	250	250	250	**1500**	
Error O	14.80%	10.80%	12.80%	2.80%	8.00%	11.60%		10.13%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.28% (8.85% - 11.42%)
95% Confidence Interval = +/- 1.53% (8.61% - 11.66%)
99% Confidence Interval = +/- 2.01% (8.12% - 12.14%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM1986 as the reference image...

Category	KIA
1	90.17%
3	79.85%
4	82.99%
5	92.59%
6	90.40%
7	91.90%

POINTS86 as the reference image…

Category	KIA
1	82.49%
3	86.85%
4	84.59%
5	96.62%
6	90.40%
7	86.22%

Overall Kappa = 87.84%

Table 4.27: Error Matrix and Kappa Indexes of POINTS92 (columns: truth) against SIM1992 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**205**	8	9	1	6	4	233	12.02%
3	18	**234**	4	0	3	8	267	12.36%
4	11	5	**226**	2	5	5	254	11.02%
5	1	1	2	**246**	0	8	258	4.65%
6	4	1	6	1	**235**	3	250	6.00%
7	11	1	3	0	1	**222**	238	6.72%
Total	250	250	250	250	250	250	**1500**	
Error O	18.00%	6.40%	9.60%	1.60%	6.00%	11.20%		8.80%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.20% (7.60% - 10.00%)
95% Confidence Interval = +/- 1.43% (7.37% - 10.23%)
99% Confidence Interval = +/- 1.89% (6.91% - 10.69%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM1992 as the reference image...

Category	KIA
1	85.58%
3	85.17%
4	86.77%
5	94.42%
6	92.80%
7	91.93%

POINTS92 as the reference image…

Category	KIA
1	78.69%
3	92.21%
4	88.44%
5	98.07%
6	92.80%
7	86.69%

Overall Kappa = 89.44%

Table 4.28: Error Matrix and Kappa Indexes of POINTS2001 (columns: truth) against SIM2001 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**201**	4	7	1	6	6	225	10.67%
3	38	**228**	14	3	1	2	286	0.28%
4	3	8	**223**	0	5	7	246	9.35%
5	3	1	1	**245**	1	8	259	5.41%
6	1	5	3	1	**232**	6	248	6.45%
7	4	4	2	0	5	**221**	236	6.36%
Total	250	250	250	250	250	250	**1500**	
Error O	19.60%	8.80%	10.80%	2.00%	7.20%	11.60%		10.00%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 1.27% (8.73% - 11.27%)
95% Confidence Interval = +/- 1.52% (8.48% - 11.52%)
99% Confidence Interval = +/- 2.00% (8.00% - 12.00%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM2001 as the reference image...

Category	KIA
1	87.20%
3	75.66%
4	88.78%
5	93.51%
6	92.26%
7	92.37%

POINTS2001 as the reference image…

Category	KIA
1	76.94%
3	89.13%
4	87.08%
5	97.58%
6	91.37%
7	86.23%

Overall Kappa = 88.00%

By analyzing these error matrices and Kappa indexes, it is possible to determine categories with the lowest classification accuracy as well as categories with the highest accuracy. As mentioned in chapter 3, when errors are equal or above the threshold of 15.00%, they are represented in red color. The same red color is applied when there are 15 or more mismatches among pixels (see inside error matrices). But if there are almost no errors, equal or below the threshold of 5.00%, they are represented in blue color. The same blue color is applied when there are 5 or less mismatches among pixels inside the error matrices. Black color represents errors with values between 5.00% and 15.00% or between 5 and 15 mismatches among pixels. Finally all the data with bold black color represent in the main diagonals of the error matrices show the level of accuracy among categories. Overall Kappa also is shown in bold black color. It is also important to remember the numbers applied to each category: 1=urban; 3=agriculture-rangeland; 4=forests; 5=water; 6=wetlands and 7=barrenlands.

In all error matrices, most errors occur between categories urban (1) and agriculture-rangeland (3): 19 errors in simulation 1986, 18 errors in simulation 1992, and 38 errors in simulation 2001. It is possible that all these errors are the product of selecting the polygons for urban development in suburbs and residential areas from the classified land-cover 1974 (origin of the simulations), because using 30m (900m^2) resolution Landsat images makes difficult to differentiate small houses (less than 300m^2) from its surroundings, generally yards, grasses and trees. Also, it is possible that the new urbanized pixels (edge and road-influenced growth plus spread and breed growth) during the process of the simulation were growing in areas of agriculture, rangeland and grasslands that did not match exactly the sample points obtained from the higher accuracy imagery. In the case of the accuracy of the simulation 1986, 15 errors occur between categories agriculture-rangeland (3) and forests (4). The same mistake in the selection of the urban areas from the classified land-cover 1974 (origin of the simulation) can explain the confusion in the classifier algorithm between agriculture-rangeland and forests in the simulation of 1986.

The producer's accuracy in category urban (1) shows errors of omission (1 - producer's accuracy) higher than 15.00% for two simulations: 18.00% in simulation 1992 and 19.60% in simulation 2001. All other categories present errors of omission below the threshold of 15.00%.

The user's accuracy in category agriculture-rangeland (3) indicates errors of commission (1 - user's accuracy) higher than 15.00% for two simulations: 16.79% in simulation 1986 and 20.28% in simulation 2001, whereas all other categories present errors of omission below the threshold of 15.00%. The reason for these errors of omission and commission were already explained two paragraphs before.

Using the simulations as the reference images, Kappa indexes of agreement were low for the category 3=agriculture-rangeland (79.85% and 75.66%) for the years 1986 and 2001 respectively; and for the category 4=forests this value was 82.99% in the year 2001.

And using the random sample points as the reference image, Kappa indexes of agreement were low especially for categories 1=urban for the years 1986 (82.49%), 1992 (78.69%) and 2001 (76.94%). This is due to the conflicts in the land-cover 1974 (origin of simulations) identifying at 30m resolution single residential houses from their yards, which are considered part of agriculture-rangeland or forest lands. Also, it is possible that the new urbanized pixels (from edge and road-influenced growth, and from spread and breed growth) during the process of the simulation were growing in areas of agriculture, rangeland and grasslands that did not match exactly the sample points obtained from the higher accuracy imagery. Another low Kappa index using the random sample points as the reference image occur with category 4=forests in the year 1986, which presents the value of 84.59%. The reason is a slightly confusion of the classifier algorithm between forests with several other land-covers in the land-cover 1974, which is the origin of all the simulations.

In the case of the highest accuracy achieved using the random sample points as the reference image, it is possible to mention the case of category 5=water for the years 1986 (96.62%), 1992 (98.07%) and 2001 (97.58%) first because this land-cover was classified with the highest accuracy possible in the land-cover 1974 and second due to the fact that the category water was maintained static (without changes) during the simulations. Therefore, few mismatches among pixels in reality exist, presenting errors of omission of just 2.80%, 1.60%, and 2.00% for the simulations 1986, 1992 and 2001.

4.9. Accuracy Evaluations of SLEUTH Simulations against Classified Land-covers

Using Idrisi Andes software package, it was possible to visually and statistically compare the land-cover maps (considered as truth) versus the simulation maps for the years 1986, 1992 and 2001. In the case of land-cover 1974 was not possible to compare against any simulation, because the first image that SLEUTH generates is the simulation from 1975.

The visual comparison was made through a map of conflicts that show in black color all the areas that do not match between the classified land-covers and the simulations, whereas the other land-covers that do match are maintained with their normal colors. These maps show really few disagreements (in black color) especially in areas of beaches and some wetlands where urban development was impossible to replicate through SLEUTH, consequently demonstrating that this model really simulates reality with a high degree of certainty and confidence.

Finally, a statistical comparison is also made through the use of error matrices and Kappa indexes of agreement.

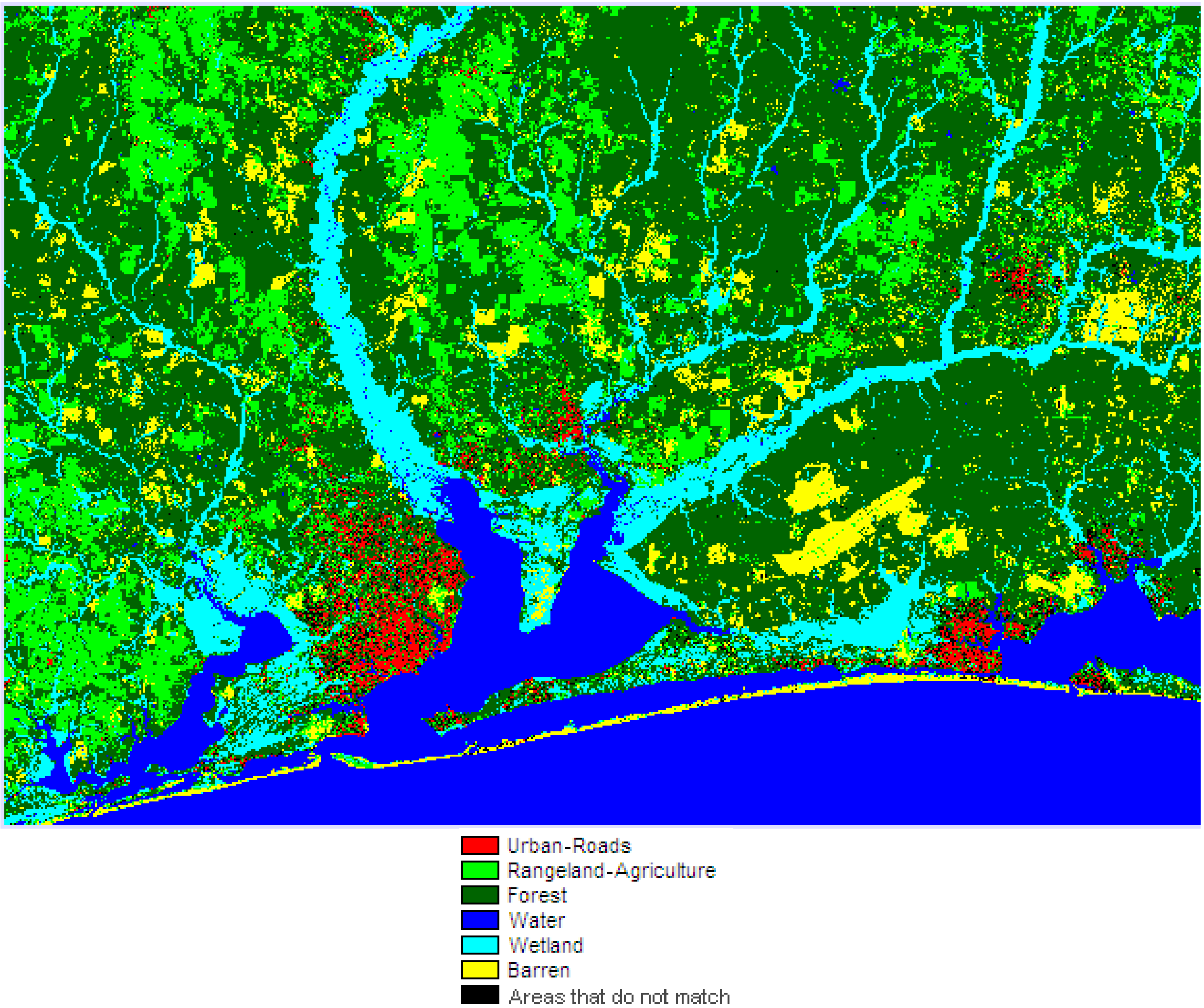


Figure 4.9: Comparison 1986 between Classified Land-cover (truth) and Simulation

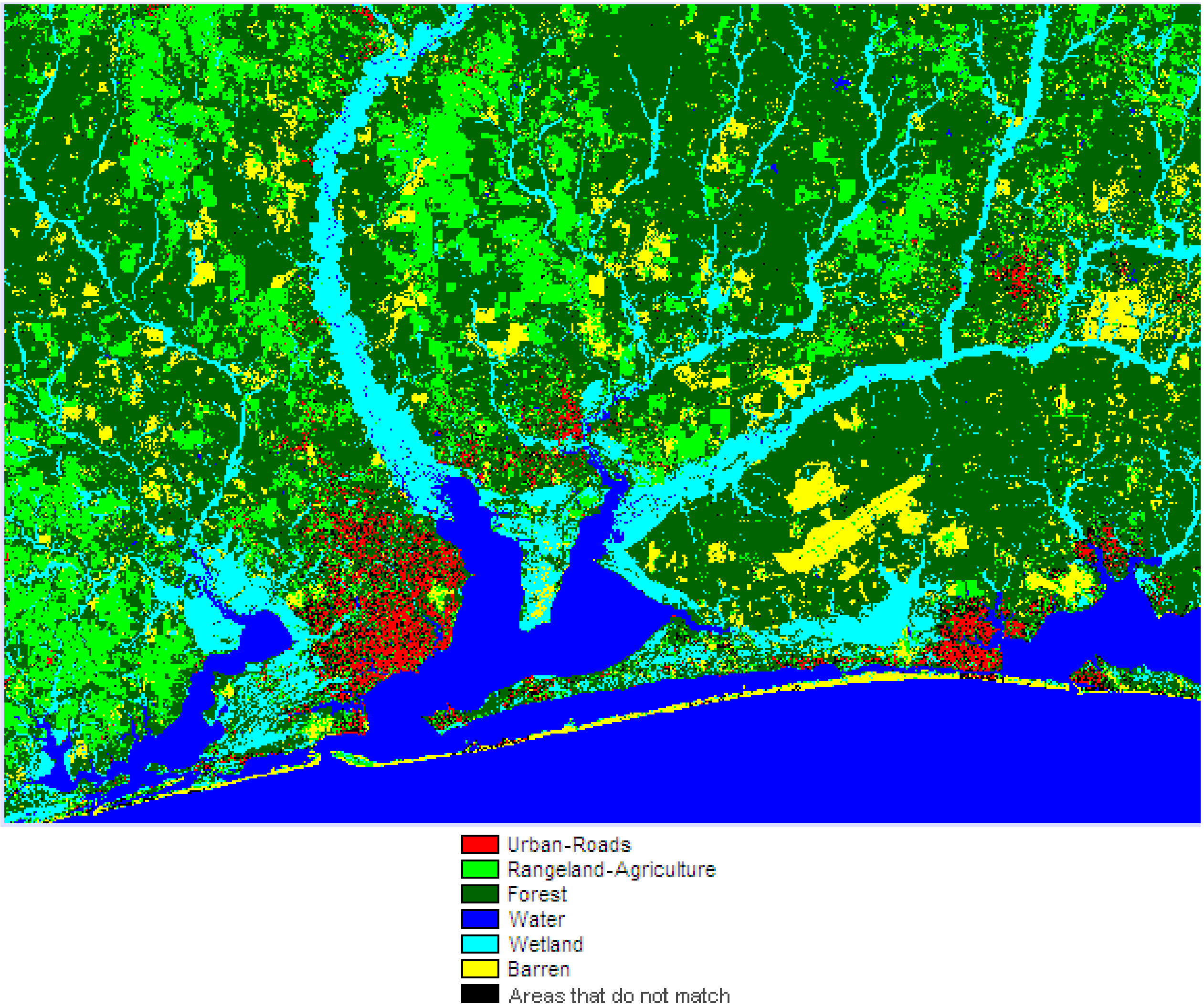


Figure 4.10: Comparison 1992 between Classified Land-cover (truth) and Simulation

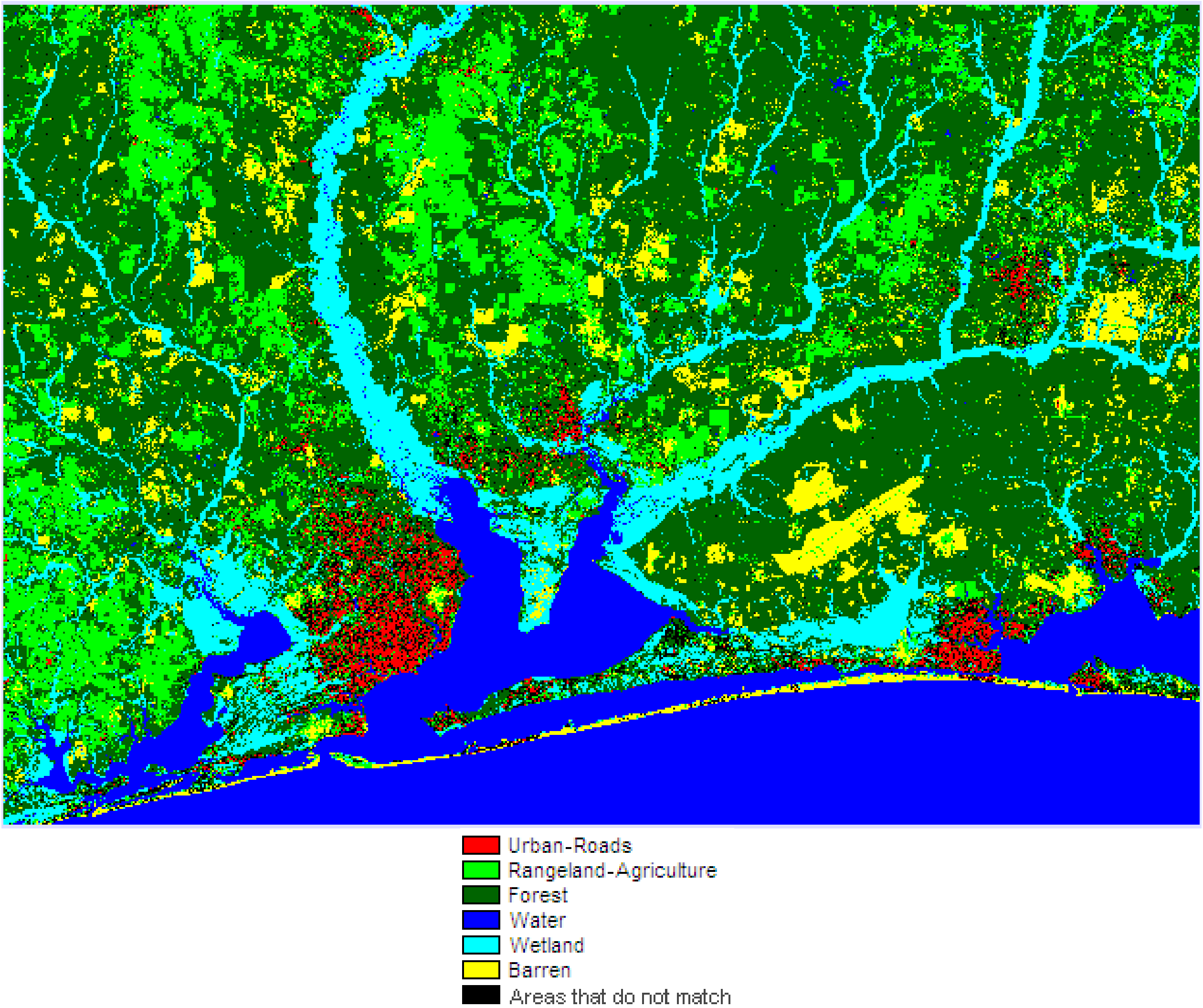


Figure 4.11: Comparison 2001 between Classified Land-cover (truth) and Simulation

After, different error matrices and Kappa indexes of agreement were generated using Idrisi Andes software package. The Kappa values vary between a maximum of 98.36% for the simulation 1986 and a minimum of 96.47% for the simulation 2001. In the case of the simulation 1992, the Kappa value was 97.78%. In other words, the accuracy diminished during the simulation process because in every step (one year), the SLEUTH results become more a more different from their origin, the classified land-cover 1974.

Table 4.29: Error Matrix and Kappa Indexes of REAL1986 (columns: truth) against SIM1986 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**176210**	20791	24509	4	32	2880	224426	21.48%
3	39448	**1577176**	12718	17	241	1536	1631136	3.31%
4	5982	10515	**5354910**	0	1711	2097	5375215	0.38%
5	5	0	5	**2126876**	0	0	2126886	0.00%
6	225	474	1669	24	**1242838**	100	1245330	0.20%
7	2478	574	1213	2	75	**652889**	657231	0.66%
Total	224348	1609530	5395024	2126923	1244897	659502	**11260224**	
Error O	21.46%	2.01%	0.74%	0.00%	0.17%	1.00%		1.15%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 0.01% (1.14% - 1.15%)
95% Confidence Interval = +/- 0.01% (1.14% - 1.15%)
99% Confidence Interval = +/- 0.01% (1.14% - 1.16%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM1986 as the reference image...

Category	KIA
1	78.08%
3	96.14%
4	99.27%
5	100.00%
6	99.78%
7	99.30%

REAL1986 as the reference image…

Category	KIA
1	78.11%
3	97.65%
4	98.58%
5	100.00%
6	99.81%
7	98.94%

Overall Kappa = 98.36%

Table 4.30: Error Matrix and Kappa Indexes of REAL1992 (columns: truth) against SIM1992 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**183644**	28289	36775	10	40	3512	252270	27.20%
3	50352	**1558158**	6294	27	369	1988	1617188	3.65%
4	9047	16827	**5331504**	4	2603	3227	5363212	0.59%
5	12	5	5	**2126852**	4	7	2126885	0.00%
6	496	573	2596	22	**1241573**	147	1245407	0.31%
7	8726	1362	1660	14	118	**643382**	655262	1.81%
Total	252277	1605214	5378834	2126929	1244707	652263	**11260224**	
Error O	27.21%	2.93%	0.88%	0.00%	0.25%	1.36%		1.56%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 0.01% (15.5% - 15.6%)
95% Confidence Interval = +/- 0.01% (15.5% - 15.6%)
99% Confidence Interval = +/- 0.01% (15.5% - 15.6%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM1992 as the reference image...

Category	KIA
1	72.17%
3	95.74%
4	98.87%
5	100.00%
6	99.65%
7	98.08%

REAL1992 as the reference image…

Category	KIA
1	72.17%
3	96.58%
4	98.32%
5	100.00%
6	99.72%
7	98.55%

Overall Kappa = 97.78%

Table 4.31: Error Matrix and Kappa Indexes of REAL2001 (columns: truth) against SIM2001 (rows: mapped)

	1	3	4	5	6	7	Total	ErrorC
1	**186985**	50714	56603	7	68	5024	299401	37.55%
3	58863	**1522706**	8645	33	844	3433	1594524	4.50%
4	39540	20516	**5272800**	1	4106	4944	5341907	1.29%
5	126	7	1	**2126719**	1	30	2126884	0.01%
6	2547	862	4080	18	**1237520**	479	1245506	0.64%
7	13520	1973	2543	10	152	**633804**	652002	2.79%
Total	301581	1596778	5344672	2126788	1242691	647714	**11260224**	
Error O	38.00%	4.64%	1.34%	0.00%	0.42%	2.15%		2.48%

Notes: 1=Urban; 3=Agriculture-Rangeland; 4=Forests; 5=Water; 6=Wetlands; 7=Barrenlands
ErrorO = Errors of Omission
ErrorC = Errors of Commission
90% Confidence Interval = +/- 0.01% (2.48% - 2.49%)
95% Confidence Interval = +/- 0.01% (2.47% - 2.49%)
99% Confidence Interval = +/- 0.01% (2.47% - 2.50%)

KAPPA INDEX OF AGREEMENT (KIA)

Using SIM2001 as the reference image...

Category	KIA
1	61.42%
3	94.75%
4	97.54%
5	99.99%
6	99.28%
7	97.04%

REAL2001 as the reference image…

Category	KIA
1	60.96%
3	94.60%
4	97.44%
5	100.00%
6	99.53%
7	97.72%

Overall Kappa = 96.47%

By analyzing these error matrices and Kappa indexes is possible to determine categories with the lowest classification accuracy as well as categories with the highest accuracy. When errors are equal or above the threshold of 15.00%, they are represented in red color. The same red color is applied when there are 15,000 or more mismatches among pixels (see inside error matrices). But if there are almost no errors, equal or below the threshold of 5.00%, they are represented in blue color. The same blue color is applied when there are 5,000 or less mismatches among pixels inside the error matrices. Black color represents errors with values between 5.00% and 15.00% or between 5,000 and 15,000 mismatches among pixels. Finally all the data with bold black color represent in the main diagonals of the error matrices show the level of accuracy among categories. Overall Kappa also is shown in bold black color. It is also important to remember the numbers applied to each category: 1=urban; 3=agriculture-rangeland; 4=forests; 5=water; 6=wetlands and 7=barrenlands.

In all error matrices, most errors occur between categories urban=1 (truth) and agriculture-rangeland=3 (mapped): 39,448 errors in simulation 1986, 50,352 errors in simulation 1992, and 58,863 errors in simulation 2001. As it was mentioned before, it is possible that all these errors are the product of selecting the polygons for urban development in suburbs and residential areas from the classified land-cover 1974 (origin of the simulations), because using 30m ($900m^2$) resolution Landsat images makes difficult to differentiate small houses (less than $300m^2$) from its surroundings, generally yards, grasses and trees. Also, it is possible that the new urbanized pixels (from edge and road-influenced growth, and from spread and breed growth) during the process of the simulation were growing in areas of agriculture, rangeland and grasslands that did not match exactly the sample points obtained from the higher accuracy imagery.

In second place are the conflicts (errors) between forests=4 (truth) and urban=1 (mapped): 24,509 errors in simulation 1986, 36,775 errors in simulation 1992, and 56,603 errors in simulation 2001. The reason for this problem is exactly the same one that generates the conflict urban versus agriculture-rangeland.

Errors occurred also between categories agriculture-rangeland=3 (truth) and urban=1 (mapped): 20,791 errors in simulation 1986, 28,289 errors in simulation 1992, and 50,714 errors in simulation 2001. The reason for this kind of conflicts it was already mentioned before.

Other kind of problems exists between categories agriculture-rangeland=3 (truth) and forests=4 (mapped): 16,827 errors in simulation 1992, and 20,516 errors in simulation 2001. These kinds of errors are generated because sometimes grasslands also contain some trees at 30m ($900m^2$) resolution making difficult to differentiate small trees from its surroundings, consequently the grassland class also contains some forest footprint.

Finally, other errors are due to pixel's mismatches between urban=1 (truth) and forests=4 (mapped) especially in the simulation 2001: 39,540 errors. The reason for this problem is exactly the same one that generates the conflict urban versus agriculture-rangeland.

The producer's accuracy in category urban (1) shows errors of omission (1 - producer's accuracy) higher than 15.00% for three simulations: 21.46% in simulation 1986, 27.21% in simulation 1992 and 38.00% in simulation 2001. All other categories present errors of omission below the threshold of 15.00%.

The user's accuracy also in category urban (3) indicates errors of commission (1 - user's accuracy) higher than 15.00% for three simulations: 21.48% in simulation 1986, 27.20% in simulation 1992 and 37.55% in simulation 2001, whereas all other categories present errors of omission below the threshold of 15.00%. The reason for these errors of omission and commission were already explained two paragraphs before.

Using the simulations as reference images, Kappa indexes of agreement were low for the category 1 = urban. These values were 78.08%, 72.17% and barely 61.41% for the years 1986, 1992 and 2001 respectively. In the case of the highest accuracy achieved using the simulations as the reference images, the category 5 = water has values of 100.00% for the years1986 and 1992 and 99.99% for the year 2001; this extremely high accuracy is because the water land-cover is maintained without any changes during the simulations. All other categories also present values above 95.00% of accuracy, what it means that there are almost not mismatches between the classified land-covers and the simulations.

And using the classified land-covers as the reference image, Kappa indexes of agreement were low especially for categories 1=urban for the years 1986 (78.11%), 1992 (72.17%) and very low for 2001 (60.96%). In the case of the highest accuracy achieved using the simulations as the reference images, the category 5 = water has values of 100.00% for the years1986 and 1992 and 2001; this extremely high accuracy is because the water land-cover is maintained without any changes during the simulations. As it was mentioned before, all other categories also present values above 95.00% of accuracy, what it means that there are almost not mismatches between the classified land-covers and the simulations.

As conclusion, the SLEUTH simulations were able to produce a very high accuracy when they were compared against the 1,500 sample points first and against the classified land-cover maps thereafter.

CHAPTER 5

CHOROPLETH AND DASYMETRIC MAPPING

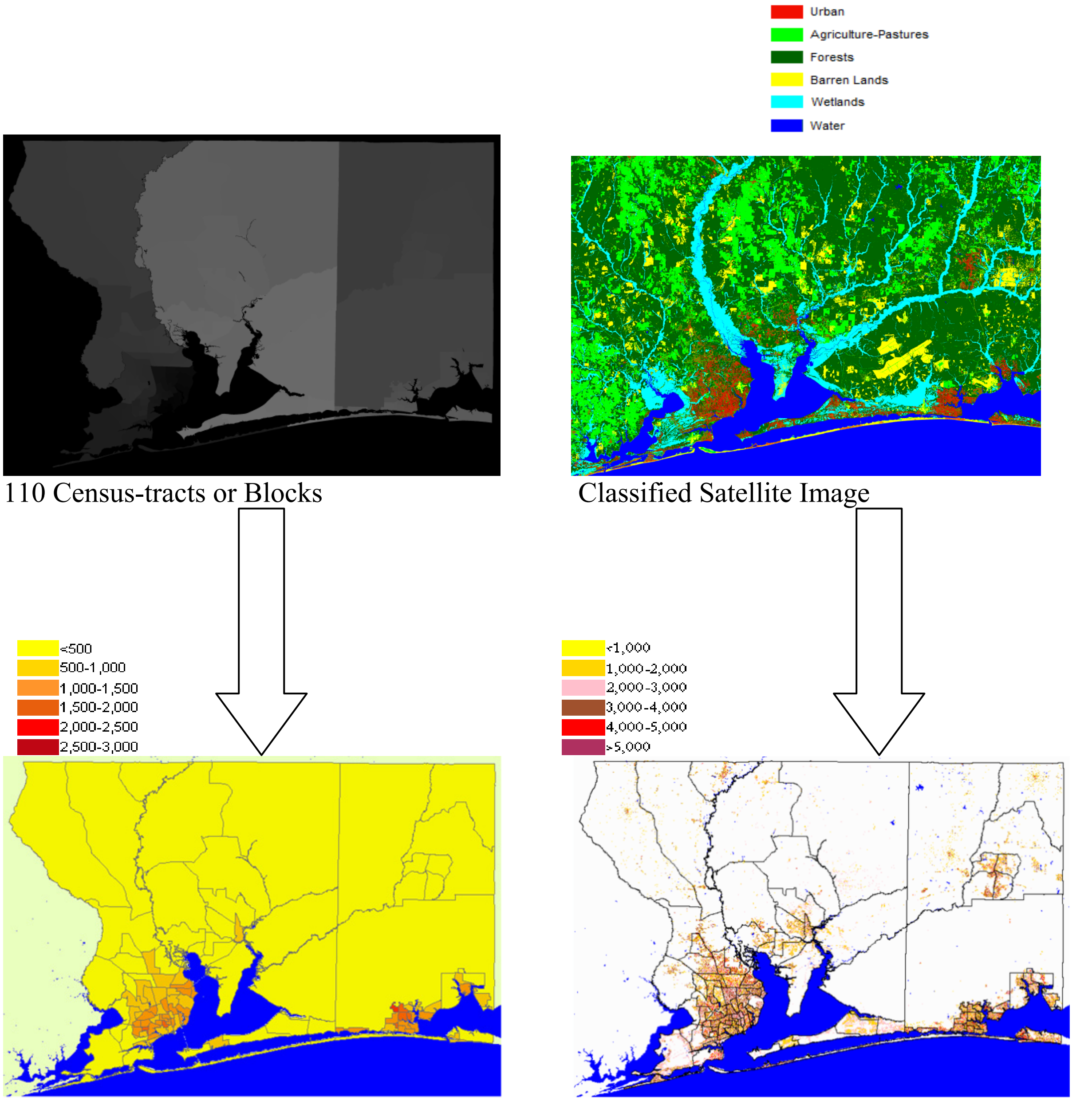
It is possible to construct past, present and future dasymetric maps at the census-tract level based on recently urbanized pixels from specific years (every 5 years) of the SLEUTH simulation.

5.1. Basic Concepts about Dasymetric Mapping

Dasymetric Mapping is a geographic technique ideally suited to map population densities based on satellite imagery and census-tracts using land-cover classified satellite imagery. The dasymetric method yields more accurate population densities than conventional choropleth mapping because it accounts for just the urbanized pixels (using medium-resolution imagery, e.g., Landsat) or just the residential pixels (using high-resolution imagery, e.g., Quick Bird or Ikonos) within the different administrative areas (Holt et al. 2004). Because census enumeration units are not always compatible with the urbanized or residential areas within the unit, choropleth mapping causes problems of accuracy and inadequate spatial data integration. The choropleth method assumes that the population has a uniform distribution throughout the political-administrative area of analysis (Harvey 2002). Therefore, the values of specific attributes (in this case population) are divided by the surface area of the different counties or census tracks, and then placed uniformly in each administrative region without considering the difference in the spatial distribution of how populated areas are in reality, generating biased estimates of population densities.

Conversely, the dasymetric mapping method considers this limitation, and uses categorical ancillary data sets (e.g. land-cover) derived from remotely sensed data to improve the distribution of spatial phenomena, generating finer grained studies in social and physical sciences (Rindfuss and Stern 1998). Therefore, this technique uses land-cover information extracted from remotely-sensed imagery (Langford et al. 1991; Fisher and Langford 1995) to classify pixels as either urbanized or non-urbanized (using medium-resolution imagery) or residential or non-residential (using high-resolution imagery). This method has the advantage of placing exactly the population of each census track in just urbanized or residential zones (Langford 2003). Then, the population of each zone (county or census-tracts) is redistributed uniformly only among those pixels classified as urbanized or residential inside each census-tract or county's boundaries, based on a combination of aerial weighting and the relative densities of ancillary classes (Mennis 2003).

Mennis (2003) successfully applied dasymetric mapping to Delaware County, Pennsylvania using census-tracts and an image from the USGS National Land-Cover Data (NLCD) derived from 2001 Landsat ETM+ imagery. Holt et al (2004) derived dasymetric densities for a 13 county Atlanta metropolitan area based on 1980-2000 census data and land-use/land-cover data derived from remotely sensed satellite imagery to determine the aerial extent of populated areas, with computations made at the census-tract level.



110 Census-tracts or Blocks

Classified Satellite Image

Choropleth Map
Density: population/area of census-tracts.

Dasymetric Map (classified urban pixels)
Density: Population/urbanized areas within census-tracts

Figure 5.1: Differences between Choropleth and Dasymetric Mapping

The formula used to calculate the population density within just urbanized or residential pixels is the following one (Mennis 2003):

$$Dc = \sum Y_s / \sum A_s$$

Where:

Dc = the estimated average population density of each pixel (either urban or residential land-cover) within each county or census-tract.

Y_s = is the total population living inside each county or census-tract (acquired from U.S. Census Bureau or estimated for the different years among decennial censuses).

A_s = represents the area (either urban or residential) within each county or census-tract (derived from Geolytics or TIGER census-tracts files that will be overlaid on "urban" land-cover data obtained through satellite image classification or SLEUTH simulation).

The methodology to construct the dasymetric maps is described below.

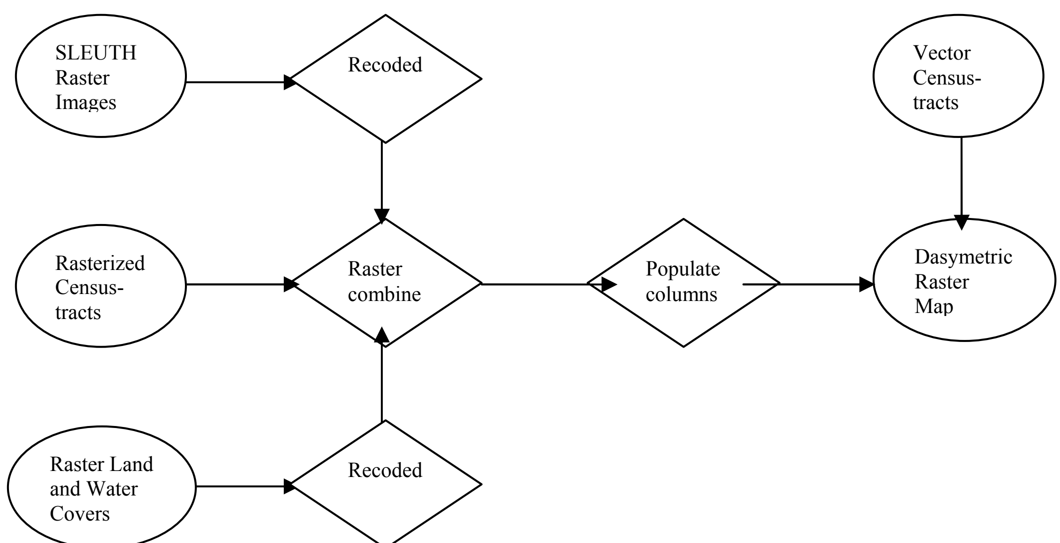


Figure 5.2: Flowchart to produce a Dasymetric Raster Map

The SLEUTH images (the Input data for the model as well as the final results of the simulation) are used to generate the dasymetric densities in raster format after GIF to TIFF conversion in Photoshop. Later, in ERDAS Imagine, every five years, these SLEUTH layers are combined with the rasterized shapefile dataset acquired from Geolytics, which contains the 110 census-tracts of the 3 counties and represents the ancillary layer. The next step is to add a raster layer of land and water covers. Finally, the raster layers that result from these combinations are populated in ArcMap with densities (obtained after dividing population just by the urban area of every census-tract) to generate dasymetric maps.

Knowing the average population density in each pixel inside a census-tract, it is possible to obtain population totals in every census-tract using the following formula:

$$Y_s = Dc \times A_s$$

Where:

Y_s = Total population in a census-tract

Dc = Average density per urban pixel

A_s = Total number of urbanized pixels within a census-tract.

To obtain the total population of the county, the numbers of people in all census-tracts pertaining to a county are added together, as shown in the following formula:

$$\sum Y_s = Y_{s1} + Y_{s2} + Y_{s3} + \cdots + Y_{sn}$$

Historical dasymetric maps will be constructed for different periods of time: the years of the Landsat classified satellite images into land-cover plus datasets produced by the SLEUTH simulation every 5 years. These images are combined with a Geolytics shapefile (http://www.geolytics.com/) that contains population data-tables at the census-tract level from every decennial census (1970 to 2000) based on U.S. Census Bureau DIME (Dual Independent Map Encoding) and TIGER (Topologically Integrated Geographic Encoding and Referencing System) files.

Geolytics provides a Neighborhood Change Database (NCDB) that contains Census data from 1970, 1980, 1990 and 2000 at the census-tract level. This database is used to analyze changes that have occurred in the United States over four decades containing details such as: population, household, income, poverty, education level, employment, and others, a total of about 1000 variables for each decade.

NCDB have two different data formats: Regular and Normalized. Regular datasets preserve the boundaries intact from the different censuses, while the Normalized datasets have in the different years (1970, 1980 and 1990) the same tracts boundaries than the ones from the year 2000, facilitating time series comparisons (looking at the changes of a given location across time) in different decades because the tract boundaries remain the same while their data had been recalculated. This Normalized NCDB will be used in this research to calculate population trends and dasymetric densities.

Not all of the U.S. counties had tracts in 1970 and 1980, so there are some rural areas that will not have data. For example Okaloosa county did not have tracts in 1970.

5.2. Obtaining Future Population Densities and Counts

Generally, the U.S. Census Bureau and other governmental institutions generate population projections based on the cohort-component method, which takes in consideration the different distribution of a population in age groups over time (Hollmann et al. 2000). This method uses estimations of births, deaths, and net migration and they are added to a specific population, as the formula shows:

$$P_t = P_{t-1} + B_{t-1,t} + D_{t-1,t} + M_{t-1,t}$$

Where:

P_t = population at time t

P_{t-1} = population at time $t-1$

$B_{t-1,t}$ = births, in the interval from time $t-1$ to time t

$D_{t-1,t}$ = deaths, in the interval from time *t-1* to time *t*

$M_{t-1,t}$ = net migration, in the interval from time *t-1* to time *t*.

In order to have more accuracy, each one of these components are estimated or projected separately (distinctions about different rates of growth according to races can also be applied) and after the components are added into the equation, producing many series of populations (one for every cohort), while the unit of time *t-1* to *t* may be of any duration (Hollmann al. 2000). The historical and projected data, every first of April, from 1970 to 2030, with its correspondent yearly rates of growth was obtained through this method in the case of the populations of Escambia, Santa Rosa and Okaloosa counties and it is shown in the following table. This information will be used as a framework of reference.

Table 5.1: Population for Escambia, Santa Rosa and Okaloosa Counties April 1, 1970-2030

Year	Escambia	Annual %	Sta. Rosa	Annual %	Okaloosa	Annual %	Total Pop.	Annual %
1970	205,334		37,742		88,187		**331,263**	
1971	211,230	2.87	39,562	4.82	91,404	3.65	**342,196**	**3.30**
1972	217,600	3.02	43,200	9.20	94,400	3.28	**355,200**	**3.80**
1973	222,906	2.44	49,801	15.28	98,002	3.82	**370,709**	**4.37**
1974	227,408	2.02	52,402	5.22	103,504	5.61	**383,314**	**3.40**
1975	227,698	0.13	51,899	-0.96	102,400	-1.07	**381,997**	**-0.34**
1976	227,808	0.05	53,202	2.51	103,904	1.47	**384,914**	**0.76**
1977	230,005	0.96	53,901	1.31	105,802	1.83	**389,708**	**1.25**
1978	230,000	0.00	54,100	0.37	107,801	1.89	**391,901**	**0.56**
1979	232,200	0.96	54,600	0.92	108,601	0.74	**395,401**	**0.89**
1980	233,794	0.69	55,988	2.54	109,920	1.21	**399,702**	**1.09**
1981	238,295	1.93	58,181	3.92	113,434	3.20	**409,910**	**2.55**
1982	241,807	1.47	59,822	2.82	117,178	3.30	**418,807**	**2.17**
1983	244,944	1.30	62,639	4.71	121,351	3.56	**428,934**	**2.42**
1984	249,078	1.69	65,240	4.15	125,538	3.45	**439,856**	**2.55**
1985	253,293	1.69	67,336	3.21	130,595	4.03	**451,224**	**2.58**
1986	256,942	1.44	70,208	4.27	134,925	3.32	**462,075**	**2.40**
1987	258,964	0.79	73,261	4.35	137,546	1.94	**469,771**	**1.67**
1988	260,445	0.57	75,630	3.23	139,814	1.65	**475,889**	**1.30**
1989	261,602	0.44	79,092	4.58	141,624	1.29	**482,318**	**1.35**
1990	262,798	0.46	81,608	3.18	143,777	1.52	**488,183**	**1.22**
1991	264,235	0.55	84,314	3.32	144,904	0.78	**493,453**	**1.08**
1992	265,247	0.38	88,745	5.26	146,452	1.07	**500,444**	**1.42**
1993	269,280	1.52	91,740	3.37	149,435	2.04	**510,455**	**2.00**
1994	273,376	1.52	95,575	4.18	151,965	1.69	**520,916**	**2.05**
1995	276,584	1.17	98,688	3.26	155,039	2.02	**530,311**	**1.80**
1996	279,143	0.93	101,059	2.40	157,630	1.67	**537,832**	**1.42**
1997	285,058	2.12	105,703	4.60	160,835	2.03	**551,596**	**2.56**
1998	287,223	0.76	109,890	3.96	163,770	1.82	**560,883**	**1.68**
1999	292,075	1.69	114,418	4.12	167,000	1.97	**573,493**	**2.25**
2000	294,410	0.80	117,743	2.91	170,498	2.09	**582,651**	**1.60**
2001	296,709	0.78	121,370	3.08	173,450	1.73	**591,529**	**1.52**
2002	299,485	0.94	124,956	2.95	176,971	2.03	**601,412**	**1.67**
2003	303,310	1.28	128,889	3.15	181,102	2.33	**613,301**	**1.98**
2004	307,226	1.29	133,721	3.75	185,778	2.58	**626,725**	**2.19**
2005	303,623	-1.17	136,443	2.04	188,939	1.70	**629,005**	**0.36**
2006	309,647	1.98	141,428	3.65	192,672	1.98	**643,747**	**2.34**
2007	311,906	0.73	142,204	0.55	196,617	2.05	**650,727**	**1.08**
2008	315,889	1.28	144,754	1.79	200,197	1.82	**660,840**	**1.55**
2009	319,875	1.26	152,429	5.30	204,030	1.91	**676,334**	**2.34**
2010	323,801	1.23	159,450	4.61	207,905	1.90	**691,156**	**2.19**
2011	327,054	1.00	164,846	3.38	211,329	1.65	**703,229**	**1.75**
2012	330,316	1.00	169,206	2.64	214,735	1.61	**714,257**	**1.57**
2013	333,641	1.01	172,820	2.14	218,163	1.60	**724,624**	**1.45**
2014	337,013	1.01	175,936	1.80	221,603	1.58	**734,552**	**1.37**
2015	340,395	1.00	178,786	1.62	225,028	1.55	**744,209**	**1.31**
2016	343,532	0.92	182,506	2.08	228,261	1.44	**754,299**	**1.36**
2017	346,647	0.91	186,192	2.02	231,456	1.40	**764,295**	**1.33**
2018	349,730	0.89	189,838	1.96	234,606	1.36	**774,174**	**1.29**
2019	352,745	0.86	193,422	1.89	237,686	1.31	**783,853**	**1.25**
2020	355,672	0.83	196,932	1.81	240,683	1.26	**793,287**	**1.20**
2021	358,538	0.81	200,364	1.74	243,602	1.21	**802,504**	**1.16**
2022	361,314	0.77	203,721	1.68	246,438	1.16	**811,473**	**1.12**
2023	364,013	0.75	207,010	1.61	249,205	1.12	**820,228**	**1.08**
2024	366,671	0.73	210,254	1.57	251,931	1.09	**828,856**	**1.05**
2025	369,307	0.72	213,466	1.53	254,631	1.07	**837,404**	**1.03**
2026	371,943	0.71	216,643	1.49	257,331	1.06	**845,917**	**1.02**
2027	374,546	0.70	219,789	1.45	260,004	1.04	**854,339**	**1.00**
2028	377,102	0.68	222,903	1.42	262,640	1.01	**862,645**	**0.97**
2029	379,580	0.66	225,973	1.38	265,219	0.98	**870,772**	**0.94**
2030	381,961	0.63	228,996	1.34	267,731	0.95	**878,688**	**0.91**

Source: Florida Office of Demographic and Economic Research http://edr.state.fl.us/population.htm

Note 1: The Historical Census Information (1970-2000) of this Office is based on US. Census Bureau Statistics

Note 2: Yellow-color (past) & Green-color (projections) means data that will be used in the calculation of census-tracts statistics.

Note 3: Census-tracts Annual Growth Rates were calculated in EXCEL using the following Formula:

From the Geolytics database, each census-tract from Escambia, Santa Rosa and Okaloosa counties were selected with their respective populations in 1970, 1980, 1990 and 2000, and then the yearly rate of growth for every census-tract was calculated in Excel using the following formula:

$$r = \left(\sqrt[n]{\frac{FP}{IP}} - 1 \right) \times 100$$

Where:

r = growth rate in % per census-tract

FP = Final Population (pop1980, pop 1990 and pop2000)

IP = Initial Population (pop 1970, pop 1980 and pop 1990)

n = number of years between PF and PI

Selecting census-tracts for the different counties using ArcMap is shown in figures A-IV.1 to A-IV.3 in appendix IV (pages 371 and 372). The population data for the census-tracts according to Geolytics is documented in tables A-IV.1 to A-IV.3 64-66 in appendix IV (pages 373 and 374).

The information at the county level obtained through the cohort-component method from the Florida's Office of Demographic and Economic Research, plus the census-tract data about population created by Geolytics, will be used together to estimate annual growth rates at the census-tract level using the following Formulas:

Formulas used to calculate Population Growth Rates in the Census-tracts

Formula used to calculate annual growth rate:

$$r = \left(\sqrt[n]{\frac{FP}{IP}} - 1 \right) \times 100$$

Where:

r = growth rate in % per census-tract

FP = Final Population (pop1980, pop 1990 and pop2000)

IP = Initial Population (pop 1970, pop 1980 and pop 1990)

n = number of years between PF and PI

Formula used to calculate average growth rates:

$$\bar{r} = \frac{r1 + r2 + r3}{3}$$

Where:

$\bar{r}$ = average growth trend 1970-2000 per census-tract

$r1$ = growth rate between 1970 and 1980

$r2$ = growth rate between 1980 and 1990

$r3$ = growth rate between 1990 and 2000

Formula to smooth projection rates:

$$\bar{r}_{smooth} = \frac{(\bar{r} + rT)}{2}$$

Where:

$\bar{r}_{smooth}$ = smoothed average growth trend 1970-2000 per census-tract

r = average growth trend 1970-2000 per census-tract

rT = average growth rate 1970-2000 for the entire county

The calculation of the population growth rates is documented in tables A-IV.4 to A-IV.6 in appendix IV (pages 375 to 377).

When the growth rates in every census-tract are known, it is easier to calculate data about the population existing in each tract through the following formulas:

Formulas used to calculate Population in every Census-tract from 1970 to 2025

Formula used to calculate population for Census-tract 1970

$$IP_{70} = \frac{\frac{FP_{80}}{\left(\frac{r}{100}+1\right)^{n}}}{C_2}$$

Where:

IP_{70} = Initial Population 1970 per census-tract

FP_{80}= Final Population 1980 per census-tract

r = rate of growth in % of every census-tract between 1970 and 1980

C_2 = Constant 2 (Sum of populations in every census-tract divided by Total County' Population according to Florida's Office of Demographic and Economic Research)

n = 10 years

Note: even if Population 1970 will not be used in this research, is necessary to calculate the values for every census-tract for further use as the initial population for the formulas concerning populations 1974 and 1975.

Formula used to calculate population corresponding to past census-tracts 1974, 1975, 1985, 1986, 1992, 1995 & 2001

$$FP = \frac{IP \times \left(\frac{r + C_1}{100}+1\right)^{n}}{C_2}$$

Where:

FP = Final Population per census-tract (it can be 1980, 1990 or 2000)

IP = Initial Population per census-tract (it can be 1970, 1980 or 1990)

r = growth rate in % per census-tract between Initial and Final Populations

C_1 = Constant 1 (difference between average growth rate in % of the County between IP to FP and average growth rate in % of the county for the whole decade)

C_2 = Constant 2 (Sum of Populations in every census-tract divided by Total County' Population according to Florida's Office of Demographic and Economic Research)

n = number of years between Initial Population and desire year (example: 1970-1974 = 4 years)

Formula used to calculate population corresponding to

future census-tracts 2001, 2005, 2010, 2015, 2020 & 2025

$$FP = \frac{IP \times \left(\frac{r_{smooth}}{100+1}\right)^{n}}{C_2}$$

Where:

FP = Final Population per census-tract (it can be 1980, 1990 or 2000)

IP = Initial Population per census-tract (it can be 1970, 1980 or 1990)

r_{smooth} = smoothed average growth trend 1970-2000 per census-tract

C_2 = Constant 2 (Sum of populations in every census-tract divided by Total County' Population according to Florida's Office of Demographic and Economic Research)

n = number of years between Final and Initial Population

Formula used to calculate population corresponding to

Okaloosa census-tracts in 1970, 1974 and 1975 (information unavailable from Geolytics)

$$FP = \frac{IP_{70} \times \left(\frac{r_{70-80}+C_1}{100}+1\right)^{n}}{C_2}$$

Where:

FP = Final Population per census-tract (it can be 1974 or 1975)

IP = Initial Population per census-tract in 1970

r = growth rate in % per census-tract between Initial Pop. 1970 and Final Populations 1980

C_1 = Constant 1 (difference between average growth rate in % of the County between IP to FP and average growth rate in % of the county for the whole decade)

C_2 = Constant 2 (Sum of Populations in every census-tract divided by Total County' Population according to Florida's Office of Demographic and Economic Research)

n = number of years between Initial Population and desire year (example: 1970-1974 = 4 years)

The historical population data and the population projections at the census-tract level are documented in tables A-IV.7 to A-IV.12 in appendix IV (pages 379 to 382).

When all these population values from the different censuses tracts are added together, their total sums match exactly the values of the county projections made by the U.S. Census Bureau (until year 2004) and the Florida's Office of Economic and Demographic Research (http://edr.state.fl.us/population.htm) since 1970 until year 2025.

Using these population datasets obtained through Excel software package plus censuses tracts derived from Geolitycs generate choropleth densities. Also, with this same information about the evolution of the population in the different censuses tracts of these three counties plus the urban areas (pixels) derived from ERDAS Imagine using Landsat-classified images and SLEUTH output simulations, past, present and future dasymetric densities for every one of the 110 census-tracts will be calculated as well. Nevertheless, before obtaining choropleth and dasymetric densities, first it is necessary to re-calculate new and more precise annual growth rates for every census-tract according to the following formula:

Formula used to calculate Annual Growth Rates in every Census-tract from 1970 to 2025

$$r = \left(\sqrt[n]{\frac{FP}{IP}} - 1 \right) \times 100$$

Where:

r = growth rate in % per census-tract

FP = Final Population

IP = Initial Population

n = number of years between PF and PI

The historical growth and projected growth rates at the census-tract level are documented in tables A-IV.13 to A-IV.18 in appendix IV (pages 383 to 387).

5.3. Choropleth Maps at the Census-tract Level in Escambia, Sta. Rosa and Okaloosa

Choropleth Densities are generated using the population datasets obtained through Excel and these results are divided by the surface values of the 110 different censuses tracts derived from Geolitycs, through the use of the following formula:

Formula used to calculate Choropleth Densities between 1974 and 1925

$$C = \frac{P}{A}$$

Where:

C = Choropleth Density

P = Population in a Census-tract

A= Total Area of a Census-tract in Square Kilometers

Note: In order to calculated the Area (A) of a Census-tract, it is necessary first to divide the original values of the surfaces of each census-tract obtained from Geolitycs initially in square meters by 1’000,000 in order to transform into square kilometers because 1’000,000 m^2 = 1 Km^2.

The choropleth densities at the census-tract level are documented in tables A-IV.19 to A-IV.30 in appendix IV (pages 388 to 397).

After these statistics were calculated in Excel, the choropleth maps were made in ESRI ArcMap, copying the population density data (dividing population values by each census-tract area) inside ArcMap tables.

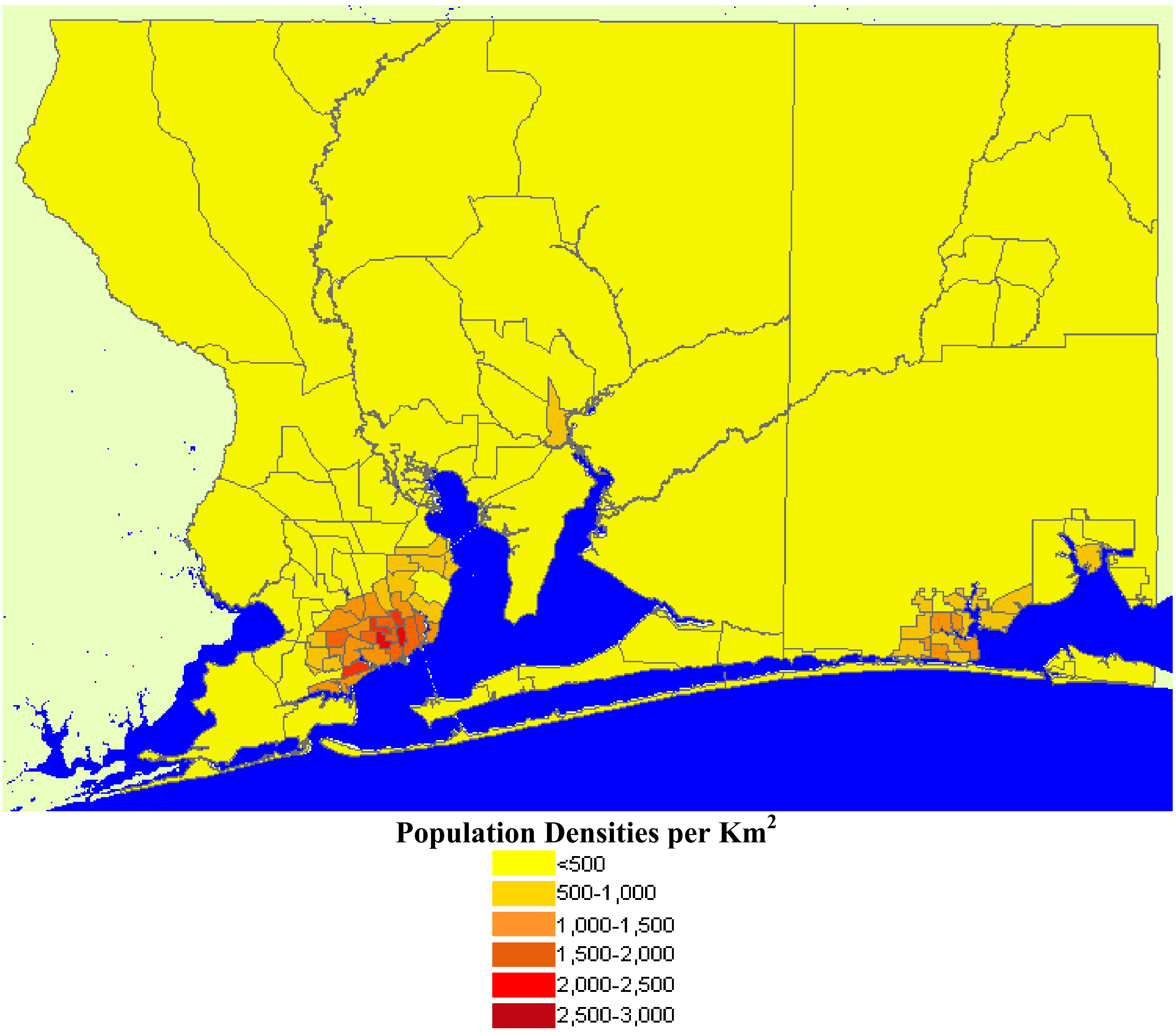


Figure 5.3: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1970

In 1970, most census-tracts had population densities below 500 inhabitants per Km^2. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Therefore, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2. Some more central census-tracts in Pensacola and Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. And these densities increase into the most centric areas of Pensacola city, existing in 1970 census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even from 2,000 to 2,500 inhabitants per Km^2.

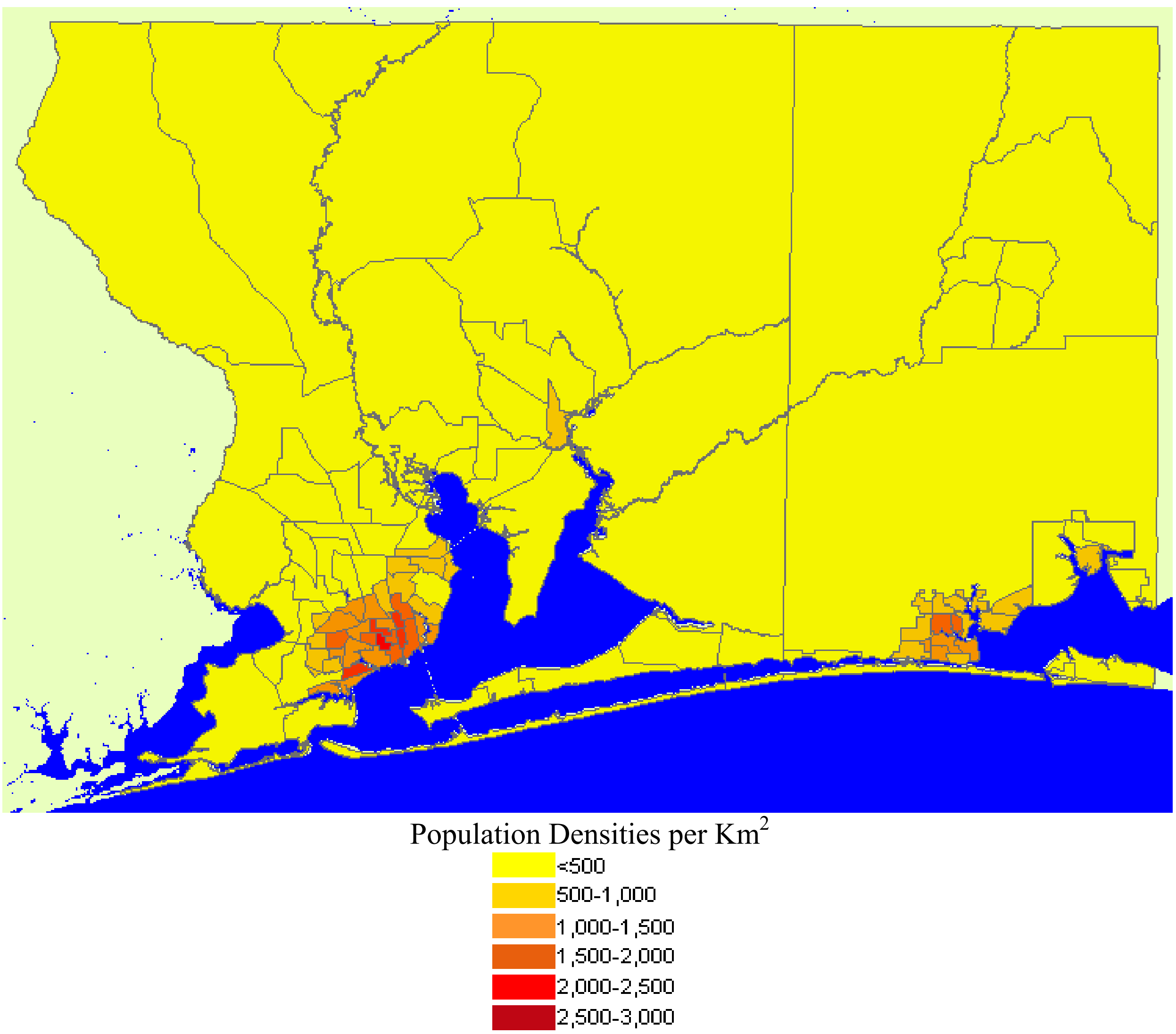


Figure 5.4: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1974

In 1974, when the first Landsat image from this research was taken, most census-tracts had also population densities below 500 inhabitants per Km^2. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Therefore, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a similar pattern with the map of choropleth densities from 1970 with the difference that a few more census-tracts are presenting these kinds of densities. Some central census-tracts in the inner cities of Pensacola and Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have a increasing trend into the downtown of Pensacola city, existing in 1974 census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even from 2,000 to 2,500 inhabitants per Km^2, in a very similar way with the 1970 choropleth map.

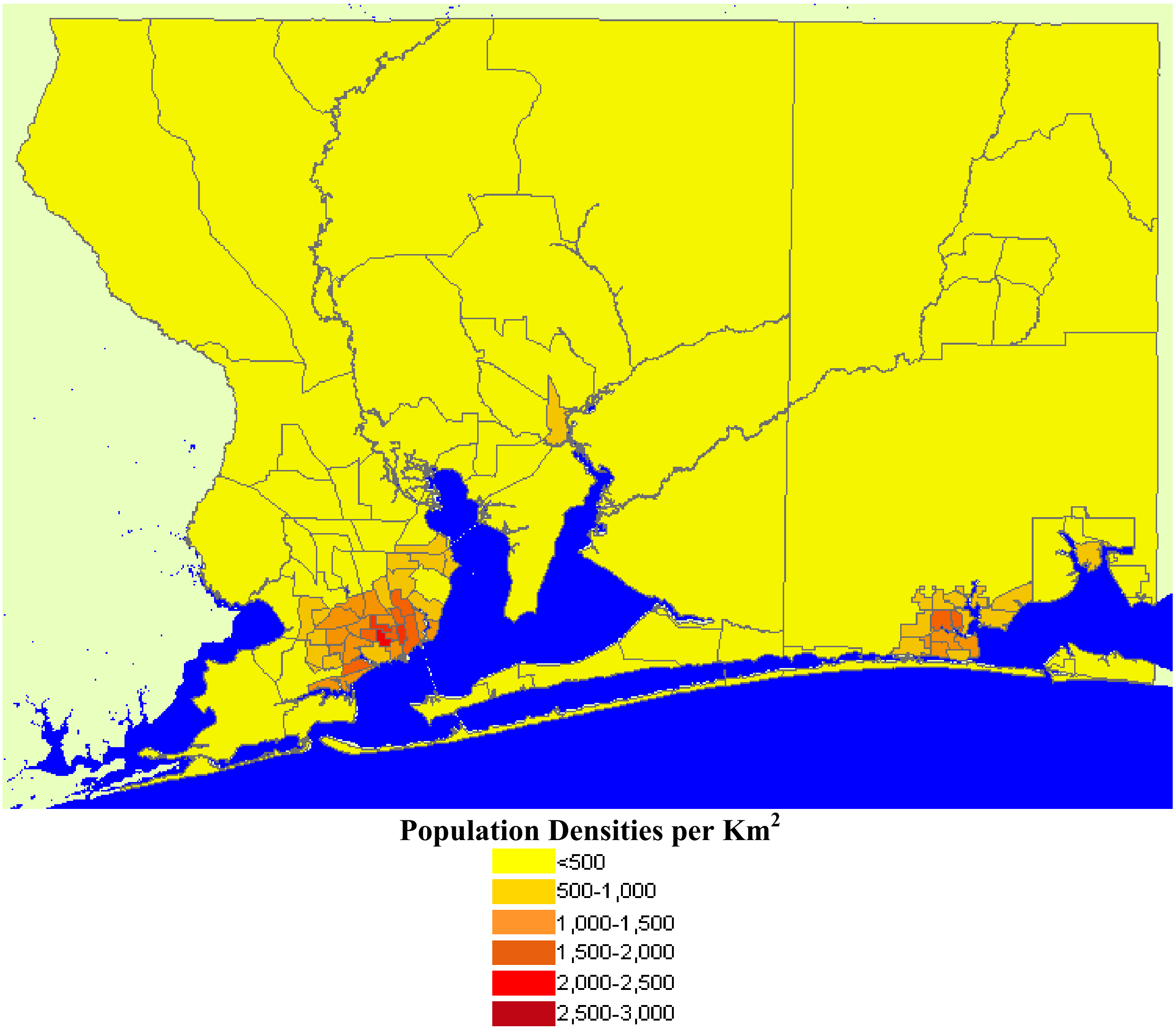


Figure 5.5: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1975

In 1975, the spatial pattern is almost the same one as the choropleth map from 1974. Here, as it was mentioned before, most census-tracts had population densities below 500 inhabitants per Km^2. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Therefore, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a similar pattern with the map of choropleth densities from 1974. Some central census-tracts in the inner cities of Pensacola and Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have an increasing trend in downtown Pensacola, existing in 1975 census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even from 2,000 to 2,500 inhabitants per Km^2.

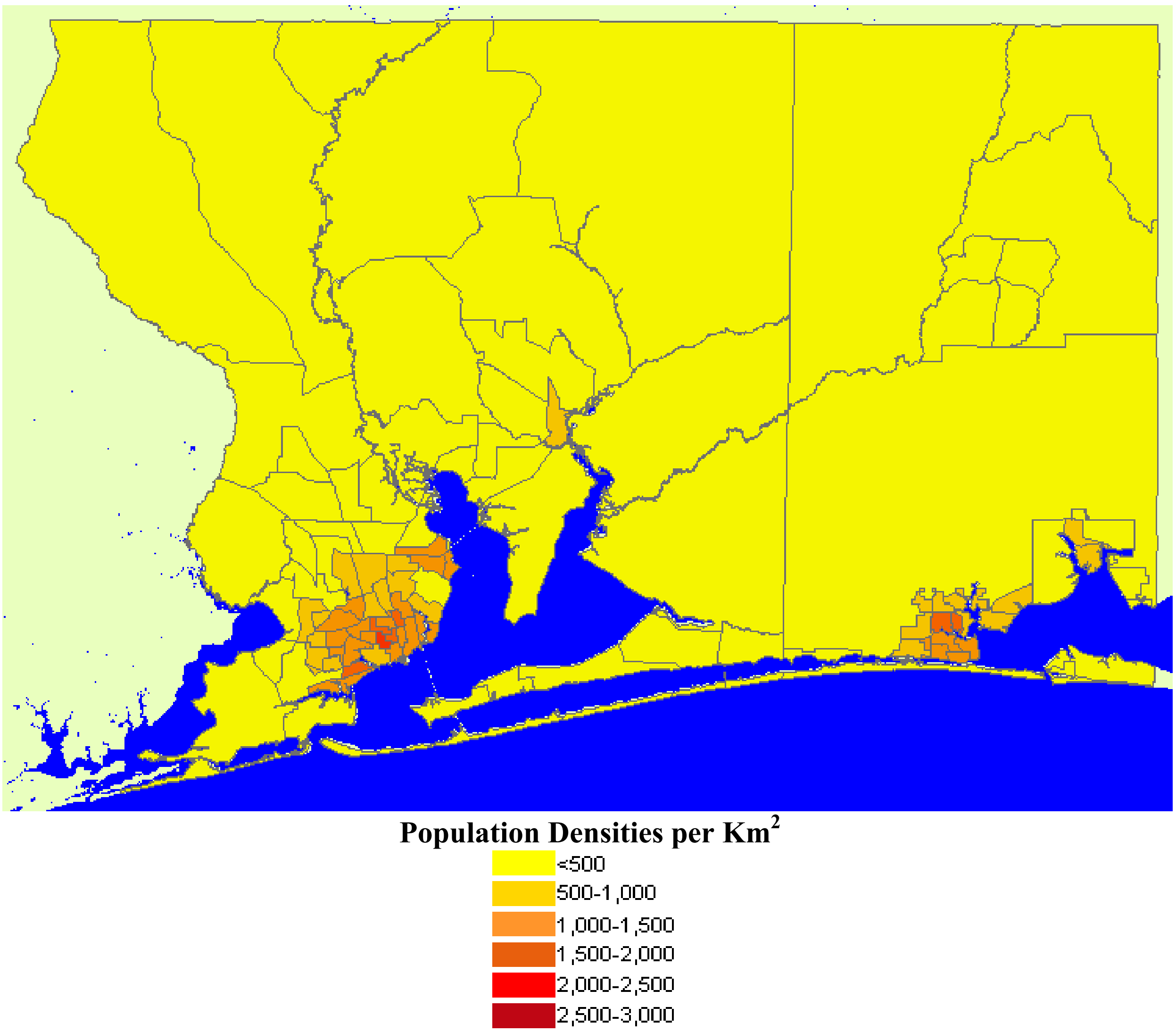


Figure 5.6: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1980

In 1980, the spatial pattern of this region presented most census-tracts with population densities below 500 inhabitants per Km^2 as it was mentioned in past years as well. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Therefore, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a similar pattern with the map of choropleth densities from 1975 but with more census-tracts with these densities towards the suburbs. Some central census-tracts in the inner city of Pensacola and some of its suburbs as well as in the center of Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have an increasing trend towards downtown Pensacola and Fort Walton Beach, existing in 1980 some census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even few of them with densities as high as 2,000 to 2,500 inhabitants per Km^2.

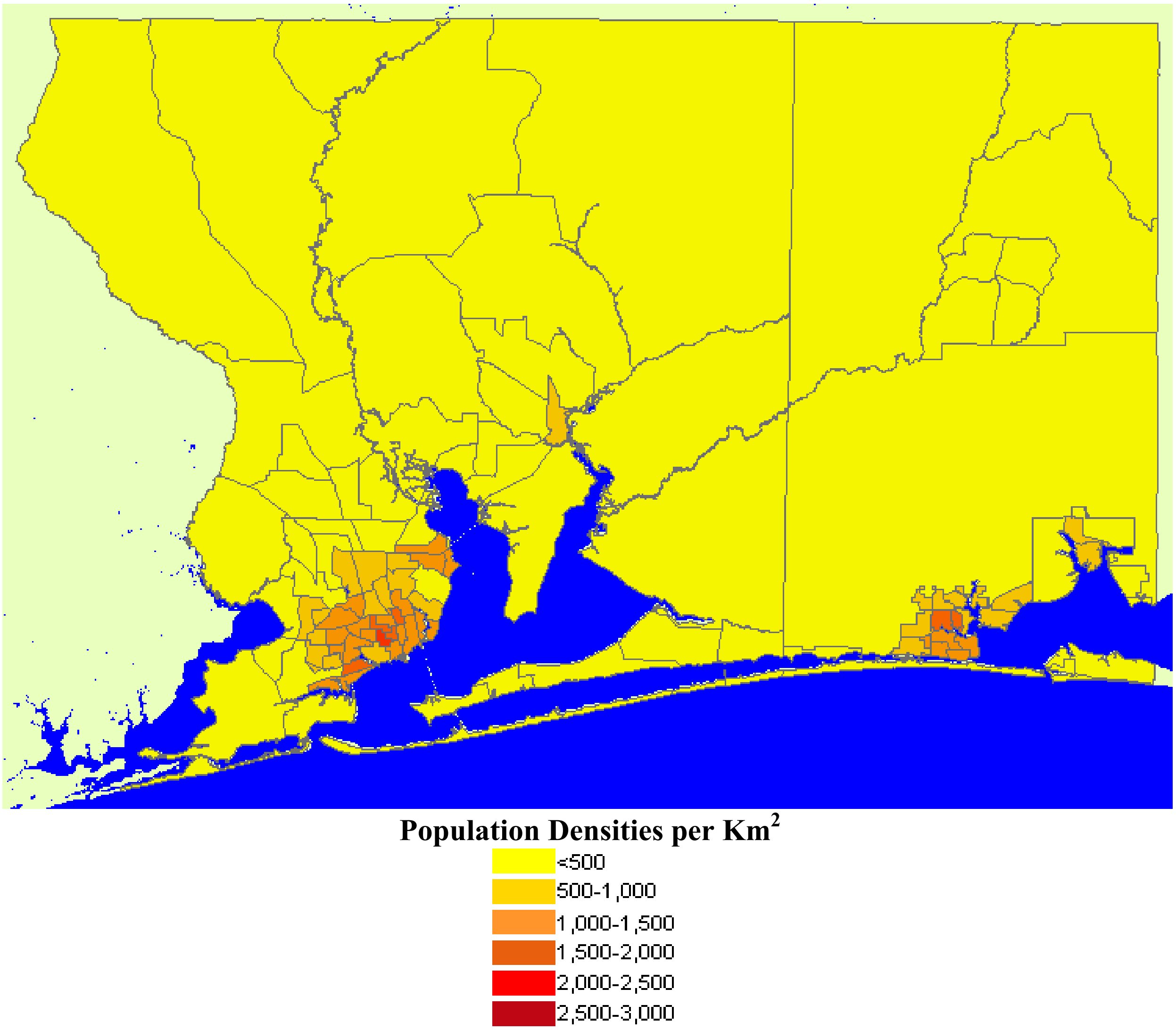


Figure 5.7: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1985

In 1985, the spatial pattern of this region presented most census-tracts with population densities below 500 inhabitants per Km^2 as it was mentioned in past years as well. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2 showing almost the same pattern of densities that the image from 1980. Here, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a similar pattern with the map of choropleth densities from 1980 but with more census-tracts with these densities towards the suburbs. Some central census-tracts in the inner city of Pensacola and some of its suburbs as well as in the center of Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have an increasing trend towards downtown of Pensacola city and Fort Walton Beach, existing in 1985 some census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even few of them with densities as high as 2,000 to 2,500 inhabitants per Km^2.

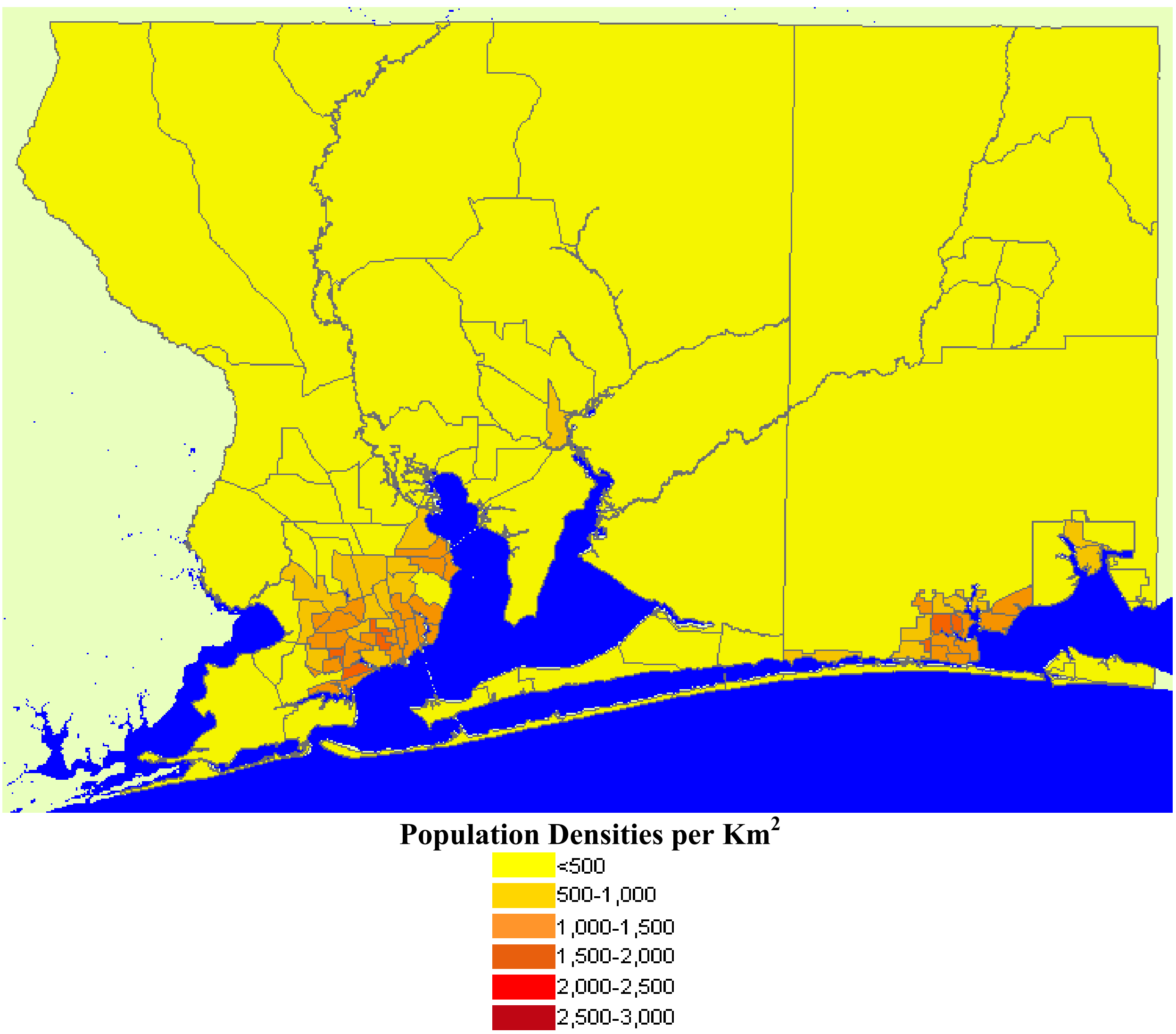


Figure 5.8: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1986

In 1986, the spatial pattern of densities at the census-tract level is very similar with the image of 1985 (just one year of difference) presenting most census-tracts with population densities below 500 inhabitants per Km^2. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Here, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a similar pattern with the map of choropleth densities from 1985 but with one more census-tract with this range of densities towards Pensacola suburbs and into the west of Fort Walton Beach in a small city called Florosa. Some central census-tracts in the inner city of Pensacola and some of its suburbs as well as in the center of Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have an increasing trend towards downtown Pensacola and Fort Walton Beach, existing in 1986 some census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even few of them with densities as high as 2,000 to 2,500 inhabitants per Km^2.

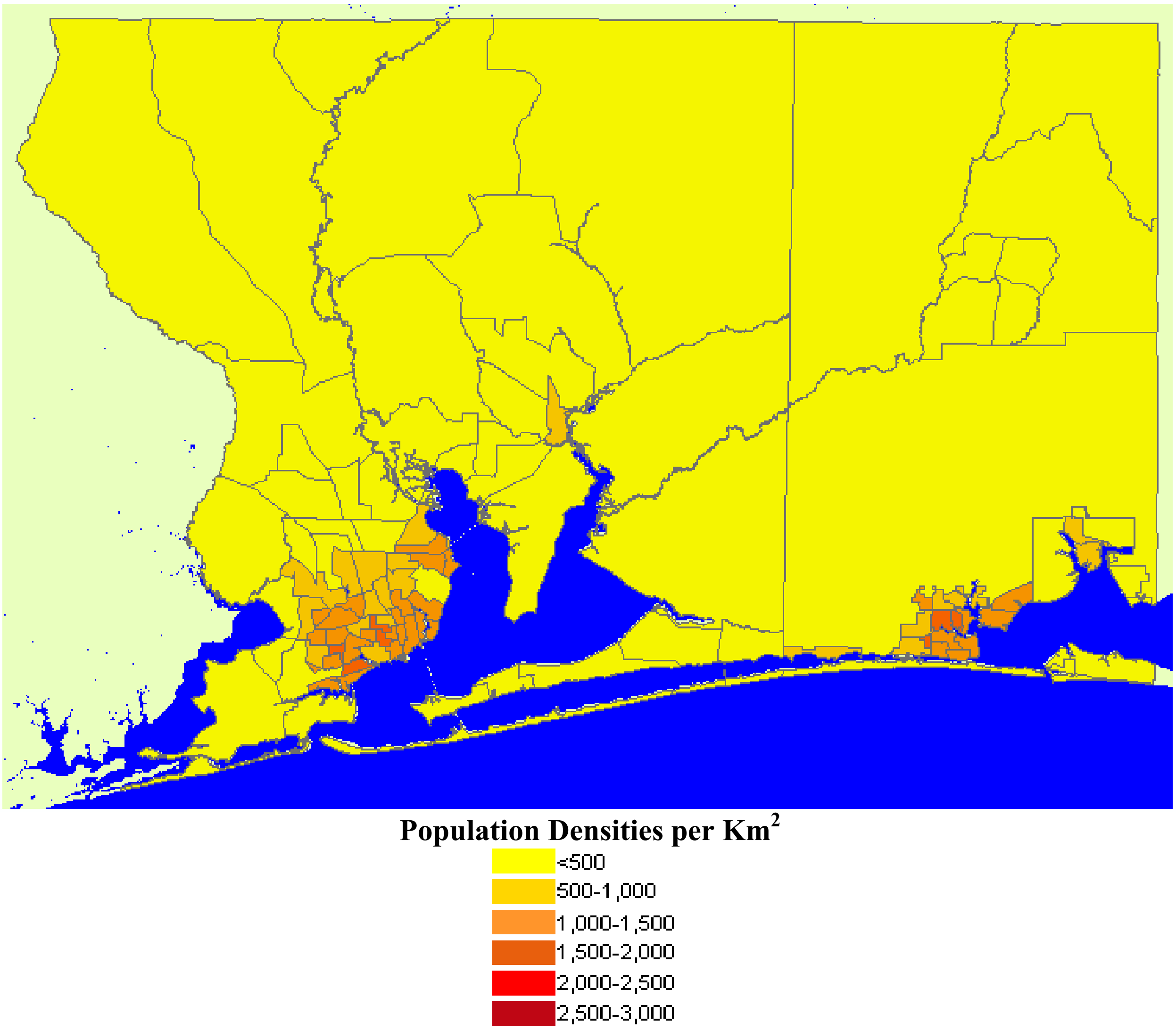


Figure 5.9: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1990

In 1990, the spatial pattern of densities at the census-tract level is exactly as the image of 1986, presenting most census-tracts with population densities below 500 inhabitants per Km^2, in a similar way as most of the past images. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Here, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2, a exactly similar pattern with the map of choropleth densities from 1986. Some central census-tracts in the inner city of Pensacola and some of its suburbs as well as in the center of Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. These densities have an increasing trend towards downtown Pensacola and Fort Walton Beach, existing in 1990 some census-tracts with 1,500 to 2,000 inhabitants per Km^2 and even few of them with densities as high as 2,000 to 2,500 inhabitants per Km^2.

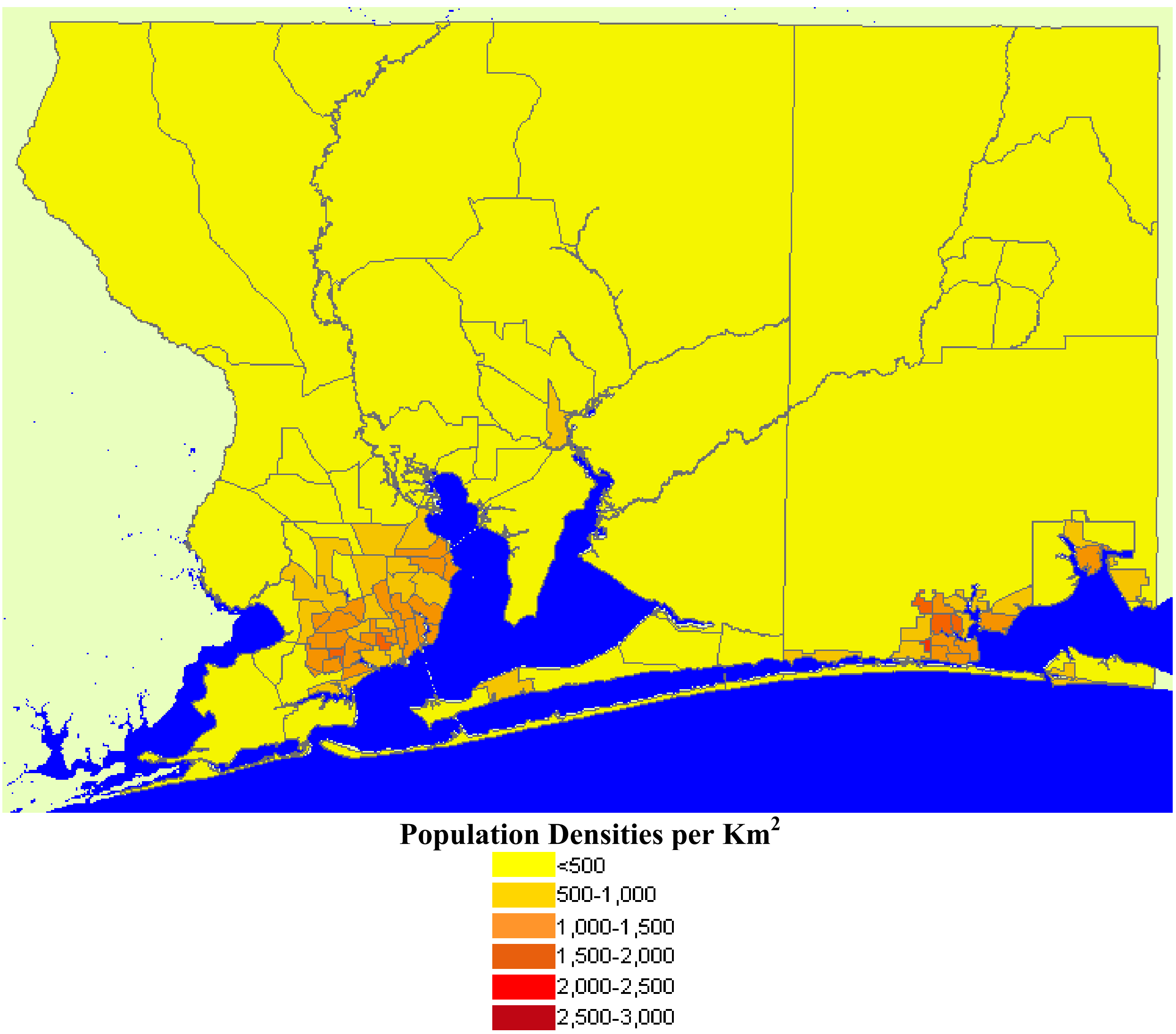


Figure 5.10: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1992

In 1992, the spatial pattern of densities at the census-tract level presents some changes in relation with the choropleth image from 1990. These changes happen in the suburbs of

Pensacola, where most census-tracts present population densities between 500 and 1,000 inhabitants per Km^2 while in its downtown some census-tracts had diminished their densities below 1,500 inhabitants per Km^2, as happened in most cities of the United States as well (Bryan al. 2007). In Milton, its densities are between 500 and 1,000 inhabitants per Km^2. Fort Walton Beach presents census-tracts with higher population densities as before (from 1,000 to 2,500 inhabitants per Km^2), maintaining few of them with densities between 500 and 1,000 inhabitants per Km^2. Also, new census-tracts with densities between 500 and 1,000 inhabitants per Km^2 appear in Oriole Beach, Valparaiso and Destin. Finally, it is necessary to say that in this image also most census-tracts present population densities below 500 inhabitants per Km^2, similar to most of the past images.

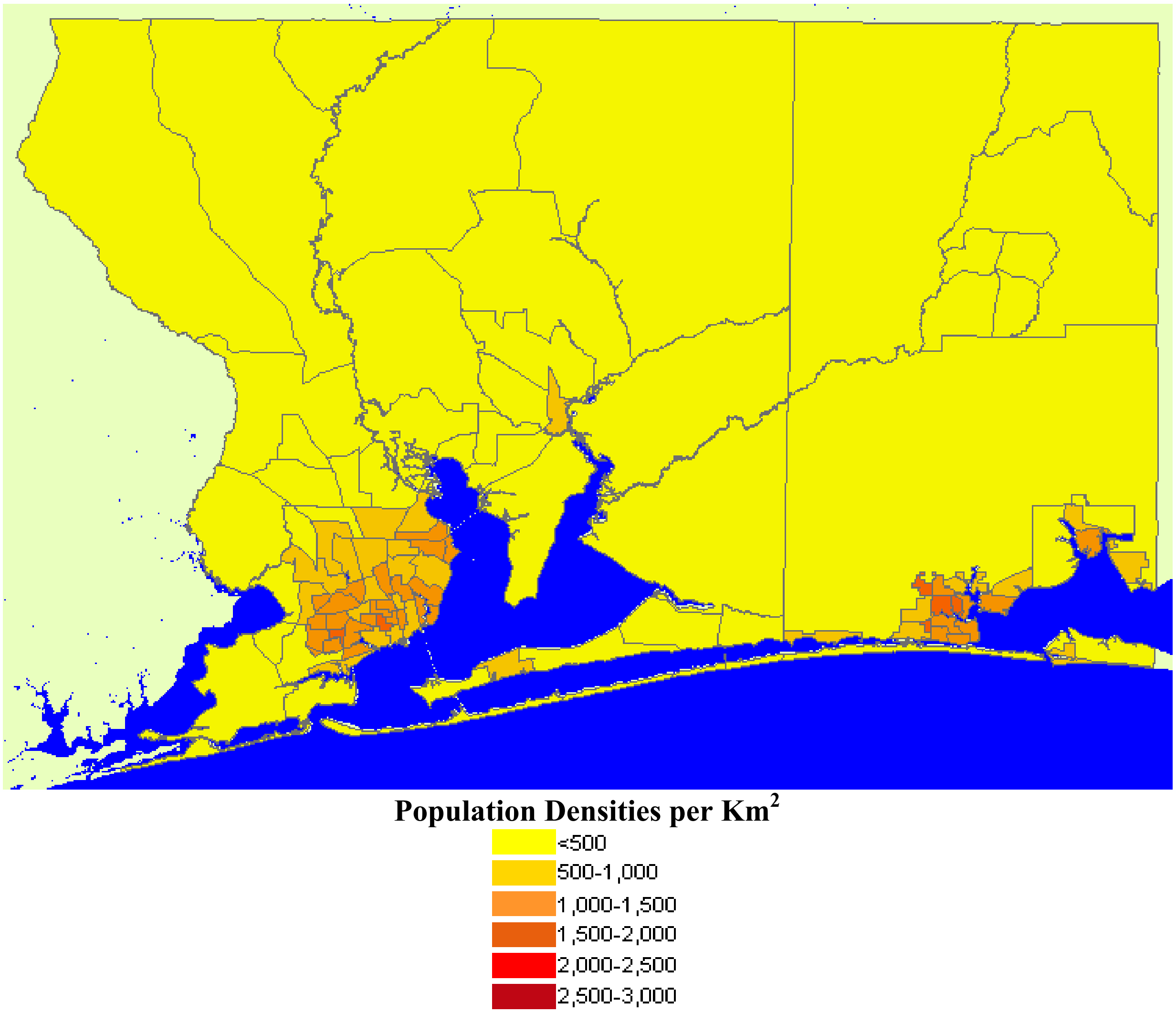
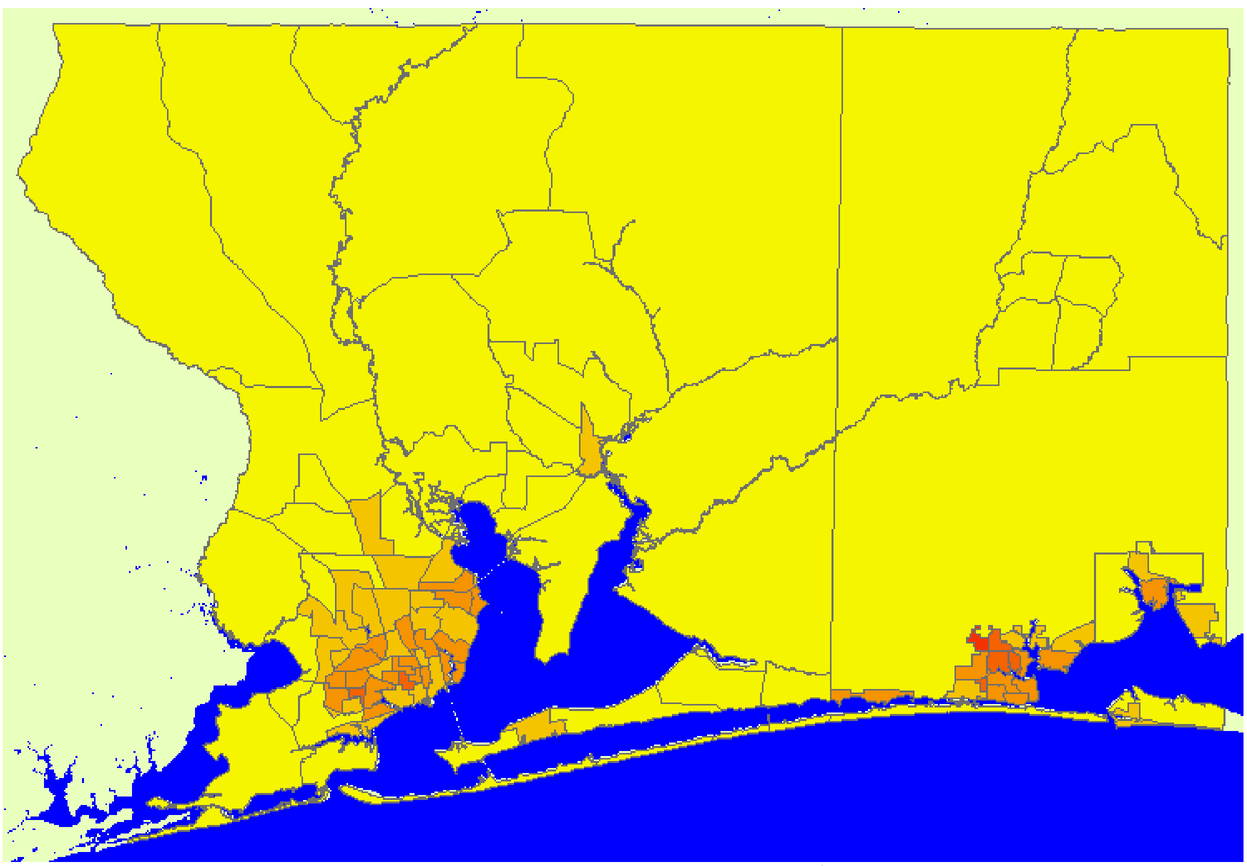


Figure 5.11: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 1995

In 1995, the spatial pattern of densities at the census-tract level presents few changes in relation with the choropleth image from 1992, such as a suburbs in the west part of Pensacola increases from less than 500 inhabitants per Km^2 to a new value between 500 and 1,000 inhabitants per Km^2, also the trend into decaying densities in downtown Pensacola still continues below 1,500 inhabitants per Km^2 (Bryan et al. 2007). It is important to say that in the suburbs of Pensacola city most census-tracts present population densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities are between 500 and 1,000 inhabitants per Km^2. Fort Walton

Beach presents a census-tract which increases its density and another one which diminishes its density, both in its center area. The densities in Fort Walton Beach are generally higher (from 1,500 to 2,000 inhabitants per Km^2) than in Pensacola city. Oriole Beach, Valparaiso and Destin also present census-tracts with densities between 500 and 1,000 inhabitants per Km^2. Finally, as it was mentioned before, most census-tracts in these three counties present population densities below 500 inhabitants per Km^2, in a similar way as most of the past images.



Population Densities per Km^2

<500
500-1,000
1,000-1,500
1,500-2,000
2,000-2,500
2,500-3,000

Figure 5.12: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2000

In 2000, the spatial pattern of densities at the census-tract level presented the following changes in relation with the choropleth map from 1995: a new suburb in the north part of Pensacola increased from less than 500 inhabitants per Km^2 to a new value between 500 and 1,000 inhabitants per Km^2, also in the west part of this city, two census-tracts diminished their densities from 1,000 to 1,500 inhabitants per Km^2 to just 500 to 1,000, continuing the trend into decaying densities in the central areas of many American cities (Bryan et al. 2007). The city of Pensacola still is presenting most census-tracts with densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities are between 500 and 1,000 inhabitants per Km^2. Some central censuses tracts from Fort Walton Beach also had increased their densities from 500 to 1,000 and 1,000 to 1,500 into new values above 1,500 inhabitants per Km^2, showing higher densities in this city in relation with Pensacola. The city of Florosa also presents in 2000 a new of 1,000 to 1,500 inhabitants per Km^2, while Oriole Beach, Valparaiso and Destin maintain the same range of densities as five years earlier (500 to 1,000 inhabitants per Km^2). Finally, as it was mentioned before, most census-tracts in these three counties present population densities below 500 inhabitants per Km^2, in a similar way as most past images.

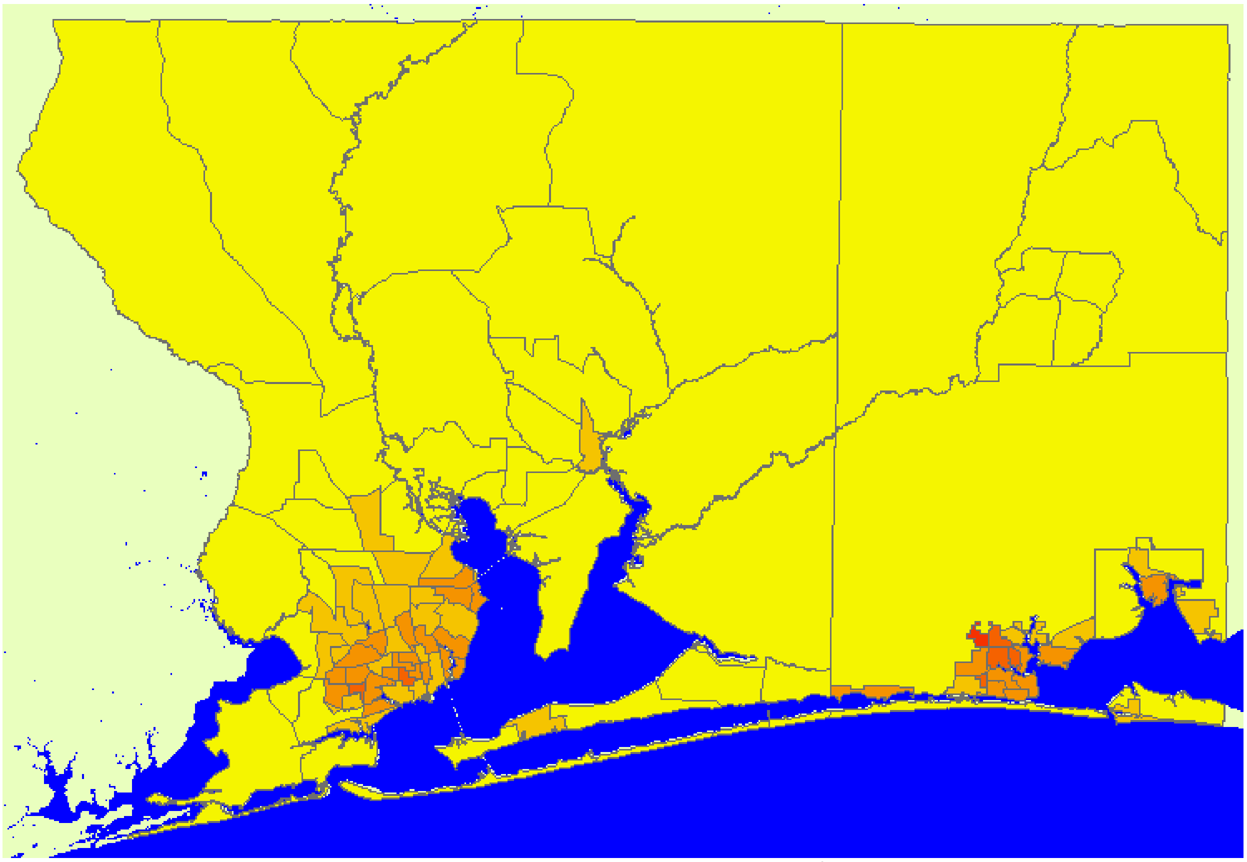


Figure 5.13: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2001

The image from 2001 is almost the same image from 2000, with small differences, so small that all census-tracts preserve their ranges and consequently their colors. The city of Pensacola shows most census-tracts with densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities are between 500 and 1,000 inhabitants per Km^2. Fort Walton Beach is the city with the highest population density in the region, where many zones have values above 1,500 inhabitants per Km^2. The city of Florosa also presents values of 1,000 to 1,500 inhabitants per Km^2, while Oriole Beach, Valparaiso and Destin presented generally densities of 500 to 1,000 inhabitants per Km^2. Finally, as it was mentioned before, most census-tracts in these three counties present population densities below 500 inhabitants per Km^2, similar to most past images.

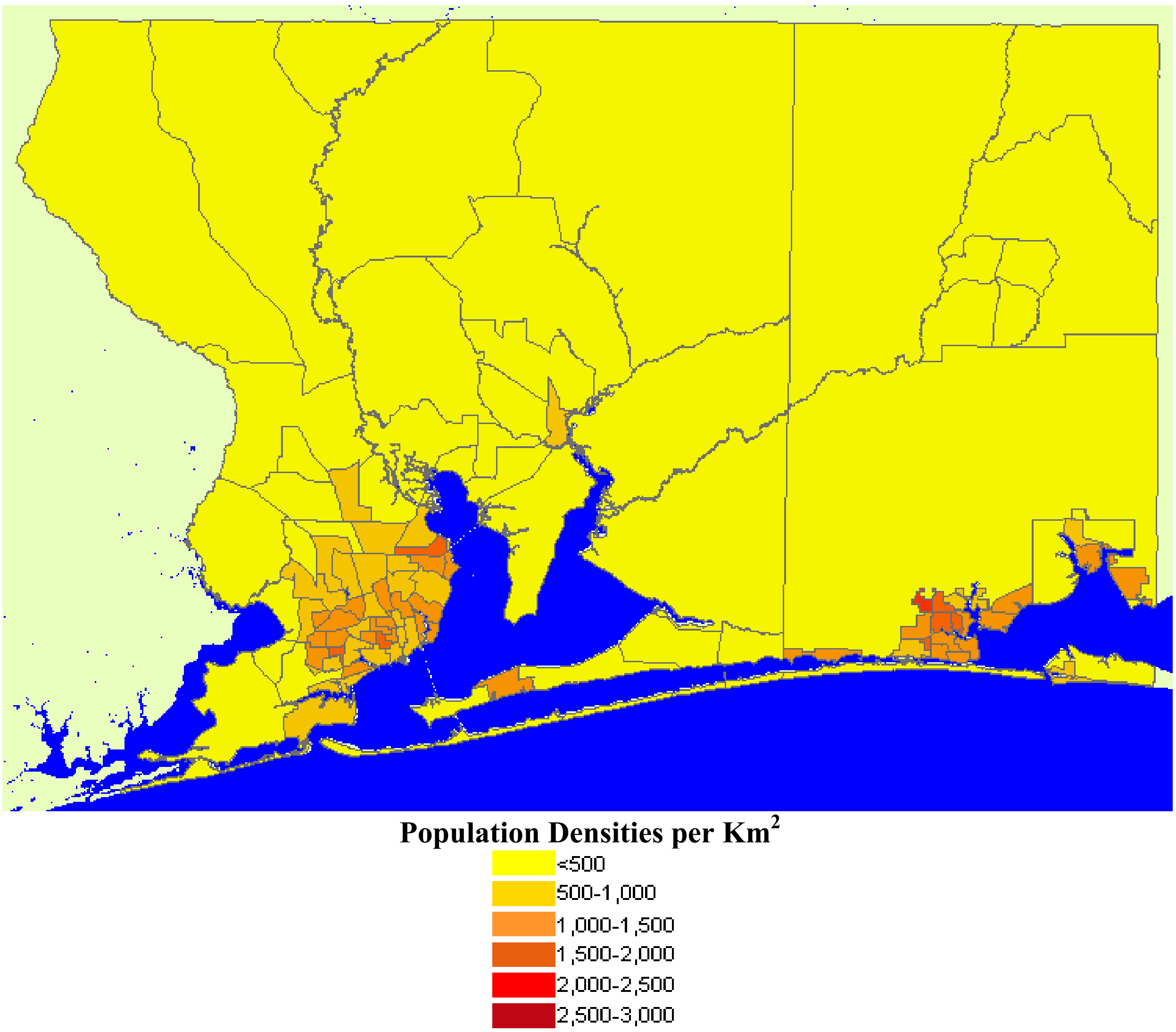


Figure 5.14: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2005

In 2005, the spatial pattern of densities at the census-tract level presented the following changes in relation with the choropleth map from 2001: a new suburb in the south part of Pensacola increased from less than 500 inhabitants per Km^2 to a new value between 500 to 1,000 inhabitants per Km^2, also in the north part of this city a suburb increased its density from 1,000 to 1,500 inhabitants per Km^2 into 1,500 to 2000 inhabitants per $Km^{2,}$ another one also increased in the west part of Pensacola from 500 to 1,000 into 1,000 to 1,500 inhabitants per Km^2 whereas inside its downtown area two census-tracts diminished their densities from 1,000 to 1,500 inhabitants per Km^2 into just 500 to 1,000, continuing the trend into decaying densities in the central areas of many American cities (Bryan et al. 2007). The city of Pensacola still is presenting most census-tracts with densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities are between 500 and 1,000 inhabitants per Km^2. The city of Oriole Beach, right in front of Pensacola, also had increased its density from 500 to 1,000 into 1,000 to 1,500 inhabitants per Km^2. In the east part of the city of Fort Walton Beach and in the city of Valparaiso two censuses tracts increased their densities from 500 to 1,000 in 2001 into new values of 1,000 to 1,500 inhabitants per Km^2 in 2005. Finally, most census-tracts in this region present densities below 500 inhabitants per Km^2.

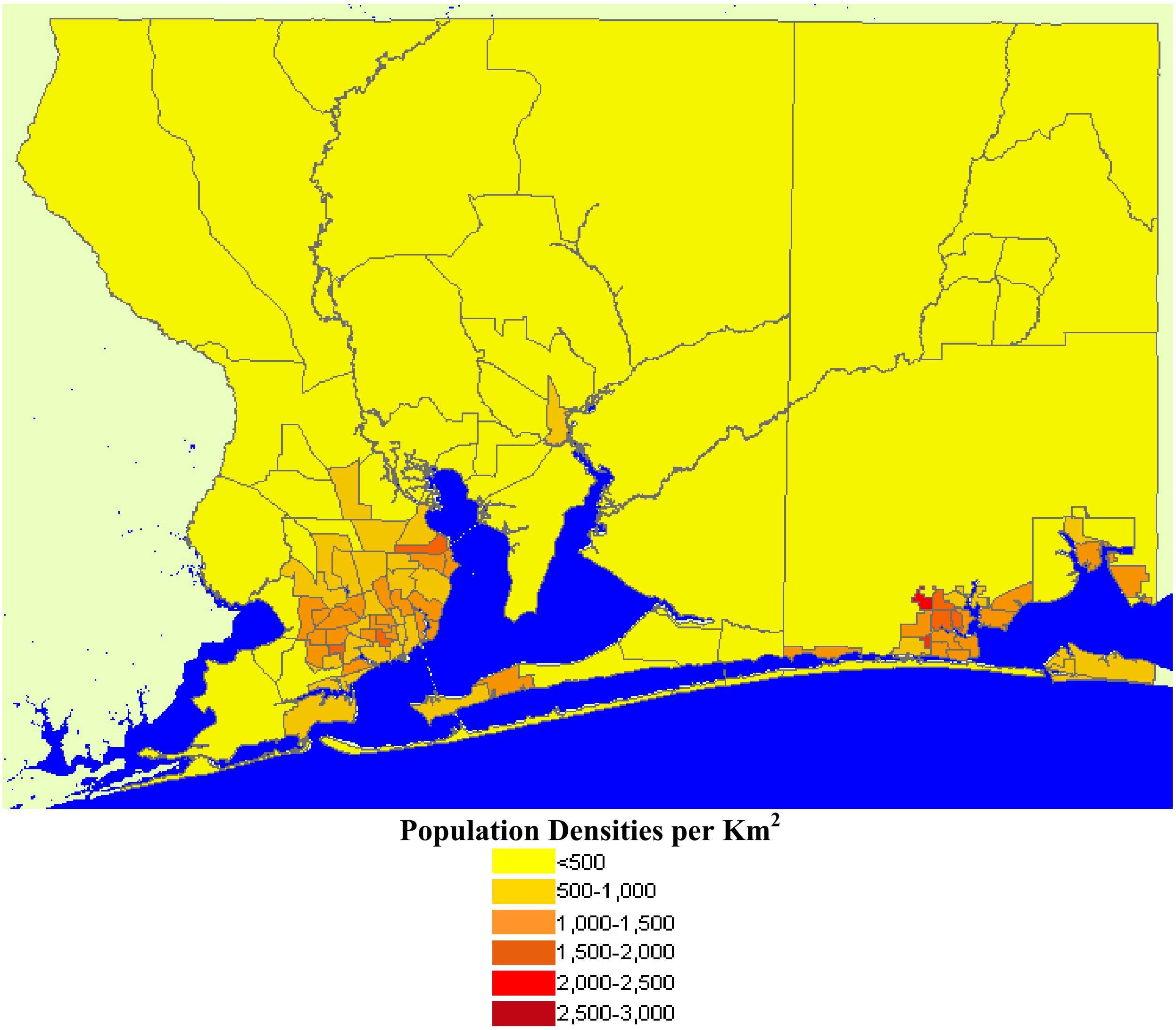


Figure 5.15: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2010

In 2010, a suburb in the west part of Pensacola will increase from less than 500 in the year 2005 into 500 to 1,000 inhabitants per Km^2, this city of Pensacola still presents most census-tracts with densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities will be between 500 and 1,000 inhabitants per Km^2. The city of Gulf Breeze and a census-tract in the east part of the city of Destin also will increase their densities from 500 to 1,000 inhabitants per Km^2 in 2005 into new values between 500 to 1,000 inhabitants per Km^2. Fort Walton Beach will show higher densities than Pensacola, with most of its census-tracts above 1,000 inhabitants per

Km^2. The cities of Oriole Beach, Florosa and the center of Niceville also will present densities between 1,000 to 1,500 inhabitants per Km^2. Finally, as it was mentioned before, most census-tracts in these three counties will present population densities below 500 inhabitants per Km^2 similar to all past images.

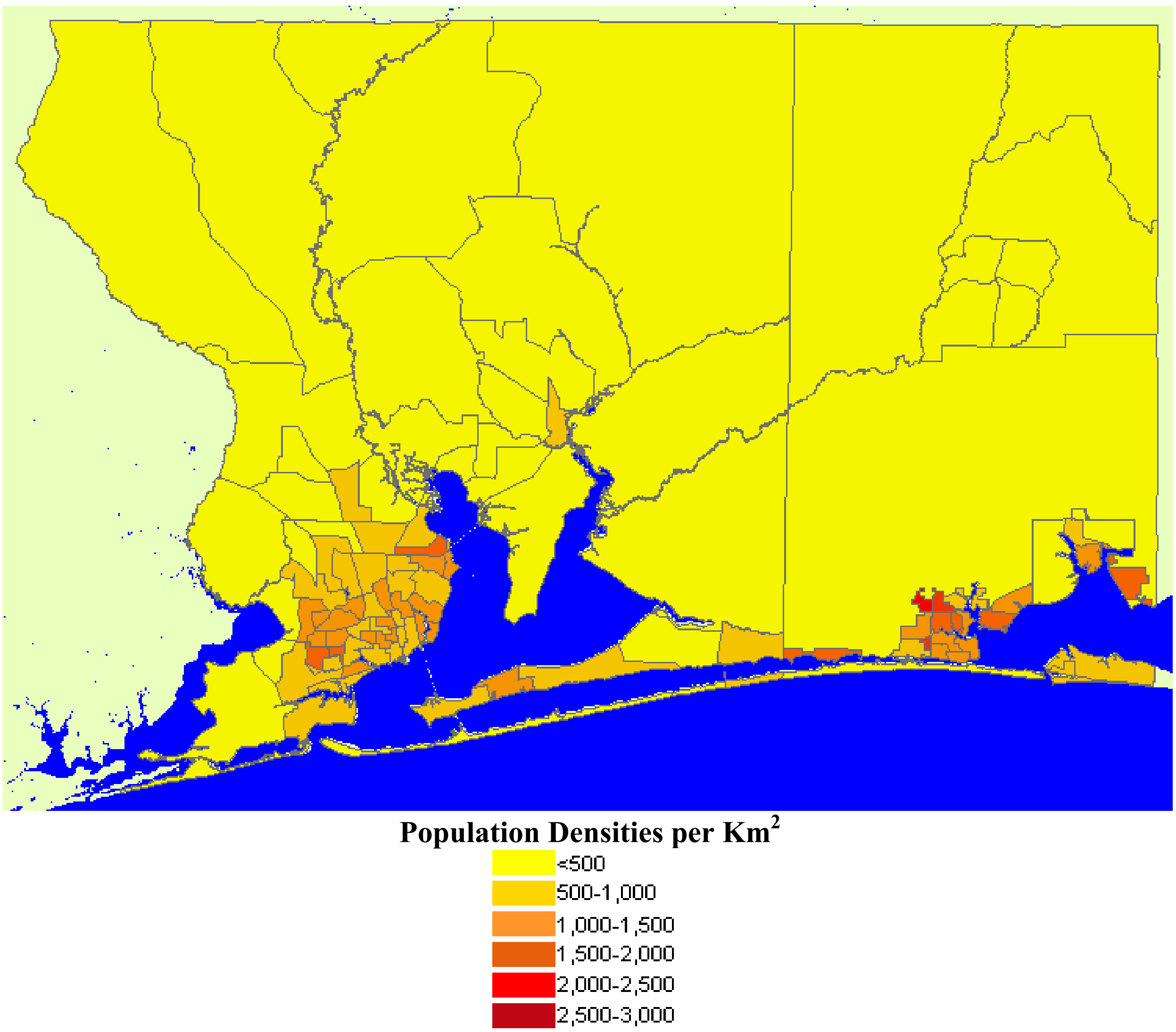


Figure 5.16: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2015

In the year 2015, most censuses tracts in Pensacola will have densities between 1,000 to 1,500 inhabitants per Km^2. The main changes will occur in a suburb in the southwest part of Pensacola, which will increase from below 500 in the year 2010 into 500 to 1,000 inhabitants per Km^2 in 2015, another one in this same southwest part of this city also will increase from 500-1,000 in 2010 into the new range 1,000-1,500 for 2015, while the downtown of Pensacola still is decreasing its density, and a census-tract in its center will diminishes from 1,000-1,500 into 500-1,000 inhabitants per Km^2. In Milton, the densities will be between 500 and 1,000 inhabitants per Km^2. The east part of Oriole Beach and Navarre-Navarre Beach also will increase their densities from 500-1,000 in the year 2010 to 1,000-1,500 inhabitants per Km^2. The city of Florosa will increase its density from the range 500 to 1,000 in 2010 into 1,500-2,000 inhabitants per Km^2 in 2015. Fort Walton Beach still will show higher densities than Pensacola, with most of its census-tracts above 1,000 inhabitants per Km^2. Here, a census-tract in its eastern part as well as a neighborhood in the south of Niceville will increase their densities from 500 to 1,000 in 2010 into 1,500-2,000 inhabitants per Km^2 in 2015. Finally, as it was mentioned before, most census-tracts in the region will present population densities below 500 inhabitants per Km^2 similar to all past images.

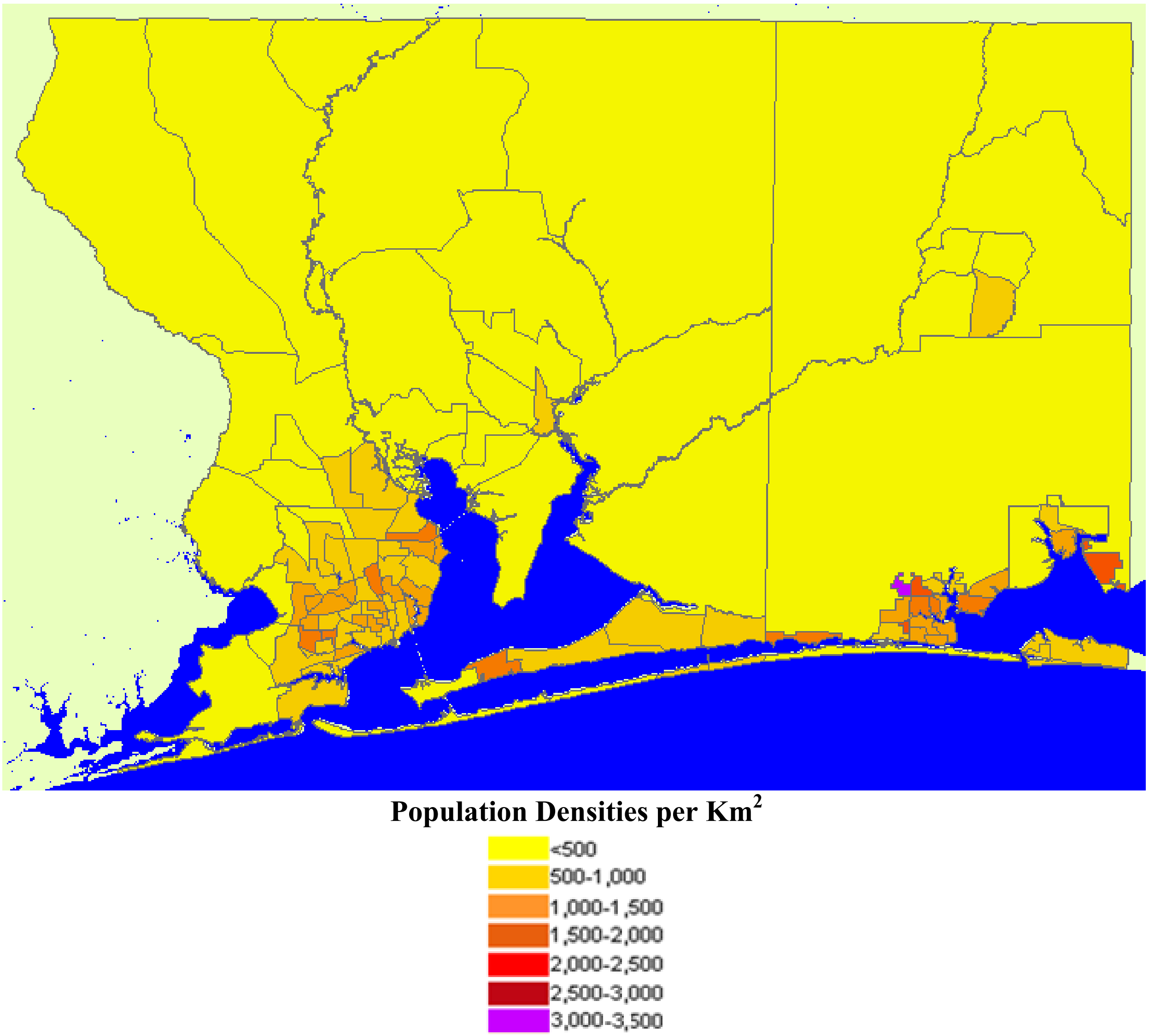


Figure 5.17: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2020

In the year 2020, most censuses tracts in Pensacola will have densities between 1,000 to 1,500 inhabitants per Km^2. The main changes in this city will occur in a suburb in the northeast part of Pensacola, which will increase from below 500 in the year 2015 into 500 to 1,000 inhabitants per Km^2 in 2020, while the downtown of Pensacola still will decrease its densities, for example a census-tract in its west center part will diminishes from 1,000-1,500 into 500-1,000 inhabitants per Km^{2}in 2020. In Milton and the southeast part of Crestview, the densities will be between 500 and 1,000 inhabitants per Km^2. The east part of Navarre-Navarre Beach also will increase its densities from 500-1,000 in the year 2010 to 1,000-1,500 inhabitants per Km^2. Fort Walton Beach still will show higher densities than Pensacola, with most of its census-tracts above 1,000 inhabitants per Km^2, and even a census-tract in its northwest part will increase its density from the range 2,500-3,000 in 2015 into 3,000-3,500 in 2020. These high densities of Fort Walton Beach are because the lack of lands due that to Eglin Air Force Base is surrounding this city as well as the city of Niceville. Finally, as mentioned before, most census-tracts in the region will present population densities below 500 inhabitants per Km^2.

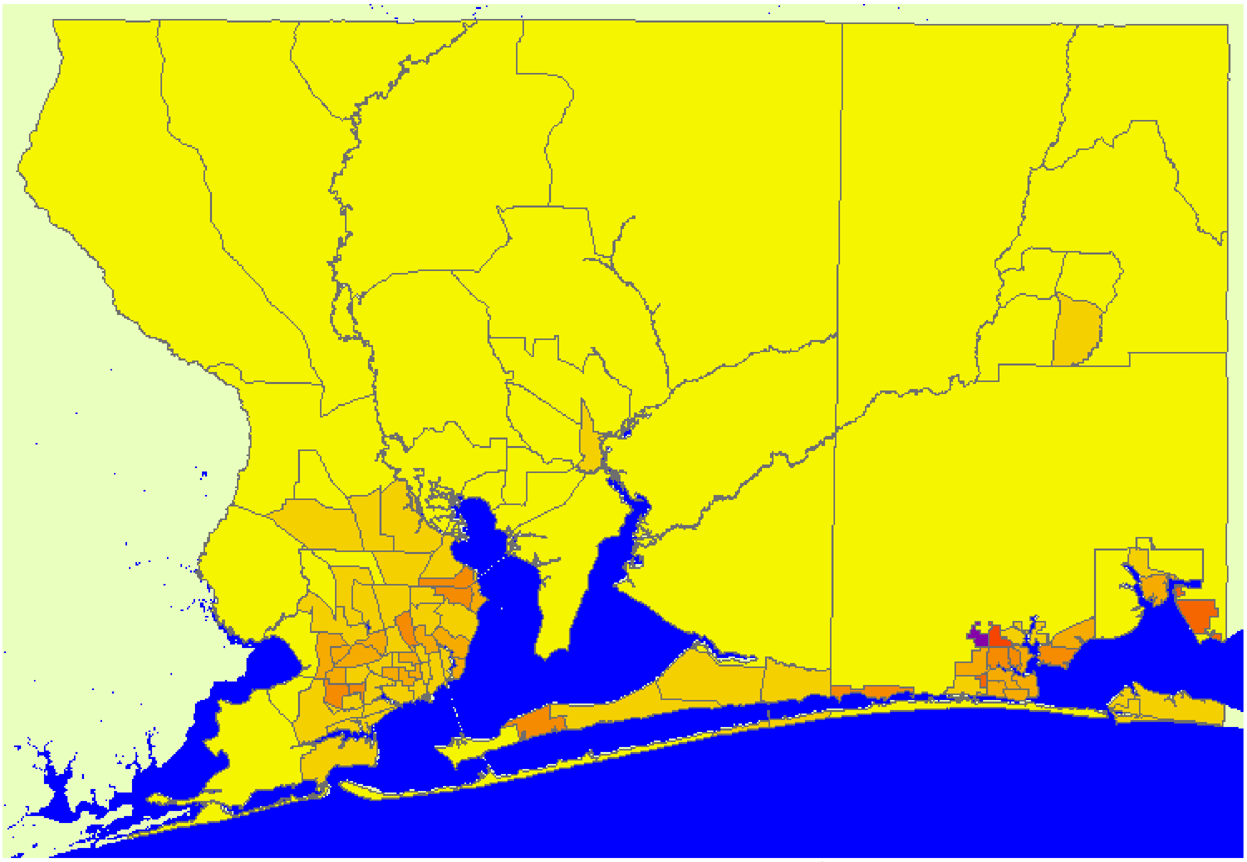


Figure 5.18: Choropleth Map of Escambia, Santa Rosa and Okaloosa Census-tracts in 2025

In 2025, most censuses tracts in Pensacola will have densities between 1,000 to 1,500 inhabitants per Km^2. The main changes in this city will occur in a suburb in the northwest part of Pensacola, which will increase from below 500 in the year 2020 into 500 to 1,000 inhabitants per Km^2 in 2020, while the downtown of Pensacola still will decrease its densities (Bryan et al. 2007). Here, some censuses tracts will diminish from 1,000-1,500 into 500-1,000 inhabitants per Km^2 in 2025. In Milton and the southeast part of Crestview, the densities will be between 500 and 1,000 inhabitants per Km^2. Fort Walton Beach still will show higher densities than Pensacola, with most of its census-tracts above 1,000 inhabitants per Km^2, and even a census-tract in its northwest part will increase its density from the range 3,000-3,500 in 2020 into a new value higher than 3,500 inhabitants per Km^2 in 2025. As already mentioned, these high densities of Fort Walton Beach are because of the lack of lands due to the Eglin Air Force Base surrounds this city as well as the city of Niceville. Finally, most census-tracts corresponding to the rural areas of this region will present population densities below 500 inhabitants per Km^2.

5.4. Dasymetric Maps at the Census-tract level in Escambia, Sta. Rosa and Okaloosa

Using the population datasets calculated in Excel since 1974 until 2025 at the census-tract level in Escambia, Santa Rosa and Okaloosa, together with the spatial information derived from the urban areas (pixels) calculated from ERDAS Imagine using Landsat-classified images and SLEUTH output simulations, it is possible to generate past, present and future dasymetric densities for every one of the 110 census-tracts through the use of the following formula:

Formula used to calculate Dasymetric Densities between 1974 and 1925

$$D = \frac{P}{A}$$

Where:

D = Dasymetric Density

P = Population in a Census-tract

A = Urbanized Area (pixels) in Kms^2 in a Census-tract

Note: To calculate the Area (A), the number of Urbanized Pixels in a Census-tract needs to be multiplied by 900 (every pixel has a resolution of 30m for 30 m) and then divided by 1'000,000 m^2 (which equals 1 Km^2).

These calculations produce results were population, area of urbanized pixels and densities are showed for each classified image and SLEUTH simulation. Also, dasymetric maps were elaborated first in EDRAS Imagine and finally in ArcMap.

The first step in the elaboration of the dasymetric maps was to transform selected GIF images (used as input results in the SLEUTH simulation) into TIFF through Adobe Photoshop software package to then reclassify (to recode) the urban areas and the rest of landscapes in all land-cover images using ERDAS Imagine software package. Here, urban areas changed original values from 1 (used as input data for the SLEUTH model) into 120, because these new reclassified values need to be higher than 110, due to the fact that there are 110 census-tracts, while the other areas (agriculture=2, pastures=3, forests=4, water=5 wetlands=6 and barrenlands=7) changed their values into zero (0).

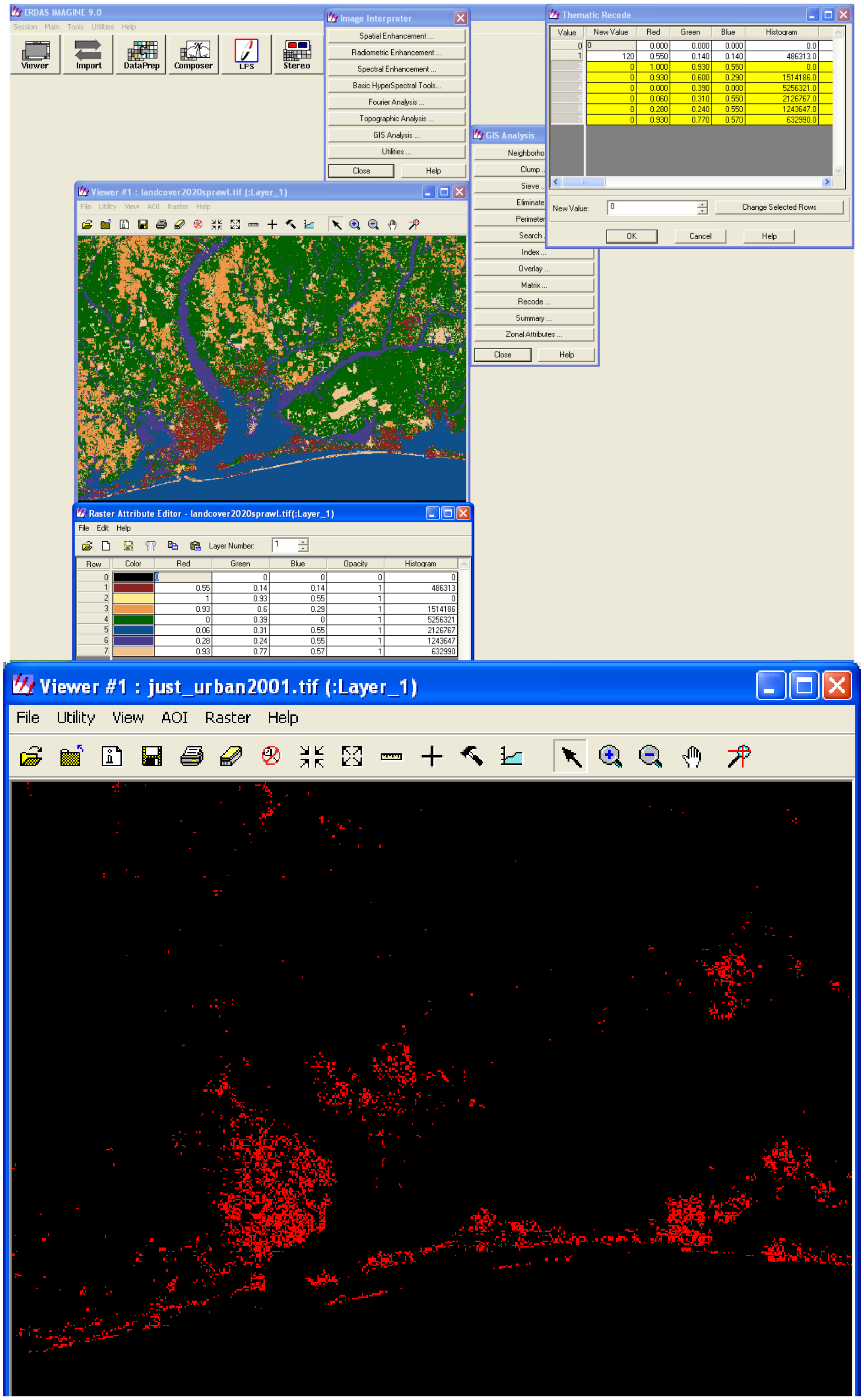


Figure 5.19: Reclassification (Recoding) of Land-cover images just in Urban Areas

Notes: Urban Areas changed values from 1 unto 120 because new reclassified values need to be higher than 110, because there are 110 census-tracts.

All other land-covers (agriculture=2, pastures=3, forests=4, water=5, wetlands=6 and, barrenlands=7) obtained the new value of zero (0).

Then, with these new recoded values for urban areas, using ERDAS Imagine Modeler, the image containing the new recoded urban pixels (urban=120) plus a previous rasterized image containing all census-tracts (from 1 to 110) were added together to produce a new image were urban pixels are differentiated in each census-tract because they have distinct values (from 121 to 230). Also, it is necessary to say that the areas without urban pixels (also called empty areas) in the different census-tracts now have distinct values (from 1 to 110).

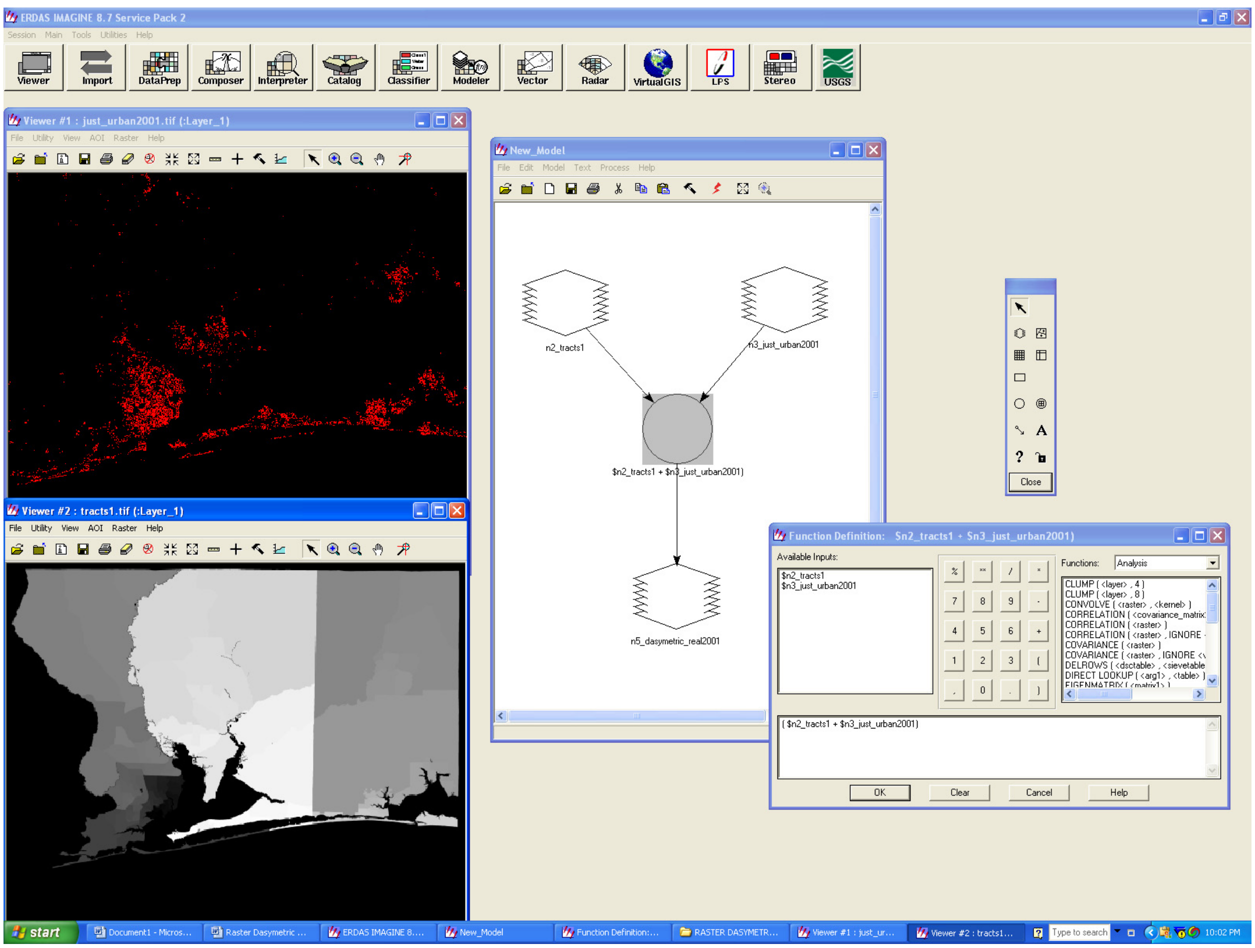


Figure 5.20: Overlaying urbanized pixels within every census-tract

After these new census-tracts were obtained, it was necessary to recode (reclassified) again the values that are equal or lower than 120 into the new value of zero (0) to homogenize the different areas without urban pixels (empty areas) of different census-tracts.

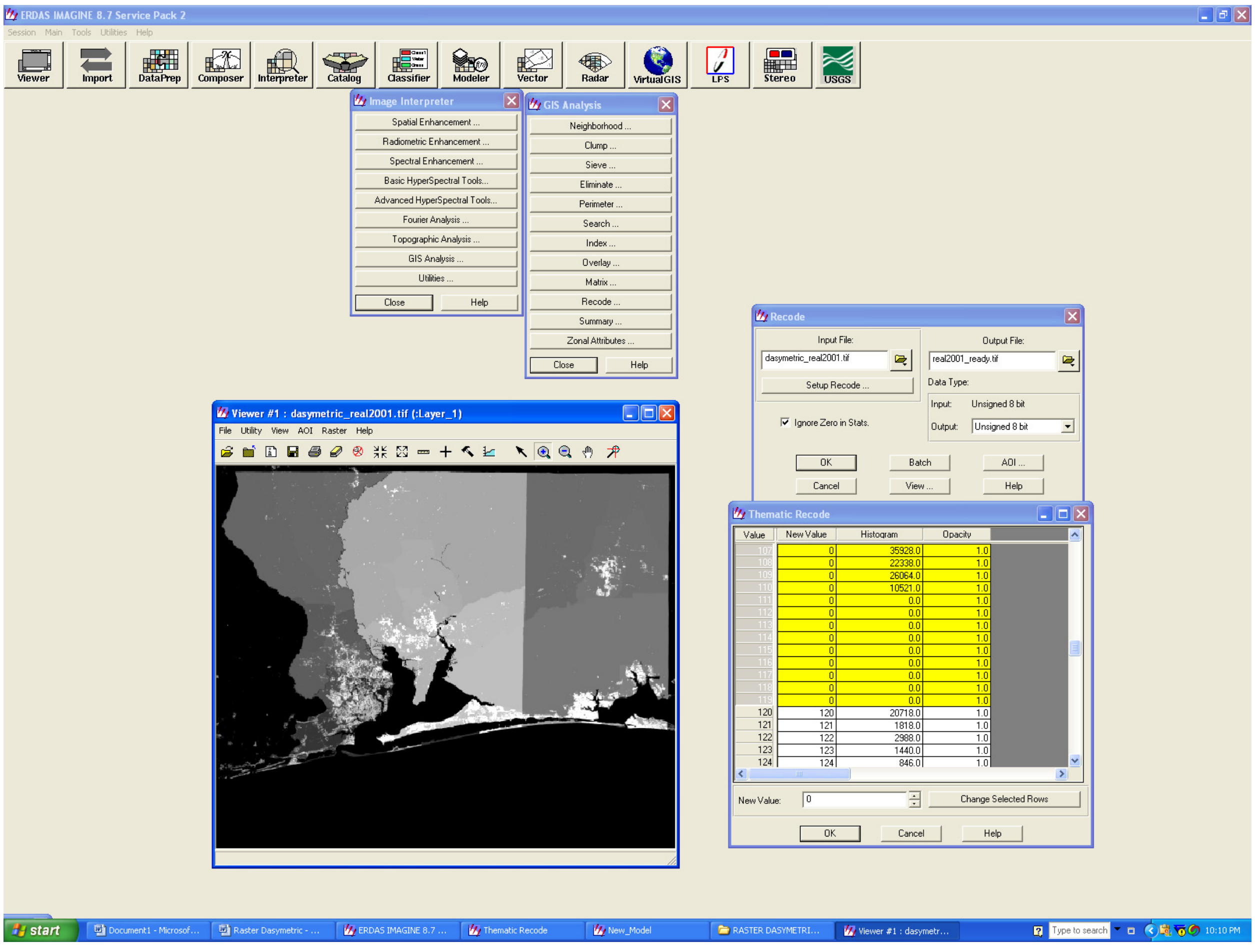


Figure 5.21: Recoding values equal or lower than 120

Note: Values lower than 120 are recoding with the new value of zero (0)

The next step is to subtract in ERDAS Imagine Modeler, the number 120 from all the values representing the urban pixels in the different census-tracts, in order to make urban pixels to coincide with their corresponding census-tract values (from 1 to 110).

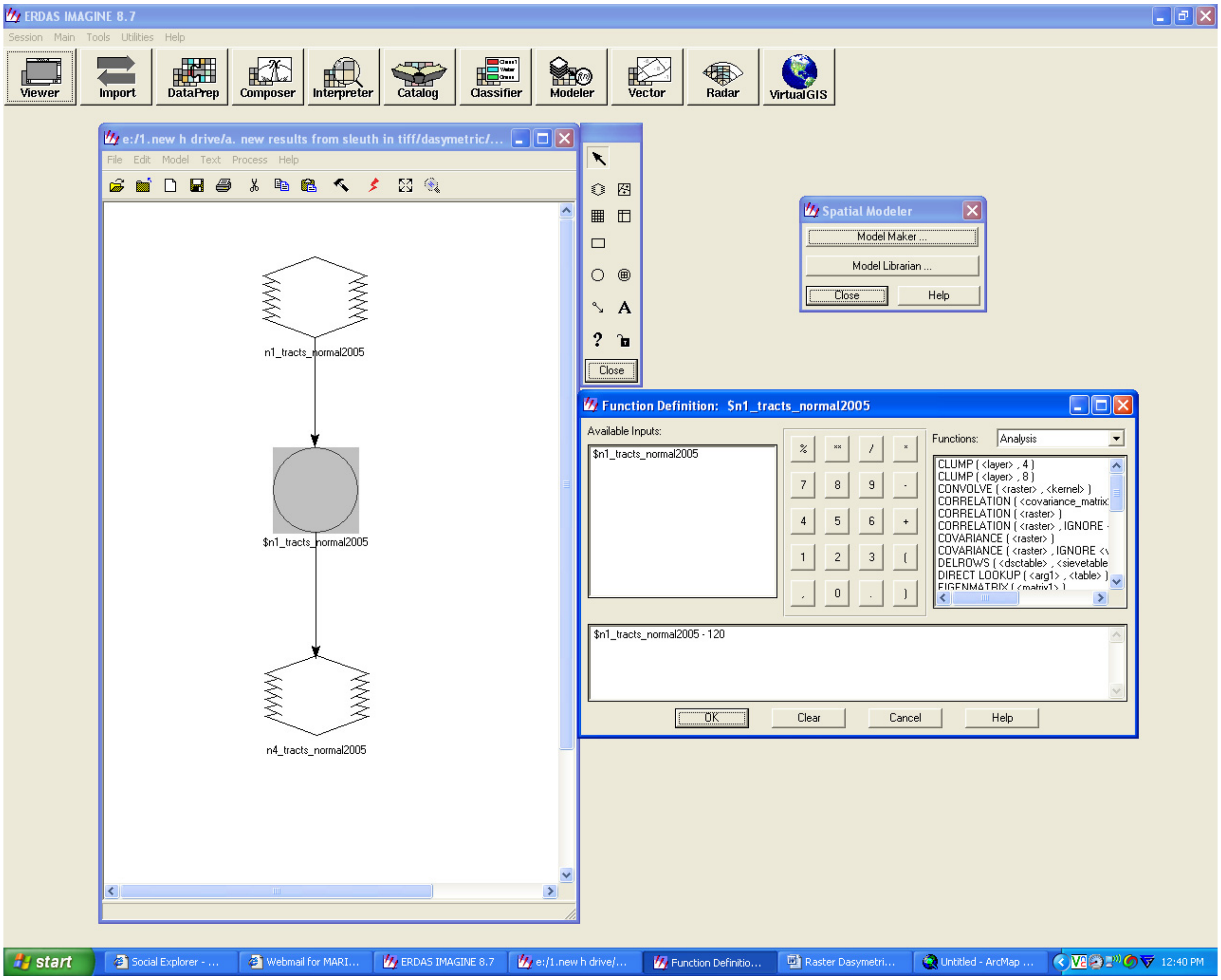


Figure 5.22: From all values in every census-tract, the number 120 is subtracted

Note: this procedure is necessary in order to make urban pixels to coincide with their corresponding census-tract values (from 1 to 110).

Because this procedure is done with census-tracts, the results are dasymetric maps without population densities values yet, and where water areas and territories outside the three counties of interest (Escambia, Santa Rosa and Okaloosa) look the same (they are not differentiated from each other); so, it is necessary to create water areas as well as the territories surrounding the region of interest. Therefore, reclassify the values of water and land-covers from the original classified images and SLEUTH results into new values higher than 110, because there are 109 census-tracts. In these maps, urban areas (value=1), agriculture-rangeland (value=3), forests (value=4), wetlands (value=6) and barrenlands (value=7) were recoded with the new value of 120. Also the land-cover water (value=5) was replaced by 115.

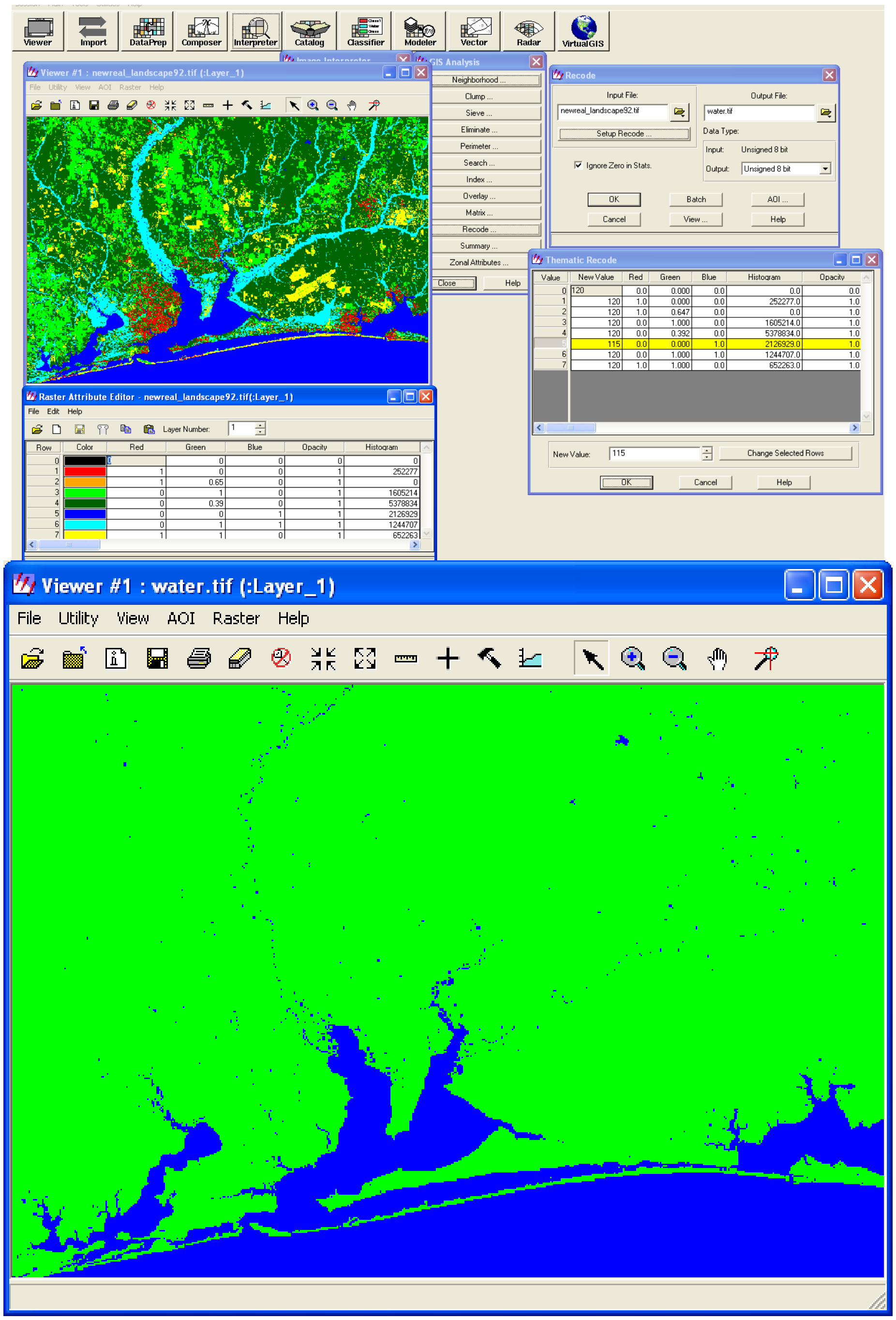


Figure 5.23: Reclassification (Recoding) of Land-cover images in Land and Water

Notes: Land areas (before Urban = 1, Agriculture-Rangelands=3, Forests=4, Wetlands=6 and Barrenlands=7) were reclassified with the new value of 120.
Water areas (before Water=5) were reclassified with the new value of 115.

This layer containing land and water covers is added to the dasymetric layer in ERDAS Imagine Modeler in order to generate a background where water and lands outside the three counties (Escambia, Santa Rosa and Okaloosa) are easily identifiable. Because the value of 120 (land areas) is added to all the region containing the urban pixels within their respective census-tracts, it is important at the end of the equation to subtract 120 in order to match the census-tracts values from Geolytics.

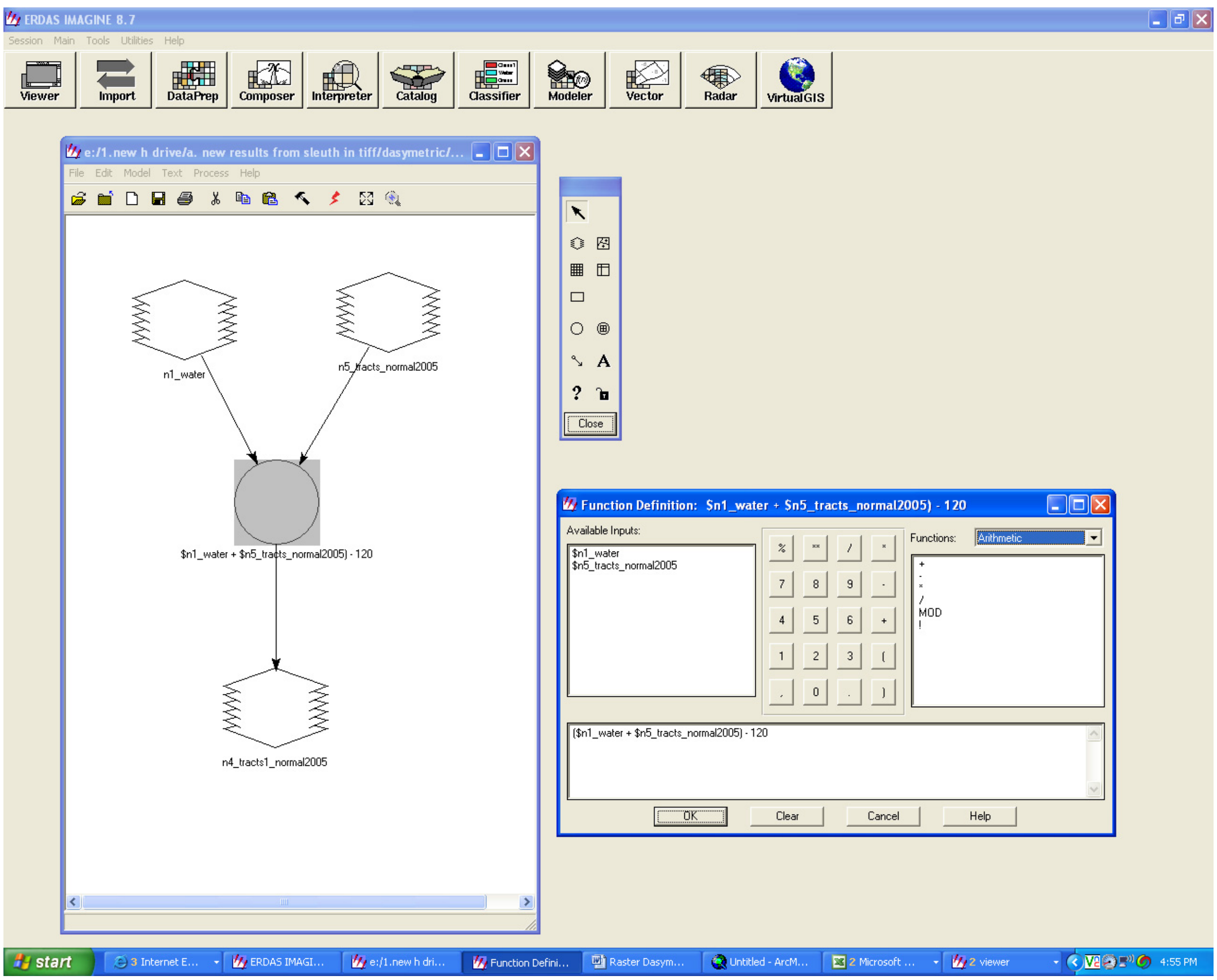


Figure 5.24: Land and Water areas are combined with the Dasymetric Maps

Note: The value 120 is subtracted at the end of the equation in order to match the census-tracts values from Geolytics.

Finally, these TIFF maps are transferred into ESRI ArcMap and the data from the pre-existing tables made in ERDAS Imagine (containing just the number of urban pixels per census-tract) are combined with the tables containing the dasymetric densities generated in EXCEL, which were generated using the formulas mentioned in this Chapter. The last step is to overlap the original shapefile layer containing the census-tracts borders from Geolytics in transparent mode above the dasymetric maps to produce a visual map where just the border lines of the census-tracts appear and inside them is possible to differentiate the densities of the urban pixels within the census-tracts. The dasymetric densities at the census-tract level are documented in tables A-IV.31 to A-IV.57 in appendix IV (pages 398 to 419).

Dasymetric densities were also made in ESRI ArcGIS, based on new maps where urban pixels from the classified land-covers and the SLEUTH simulations where first vectorized and then intersected together with the choropleth maps showing census-tracts. Finally population values were divided by urban pixels in each census-tract, generating in this way the different dasymetric maps of population densities (see flowchart of previous figure 5.2 in this chapter and figures 5.25 to 5.52).

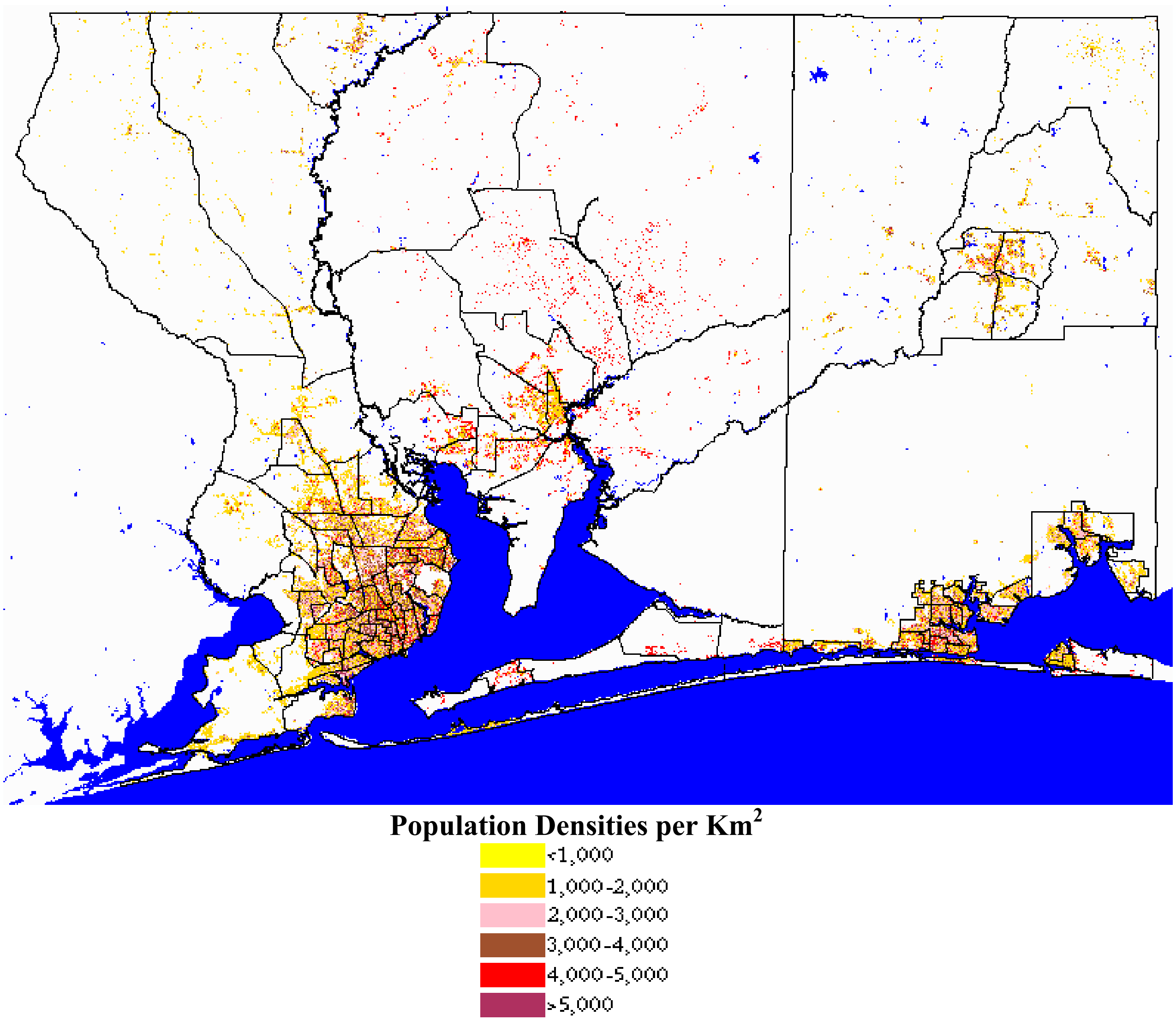


Figure 5.25: Dasymetric Map of Landsat Classified Image for Escambia, Santa Rosa and Okaloosa 1974

In 1974, Pensacola City presents most of its census-tracts with dasymetric densities between 2,000 to 3,000 inhabitants per Km^2. Some census-tracts in the downtown area have densities of 4,000 to 5,000 and a few ones even greater than 5,000 inhabitants per Km^2. The density is lower in the suburbs (less than 2,000 inhabitants per Km^2). Fort Walton Beach has a similar pattern as Pensacola (high density in downtown and decreasing density in suburbs). Gulf Breeze also presents densities above 4,000 inhabitants per Km^2. Instead, the cities of Milton and Crestview show very low population densities (less than 2,000 inhabitants per Km^2) while the densities are low on the beaches of Santa Rosa island and others because much of these areas in 1974 were barren lands.

The red pixels in many rural areas show very high population densities. The reason is that Landsat images (medium-resolution at 30m) do not represent accurate the population density in rural areas where small houses (less than 300 m^2) are located on large pieces of land, presenting consequently many inaccuracies because urbanized pixels may be designated as grass or forest instead of urban and falsely low numbers of urban pixels increases population density.

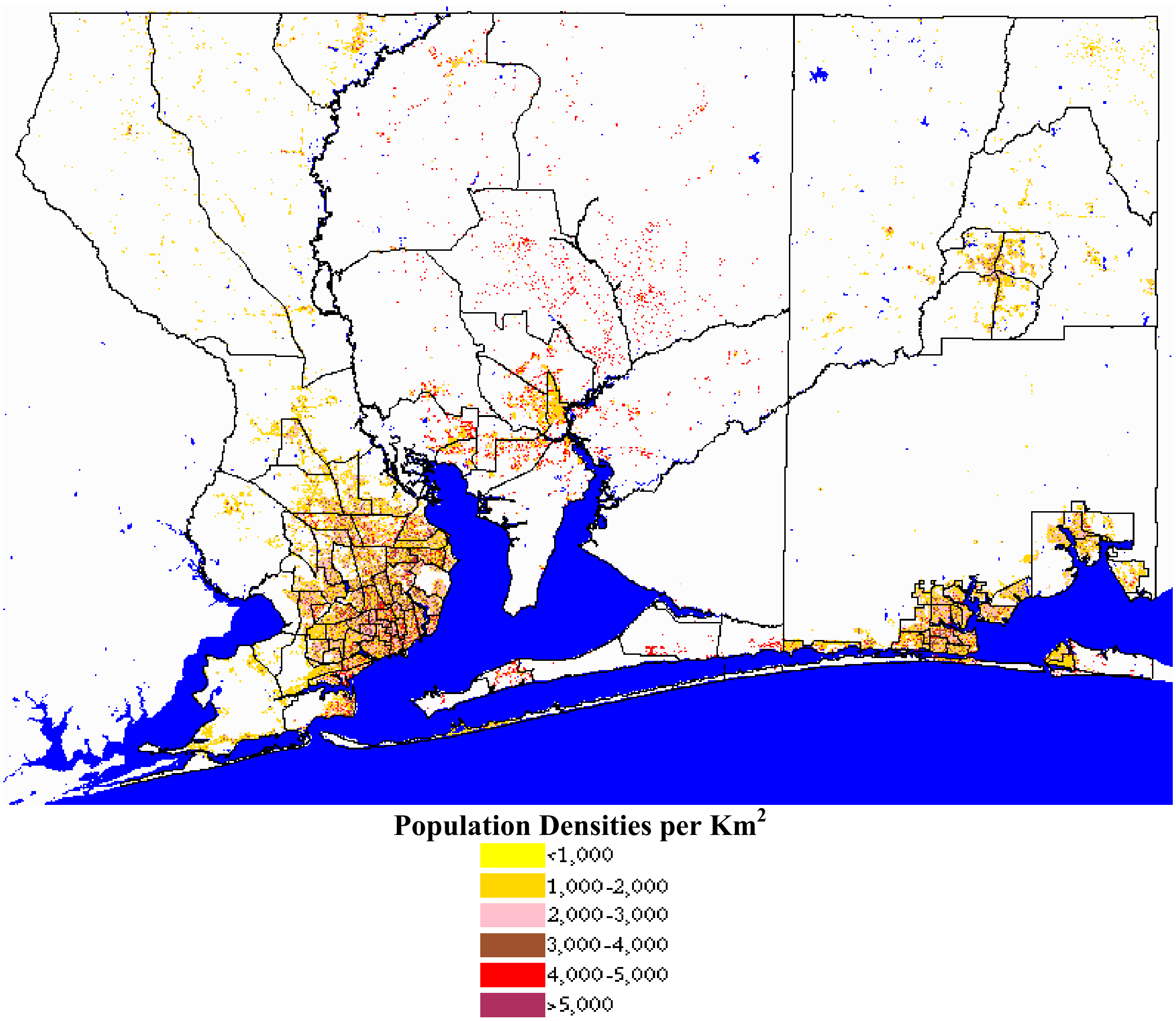


Figure 5.26: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1975

In 1975 (the first simulation generated by the SLEUTH model) Pensacola City presents dasymetric densities with very small changes in relation with the Classified Landsat image of 1974. These changes are not noticeable with the human eye, but evident in the census-tract's statistics. Therefore, it is possible to say that most census-tracts in Pensacola City and Fort Walton Beach present dasymetric densities between 2,000 to 3,000 inhabitants per Km^2. Some census-tracts in downtown areas have densities of 4,000 to 5,000 and a few ones even greater than 5,000 inhabitants per Km^2 while densities are lower in the suburbs (less than 2,000 inhabitants per Km^2). Gulf Breeze also presents densities above 4,000 inhabitants per Km^2. Instead, the cities of Milton and Crestview show very low population densities (less than 2,000 inhabitants per Km^2) while the densities are lower on the beaches of Santa Rosa island because much of these areas in 1974 were barren lands. Finally, the same problem mentioned before appears also in this first SLEUTH simulation and it is related with red pixels in many rural (very high rural densities).

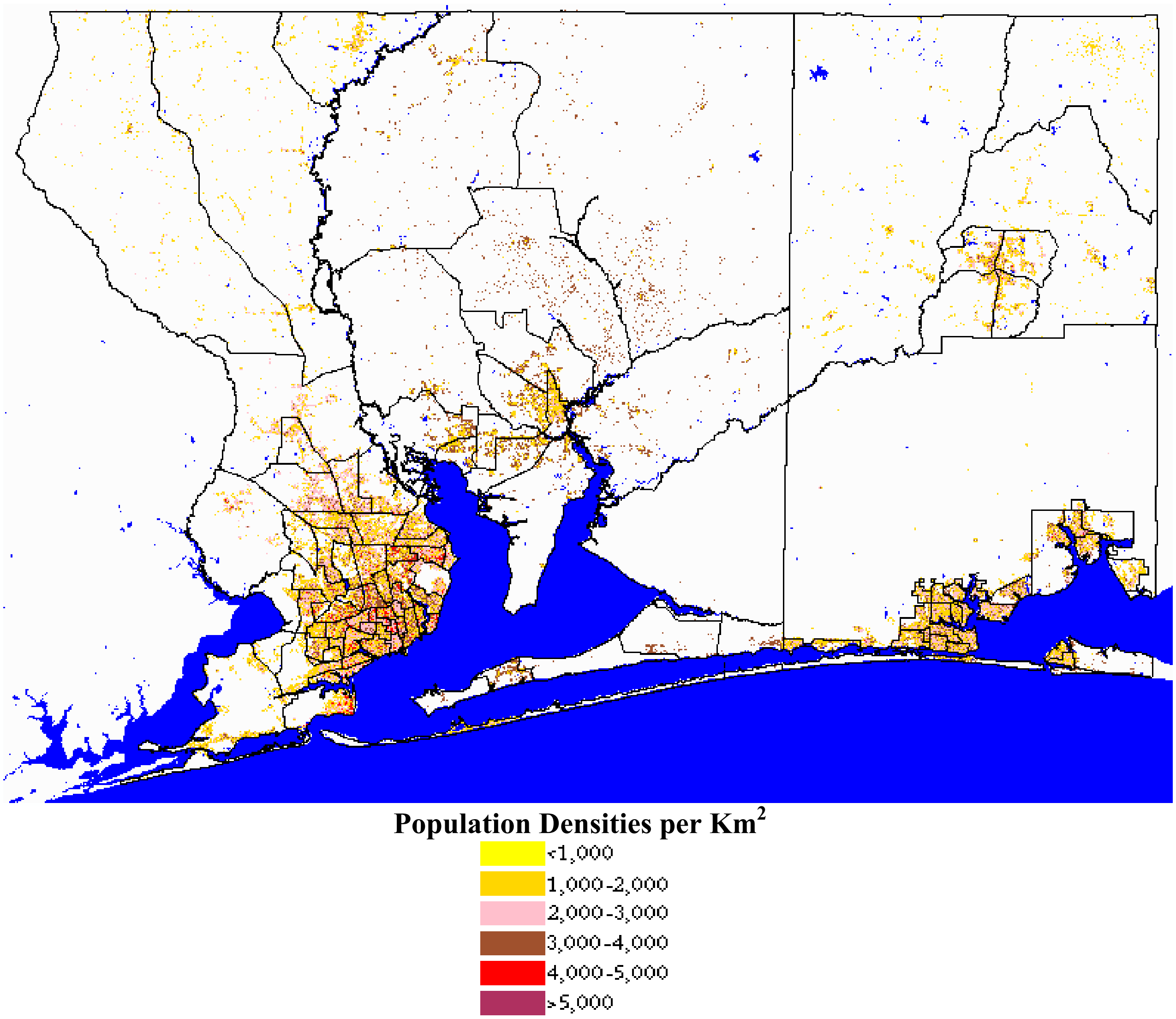


Figure 5.27: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1980

For 1980, the population densities decreased in Pensacola and especially in Fort Walton Beach, the last one for example decreased significantly, no longer showing densities of 4,000 to 5,000 inhabitants per Km^2 and matching the pattern for decreasing density in downtown areas seen in some other cities in the U.S. (Bryan et al. 2007). There is a decrease in population density in rural areas because urban pixels are more accurately representing structures, resulting in a more accurate population density. As it was mentioned before, the density is lower in the suburbs (less than 2,000 inhabitants per Km^2). Gulf Breeze also presents a reduction in its densities to levels below 4,000 inhabitants per Km^2. Instead, the cities of Milton and Crestview as well as the because of Santa Rosa island and others still showed low densities below 2,000 inhabitants per Km^2.

In the year 1980 many red pixels of past years in the rural areas appear right now in brown color, showing densities slightly lower (from 3,000 to 4,000 inhabitants per Km^2) because the rate of generation of random pixels in the SLEUTH model in rural areas was higher than the rate of population growth in these same areas, reducing consequently the density.

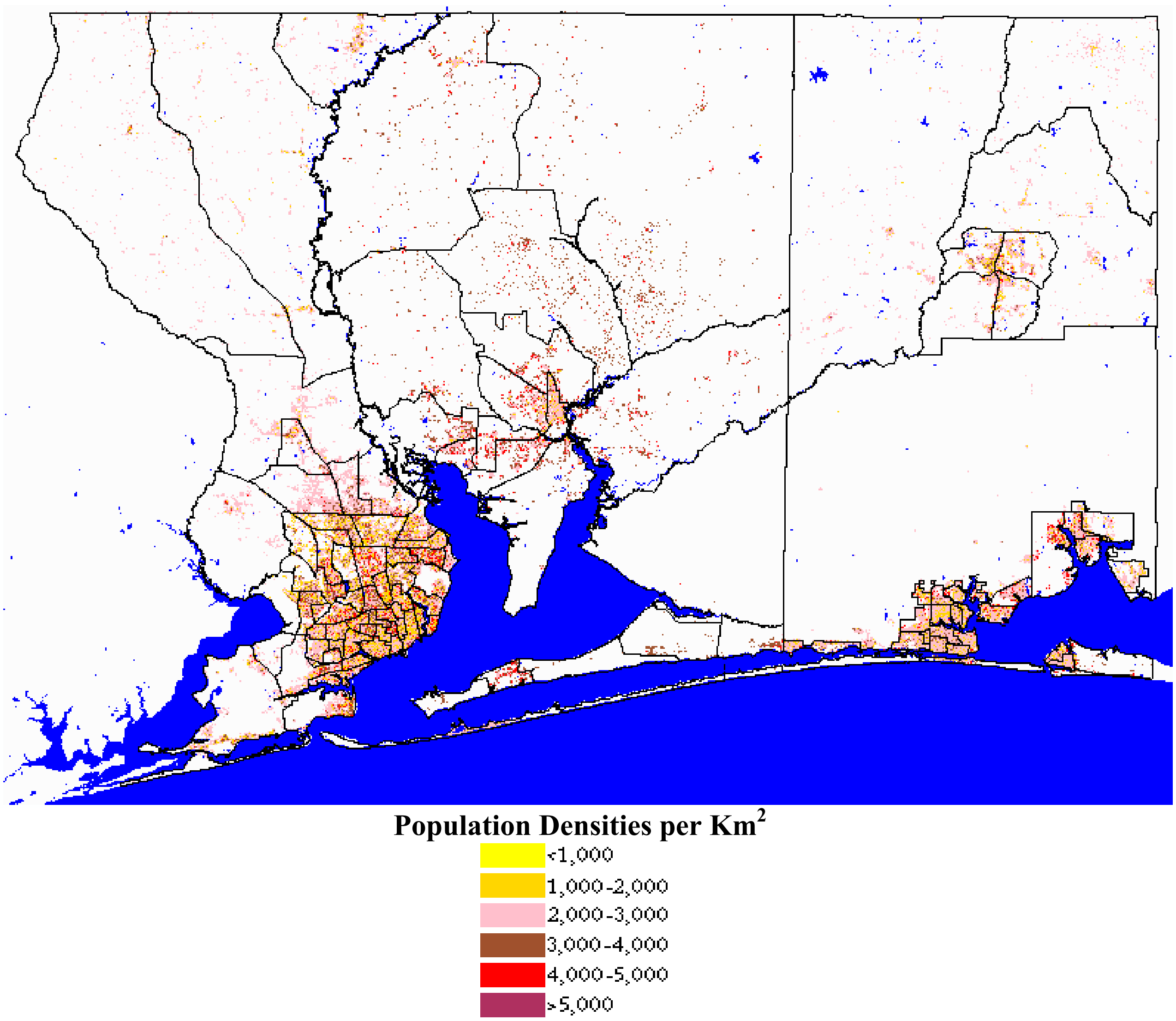


Figure 5.28: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1985

In 1985, Pensacola City and Fort Walton Beach present dasymetric densities above 4,000 inhabitants per Km^2 in some census-tracts located in downtown areas. In the case of the suburbs of these two cities, their population densities has increased in the suburbs of Pensacola city to 2,000-3,000 inhabitants per Km^2 (pink) and in the case of Fort Walton Beach the values raised from 1,000-2,000 inhabitants per Km^2 to 2,000-3,000. Population densities also increased in Milton and Crestview until 3,000 inhabitants per Km^2. In the case of the beaches of Santa Rosa island and others, also is possible to notice a higher levels of densities (until 3,000 inhabitants per Km^2).

The same problem mentioned before about the existence of red pixels in many rural areas showing unrealistically very high population densities also appears in this image. The reason is related with the fact that the rate of generation of random pixels in the SLEUTH model in rural areas was lower than the rate of population growth in these same areas, increasing consequently the density to levels as high as 4,000 to 5,000 inhabitants per Km^2 in the case of the less accurate rural zones.

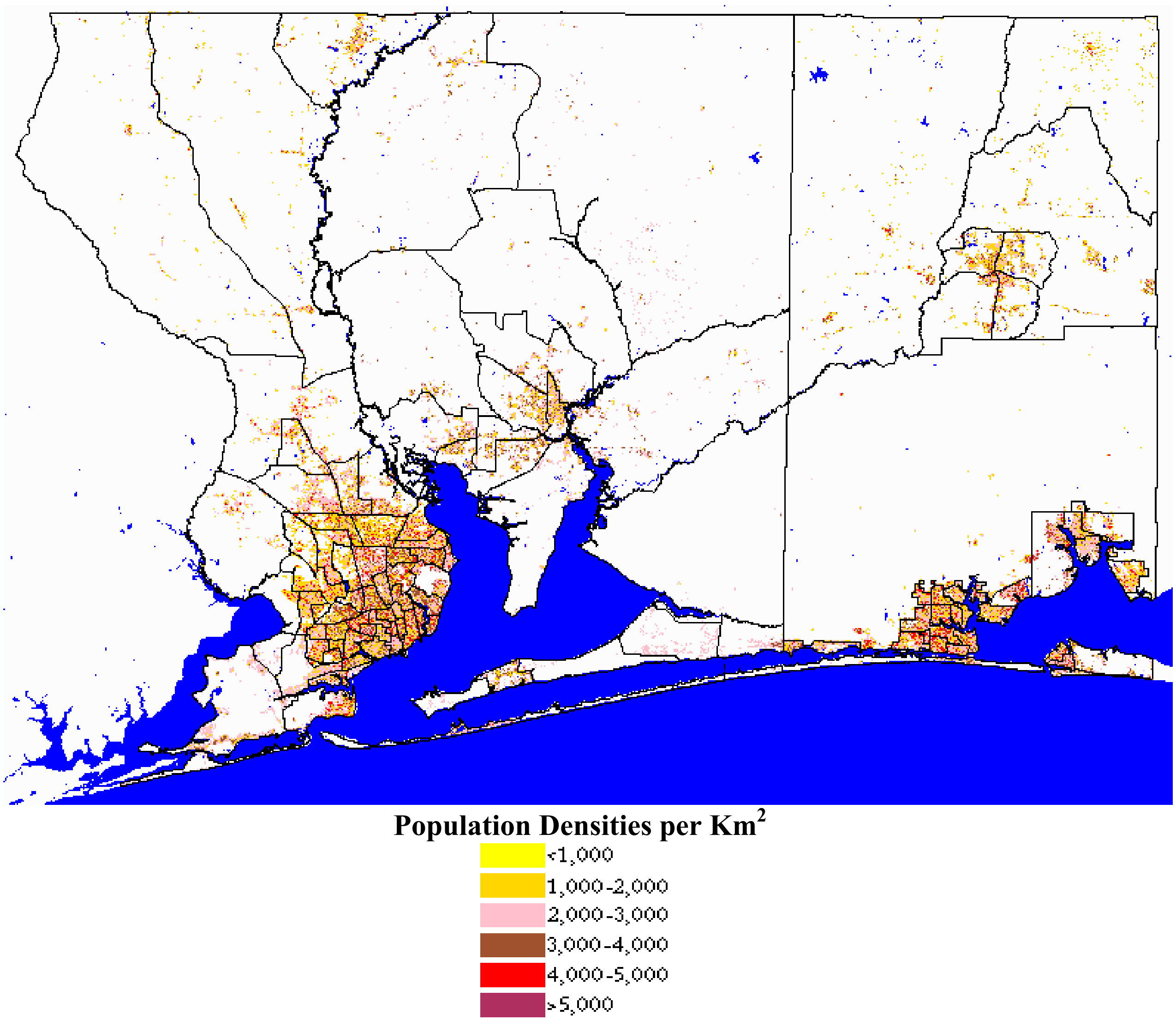


Figure 5.29: Dasymetric Map of Landsat Classified Image for Escambia, Santa Rosa and Okaloosa 1986

In 1986, the classified Landsat image is similar to the SLEUTH-derived image for 1986, but there is more yellow color (1,000-2,000 inhabitants/Km2) in the suburbs of Pensacola and in Fort Walton Beach as well as in some rural areas as well. The dasymetric densities in the downtown areas of these two cities achieved in some census-tracts levels above 4,000 inhabitants per Km^2. Milton and Crestview present densities between 1,000-2,000 inhabitants per Km^2. And the beaches of Santa Rosa island and others have densities until 3,000 inhabitants per Km^2.

In this classified image, many rural areas present dasymetric densities until 2,000 inhabitants per Km^2, showing a more realistic pattern of lower densities in the country. Nevertheless, there are also pink areas in rural areas (2,000-3,000 inhabitants per Km^2) showing instead an unrealistic pattern because the Landsat images (30m resolution) do not represent accurate the population density in rural areas where small houses (less than 300 m^2) are located on large pieces of land, and many urbanized pixels may be designated as grass or forest instead of urban and falsely low numbers of urban pixels increases population density.

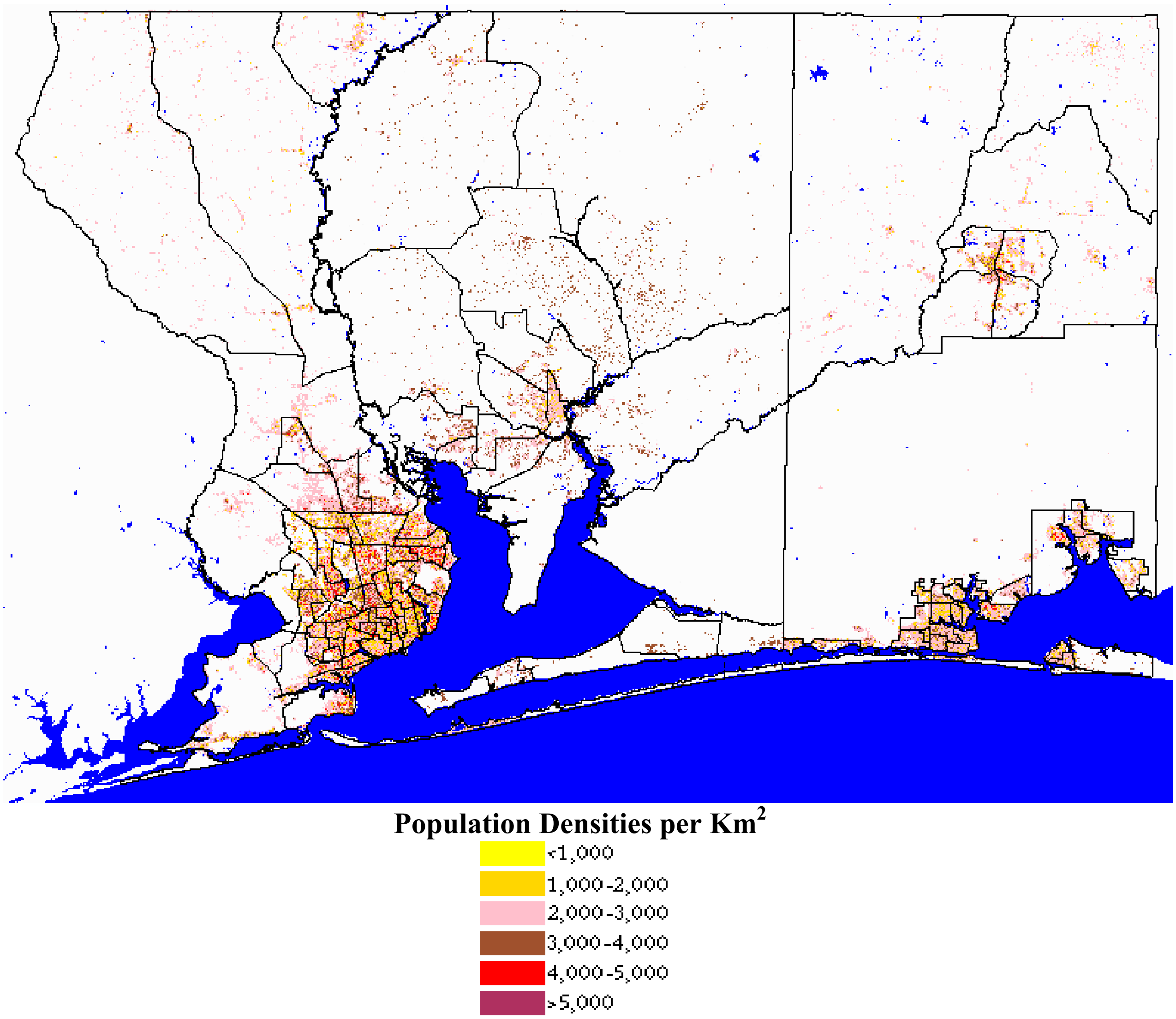


Figure 5.30: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1986

In 1986, the simulated image shows is very similar to the simulation from 1985 because both are derived from the SLEUTH model with just one year of difference. Here, the cities of Pensacola City and Fort Walton Beach present dasymetric densities above 4,000 inhabitants per Km^2 in censuses tracts located in their centers, while many of their suburbs contain population densities of 2,000-3,000 inhabitants per Km^2 (pink). Milton and Crestview present densities a high as 3,000 inhabitants per Km^2. The beaches of Santa Rosa island and others have densities up to 3,000 inhabitants per Km^2 as well.

Finally, many rural areas contain the existence of pixels showing unrealistically very high population densities. The reason is that the rate of generation of random pixels in the SLEUTH model in rural areas was lower than the rate of population growth in these same areas, increasing consequently the density to levels as high as 4,000 inhabitants per Km^2 and even 5,000 inhabitants per Km2 in the case of the less accurate rural zones.

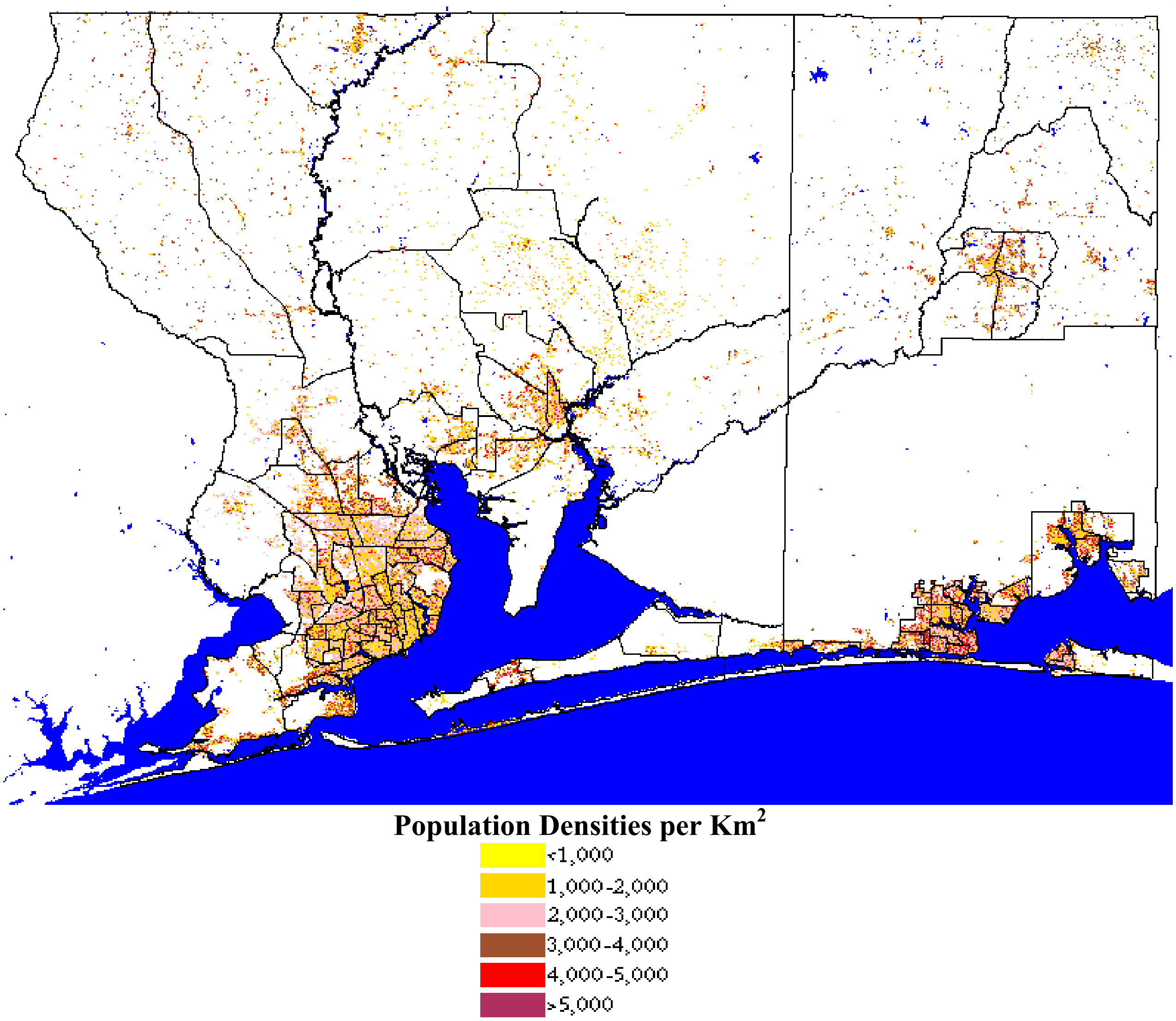


Figure 5.31: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1990

In 1990, many census-tracts of Pensacola City present a change from pink (2,000-3,000 inhabitants per Km^2) to gold (1,000-2,000 inhabitants per Km^2) while others, especially in the downtown areas still maintains densities as high as 4,000 inhabitants. The city of Fort Walton has increased markedly in population density (towards red or 4,000-5,000 inhabitants per Km^2) because of the Eglin Naval Base which prevents growth anywhere other than the city itself. Thus, there is no urban sprawl outside of Fort Walton Beach. Gulf Breeze also presents densities of 4,000-5,000 inhabitants per Km^2. Instead, the cities of Milton and Crestview show very low population densities (less than 2,000 inhabitants per Km^2) while the densities have increased on the beaches of Santa Rosa island and others because of the affluence of urban development towards or near to the sea.

There are also some brown pixels (3,000-4,000 inhabitants per Km^2) in many rural areas together with yellow pixels (less than 2,000 inhabitants per Km^2) in the countryside as well. The first ones show a lower accuracy while the second ones match reality better.

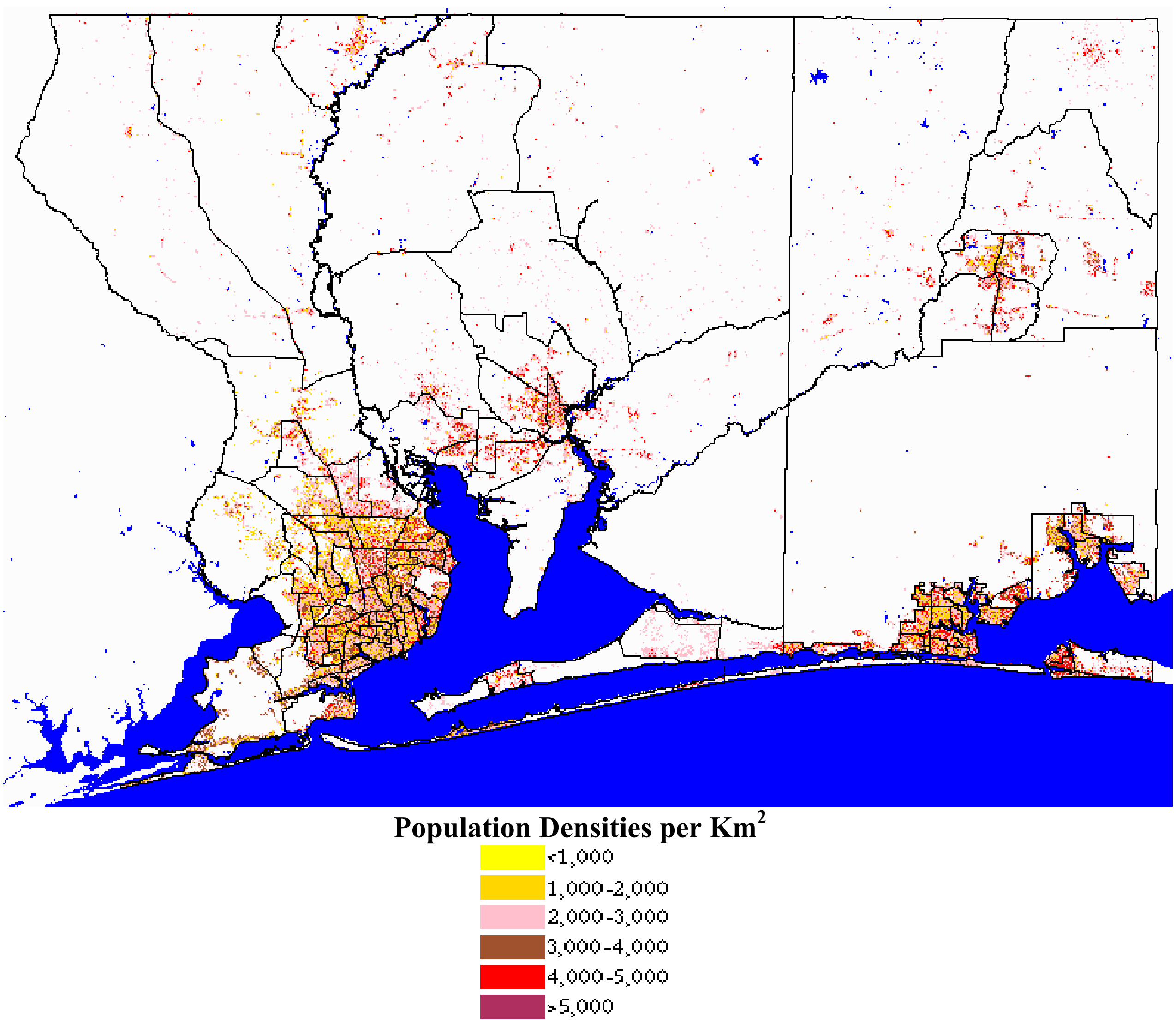


Figure 5.32: Dasymetric Map of Landsat Classified Image for Escambia, Santa Rosa and Okaloosa 1992

In 1992, according to the classified Landsat image, dasymetric densities in Pensacola City present some census-tracts with 1,000-2,000 inhabitants per Km^2 while others are higher: 2,000-4,000 inhabitants per Km^2. Fort Walton Beach has a similar pattern as Pensacola (high density in downtown and decreasing density in suburbs). Gulf Breeze also presents densities until 4,000 inhabitants per Km^2. And even the cities of Milton and Crestview densities between 2,000-3,000 inhabitants per Km^2. Finally, the beaches of Santa Rosa island and others have densities until 3,000 inhabitants per Km^2.

Repetitively mentioned before, red pixels in many rural areas show very high population densities. The reason is that Landsat images (medium-resolution at 30m) do not represent accurate the population density in rural areas where small houses (less than 300 m^2) are located on large pieces of land, presenting consequently many inaccuracies because urbanized pixels may be designated as grass or forest instead of urban and falsely low numbers of urban pixels increases population density.

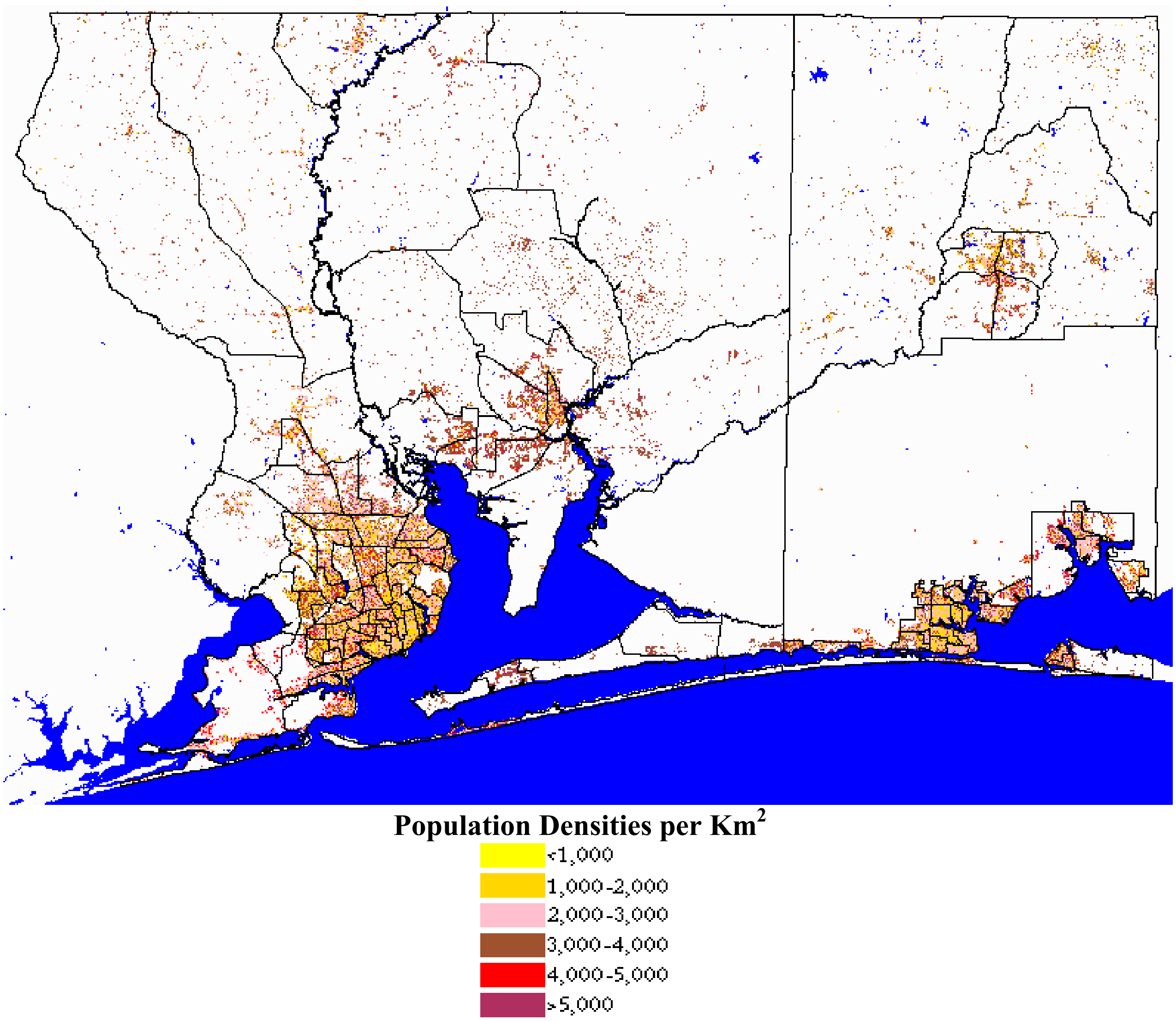


Figure 5.33: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1992

In the SLEUTH simulation of 1992, densities in Pensacola City present some census-tracts with 1,000-2,000 inhabitants per Km^2 while others are higher: 2,000-4,000 inhabitants per Km^2. Fort Walton Beach has a similar pattern as Pensacola. Gulf Breeze also presents densities of 3,000-4,000 inhabitants per Km^2. In the cases of the cities of Milton and Crestview, their densities achieved until 3,000 inhabitants per Km^2. Finally, the beaches of Santa Rosa island and others have densities until 3,000 inhabitants per Km^2 as well.

As it was mentioned many times before, the red (4,000-5,000 inhabitants per Km^2) and brown pixels (3,000-4,000 inhabitants per Km^2) in many rural areas show very high population densities because the rate of generation of random pixels (spontaneous growth and new spreading center growth) in the SLEUTH model in rural areas was lower than the rate of population growth in these same areas, increasing consequently the density levels.

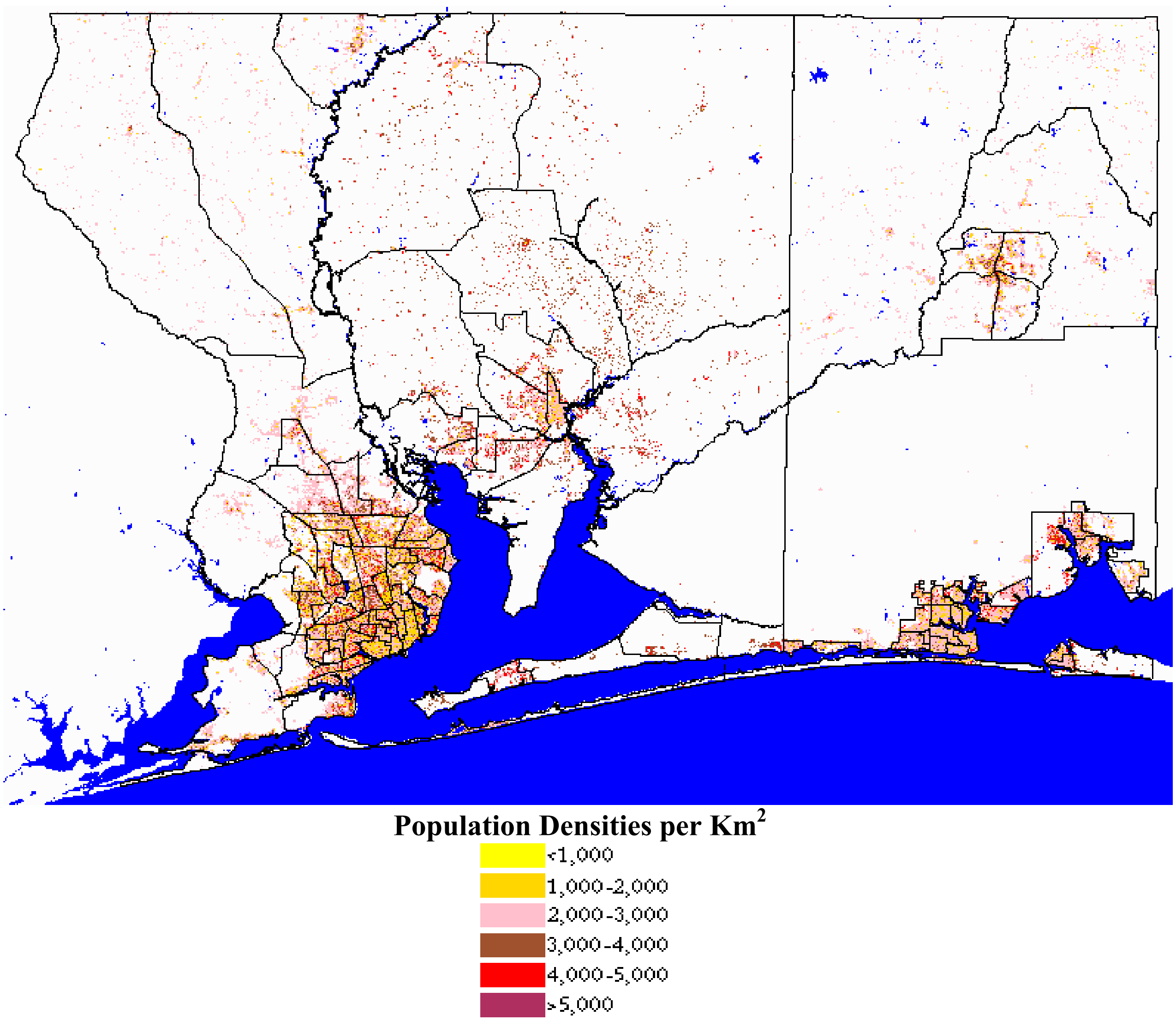


Figure 5.34: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 1995

In 1995, the city of Pensacola's central areas present lower population densities than before, due to that many of its census-tracts contain densities below 3,000 inhabitants per Km^2 matching the pattern for decreasing density in downtown areas seen in other cities in the United States (Bryan, Minton et al. 2007). In the suburbs of Pensacola, census-tracts do not show any more low densities than in the inner city, instead the densities are more homogenous throughout the entire metropolitan area. Fort Walton Beach also shows a reduction in the levels of densities inside its center, below 3,000 inhabitants per Km^2. Gulf Breeze still presents densities above 4,000 inhabitants per Km^2. Finally, and as usually, the cities of Milton and Crestview show lower population densities (less than 3,000 inhabitants per Km^2) while the densities are high on the beaches of Santa Rosa island and others.

The red and brown pixels in many rural areas show very high population densities that do not match reality and the reason for this pattern was already explained before in the analysis of densities of other SLEUTH simulations.

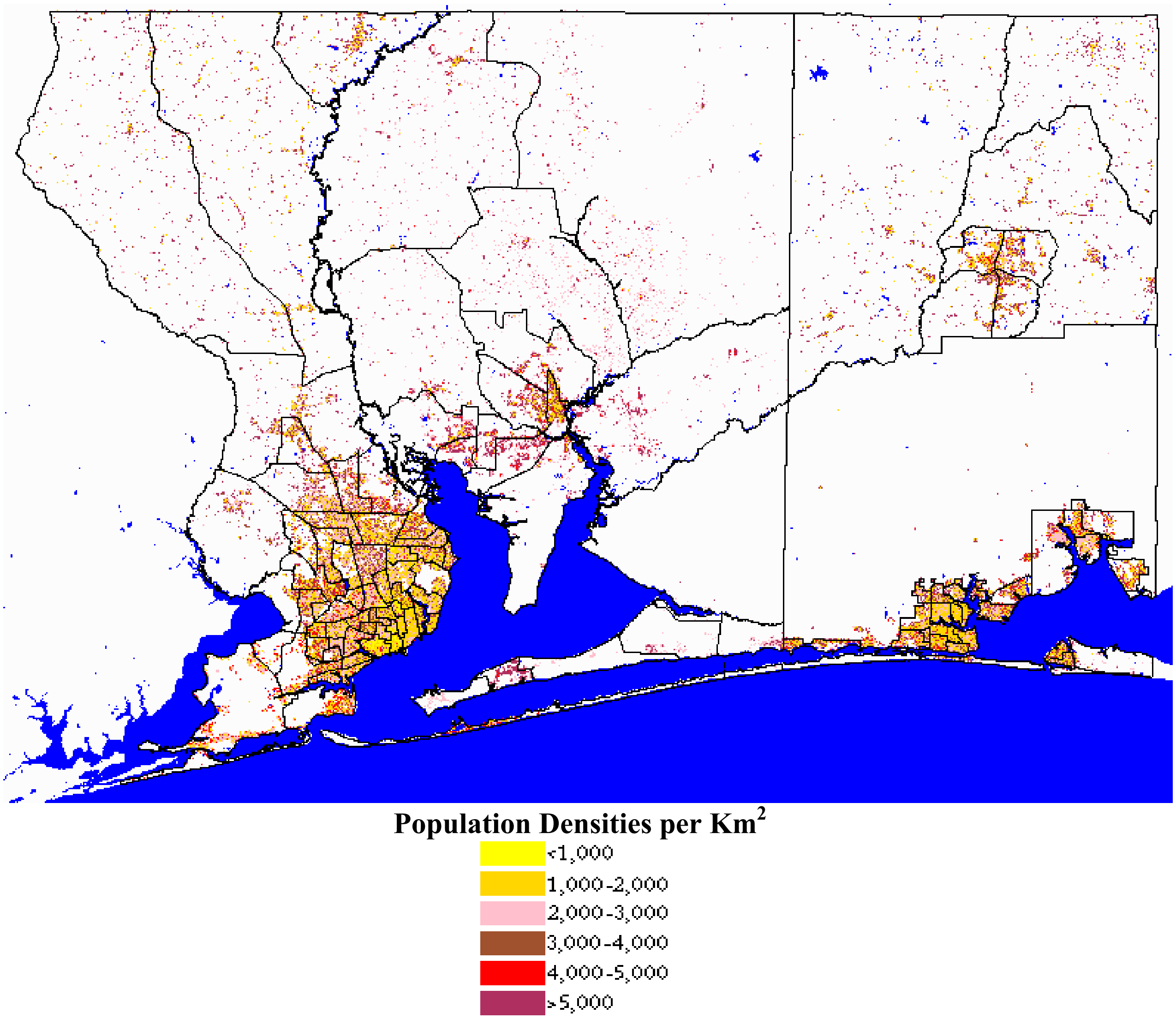


Figure 5.35: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 2000

In the SLEUTH simulation for the year 2000, the densities in the downtown of Pensacola present censuses tracts lower population density than before due that many residential areas became just commercial or services zones or due to the fact that people move away into the suburbs; therefore densities in the inner city are below 3,000 inhabitants per Km^2, with many census-tracts below 2,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Fort Walton Beach has a similar pattern as

Pensacola, with densities also below 3,000 inhabitants per Km^2. Gulf Breeze presents densities of 3,000-4,000 inhabitants per Km^2. In the cases of the cities of Milton and Crestview, their densities achieve values until 3,000 inhabitants per Km^2. Finally, the beaches of Santa Rosa island and others have densities between 3,000-4,000 inhabitants per Km^2.

As it was mentioned many times before, the red (4,000-5,000 inhabitants per Km^2) pixels in many rural areas show very high population densities that do not match reality; the reason is the high rate of spontaneous growth and new spreading center growth.

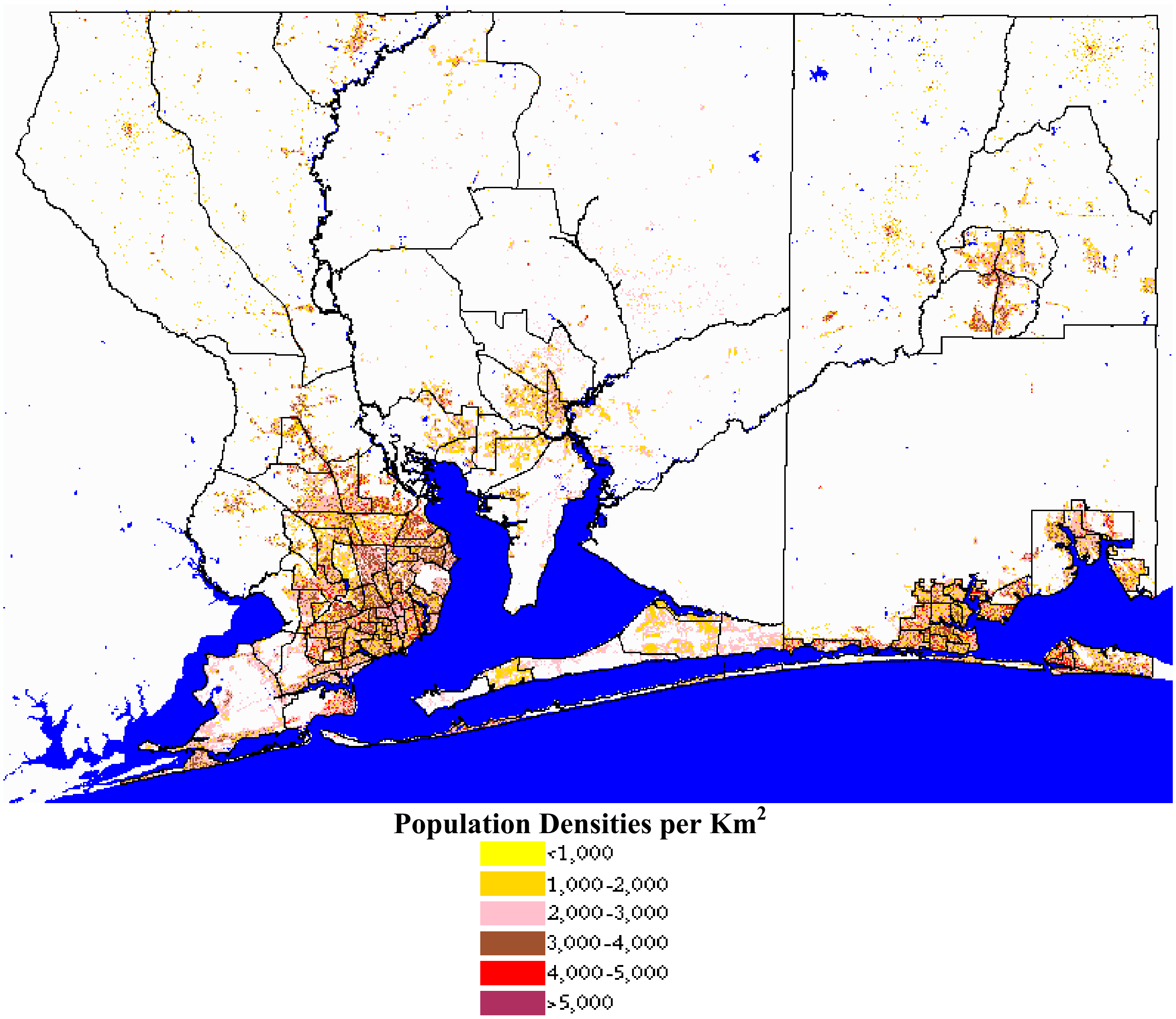


Figure 5.36: Dasymetric Map of Landsat Classified Image for Escambia, Santa Rosa and Okaloosa 2001

In 2001, according to the classified Landsat image, the dasymetric densities in Pensacola City present some census-tracts with low densities, between 2,000-3,000 inhabitants per Km^2 while others are higher: 3,000-4,000 inhabitants per Km^2; nevertheless, this image show higher densities than the SLEUTH simulation for the same year 2001. Fort Walton Beach has a similar pattern as Pensacola (high density in downtown and decreasing density in suburbs). Instead, Gulf Breeze presents lower densities than the simulations, just between 1,000-2,000 inhabitants per

Km^2. And the cities of Milton and Crestview have densities between 2,000-3,000 inhabitants per Km^2 or even less in some census-tracts.

Finally, the beaches of Santa Rosa island and others have densities above 3,000 inhabitants per Km^2.This classified image also shows a more accurate picture of the rural areas, with low densities with pixel values below 2,000 inhabitants per Km^2, representing reality in the way it is: higher densities in the cities and lower ones in the countryside.

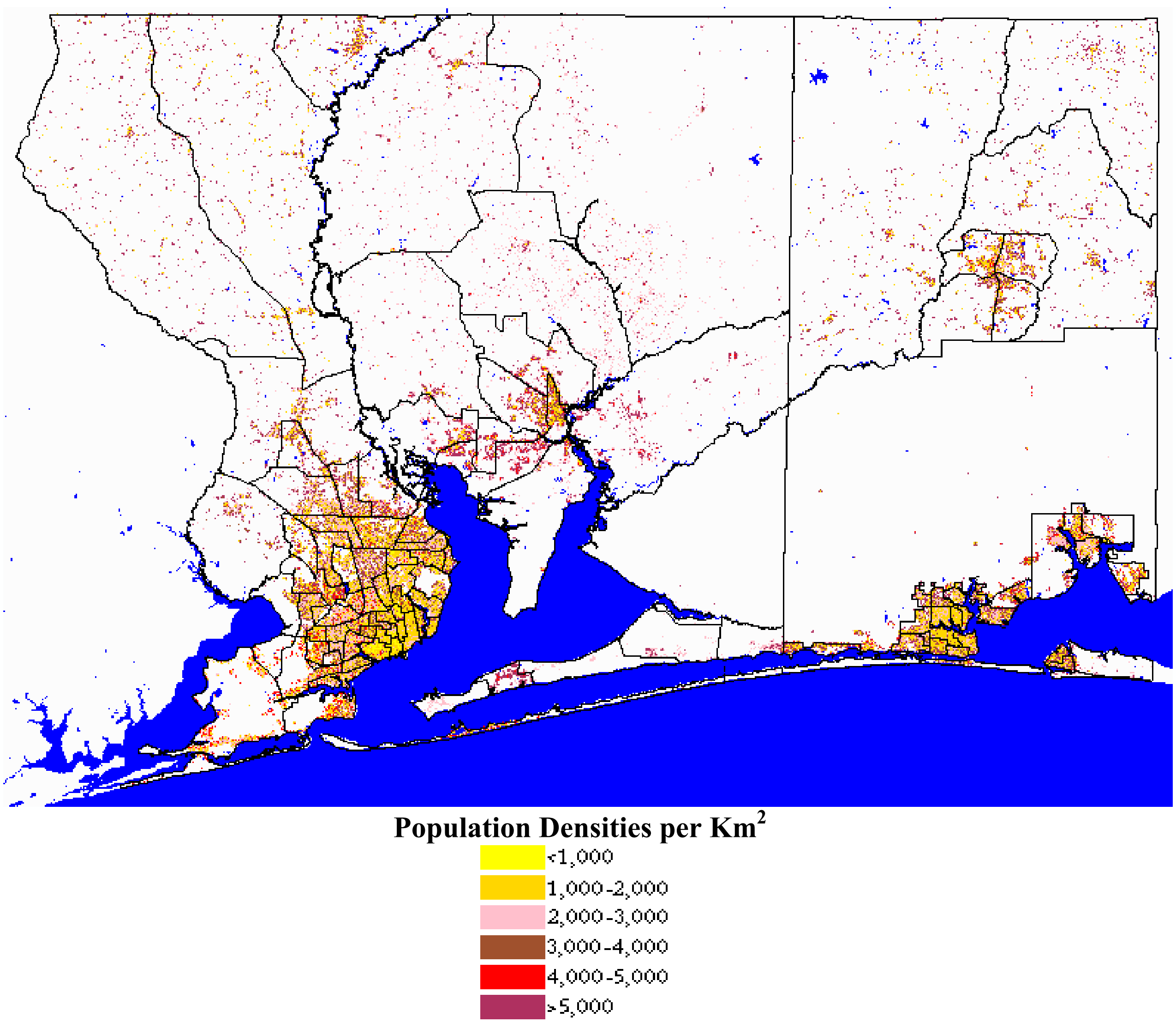


Figure 5.37: Dasymetric Map of SLEUTH Simulation for Escambia, Santa Rosa and Okaloosa 2001

Because this SLEUTH simulation is just one year after the 2001 simulation, the pattern is almost the same, where the downtowns of Pensacola and Fort Walton Beach present lower population densities than before (Bryan et al. 2007), below 3,000 inhabitants per Km^2, with many census-tracts below 2,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze presents densities of 3,000-4,000 inhabitants per Km^2. In the cases of the cities of Milton and Crestview, their densities achieve values until 3,000 inhabitants per Km^2. Finally, the beaches of Santa Rosa island and others have densities between 3,000-4,000 inhabitants per Km^2.

As it was mentioned many times before, the red (4,000-5,000 inhabitants per Km^2) pixels in many rural areas show very high population densities that do not match reality and the reason is the high rate of spontaneous growth and new spreading center growth in relation to the increase of population in these countryside areas.

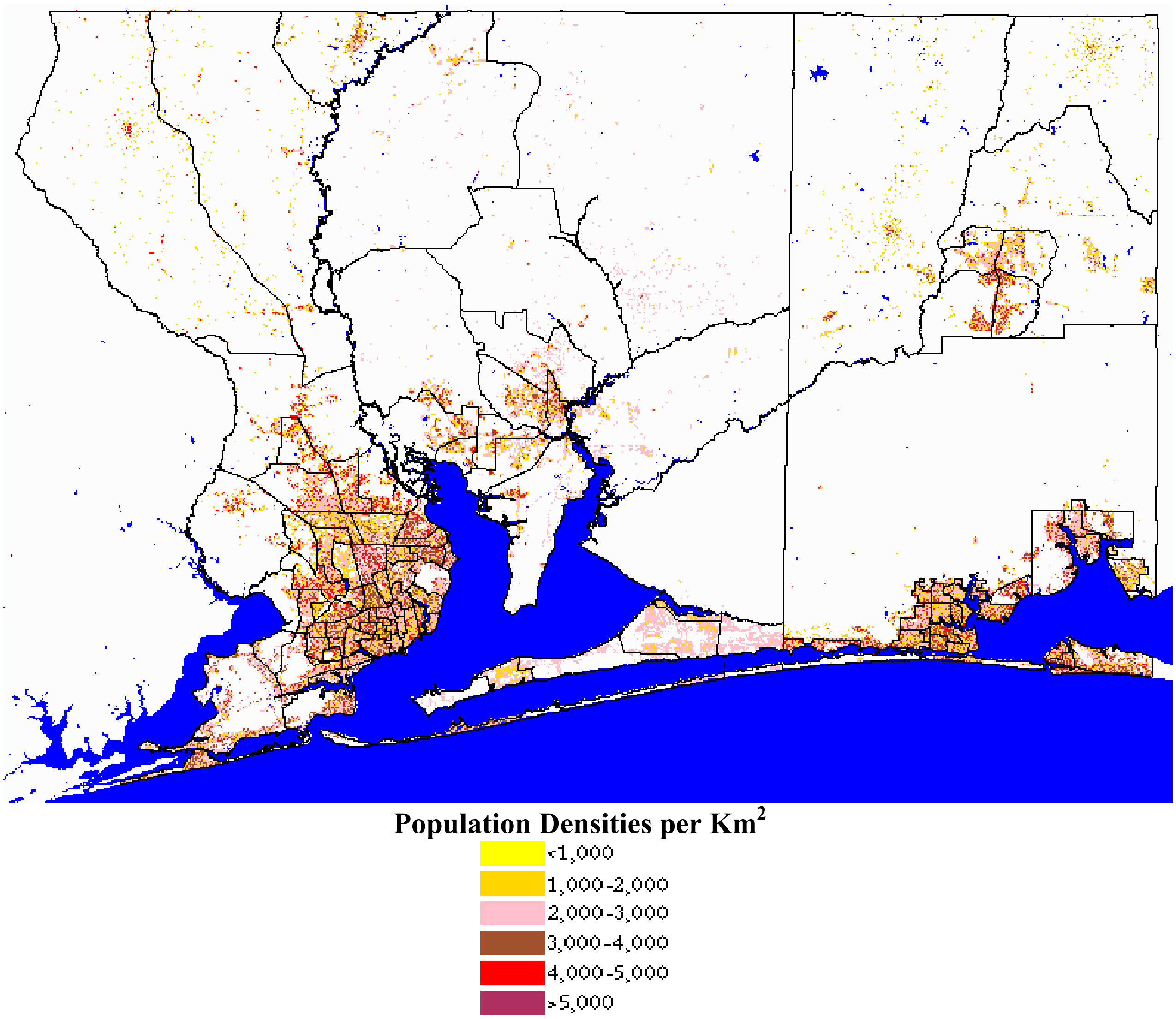


Figure 5.38: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2005 smart

The smart growth trend yearly increases more and more the dasymetric densities in the census-tracts. In the SLEUTH simulation of 2005 (smart growth), the downtowns of the cities of Pensacola and Fort Walton Beach show census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, and even some of them have densities of 4,000 to 5,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze also presents densities of 2000 and 3,000 inhabitants per Km^2. Instead, the city of Milton shows lower population densities (until 3,000 inhabitants per Km^2) as well as Crestview. Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island. The other beaches present higher population densities (until 5,000 inhabitants per Km^2).

The yellow and pink pixels (between 1,000 to 3,000 inhabitants per Km^2) in many rural areas match reality with higher accuracy as before. The reason why this situation is fixed in relation with other past simulations is the fact that these simulations are modeled using the classified image of the year 2001 instead of the one from 1974 as it was used before.

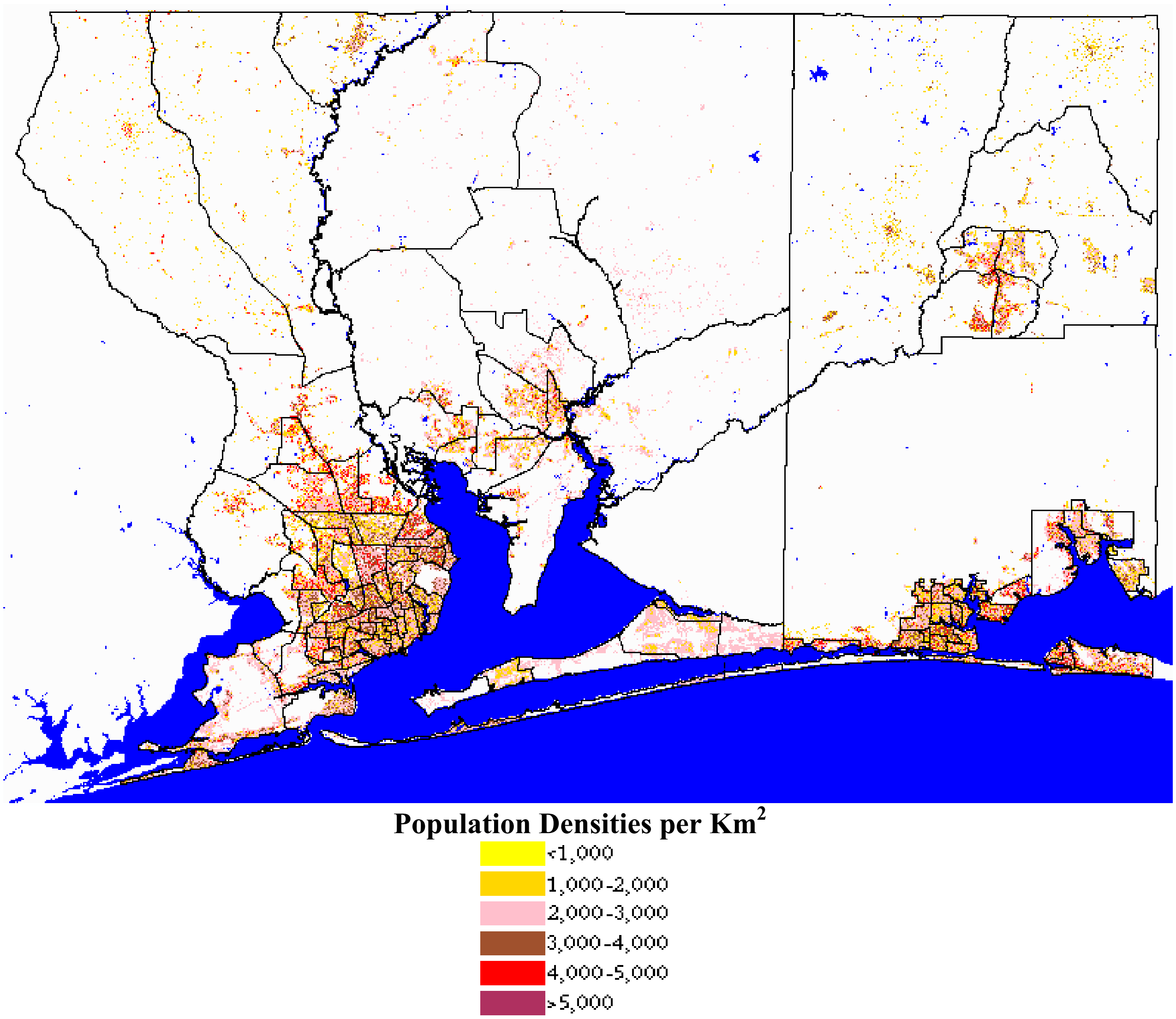


Figure 5.39: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2005 normal

In the SLEUTH simulation of 2005 (normal growth), the downtowns of the cities of Pensacola and Fort Walton Beach show census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, and even a few of them have densities of 4,000 to 5,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze also presents densities of 1,000 to 3,000 inhabitants per Km^2. Instead, the city of Milton shows lower population densities (until 3,000 inhabitants per Km^2) and the city of

Crestview has some census-tracts with densities above 4,000 inhabitants per Km^2. Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches present higher population densities (until 5,000 inhabitants per Km^2).

The yellow and pink pixels (between 1,000 to 3,000 inhabitants per Km^2) in many rural areas match reality with higher accuracy as before. The reason why this situation happen is in relation with other past simulations is the fact that these simulations are modeled using the classified image of the year 2001 instead of the one from 1974 as it was used before.

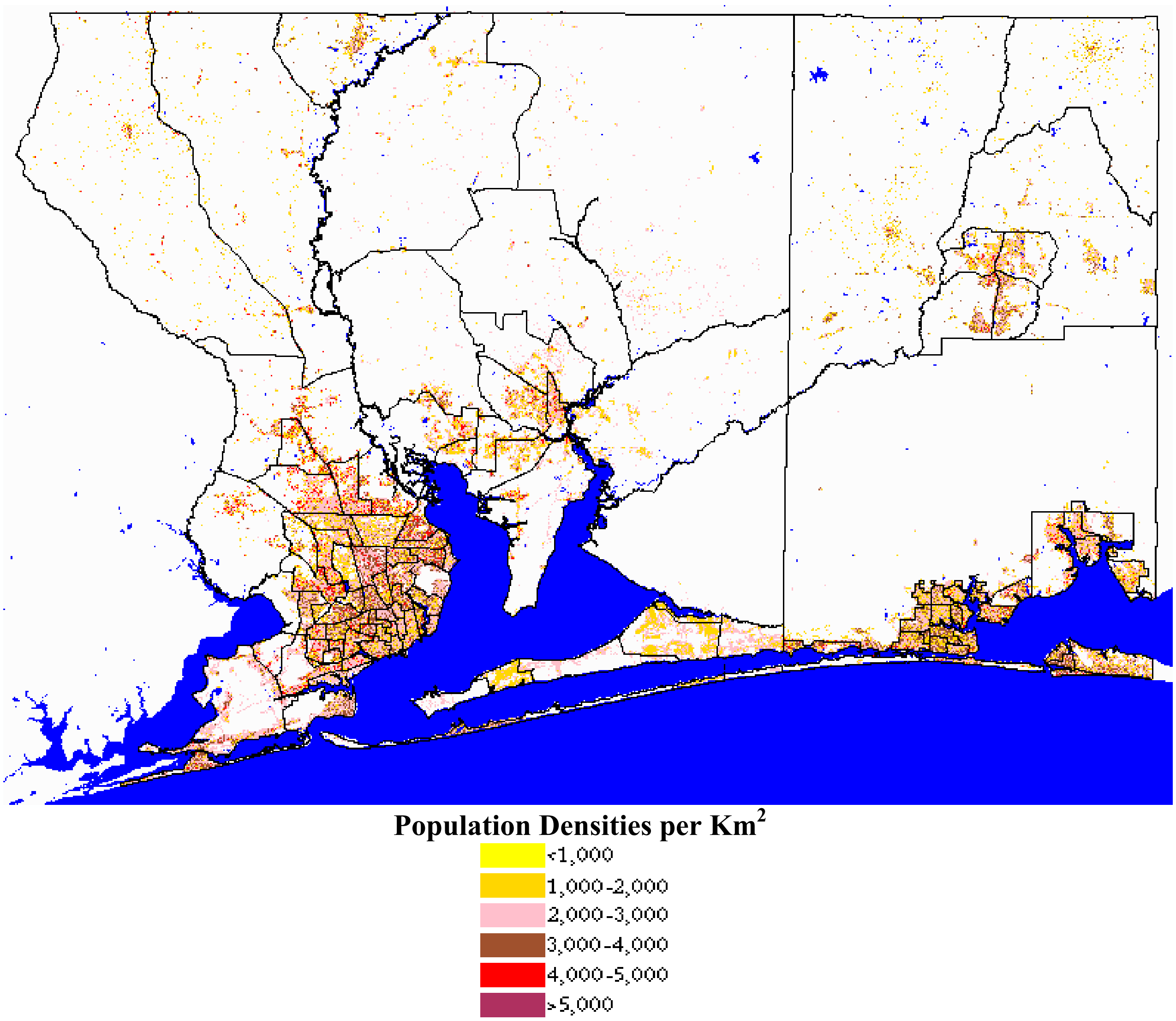


Figure 5.40: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2005 sprawl

The urban sprawl trend decreases yearly the dasymetric densities in the census-tracts. The SLEUTH simulation of 2005 (urban sprawl growth), shows the cities of Pensacola and Fort Walton Beach with census-tracts with densities between 2,000 to 4,000 inhabitants per Km^2, some of them have densities even of 4,000 to 5,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze presents densities of 2000 and 3,000 inhabitants per Km^2. But, the city of Milton shows lower population densities (until 3,000 inhabitants per Km^2) and the city of Crestview has some census-tracts with densities above 4,000 inhabitants per Km^2. Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island. The other beaches present higher population densities (until 5,000 inhabitants per Km^2).

The yellow and pink pixels (between 1,000 to 3,000 inhabitants per Km^2) in many rural areas match reality with higher accuracy as before. The reason why this situation is fixed in relation with other past simulations is the fact that these simulations are modeled using the classified image of the year 2001 instead of the one from 1974 as it was used before.

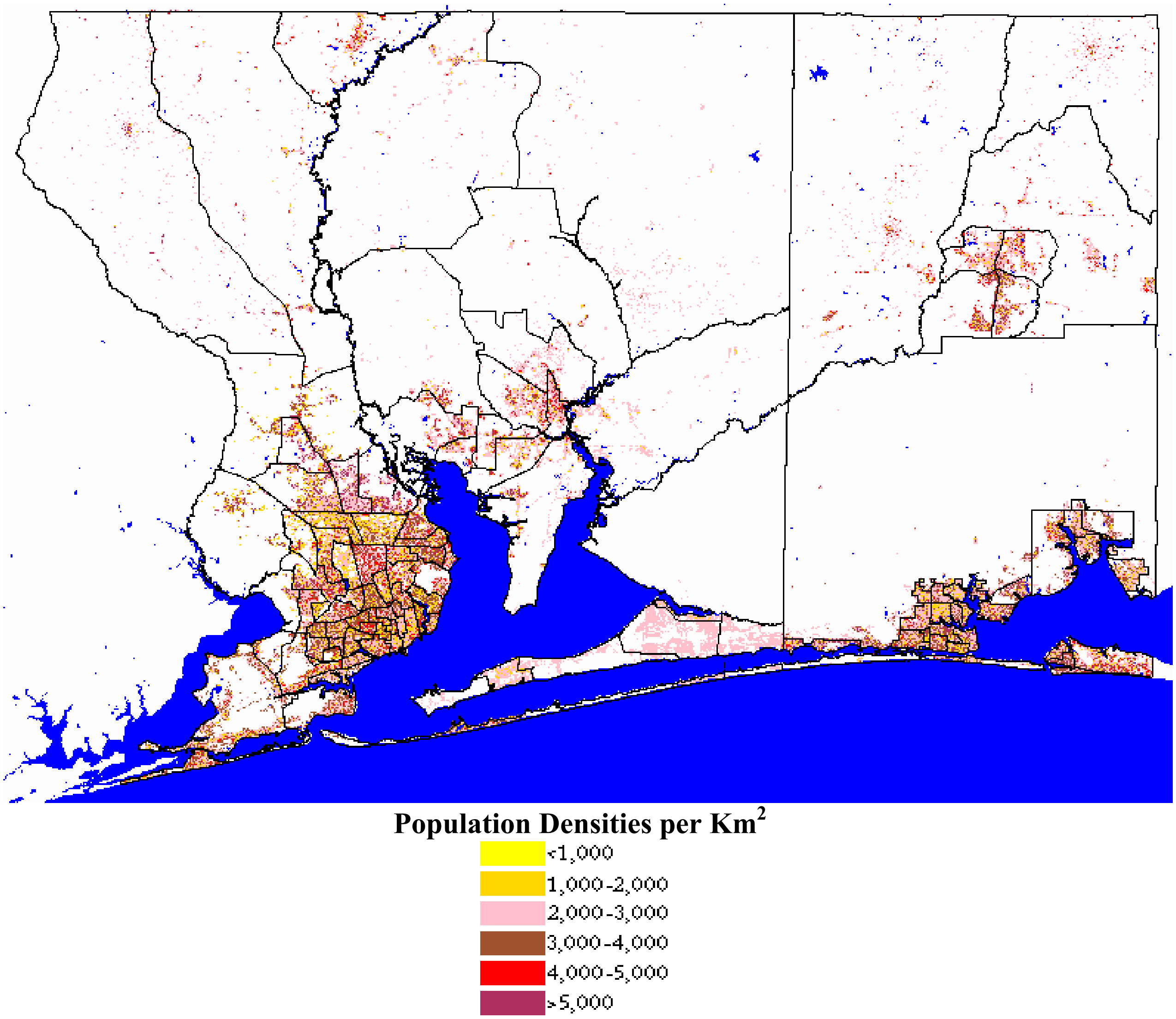


Figure 5.41: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2010 smart

As stated before, the smart growth trend yearly increases the dasymetric densities in the census-tracts because population grows whereas the city growth is constrained by county and cities regulations. In the SLEUTH simulation of 2010 (smart growth), the downtown of Pensacola and Fort Walton Beach have census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, and even some of them have densities of 4,000 to 5,000 inhabitants per Km^2. The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze also presents densities of 2000 and 3,000 inhabitants per Km^2. The cities of Milton and Crestview have increased their densities and they present values between 2,000 and 3,000 inhabitants per Km^2. Finally, the densities in Santa Rosa island and other beaches have also increase and in 2010 they present densities above 4,000 inhabitants per Km^2.

The rural areas also have changed many yellow census-tracts (below 2,000 inhabitants per Km^2) for pink ones (between 2,000 to 3,000 inhabitants per Km^2) due to the smart growth policies.

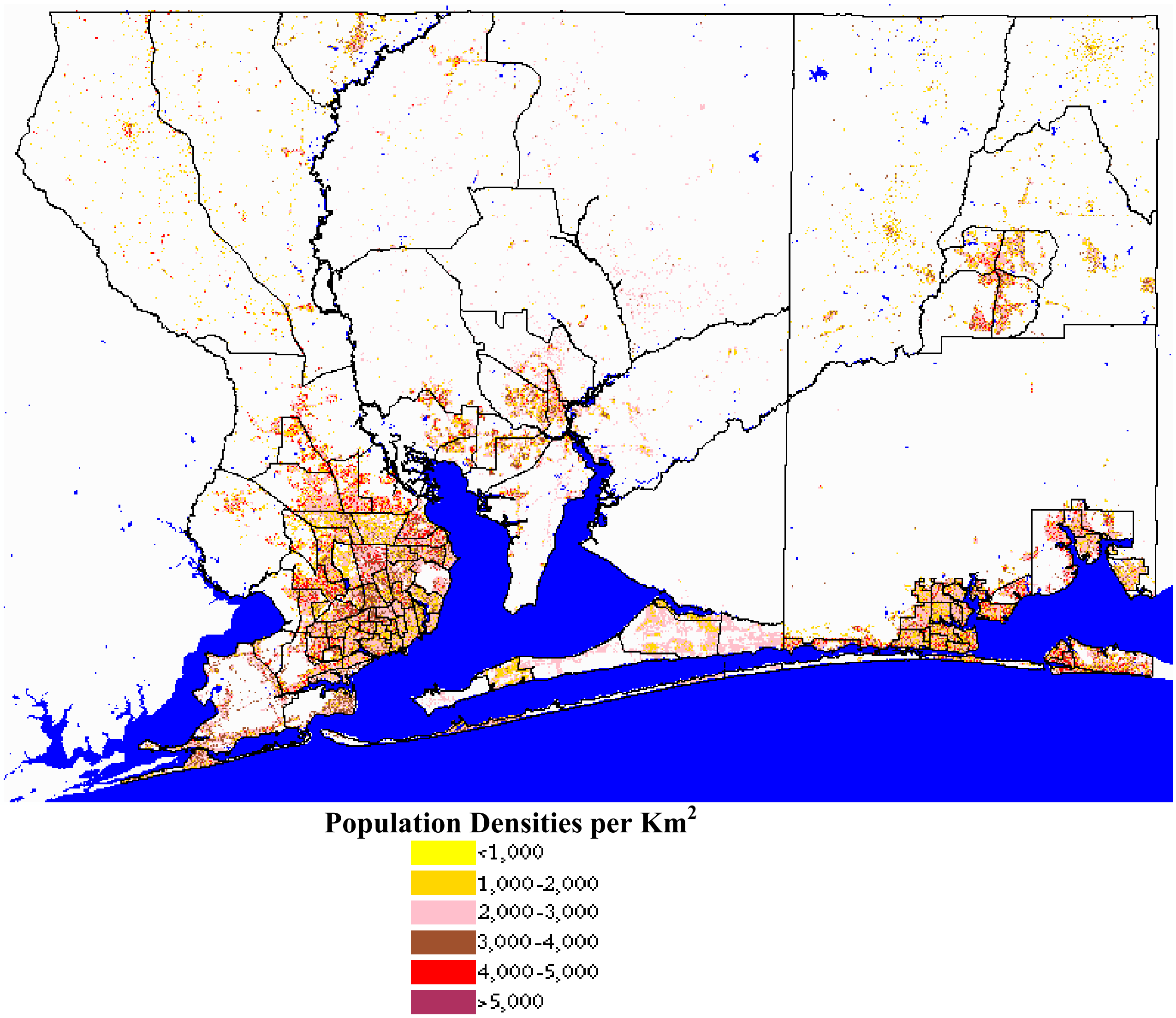


Figure 5.42: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2010 normal

In the SLEUTH simulation of 2010 (normal growth), the downtowns of the cities of Pensacola and Fort Walton Beach show census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, and even a few of them have densities above 4,000 inhabitants per Km^2. The suburbs of Pensacola also show similar densities to the ones in the center of the city. Gulf Breeze also exhibits densities of 1,000 to 3,000 inhabitants per Km^2. The cities of Milton and Crestview show lower population densities until 3,000 inhabitants per Km^2). Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches present higher population densities (until 5,000 inhabitants per Km^2).

The yellow and pink pixels (between 1,000 to 3,000 inhabitants per Km^2) in many rural areas match reality with higher accuracy as before. The reason why this situation happened was explained before as these simulations are modeled using the classified image of the year 2001 instead of the one from 1974 as it was used before.

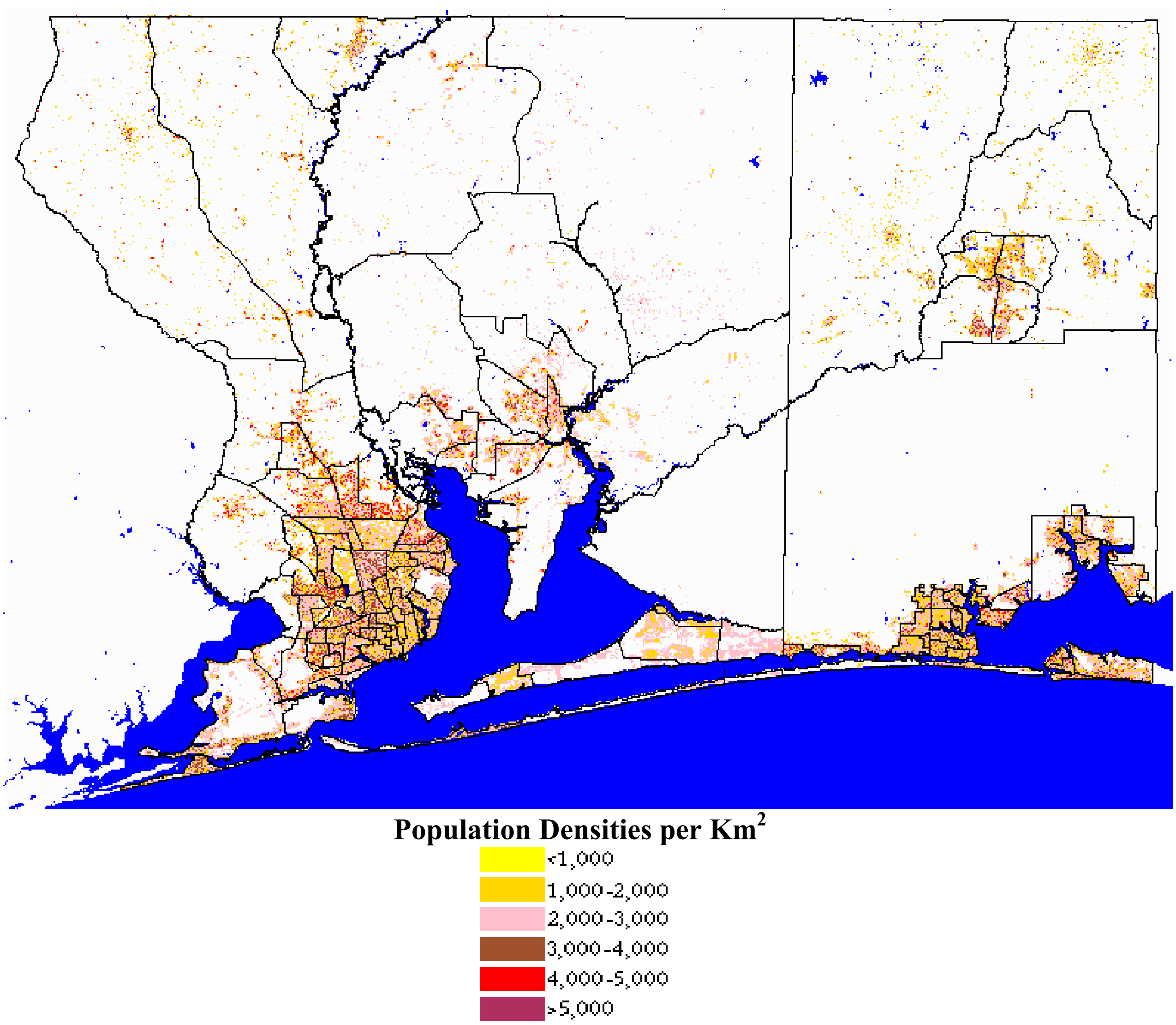


Figure 5.43: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2010 sprawl

The urban sprawl trend yearly decreases the dasymetric densities in the census-tracts because of population growth in cities without any constrains to their expansion. This SLEUTH simulation of 2010 (urban sprawl growth), shows the cities of Pensacola and Fort Walton Beach with census-tracts with densities between 1,000 to 3,000 inhabitants per Km^2, a decrease in relation with the sprawl simulation from 2005 . The suburbs of Pensacola also present similar densities to the ones in the center of the city. Gulf Breeze presents densities of 2,000 and 3,000 inhabitants per Km^2. The city of Milton shows population densities of until 3,000 inhabitants per Km^2 and the city of Crestview has some census-tracts with densities between 2,000 and 3,000 inhabitants per Km^2. Finally, densities are below 3,000 inhabitants per Km^2 in Santa Rosa island, while the other beaches present higher population densities but lower than before (until 4,000 inhabitants per Km^2).

The yellow and pink pixels (between 1,000 to 3,000 inhabitants per Km^2) in many rural areas match reality with higher accuracy as before and the trend here is also a decreasing one.

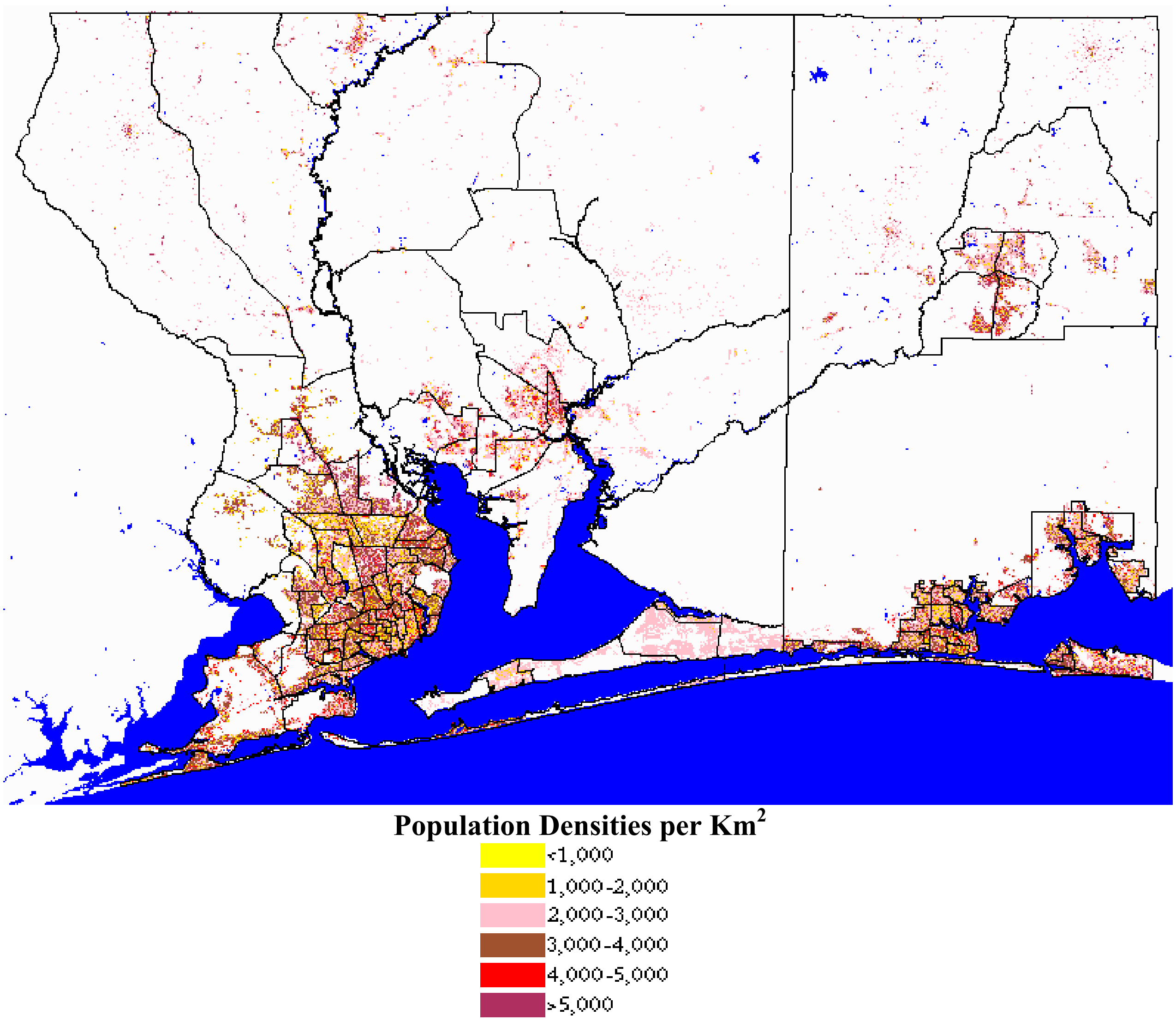


Figure 5.44: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2015 smart

Because of the smart growth restrains, the dasymetric densities still are increasing in the census-tracts. In this SLEUTH simulation of 2015 (smart growth), the downtowns of Pensacola and Fort Walton Beach have census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, with many of them above 4,000 inhabitants per Km^2. The suburbs of Pensacola also show similar densities to the ones in the center of the city. Gulf Breeze and Navarre presents densities of 2000 and 3,000 inhabitants per Km^2. The cities of Milton and

Crestview also have substantially increased their densities and they presented values between 2,000 and 3,000 inhabitants per Km^2 or even more. Finally, the densities in Santa Rosa island and other beaches have also increased and in 2015 they present densities above 4,000 inhabitants per Km^2.

The rural areas also have increased their densities and in 2015 they will have all census-tracts above 2,000 inhabitants per Km^2 and even more, due again to the smart growth policies, which constrain the urban expansion while population still is growing.

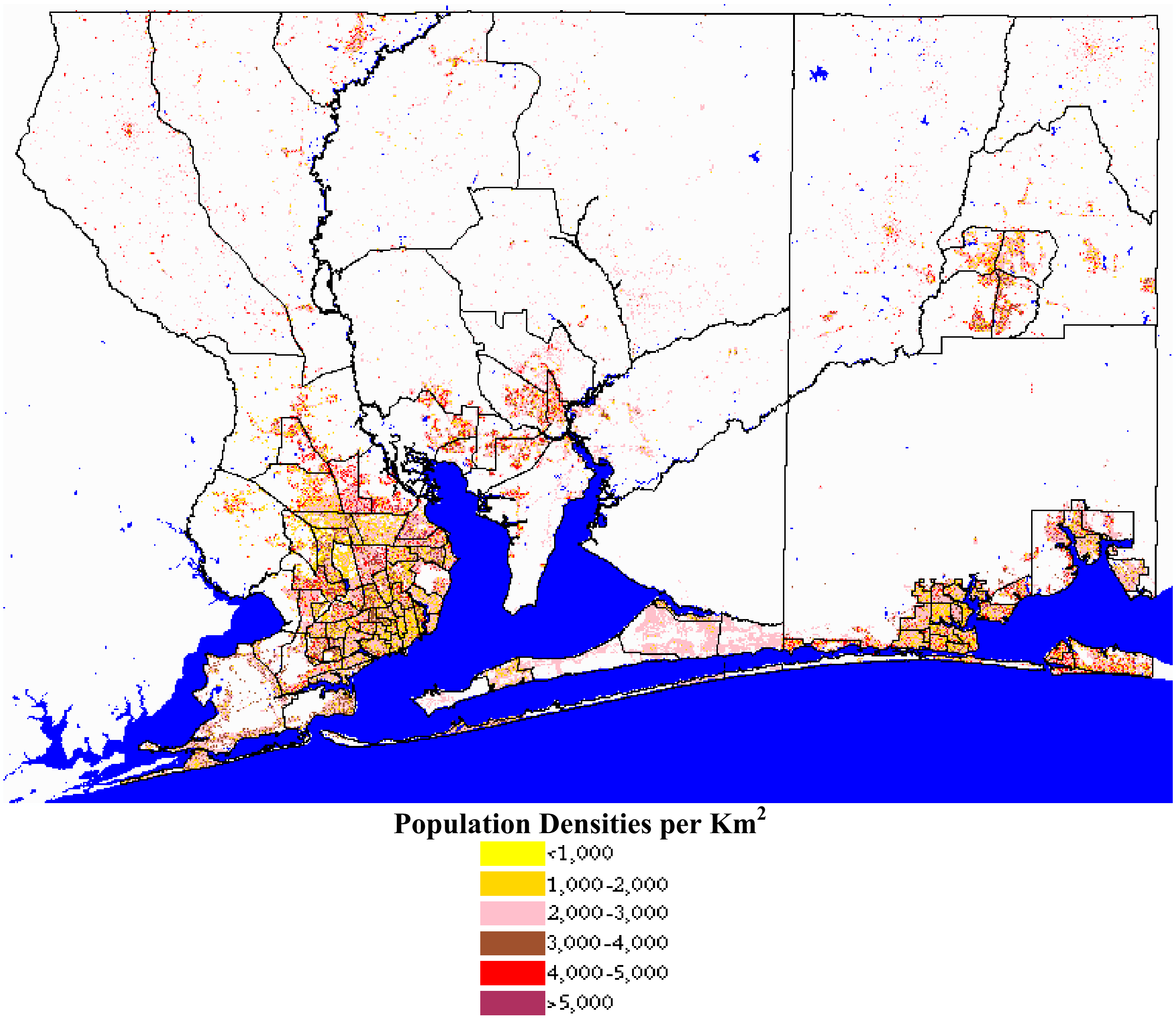


Figure 5.45: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2015normal

In the SLEUTH simulation of 2015 (normal growth), the downtowns of the cities of Pensacola and Fort Walton Beach will show census-tracts with dasymetric densities between 2,000 to 4,000 inhabitants per Km^2, with just a few of them with densities above 4,000 inhabitants per Km^2. Some census-tracts in the suburbs of Pensacola also will present similar densities to the ones in the center of the city. Gulf Breeze will present densities of 2,000 to 3,000 inhabitants per Km^2. The cities of Milton and Crestview will show population densities of until

3,000 inhabitants per Km^2. Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches will present higher population densities (until 5,000 inhabitants per Km^2).

The pink pixels (between 2,000 to 3,000 inhabitants per Km^2) in many rural areas show an increase in density in the countryside due that the generation of spontaneous and new spreading center growth is in a lower rate than the population growth.

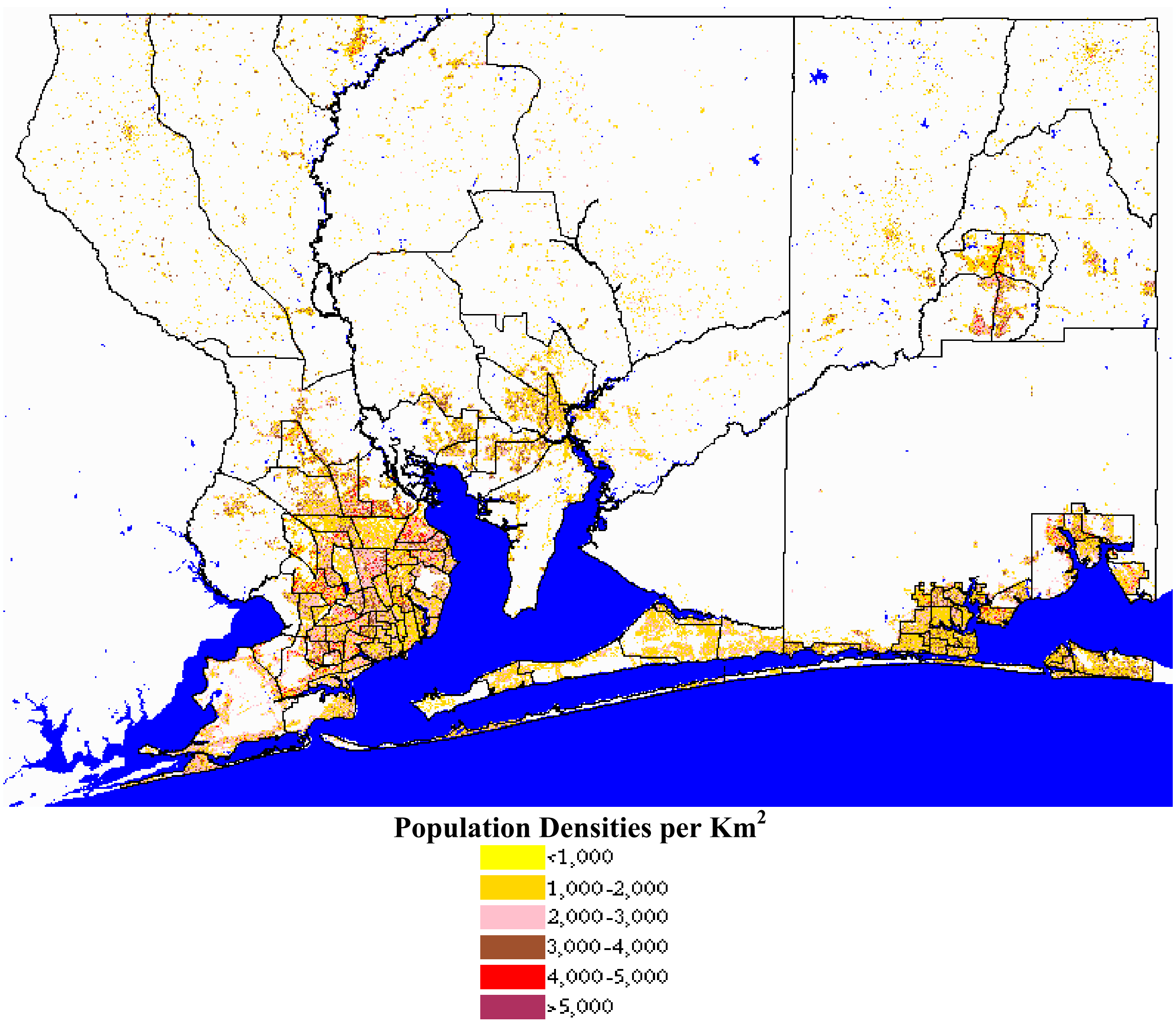


Figure 5.46: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2015 sprawl

Because of the lack of control in urban expansion due to urban sprawl policies, the dasymetric densities still are decreasing in all census-tracts. This SLEUTH simulation of 2015 (urban sprawl growth), shows the cities of Pensacola and Fort Walton Beach with census-tracts' densities between 1,000 to 3,000 inhabitants per Km^2. The suburbs of Pensacola also exhibit similar densities to the ones in the center of the city. Gulf Breeze will present densities of 1,000 to 2,000 inhabitants per Km^2, a decrease with relation to the 2010 urban sprawl simulation The city of Milton shows population densities of until 2,000 inhabitants per Km^2 and the city of Crestview will have some census-tracts with densities between 1,000 and 2,000 inhabitants per Km^2. Finally, the densities are also below 2,000 inhabitants per Km^2 in Santa Rosa island and in the other beaches with urban settlements along the Gulf coast.

The rural areas exhibit in 2015 just yellow pixels (below 1,000 or from 1,000 to 2,000 inhabitants per Km^2) matching reality with higher accuracy as before because rural areas have densities lower than urban ones.

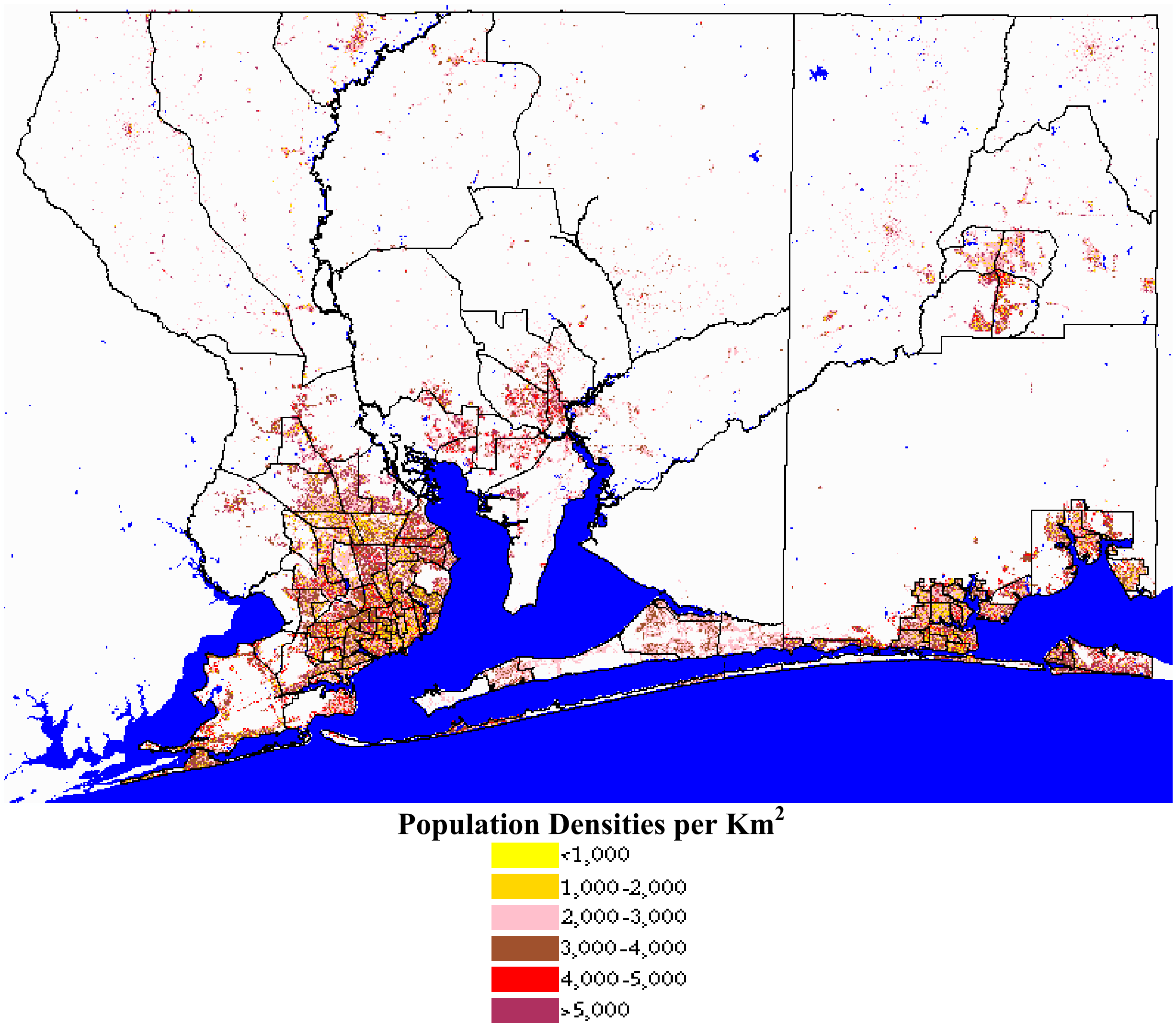


Figure 5.47: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2020 smart

For the simulation 2020, the trend in densities still will be increasing because of the smart growth policies. Here, the downtowns of Pensacola and Fort Walton Beach will have many census-tracts with dasymetric densities above 3,000 inhabitants per Km^2, with many of them even above 4,000 inhabitants per Km^2. The suburbs of Pensacola also will show similar densities to the ones in the center of the city. Gulf Breeze and Navarre presents densities of 2,000 to 4,000 inhabitants per Km^2. The cities of Milton and Crestview also will increase substantially their densities and they will exhibit values between 3,000 and 4,000 inhabitants per Km^2 or even more. Finally, the densities in Santa Rosa island and other beaches have also increase and in 2020 they will present densities above 4,000 inhabitants per Km^2.

The rural areas also will increase their densities and in 2020 they will have all census-tracts above 3,000 inhabitants per Km^2 and even more again due to the smart growth policies, which constrain a lot the urban expansion while population still is growing.

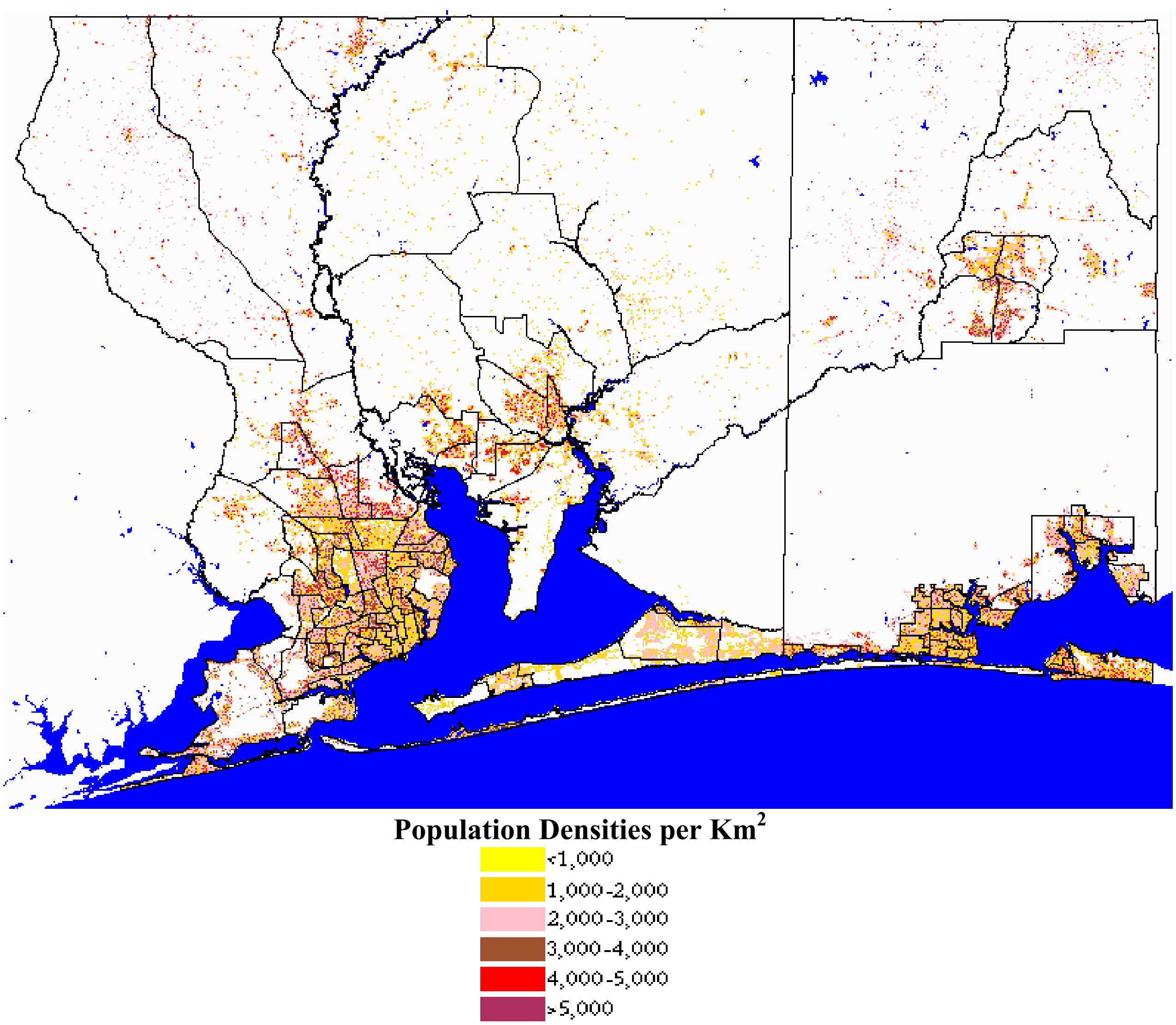


Figure 5.48: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2020 normal

In the SLEUTH simulation of 2020 (normal growth), the downtowns of Pensacola and Fort Walton Beach will show most census-tracts with dasymetric densities between 2,000 to 3,000 inhabitants per Km^2, a decrease with reference to years before, with a few census-tracts in these areas with densities above 4,000 inhabitants per Km^2. Some census-tracts in the suburbs of Pensacola will present similar densities to those of the center of the city. Gulf Breeze will exhibit densities below 2,000 inhabitants per Km^2, also a decrease in relation to the normal simulation of 2015. The cities of Milton and Crestview will show population densities of until 3,000 inhabitants per Km^2. Finally, the densities are between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches will present higher population densities (until 4,000 inhabitants per Km^2).

The yellow (between 1,000 to 2,000 inhabitants per Km^2) and pink pixels (between 2,000 to 3,000 inhabitants per Km^2) outside the cities represent the densities in the rural areas of this region.

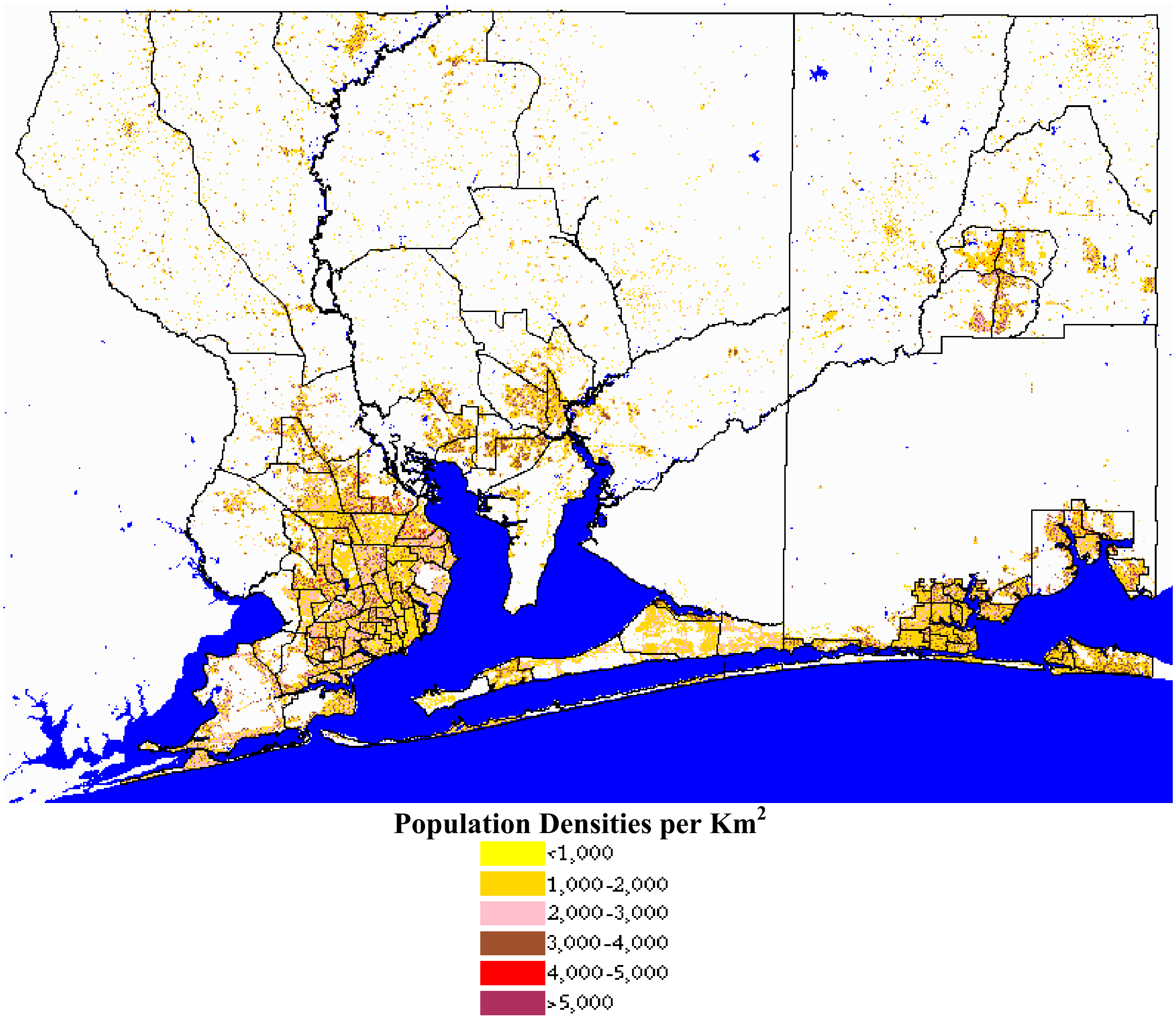


Figure 5.49: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2020 sprawl

This SLEUTH simulation of 2020 is showing a decrease in densities because of the lack of control in urban expansion due to urban sprawl policies. The cities of Pensacola and Fort Walton Beach will have census-tracts with densities between 1,000 to 2,000 inhabitants per Km^2 with few census-tracts between 2,000 to 3,000 inhabitants per Km^2. The suburbs of Pensacola also will show similar densities to the ones in the center of the city. Gulf Breeze and Navarre will present densities of 1,000 to 2,000 inhabitants per Km^2. The cities of Milton and Crestview will show population densities of up to 2,000 inhabitants per Km^2 with few census-tracts above 3,000 inhabitants per Km^2. Finally, the densities are also below 2,000 inhabitants per Km^2 in Santa Rosa island and in the other beaches with urban settlements along the Gulf coast.

The rural areas will present in 2020 just yellow pixels (below 2,000 inhabitants per Km^2) matching reality with higher accuracy than before because the countryside have densities lower than urban areas.

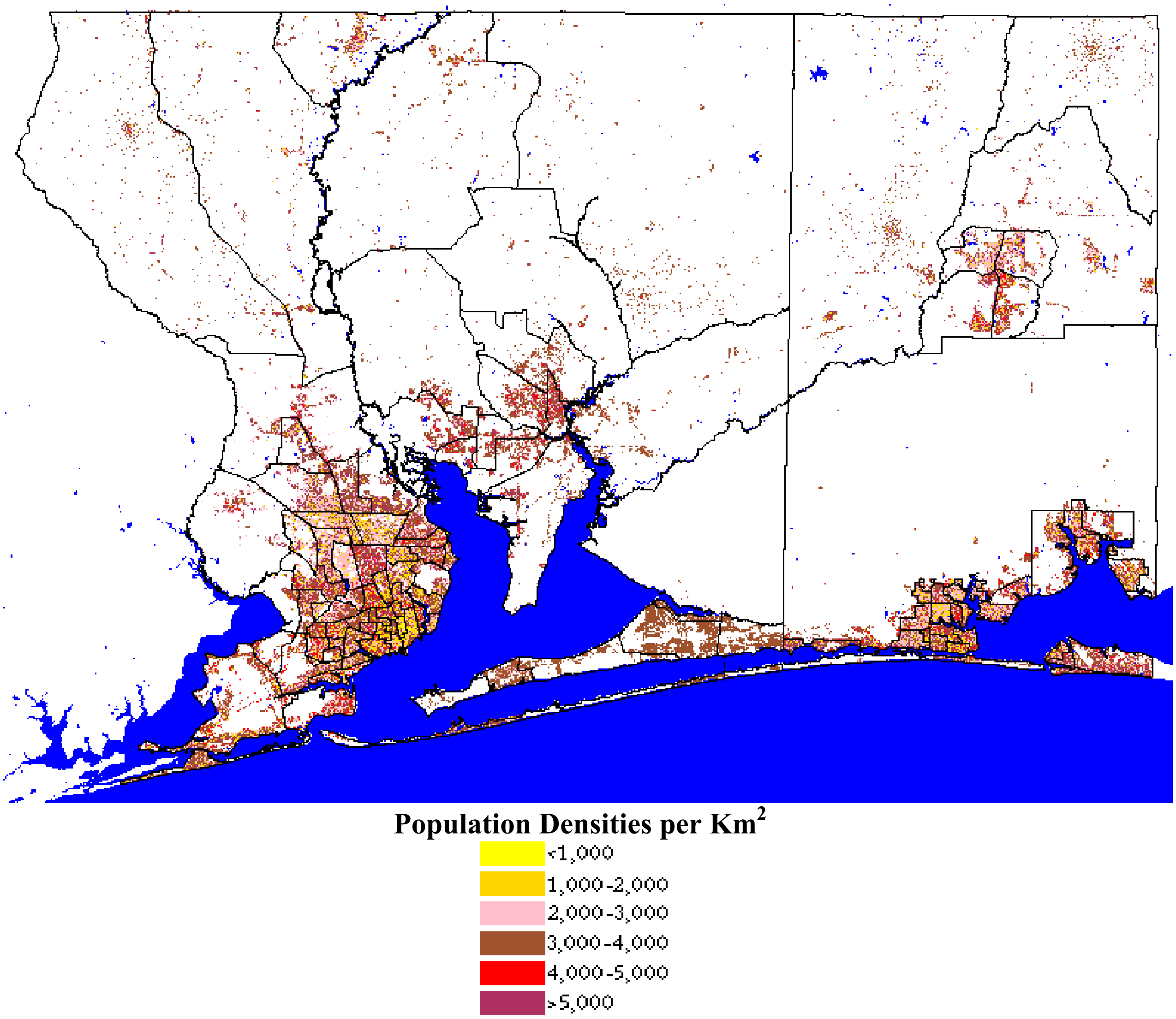


Figure 5.50: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2025smart

In the last smart growth simulation of 2025, the densities are very high because of constrains to urban growth. The downtowns of Pensacola and Fort Walton Beach will have many census-tracts with dasymetric densities above 4,000 inhabitants per Km^2, with many of them even above 5,000 inhabitants per Km^2 and just a few with densities below 2,000 inhabitants per Km^2. The suburbs of Pensacola also will have similar densities to the ones in the center of the city. Gulf Breeze and Navarre shows densities between 3,000 to 4,000 inhabitants per Km^2. The city of Milton will have a density between 3,000 and 4,000 inhabitants per Km^2 whereas the city of Crestview will present values between 2,000 and 4,000 inhabitants per Km^2 or even more. Finally, the densities in Santa Rosa island and other beaches will increase and they will present densities above 3,000 inhabitants per Km^2 and even more.

The rural areas also will increase their densities and in 2025 they will have all census-tracts above 3,000 inhabitants per Km^2 again due to the smart growth policies, where not enough urban pixels are generated by spontaneous and new spreading center growth.

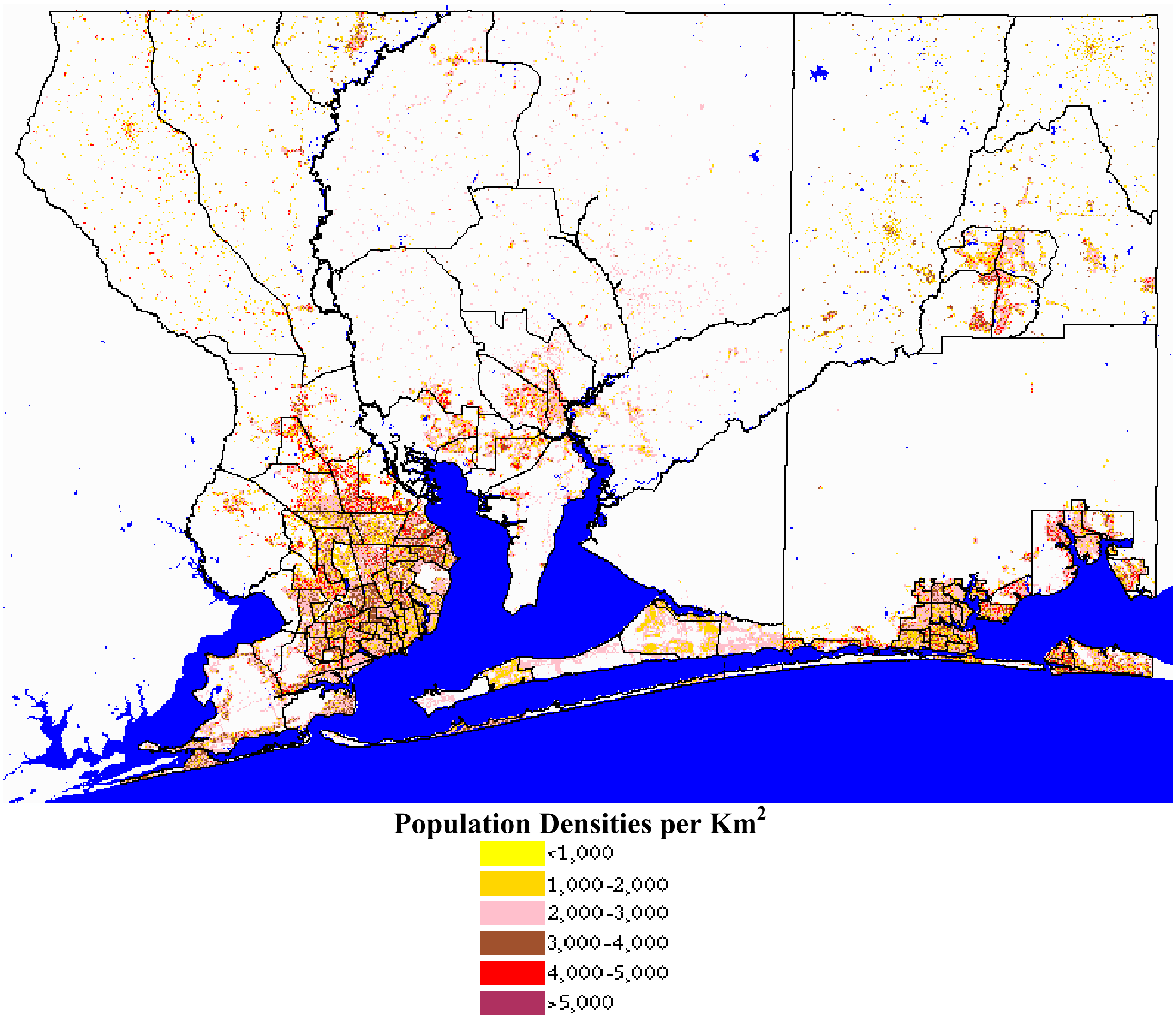


Figure 5.51: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2025 normal

In the SLEUTH simulation of 2025 (normal growth), the downtowns of the cities of Pensacola and Fort Walton Beach will show most census-tracts with dasymetric densities between 2,000 to 3,000 inhabitants per Km^2, as it was mentioned before, with a few census-tracts in these areas with densities above 4,000 inhabitants per Km^2. Some census-tracts in the suburbs of Pensacola will show similar densities to the ones in the center of the city. Gulf Breeze will exhibit densities below 3,000 inhabitants per Km^2, an increase in relation with the normal simulation of 2020. The cities of Milton and Crestview will show population densities of until 3,000 inhabitants per Km^2. Finally, the densities will be between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches will present higher population densities (until 4,000 inhabitants per Km^2).

The yellow (between 1,000 to 2,000 inhabitants per Km^2) and pink pixels (between 2,000 to 3,000 inhabitants per Km^2) outside the cities represent the densities in the rural areas of this region and most of them where generated by spontaneous and new spreading center growth.

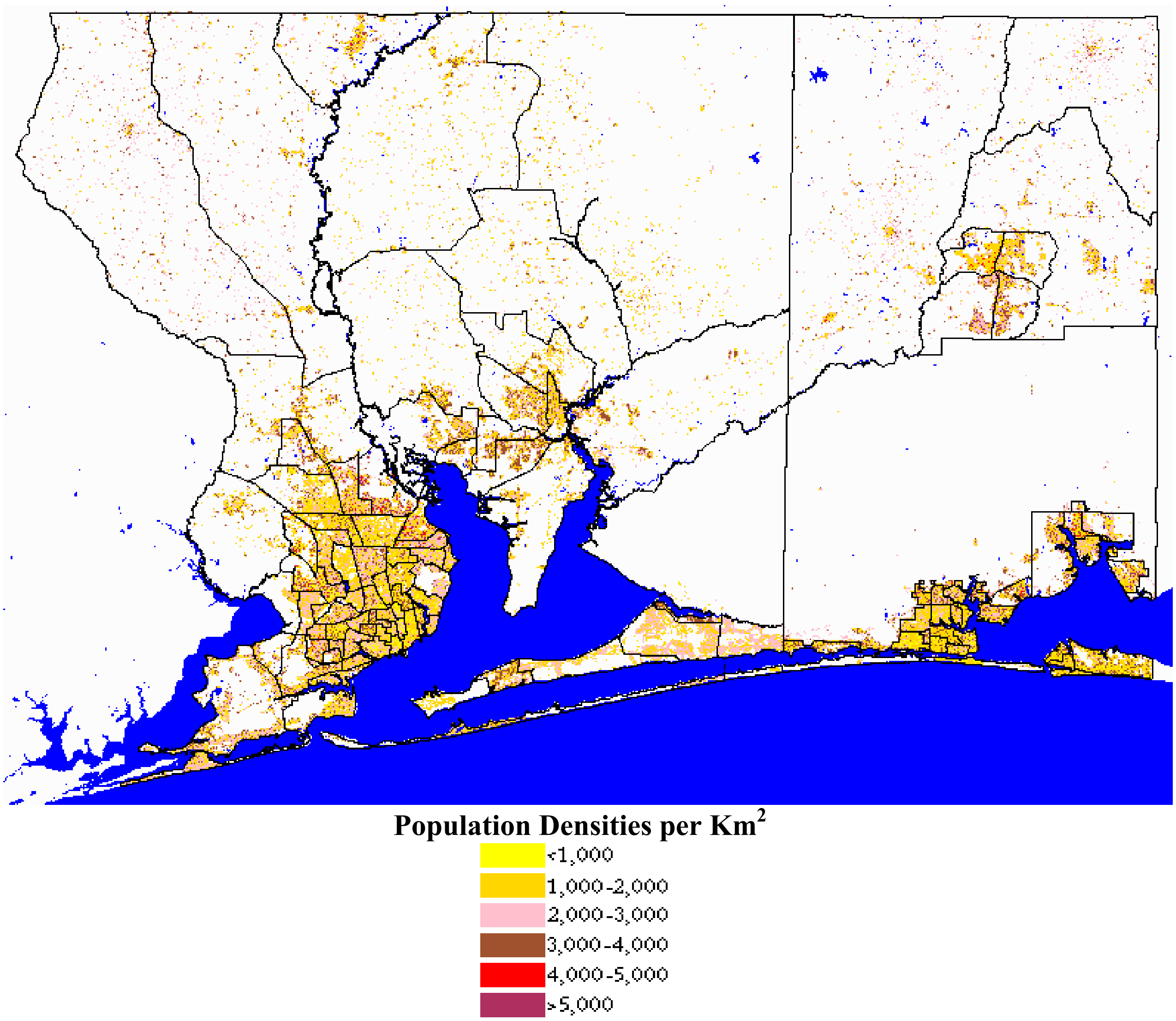


Figure 5.52: Dasymetric Map of SLEUTH Simulation for Escambia, Sta. Rosa & Okaloosa 2025 sprawl

Finally, the SLEUTH simulation of 2025 shows a decrease in densities due to the urban sprawl policies. In the centers of the cities of Pensacola and Fort Walton Beach most census-tracts will have densities between 1,000 to 2,000 inhabitants per Km^2 or even less than 1,000 inhabitants per Km^2 with few census-tracts between 2,000 to 3,000 inhabitants per Km^2. The suburbs of Pensacola also will exhibit similar densities to the ones in the center of the city. Gulf Breeze will show densities between 1,000 until 4,000 inhabitants per Km^2. The cities of Milton and Crestview will have population densities of until 2,000 inhabitants per Km^2 with few census-tracts above 3,000 inhabitants per Km^2. The densities are also below 2,000 inhabitants per Km^2 in Santa Rosa island and in the other beaches containing urban settlements.

The rural areas will present in 2025 just yellow pixels (below 2,000 inhabitants per Km^2) matching reality with higher accuracy than before because the countryside in fact have densities lower than urban areas.

CHAPTER 6

CENSUSES FROM THE CLASSIFFIED AND SIMULATED IMAGES

6.1. Population as a Dependent Variable from Urban Areas

After dasymetric densities had been calculated and represented spatially in Chapter 5, the same information about demographic data and urbanized surfaces is used to know the degree to which urban areas are predicting population statistics through a chronological series of linear regressions for the 110 census-tracts, where population becomes the dependent variable (*Y*) of urban areas (*X*).

The dependent or response variable *Y* (population) in a linear regression equation is modeled by a least squares function of the independent or explanatory variable *X* (urban areas) (Sirkin 2006). This function is a linear combination of two model parameters or regression coefficients: *a* (*Y*-intercept: the value of *Y* when $X = 0$) and *b* (slope of the regression line) and an error term, which is treated as a random variable representing the unexplained variation in the dependent variable (Rogerson 2006).

The input data for this linear regression model consist of two kinds of data: first, the count of the number of urbanized pixels in every census-tract obtained from urban land-cover through satellite image classification or SLEUTH simulation (spatial independent variable *X*); and second, the statistics about population for every census-tract obtained from censuses (Geolytics) and estimated or projected from known values (statistical dependent variable *Y*). The regression formula for this specific case is the following one:

$Y = a + b * X$ has been replaced by: $P_{act} = a + b * \mathrm{A}$

Where:

P_{act} is the number of actual population (dependent variable: Y)

a is a constant (a regression coefficient) and represents the y-intercept: the value of y when x =0.

$\bar{a} = \bar{Y} - \bar{b} * \bar{X}$ has been replaced by: $\bar{a} = \bar{P}_{act} - \bar{b} * \bar{A}$

b is a constant (a regression coefficient) and represents the slope of the regression line.

$$b = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sum X^2 - \frac{(X)^2}{n}} \quad \text{has been replaced by:} \quad b = \frac{\sum A * Pact - \frac{(\sum A)(\sum Pact)}{n}}{\sum A^2 - \frac{(\sum A)^2}{n}}$$

A is the number of urbanized pixels (independent variable: X). A or Area is the result of counting just the urbanized pixels (through the use of a binary mask) in every census-tract from the land-cover data derived from satellite image classification or from the SLEUTH simulation.

After the linear equation is generated using SPSS software package, the following results are produced:

Pearson Correlation Coefficient (R) is a common measure between two variables *X* and *Y* that reflects the degree of linear relationship between them, ranging from +1 (a perfect positive linear relationship between variables) to -1 (a perfect negative linear relationship between variables), while a correlation of 0 means there is no linear relationship between the two variables. In practice, these values are rarely if ever 0, 1, or -1 (Rogerson 2006). Because correlation does not imply causation, a high correlation between two variables does not represent enough evidence that changes in one variable will generate changes in the other variable.

Coefficient of Determination (R^2) is the square of the correlation coefficient between the constructed predictor *X* and the response variable *Y* (Sirkin 2006). This statistical measure indicates the degree in which the regression line approximates the real data points, being a R^2 of 1.0 the regression line that perfectly fits the data, explaining all the variability in *Y*, while $R^2 = 0$

indicates no linear relationship between the independent variable X with its dependent variable Y.

Adjusted Coefficient of Determination (Adjusted R^2) adjusts for the unbiased variances of the errors and of the observations in a model and unlike R^2, this index increases only if the new values improve the model more than would be expected by chance (Sirkin 2006). The adjusted R^2 can be negative, and will always be less than or equal to R^2.

Standard Errors of the Coefficients are the estimated standard deviations of the differences (errors) in the regression for coefficients *a* and *b* (Rogerson 2006). It results from the standard deviation of the individual differences or individual errors between the values and the regression line and therefore, it is a measure of the precision with which the regression coefficients are measured.

t tests results from dividing the values of constants *a* and *b* by their respective standard errors (standard deviations) and they are used to assess if the null hypothesis (H_0) is true or not. A null hypothesis (H_0) is a scenario set up to be nullified or statistically refuted if observations are the result of chance.

F test consists on the square of the t-test for the *b* coefficient and it is used to evaluate the significance of the regression model as a whole, in other words, to test the significance of R and therefore R^2 as well.

P values are used to assess the t tests of *a* and *b* coefficients. The P value of *b* is the same value than the P value for the F test (square of t test for *b*). These values are the result of the software package comparison between the t statistics on the variables with the values in the distribution (Rogerson 2006). P values are used with a degree of confidence, usually higher than 95% to reject the null hypothesis, in other words that the data (in this case, the dependent variable population) does not result from chance. If P value or Probability (F) < 0.05, the model is considered significantly better than would be expected by chance alone and it is possible to reject the null hypothesis (Sirkin 2006), confirming in the other hand the dependency of a linear relationship of *Y* (population) from *X* (urban areas).

The regression equation is finally represented through a cumulative plot of frequencies (probability distribution) with a straight line that represents the linear regression equation starting at 0,0 and ending at 1,1, in a similar way of a Lorenz Curve used in Economics to measure incomes or net worth distributions. See tables A-V.1 to A-V.28 and figures A-V.1 to A-V.28 in appendix V (pages 420 to 447).

Table 6.1: Summary of Linear Regressions for Actual Populations based on Urban Areas

Images	R	R^2	Adjusted R^2	F tests	P value
Historical Classified Images and Simulations					
Classified 1974	**67.80**	**46.00**	**45.50**	**92.07**	**0.00**
Simulation 1975	69.40	48.10	47.60	100.15	0.00
Simulation 1980	73.50	54.00	53.50	126.55	0.00
Simulation 1985	72.50	52.60	52.10	119.78	0.00
Classified 1986	**71.10**	**50.60**	**50.20**	**110.70**	**0.00**
Simulation 1986	71.50	51.20	50.70	113.17	0.00
Simulation 1990	64.40	41.50	41.00	76.70	0.00
Classified 1992	**72.00**	**51.80**	**51.40**	**116.19**	**0.00**
Simulation 1992	62.50	39.00	38.40	69.08	0.00
Simulation 1995	58.60	34.40	33.80	56.61	0.00
Simulation 2000	48.00	23.00	22.30	32.31	0.00
Classified 2001	**77.80**	**60.60**	**60.20**	**165.82**	**0.00**
Simulation 2001	47.10	22.10	21.40	30.71	0.00
Projections of Simulations					
Simulation 2005 smart	78.40	61.40	61.10	171.93	0.00
Sim 2005 normal	**79.00**	**62.30**	**62.00**	**178.80**	**0.00**
Simulation 2005 sprawl	78.90	62.30	62.00	178.60	0.00
Simulation 2010 smart	78.70	61.90	61.50	175.17	0.00
Sim 2010 normal	**80.00**	**64.00**	**63.60**	**191.62**	**0.00**
Simulation 2010 sprawl	80.50	64.80	64.50	198.62	0.00
Simulation 2015 smart	78.40	61.40	61.10	172.14	0.00
Sim 2015 normal	**80.70**	**65.20**	**64.80**	**201.92**	**0.00**
Simulation 2015 sprawl	81.30	66.10	65.80	210.98	0.00
Simulation 2020 smart	78.20	61.10	60.70	169.47	0.00
Sim 2020 normal	**81.30**	**66.00**	**65.70**	**210.07**	**0.00**
Simulation 2020 sprawl	82.20	67.60	67.30	224.99	0.00
Simulation 2025 smart	77.80	60.50	60.10	165.23	0.00
Sim 2025 normal	**81.60**	**66.50**	**66.20**	**214.82**	**0.00**
Simulation 2025 sprawl	82.40	68.00	67.70	229.14	0.00

Notes: Just the land-cover of urbanized pixels is used in the Classified Images and Simulations.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).
The independent variable (*X*) corresponds to constant *b* and the dependent variable (*Y*) are Population Estimations.
Classified images and simulations with normal trend growth are shown in bold and they are control parameters.

In table 6.1 notice that the higher the F test, also the higher the values of correlations and coefficient of determination will be. Is important, that the F test results for all linear regressions present P values < 0.05; therefore, all regression models reject their null hypothesis (H_0) and population values do not result from chance, but instead from urbanized pixels measured in Km^2 within each one of the 110 census-tracts.

Among all classified images, the image from 2001 shows the highest correlation coefficient (R=77.8%), and between 60.60% (according to R^2) and 60.20% (considering adjusted R^2) of the variation in the dependent variable Population (*Y*) can be explained by the independent variable urban Areas (*X*), whereas the remaining percentage (between 39.40% and 39.80%) can be explained by unknown, extraneous values or inherent variability.

The classified image 1992 also presents a high correlation coefficient (R=72.00%), but the coefficient of determination (R^2=51.80%) and adjusted coefficient of determination (adjusted R^2=51.40%) which explain the variation in the dependent variable Population (*Y*) by the independent variable urban Areas (*X*) are much lower compared against the classified image from 2001, whereas the remaining percentage (between 48.20% and 48.60%) can be explained by unknown, extraneous values or inherent variability.

The classified image 1986 presents very similar statistics than the classified image from 1986 with a slightly smaller correlation coefficient (R=71.10%), and with similar coefficients of determination (R^2=50.60%) and adjusted coefficient of determination (adjusted R^2=50.20%). In this image from 1986 the remaining percentage (between 49.40% and 49.80%) can be explained by unknown, extraneous values or inherent variability.

The classified image 1974 presents among the group of all four classified images the smaller correlation coefficient (R=67.80%) and very poor values for the coefficient of determination

(R^2=46.00%) and adjusted coefficient of determination (adjusted R^2=45.50%), and here most of the percentage (between 54.00% and 54.50%) can be explained by unknown, extraneous values or inherent variability.

The main reason for these classified images having higher R, R^2 and adjusted R^2 values than others, is that when their accuracy was assessed against 1,500 random sample points collected from high-resolution digital photographs in Chapter 3, they also presented different Kappa index of agreement for their urban land-covers. In this context, the classified image 1974 had the lowest Kappa index for urban land-cover (87.89% using land-cover 1974 as the reference image and 78.77% using points 1974 as the reference image) whereas the classified image 2001 has the highest Kappa index for urban areas (93.30% using land-cover 2001 as the reference image and 85.79% using points 2001 as the reference image) and identically, the image from 1974 also has the lowest coefficients of correlation and determination while the image from 2001 shows the best correlation and regression results. Nevertheless, in the case of the classified images from 1986 and 1992, the results not necessarily match this pattern; instead according to the Kappa indexes, the correlation and regression values from the image of 1986 (91.28% using land-cover 1974 as the reference image and 84.36% using points 1974 as the reference image) are higher than expected in relation to the ones from the image of 1992 (84.37% using land-cover 1974 as the reference image and 79.56% using points 1974 as the reference image).

Among the group of the historical simulated images from 1975 until 2001, Simulation 1980 has the highest correlation coefficient (R=73.50%), coefficient of determination (R^2=54.00%) and adjusted coefficient of determination (adjusted R^2=53.50%) between urban areas and population. The next best values present Simulation 1985 with R=72.50%, R^2=52.60% and adjusted R^2=52.10%. Slightly lower values present Simulation 1986, with R=71.50%, R^2=51.20% and adjusted R^2=50.70%.

The rest of simulations present low values for their correlations and very poor statistics (below the threshold of 50%) for their coefficients of determinations and adjusted coefficient of determination. In this scenario, simulation 1975 presents a correlation coefficient of R=69.40%, while its R^2 and adjust R^2 are 48.10% and 47.60% respectively. Simulation 1990 have R=64.44%, R^2=41.50% and adjusted R^2=41.0%. Simulation 1992 presents also similar values to the ones of simulation 1990: R=62.50%, R^2=39.00% and adjusted R^2=38.40%. Simulation 1995 has R=58.60%, R^2=34.40% and adjusted R^2=33.80%. The historical simulations with the lowest values are the last ones, from years 2000 and 2001. For example, simulation 2000 presents the following values: R=48.05, R2=23.00% and adjusted R2=22.30% whereas simulation 2001 has R=47.10%, R^2=22.10% and adjusted R^2=21.40%. In all these cases the remaining percentage (more than 50%) can be explained by unknown, extraneous values or inherent variability.

The reason these simulations present higher values than others is because of small errors which accumulate over time through the simulation process from 1974 until 2001. These errors were already evaluated in Chapter 4 through error matrices and kappa indexes of agreement, comparing the collected 1,500 sample points from high-resolution photographs against the SLEUTH simulations for years 1986, 1992 and 2001, not being possible to have Kappa indexes for all simulations. In this scenario, the closer in time (number of years) the simulation is from its beginning (year 1974), in general the higher will be its correlation and coefficient of determination; in the other hand, the farther away the simulation is from in time from its beginning in 1974, in general the lower will be its correlation and coefficient of determination. Consequently, simulation 1986 have the highest Kappa index for urban land-cover (90.17%

using land-cover 1974 as the reference image and 82.49% using points 1974 as the reference image) as well as one of the highest values for R, R^2 and adjusted R2 among all historical simulations. The simulation 1992 has a middle Kappa index for urban land-cover (87.20% using land-cover 1974 as the reference image and 76.94% using points 1974 as the reference image). And finally, simulation 2001 has the lowest Kappa index for urban areas (93.30% using land-cover 2001 as the reference image and 85.79% using points 2001 as the reference image), matching these values also with the lowest values for R, R^2 and adjusted R2 for this last historical simulation.

Even if the values of the historical simulations are generally poor, the values of the simulations into the future made from the last classified image of 2001 into the future (2025) are quite high, with the highest coefficients for smart growth in 2010, whereas normal trend and urban sprawl simulations have astonishing their highest measures for year 2025.

The smart growth simulation in 2005 presents the following values: R=78.40%, R^2=61.40% and adjusted R^2=61.10%. This same trend in the simulation 2010 will barely increase to R=78.70%, R^2=61.90% and adjusted R^2=61.50%, slightly diminishing for 2015 to R=78.40%, R^2=61.40% and adjusted R^2=61.10%. For 2020, the smart growth trend will still diminish to R=78.20%, R^2=61.10% and adjusted R^2=60.70% and these values will be a little bit lower for this trend in simulation 2025: R=77.80%, R^2=60.50% and adjusted R^2=60.10%. Therefore, always in the smart growth trend for all simulations, the unexplained, extraneous values or inherent variability will be below 33% for correlations (R) and below 40% for R^2 and adjusted R^2.

The normal trend simulation in 2005 presents these values: R=79.0%, R^2=62.30% and adjusted R^2=62.00%. This same trend in the simulation 2010 will increase to R=80.00%,

R^2=64.00% and adjusted R^2=63.60%. These small increments will remain until 2025, presenting the normal trend simulation in 2015 these values: R=80.70%, R^2=65.20% and adjusted R^2=64.80%; in 2020 R=81.30%, R^2=66.00% and adjusted R^2=65.70% and finally as it was mentioned before, the highest value will be for the normal trend simulation in 2025, when R=81.60%, R^2=66.50% and adjusted R^2=66.20%. Consequently, generally for normal trend simulations, the unexplained, extraneous values or inherent variability will be below 32% for correlations coefficients (R) and below 38% for coefficients of determinations (R^2) and adjusted R^2.

Finally, in the case of the urban sprawl simulations, they present the higher correlations and coefficients of determinations among all simulations. In 2005, the urban sprawl simulation presented R=78.90%, R^2=62.30% and adjusted R^2=62.00%. These values will progressively increase in this trend until year 2025. Following this trend, for 2010, the urban sprawl simulation will have R=80.50%, R^2=64.80% and adjusted R^2=64.50%. This same trend in the simulation of 2015 will present the following values: R=81.30, R^2=66.10% and adjusted R^2=65.80%. For 2020, these measures will slightly increase to R=82.20%, R^2=67.60% and adjusted R^2=67.30% and finally for the urban sprawl simulation in 2025 will present its highest coefficients: R=82.40%, R^2=68.00% and adjusted R^2=67.70%. In this urban sprawl scenario, always the unexplained, extraneous values or inherent variability will be below 31% for correlations (R) and below 37% for R^2 and adjusted R^2.

It is more difficult to explain based on solid proofs the behavior of simulations into the future because of the lack of physical evidence (imagery). Nevertheless, because of the linear regression model, it is possible that the coefficients of correlation and regression for the simulation based on smart growth trend will be higher near the beginning of the simulation process (year 2001) because this trend tends to increase just slightly the number of urbanized pixels; consequently, increasing population densities and the differences in the cloud of points (represented by census-tracts) in relation with the regression line. These differences are more difficult to evaluate when the graphics are made of cumulative frequencies instead of raw values, as is the case in this dissertation; nevertheless, this differences are showed in the values of R, R^2 and adjusted R^2.

Contrary to what happens with the smart growth trend, in the case of the normal trend and urban sprawl simulations because both tend to increase in a moderate and faster speeds the numbers of urbanized pixels, consequently maintaining or diminishing population densities and the differences in the cloud of points (represented by census-tracts) in relation with the regression line as it can be verify in the values of R, R^2 and adjusted R^2 specially in the final years when the regressions were applied to the simulations 2025 using normal and sprawl trends.

6.2. Censuses from the Sky using the Allometric Growth Model

Censuses from the sky had been done since the 1960s with satisfactory results, obtaining spatial distributions of populations in specific areas of analysis to generate adequate policies and to develop economic and spatially demographic planning of these regions (Lo 1986). Remote sensing sensors provide faithful population size estimates that approach the accuracy of traditional censuses based on mass surveys done in situ (Jensen and Cowen 1999). In some areas of the developing world, where censuses are infrequent, or when there is necessary to find intercensal data, remote sensing may provide a useful way to obtain this information.

There are different approaches to find population estimation from remote sensing imagery, and these methods vary according to the type of population and in relation to the scale of analysis (Lo 1986). In general, four types of techniques are identifiable:

Estimation of population based on measured land-cover/use areas. This method will be applied in this research because is ideal for medium-resolution imagery (in this particular case, the images are Landsat at 30 m resolution using Anderson level I classification system) and it is based on pixel counts at the census-tract level, which are compared against population data through small regression samples to obtain the values of the *a* and *b* coefficients that later on will be used for the allometric growth model to finally calculate population estimates (Olonrufemi 1984).

Estimation of population generated from land-cover/use areas, which is based on pre-estimates of population densities per square unit (can be in Km^2, hectares or acres) of each land-use type (especially different types of residential and mixed use) that need to be measured, multiply by the densities values and finally added together (Watkins 1984).

Estimation of population based on counts of dwelling units (used in high-resolution imagery), where the features of the residencies can be recognized and interpreted from the imagery (roof types, numbers of floors, parking lots, landscaping vegetation) and also exist a certain estimate of the average number of residents per every housing unit type (Lo 1979).

Estimation of population based on spectral radiance characteristics by individual pixels (rooftops are different from their surroundings) where fractal regions are formed and correlated against population datasets (Hsu 1973).

It is important to evaluate the degree of accuracy not just spatially (through error matrices and Kappa indexes) but also demographically between the classified Landsat images and the SLEUTH simulations with the real, estimated and projected population data at the census-tract level. Therefore, in order to generate these comparisons is necessary to use just the urban pixels (the only ones that contain population) within the census-tracts from the maps already generated in the classified images and SLEUTH simulations. This statistical technique is called Censuses from the Sky, and it consists of two steps: First, in applying a linear regression to a small sample compose of a few census-tracts (just 10 were selected in this particular case) containing the number of urbanized pixels (spatial independent variable *X*) and the demographic data (statistical dependent variable *Y*) to obtain the unknowns *a* and *b* coefficients. The second step consists on using these two coefficients into the allometric growth model to derive the population estimations. Finally, the actual or real population values are compared against the estimated population values that resulted from the application of the allometric growth model (censuses from the sky) using their differences in absolute and percentage values as well as the Root Mean Square Error (RMSE).

This research compares the estimated populations obtained in the censuses from the sky through the allometric growth model (logarithmic linear regression) against the actual populations obtained through the dasymetric density method in Chapter 5; but, if densities from these two methods will be compared as well, it will be possible to appreciate that always the linear regressions used in the censuses from the sky tend to smooth the density gaps among the different census-tracts, because depending on the urban configuration of the city in a certain moment of time (different zones, different residential densities, different heights of buildings within a census-tract and among them) is possible that in reality the best regression pattern for the cloud of points is not necessarily linear, but instead a power, cubic or quadratic regression.

6.3. Linear Regression Model for just 10 Census-tracts

The main idea behind this process also known as model calibration is to apply a linear regression to a small sample of censuses tracts (just 10 of them were selected: numbers 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100) with their correspondence number of urbanized pixels as well as their demographic values, in order to obtain the unknowns *a* (y-intercept of the regression line or the value of Y when $X = 0$) and *b* coefficients (the slope of the regression line).

As it was mentioned before, the input data for this linear regression model consist of two kinds of data: first, the count of the number of urbanized pixels in every census-tract obtained from urban land-cover through satellite image classification or SLEUTH simulation (spatial independent variable X); and second, the statistics about population for every census-tract obtained from censuses (Geolytics) and estimated or projected from known values (statistical dependent variable Y).

In this particular case, the formula used for the linear regression equation is identical to the one used before at the beginning of this chapter for the regression of the 110 census-tracts, where the independent variable X consists on the Area of urban Pixels in Km^2 whereas its dependent variable Y constitutes the Actual Population.

These regression samples, many times the P values are higher than the 5% threshold, ($P < 0.05$); nevertheless, it does not really matters because it is well known that when the regression coefficient is applied for all 110 census-tracts, the P value is zero (0), so the population data (independent variable Y) does not exist by chance and the null hypothesis (H_0) is rejected.

In these linear regression samples, what matters the most is to obtain the values of the *a* and *b* coefficients that later on will be used for the calculation of the allometric growth model. Therefore, the results of the correlation coefficients (R), coefficient of determination (R2), adjusted coefficient of determination (adjusted R2), t tests, F test and P values will not be analyzed in a summary table at the end of the regression models, instead the next point will be the calculation of the allometric growth model to generate the census form the sky and obtain the estimated populations. Finally these results will be compared against the actual populations in a summary table to assess the accuracy of the classified images and SLEUTH simulations in the prediction of demographic data. See tables A-V.29 to A-V.56 and figures A-V.29 to A-V.56 in appendix V (pages 448 to 475).

6.4. Allometric Growth Model for all 110 Census-tracts

The concept of allometric growth model originally comes from biology and the main idea behind is that the growth of living organisms (in this case is replaced by cities) is conceived as the relationship between just two attributes of that organism: in this case it will be its urbanized areas (independent variable X) and its population (dependent variable Y).

Once constants a and b had been previously determined through a linear regression applied to just 10 censuses tracts and the a and b coefficients were obtained, right now it is possible to apply the allometric growth model to estimate populations in all 110 census-tracts per image using Microsoft EXCEL software package.

The equation for the allometric growth model is the same as the one from a linear regression but instead of the absolute X and Y values, this model uses their logarithms. Therefore, it is necessary to transform first the values corresponding to the area of urban pixels (independent variable X) into their logarithmic values, and because of this transformation, the estimated population (dependent variable Y) also will result in logarithmic form. After these transformations are done, it is possible to apply the allometric growth model to all 110 census-tracts to obtain the estimated population values, which at last need to be converted into their Antilogarithmic (absolute) values, in a process known as Censuses from the Sky, because the demographic data was derived from the number of urban pixels in every image.

$\log Y = a + b * \log X$ has been replaced by: $\log \mathrm{P}_{est} = a + b * \log \mathrm{A}$

Where:

log P_{est} is the logarithm of the number of the estimated population (dependent variable *Y*) that results from the allometric growth formula. After, log P_{est} can be easily transformed into P_{est} (the estimate number of population) through the use of an Antilogarithmic function. Finally the values of P_{est} for every census-tract can be added together to obtain the total population of the whole counties.

a is a regression coefficient obtained initially in the model calibration process for just 10 census-tracts and it represents the y-intercept: the value of *Y* when *X* = 0.

$\overline{a} = Y - \overline{b} * X$ has been replaced by: $\overline{a} = P_{est} - \overline{b} * A$

b is another regression coefficient obtained initially in the model calibration process for just 10 census-tracts and it represents the slope of the regression line.

$$b = \frac{\sum XY - (\sum X)(\sum Y)/n}{\sum X^2 - (X)^2/n} \quad \text{has been replaced by:} \quad b = \frac{\sum A * Pest - (\sum A)(\sum Pest)/n}{\sum A^2 - (\sum A)^2/n}$$

log A is the logarithm of the number of urbanized pixels (independent variable: X). A or Area is the result of counting just the urbanized pixels (through the use of a binary mask) in every census-tract from the land-cover data derived from satellite image classification or from the SLEUTH simulation.

6.5. Accuracy Evaluation of the Censuses form the Sky

Results of the allometric growth model are the population estimated values (P_{est}) in every census-tract, which need to be added together at the county level and compared against the real or actual populations values (P_{act}) that already were acquired from past censuses (Geolytics) or statistical estimations and projections.

There are basically three types of accuracy evaluations between the estimated and the actual population values: the differences in absolute numbers between actual and estimated populations, the differences in percentages between both populations and the Root Mean Square Error (RMSE) between actual and estimated populations (Sirkin 2006).

The differences in absolute numbers and percentages between actual and estimated populations were calculated after adding each one of the 110 census-tracts values for every one of the three counties: Escambia, Santa Rosa and Okaloosa. Instead, the RMSE was calculated first in every one of the 100 census-tracts that were unused prior for the model calibration to obtain the *a* and *b* coefficients, and finally these census-tracts values were added in each county.

For the RMSE, the individual differences or errors that correspond to the addition of the vertical distances of each of the points from the regression line are squared and finally divided by the total number of census-tracts (Rogerson 2006), as shown in the following formula:

$$RMSE = \sqrt{\sum \left(P_{est} - P_{act}\right)^2 / N}$$

Where:

RMSE = Root Mean Square Error

P_{est} = estimated population (derived from the allometric growth model)

P_{act} = actual population (derived from censuses, estimations and projections)

N = Number of census-tracts (in this case 100)

The accuracy evaluation of censuses from the sky has been used in big cities, but it tends to underestimate their population because of the existence of high buildings especially in the Central Business District (CBD). The allometric growth model also underestimates or overestimates the population in middle size towns. Nevertheless, this method had been used successfully in smaller cities, giving population estimation results very similar to the real census counts (Lo 1986). Due to the reasons mentioned before, this model has to be calibrated to compute the population of different cities depending on their size and country. For example, cities in developing countries, Europe or Japan tend to be more concentrated and more densely populated than cities in the United States.

Other inaccuracies in this model result from the spatial resolution of the pixels; for example, in a Landsat TM image, a pixel of 30m x 30m may contain people living in isolated small houses (e.g. 10m x 10m), and due to their small sizes, after the image has been classified, these small features contained within single pixels may appear as forests or grass, so they will not be populated and therefore will constitute most of the errors in rural areas. See tables A-V.57 to A-V.140 in appendix V (pages 476 to 531).

Table 6.2: Summary of Census from the Sky for all Analyzed Images

Images	Urbanized Areas in Km^2	Actual Population	Estimated Population	Difference between Actual and Estimated Populations	Difference in percentage between both Populations	RMSE between Actual and Estimated Populations
Historical Classified Images and Simulations						
Classified 1974	**153.16**	**383,314**	**484,610**	**+101,296**	**+26.43**	**2,510.77**
Simulation 1975	156.54	381,993	471,523	+89,530	+23.44	2,277.78
Simulation 1980	174.27	392,185	445,654	+53,469	+13.63	1,486.91
Simulation 1985	192.25	451,223	497,707	+46,484	+10.30	1,414.76
Classified 1986	**194.45**	**462,070**	**420,666**	**-41,404**	**-8.96**	**1,211.23**
Simulation 1986	195.96	462,070	504,019	+41,949	+9.08	1,405.18
Simulation 1990	211.69	488,183	513,811	+25,628	+5.25	1,488.86
Classified 1992	**217.26**	**500,454**	**455,020**	**-45,434**	**-9.08**	**1,324.93**
Simulation 1992	220.19	500,454	522,495	+22,041	+4.40	1,578.56
Simulation 1995	233.31	530,309	567,276	+36,967	+6.97	1,992.46
Simulation 2000	255.57	582,651	679,660	+97,009	+16.65	3,494.65
Classified 2001	**255.00**	**591,530**	**547,037**	**-44,493**	**-7.52**	**1,721.66**
Simulation 2001	260.02	591,530	695,395	+103,865	+17.56	3,664.09
Projections of Simulations						
Sim 2005 smart	260.88	629,005	568,180	-60,825	-9.67	2,006.31
Sim2005normal	**271.62**	**629,005**	**614,638**	**-14,367**	**-2.28**	**1,884.30**
Sim 2005 sprawl	280.31	629,005	590,929	-38,076	-6.05	1,918.16
Sim 2010 smart	263.72	691,161	646,688	-44,473	-6.43	2,394.14
Sim2010normal	**292.96**	**691,161**	**656,060**	**-35,101**	**-5.08**	**2,287.02**
Sim 2010 sprawl	313.39	691,161	658,707	-32,454	-4.70	2,257.32
Sim 2015 smart	266.56	744,206	692,847	-51,359	-6.90	2,905.01
Sim2015normal	**314.10**	**744,206**	**713,796**	**-30,410**	**-4.09**	**2,680.47**
Sim 2015 sprawl	347.81	744,206	712,989	-31,217	-4.19	2,641.50
Sim 2020 smart	269.64	793,291	736,751	-56,540	-7.13	3,460.02
Sim2020normal	**337.23**	**793,291**	**772,571**	**-20,720**	**-2.61**	**3,095.31**
Sim 2020 sprawl	382.00	793,291	772,655	-20,636	-2.60	3,027.78
Sim 2025 smart	272.28	837,405	771,231	-66,174	-7.90	4,074.41
Sim2025normal	**361.63**	**837,405**	**830,817**	**-6,588**	**-0.79**	**3,529.62**
Sim 2025 sprawl	417.47	837,405	828,185	-9,220	-1.10	3,483.53

Notes: RMSE values were calculated between actual populations and estimated populations, showing the square sum of errors generated from the other 100 census-tracts not previously used for the calculation of the coefficients of correlation and determination.

Analyzing this table is possible to notice that the higher the surface of the urban areas (measured in Km^2), the higher is also their populations, with the exceptions of the classified Landsat images for years 1986, 1992 and 2001 with their respective simulations, because for every one of these mentioned years, both have exactly the same population values at the census-tract level as well as in their total sums. The same happens with the simulations made from 2005 until 2025, because for every one of the selected years (2005, 2010, 1015, 2020 and 2025), the smart growth, normal and urban sprawl trends have exactly the same population at the census-tract level and in their total sums, regardless of the amount of urbanized areas.

Also, it is very important to indicate that this table summarizes comparisons between actual versus estimated populations, showing total differences in absolute and percentage values for the whole population of every image in time, as well as for their Root Mean Square Errors (RMSE) which implies differences at the census-tract level. It is very interesting that results from future simulations (2005 until 2025) show small differences between the total values of the actual population in relation to the estimated population, while their total RMSE (measured at the census-tract level) indicates high levels of errors. The reason for this asymmetry is simply because when the values of the estimated population at the census-tract level are added together, sometimes they are lower and sometimes they are higher than the ones from the actual population, and by coincidence, at the end of the sum, the total value of the estimated population can be similar to the one obtained from the sum of the actual population; therefore RMSE is always the best measure to evaluate the accuracy of the census from the sky.

In addition, because population estimates depend on the amount of urbanized areas according to the allometric growth model, and actual populations in the linear regression analyses made at the beginning of this chapter constitute the dependent variable Y of urban areas (independent variable *X*), it is possible to compare the differences in absolute and percentage values between the Total results of the estimated versus the actual populations for the whole region (Escambia, Santa Rosa and Okaloosa counties) from table 6.2 against the correlation (R) and regression coefficients (R^2 and adjusted R^2) from table 6.1 (a linear regression of all 110 census-tracts between urban areas and actual populations). Doing this comparison, is possible to notice that in some cases (especially with normal and urban sprawl simulations) the lower the regression indexes are between urban areas and actual populations, the higher the differences are between estimated and actual populations, and vice versa. The reason for these anomalies is the same already explained: the coincidence at the end of the sum of adding sometimes lower and sometimes higher estimated population values in relation to the total actual population.

Finally, this pattern sometimes does not occur between the Root Mean Square Errors (RMSE) for the 100 census-tracts and the measures obtained through linear regression analysis (with the exceptions of classified and simulated images from 1980 to 1992); these results are totally different and the lack of coincidence between the results of these two tables (correlation, coefficient of determination in relation with RMSE) relates with the way how formulas were designed to calculate these indexes, being enough to say that even if the measurement of values from the cloud of points to the regression line is always the same, the calculation of these errors varies according to the formulas used, becoming a whole new statistical topic beyond the area of interest of this research. The pattern that is always present in the analysis of RMSE results is the fact that the closer the simulations are from their origins (year 1974 for historical simulations and year 2001 for future simulations), the lower are their RMSEs, and vice versa.

Among the group of the classified images, the one from 2001 has the lowest difference in percentage between actual versus estimated populations (-7.52%), with a difference of -44,493 persons less than expected according to the results generated in the census from the sky through the use of the allometric growth model. In this classified image from 2001, the square sum of individual errors (differences) at the census-tract level, which were generated from the other 100 census-tracts not previously used for the calculation of the coefficients of correlation and determination or RMSE between actual and estimated populations has the value of 1,721.66; implying that even from all classified images, the one form 2001 has the smallest differences in values between total actual population and the estimated population, at the census-tract level these differences are greater. Also this image according to table 6.1 has the highest regression indexes among all classified images: R=77.80% R^2=60.60% and adjusted R^2= 60.20%. These high coefficients explain why differences are also small between the actual and the estimated values generated in the census from the sky. The explanation used in these cases can also be applied for the rest of images as follows: the high coefficient of determination (R^2) shows a high dependency of population from urban areas, and because these same urban areas are used to predict new population estimates though the allometric growth model, obviously the differences between actual and estimated populations will be small as well.

The next classified image with the second best percentage between both populations, is the one from 1986 with -8.9605% of mismatches and just -41,204 persons less than expected (this value is even lower than in the classified image from 2001 because also there was a smaller amount of people living 15 years before) according to the results generated in the census from the sky. In this classified image from 1986, the RMSE between actual and estimated populations equals just 1,211.23; implying the smallest differences among all images (not just classified ones) at the census-tract level, therefore this image should be considered as the best match among all censuses from the sky. Finally, according to table 6.1, this image presents the following regression measures: R=71.10% R^2=50.60% and adjusted R^2=50.20%, values that are considered not very high; but surprisingly, the amount of urban pixels per census-tract did predict the most accurate population estimates at this small level of analysis.

In the case of classified image 1992, the difference in percentage between both populations (actual minus estimated) is -9.08% while in absolute numbers is -45,434 persons according to the census made from the sky. This same image has a low RMSE of just 1,324.93, slightly higher than the classified image from 1986, consequently showing small differences at the census-tract level between actual and estimated population values. Nevertheless, this image presents slightly higher regression coefficients (R=72.00% R^2=51.80% and adjusted R^2=51.40%) than the classified image from 1986: R=72.00% R^2=50.60% and adjusted R^2=50.20%, percentages that are not really high; but at the micro level according to the total RMSE value, the prediction were very accurate for population estimates inside each census-tract.

The last classified image, the one from 1974 shows the less accuracy in the values generated through the allometric growth model between actual and estimated populations; for example, the percent difference between both populations is +26.43% or as high as an overvalue of +101,296 persons, while its RMSE (2,510.77) is also the least accurate and consequently the highest among all classified images, clearly showing a huge gap in total population results as well as notorious mismatches at the census-tract level. The regression values of R=67.80% R^2=46.00% and adjusted R^2=45.50% also are the lowest among all classified images and they constitute additional proof that determines the lack of accuracy at the micro (census-tract) and macro level (the three counties together). The main cause of this problem is the lower resolution (79m) of the original Landsat MSS from 1974 that affected its land-cover classification process in relation to the later Landsat TM (30m) used in the land-cover classifications of the 1986, 1992 and 2001 images.

Among the group of historical simulations (from 1974 to 2001), simulation 1992 presents the lowest difference in percentage between both actual and estimated populations (+4.40%) or an error of +22,041 persons in absolute terms, having a RMSE of 1,578.56, which is a low value in relation with other simulations inside this group; but, it is not the smallest one. Therefore, this simulation shows better estimated population results at the regional level (the three counties added together) than at the individual census-tract level. The regression values for simulation 1992 were R=62.50%, R^2=39.00% and adjusted R^2=38.40%, being extremely low (especially the coefficient of determination); nevertheless, the population estimates at the regional level were well predicted, because as it was mentioned before, when the values of the estimated population at the census-tract level are added together, sometimes they are lower and sometimes they are higher than the ones from the actual population, and by coincidence, at the end of the sum, the total value of the estimated population can be similar to the one obtained from the sum of the actual population; therefore, RMSE is always the best measure to evaluate the level of accuracy of the census from the sky.

Other simulation with similar characteristics to the one from 1992 is simulation 1995, which shows a difference in percentage between both populations of +6.97% or +36,967 persons, whereas its RMSE is 1,992.46, being the reason for these asymmetries already explained and therefore, is not uncommon the fact that the regression values for simulation 1995 were also very low: R=58.60%, R^2=34.40% and adjusted R^2=33.80%.

Simulations 1980, 1985, 1986 and 1990 are the most accurate at the micro or census-tract level because they present the lowest RMSE values. In fact, simulation 1986 presents the lowest

RMSE (1,405.18) within the group of the historical simulations, in second place is simulation 1985 with a RMSE of 1,414.76, the third place corresponds to simulation 1980 (RMSE=1,486.91) and the fourth to simulation 1990 with RMSE=1,488.86. All these very good RMSE values also match high regression coefficients, for example, simulation 1986 has a R=71.50% R^2=51.20% and adjusted R^2=50.70%; simulation 1985 presents a R=72.50%, R^2=52.60% and adjusted R^2=52.10%; simulation 1980 shows the highest regression coefficients among the group of the historical simulations: R=73.50% R^2=54.00% and adjusted R^2=53.50% and, simulation 1990 has the following values: R=64.40%, R^2=41.50%, and adjusted R^2=41.00%. Finally, the difference in percentage between actual and estimated populations for simulations 1980, 1985, 1986 and 1990 are +13.63%, +10.30%, +9.08%, +5.25% respectively, or +53,469 individuals for simulation 1980, +46,484 persons for simulation 1985, +41,949 inhabitants for simulation 1986 and just +25,628 peoples for simulation 1990. As a conclusion, this group of images presents the best results among all simulations: high regression coefficients, low RMSEs and low differences in percentages and absolute values between total sums of actual versus estimated populations.

Finally, the worst results among all historical simulations come from simulations 1974, 2000 and 2001, presenting all of them high RMSE values, such as 2,277.78 for simulation 1975, 3,494.65 for simulation 2000 and 3,664.09 for simulation 2001 (the highest RMSE value among all images), indicating a great number of errors and mismatches at the census-tract level; these three simulations also have among all images the highest percent differences (with the exception of classified image 1974) and absolute numbers between actual and estimated populations, for example simulation 1975 has a difference of +23.44% or +89,530 persons in relation to the values for actual population; simulation 2000 presents a difference between both populations of

+16.65% or +97,009 individuals; and finally, simulation 2001 shows values of +17.56 or +103,865 inhabitants (the highest difference among all images for absolute terms) as the differences between total actual and estimated values. The reason for these strong inaccuracies at the micro (census-tract) and macro levels (the three counties together) can be explained in the case of simulation 1975 because this image is immediately derived in the SLEUTH model from classified image 1974 (just one year of difference), which had the lowest land-cover classification accuracy due to the original resolution of the Landsat MSS image (79m) in relation to the later Landsat TM (30m) used to derived the classified images 1986, 1992 and 2001. Therefore, also the regression coefficients of simulation 1975 (R=69.40% R^2=48.10% and adjusted R^2=47.60%) are very similar to the ones from classified image 1974. In the case of simulations from years 2000 and 2001, the high errors censing from the sky at the micro and macro levels are the consequence that both images present the lowest values for correlation and regression coefficients, in fact simulation 2000 shows R=48.00% R^2=23.00% and adjusted R^2=22.30% whereas simulation 2001 is even worst presenting R=47.10% R^2=22.10% and adjusted R^2=21.40%. Obviously, the mismatches analyzed in Chapter 4 between classified image 2001 and ground-truth sample points with the simulated image 2001 were also the greatest ones among all classified images with their respective simulations; therefore, it is possible to say that the source of all these differences are originated in the continuous accumulation of errors through time (during 26-27 years) that normally happens when the SLEUTH model is applied.

The last group with projected simulations from 2005 until 2025 is characterized by high RMSE values, implying errors at the census-tract level between urbanized areas (from which population estimates are derived though the allometric growth model) and actual populations; in the other hand, this group of simulations has a pattern of low differences in percentages and absolute numbers between actual and estimate populations which increase over time for all three scenarios, coexisting together with high indexes of regression (R, R^2 and adjusted R^2) which in the case of normal and urban sprawl trends tend to decrease over time.

Following the mentioned pattern, the smart growth simulation of 2005 has the lowest RMSE (2,006.31), a value that for the smart growth simulation of 2010 will increase into 2,394.14, and later this same trend will be 2,905.01 for 2015, and as high as 3,460.02 for 2020, becoming finally the worst RMSE value among all projected simulations in 2025 (4,074.41), so the inaccuracies among urban pixels at the micro level (census-tracts) tend to increase more and more every five years since the beginning of this simulation trend. Nevertheless, at the macro level (total population estimates), in the case of smart growth simulation 2005 the differences in percentage between both populations is -9.67% or -60,825 persons, constituting the highest errors among the group of all projected simulations. In the case of the smart growth simulation for 2010, these values will be -6.43% or -44,473 inhabitants, achieving their lowest levels for this scenario in 2015 with just -6.90% or -51,359 individuals, to after increase to -7.13% or -56,540 peoples for 2020 and slightly higher values of -7.90% or -66,174 residents for 2025. The main reason behind these total difference between both populations can be attributable to the high regression coefficients of this trend, which for smart growth 2005 are R=78.40%, R^2=61.40% and adjusted R^2=61.10%, achieving the highest percentages for year 2010 (R=78.70% R^2=61.90% and adjusted R^2=61.50%), dropping consecutively after to R=78.40%, R^2=61.40% and adjusted R^2=61.10% for year 2015, and to R=78.20%, R^2=61.10% and adjusted R^2=60.70% for 2020, to finalize this smart growth trend in year 2025 with the values of R=77.80%, R^2=60.50% and adjusted R^2=60.10%.

In the case of the normal growth trend, the simulation from 2005 has the lowest RMSE (1,884.30), this value increases with time; therefore, in 2010 will be 2,287.02, for 2015 2,680.47, in the year 2020 its RMSE is 3,095.31, and finally in 2025 will be 3,529.62. In other words, the errors in the number of urban pixels at the micro level (census-tracts) tend to increase over time since the beginning of the normal growth trend. Nevertheless, in the case of actual population versus estimates, normal growth simulation 2005 presents low differences between both populations, just -2.28% or -14,367 persons, these values will increase for simulation 2010 until -5.08% or -35,101 inhabitants, to after consecutively decrease until the end of the simulation, becoming in 2015 -4.09% or -30,410 individuals, in 2020 -2.61% or -20,720 residents and finally in 2025 barely -0.79% or -6,588, the lowest differences at the macro level (Escambia, Santa Rosa and Okaloosa counties) among all simulations. There are two reasons behind these extremely low total difference values; the first one is attributable to the high regression coefficients of this trend, which for simulation 2005 normal are R=79.00%, R^2=62.30% and adjusted R^2=62.00%; with constantly increasing rates, as is showed in the 2010 values: R=80.00%, R^2=64.00% and adjusted R^2=63.60%, ascending to R=80.70%, R^2=65.20% and adjusted R^2=64.80% for year 2015, and to R=81.30%, R^2=66.00% and adjusted R^2=65.70% for 2020, finalizing this normal simulations trend in year 2025 with the values of R=81.60%, R^2=66.50% and adjusted R^2=66.20%. Nevertheless, these high coefficient values cannot explain alone these extremely low differences; so, the second reason has to do with the values of the estimated population at the census-tract level that are added together, sometimes they are lower and sometimes they are higher than the ones from the actual population, and by coincidence, at the end of the sum, the total value of the estimated population are similar to the one obtained from the sum of the actual population, as is happening in this normal trend scenario.

In the urban sprawl scenario the pattern is very similar to the one from normal growth; therefore, urban sprawl simulation 2005 also has the lowest RMSE (1,918.16), constantly increasing over time, so in 2010 the RMSE value is 2,257.32, for 2015 ascends to 2,641.50, in the year 2020 the RMSE is 3,027.78, and finally in 2025 the value is as high as 3,483.533. As it was mentioned before, the errors in the number of urban pixels at the census-tracts level tend to increase over time according to the urban sprawl scenario. At the macro level (total population estimates) the panorama seems different for the urban sprawl trend; in this scenario simulation 2005 shows the highest differences in percentage and absolute numbers between both populations: -6.05% or -38,076 persons, but these values will constantly diminish until the end of the simulations in 2025, so for urban sprawl simulation for 2010, these values will dropped to -4.70% or -32,454 inhabitants, in 2015 they will be just -4.19% or -31,217 individuals, decreasing to -2.60% or -20,636 peoples for 2020 and to just -1.10% or -9,220 residents for 2025. The main reason behind these total differences are the same already mentioned for the case of the normal trend simulations. The first one, related with high regression coefficients shows the following values for urban sprawl 2005: R=78.90%, R^2=62.30% and adjusted R^2=62.00%, increasing to R=80.50%, R^2=64.80% and adjusted R^2=64.50% in year 2010, after to R=81.30%, R^2=66.10% and adjusted R^2=65.80% for 2015, ascending to R=82.20%, R^2=67.60% and adjusted R^2=67.30% for 2020, to finalize this urban sprawl trend in 2025 with the values of R=82.40%, R^2=68.00% and adjusted R^2=67.70%. But, of course, these differences among total actual and estimated populations are very low to be explained just by the high regression coefficients, so the second reason is related to the fact that positive and negative values added together sometimes by coincidence, can achieve a total value for the estimated population similar to the sum of the actual population, as is happening in this urban sprawl scenario.

CHAPTER 7

CONCLUSIONS AND RECOMMENDATIONS

7.1. Conclusions

Chapter 1 consists on a short introduction of the organization of this dissertation where the Problem Rationale has been also established.

Chapter 2 is an overview of main physical, historical and especially demographic characteristics derived from past censuses (since 1970) in Escambia, Santa Rosa and Okaloosa counties. This region consist of more than 8,000 Km^2 with a total population of 600,000 inhabitants according to the last census of the year 2000 with a subtropical climate characterized by humid and hot summers and mild winters. The main city is Pensacola Metropolitan Area with a population above 400,000 inhabitants. In the national context, it can be considered as a typical middle size urban area.

These three counties have the oldest history in the United States because here for the first time in 1559 Spaniards found a settlement in the continental United States. This region also changed hands between five countries: Spain, France, Great Britain, the Confederate States, and finally became part of the United States since the Civil War, with the city of Pensacola being destroyed and re-built many times by wars. Pensacola also was the capital of Florida until 1832, when Tallahassee became the new capital.

Chapter 3 is related to imagery classification, accuracy evaluation and the preparation of the other layers necessary as SLEUTH model inputs. The most important spatial data of this research consisted of four Landsat satellite images (one Landsat MSS image with a spatial resolution of

79 m from 1974 and three Landsat TM images with a spatial resolution of 30 m from 1986, 1992 and 2001), which were classified in Idrisi software package according to the USGS Anderson Level I scheme because of the SLEUTH model limitation to this level. After classification, these images were edited in Adobe Photoshop software package to correct spots containing cloudy areas, bridges were transformed into water, highways were converted into grasslands, and finally airports were changed into barrenlands. The final results from these classifications showed land-cover maps of an area of 10,134.20 Km^2 with their respective chronological statistics. Here, most changes through time happened in the urban-roads land-cover, which almost duplicate its size form just 1.5542% (157.51 Km^2) of the total surface in 1974 into 2.67843% (271.42 Km^2) in 2001, a total expansion of 113.91 Km^2. The other land-cover types (rangeland-agriculture, forest, wetlands and barrenlands) slightly increased or decreased in area during these 27 years of analysis. Most of the decrease in rangeland-agriculture, forests, and barrenlands were attributed to urban expansion, especially into numerous beaches inside Santa Rosa island and others. The category wetland was not affected by urbanization because it constitutes protected areas while water land-cover also remained constant in time.

After these images were classified and edited, accuracy classification was performed selecting a total of 1,500 random sample points from higher-resolution imagery: USGS Aerial photos taken in 1976 and Color Infrared National High Altitude Photography from 1986 in order to obtain ground-truth sample points to test the classification accuracy of the land-cover derived from the Landsat 1974 MSS and 1986 TM images. USGS National Land-cover Data (NLCD) from the year 1992 with a spatial resolution of 30 m (accuracy classification higher than 85%) and 3.75 min DOQQs (color infra-red) from January 1999 in order to obtain ground-truth sample points to test the classification accuracy of the land-cover derived from the Landsat 2001 TM image. The results from these evaluations were depicted through error matrices and kappa indexes of agreement, and from them it was possible to conclude that most errors in the images occurred between categories urban (1) and agriculture-rangeland (3) because using 30 m (900 m^2) resolution Landsat images makes difficult to differentiate small houses (less than 300 m^2) from its surroundings, generally yards, grasses and trees. The same mistake in the selection of the urban areas can explain the confusion in the classifier algorithm between agriculture-rangeland and forests in land-cover 1986. All other categories in the error matrices present less than 15 errors per each 250 points. In a similar way, most Kappa indexes of agreement show values above the threshold of 85.00%, being necessary to say that the highest accuracies in the classification of the satellite images exist in category 5=water, where few mismatches among pixels in reality exist. The reason for this great accuracy has to be with the fact that water absorbs all energy in the near IR and mid IR, reflecting almost no energy at all and consequently appears totally dark in these wavelengths (Lillesand and Kieffer 2000), therefore, it is much easy that the classifier algorithm will separate with a high degree of accuracy this land-cover from the rest of the landscape.

The other input layers necessary to configure the SLEUTH model were produced in ERDAS Imagine, such as the layer of slope and hill-shaded relief, which both were derived from a Digital Elevation Model (DEM) at 30 m resolution form EROS-USGS. The national parks and military bases were generated from the digital database of Southwest Florida Water Management District and this layer was unified with the wetlands areas derived from the Landsat-classified images to create the layer of the excluded areas. The layers of the urban areas were derived from the classified images as well and the transportation layer was generated using three local GIS datasets of the counties of Escambia, Santa Rosa and Okaloosa for smaller streets plus the information from the Florida Department of Transportation for main highways.

Chapter 4 responds to the initial questions: how does the SLEUTH model depict the different changes in urban and landscapes in this study area? And, is it possible not just to extrapolate the past-present trend into the future, but to replicate alternative scenarios such as smart growth and urban sprawl? Therefore, this section of the research talks about the implementation of the SLEUTH simulations within two high-performance computers owned by University of Georgia. They simultaneously used many central processing units (CPUs) to divide tasks and to generate results in the fastest way possible. All these simulations are performed through brute force Monte Carlo runs, a computational algorithm which relies on random sampling to compute the results, converting the whole system into a stochastic one.

To run the model, first it is necessary to perform some calibrations to determine the best fit values between the land-cover trend and the simulation from past (since 1974) to present (2001) for the five growth coefficients (road-gravity, spontaneous, breed, edge-growth and slope-resistance growth). These calibrations consist of finding statistic metrics (measures) of historical fit such as Lee and Salee Index and Product. The Lee and Salee index consist of a shape measurement of spatial fit between the urban simulation growth and the known urban extent for the control years. The Product index is the multiplication of all other spatial metrics.

The first stage is also called coarse calibration and consisted of 7,776 simulations using 36 processors simultaneously to find the first and second highest Lee and Salee indexes among all simulations. In a second step called fine calibration, 10,125 simulations were run using 45 processors simultaneously to find the highest Product from the control_stats.log file. The last stage is the final calibration, and here also the highest Product was chosen among 5,184 simulations using 36 processors simultaneously. With these results, finally the highest pop-area value from the avg.log file was chosen among 7 simulations to derive the best forecasting coefficients. The best fit values founded between the land-cover transition and the simulations were: diffusion: 13%; spread: 6%; breed: 52%; slope-resistance: 60%; and road-gravity: 89%. In total, 23,092 simulations ran to determine the best formula which yields the simulation that best matches the land-cover map transition from 1974 to 2001. All these simulations were developed in just 112 hours 49 minutes and 32.64 seconds involving a total of 118 processors.

Then, using this formula that predicted the pattern of growth seen in Escambia, Santa Rosa, and Okaloosa counties from year 1974 to 2001, predictions were developed from present into the future (year 2,001 to 2,025). These present-future simulations were based on three different scenarios: a Normal Trend transition (from 1974 to 2025), maintaining the coefficients founded in the past-present calibrations (diffusion: 13%; breed: 52%; spread: 6%; slope-resistance: 60%; and road-gravity: 89%), plus two other scenarios: smart growth and urban sprawl. In the case of smart growth and urban sprawl, the three coefficients that affect the most: road-gravity (89%), slope (60%) and breed (52%) were maintained with the same values but diffusion and spread coefficients were reduced in 50% each one (diffusion: 6%; breed: 52%; spread: 3%; slope-resistance: 60%; and road-gravity: 89%). And for a higher rate of urban sprawl (from 2001 to 2025), diffusion and spread coefficients were increased in 50% each one, whereas the others coefficients preserved as well their original values (diffusion: 20%; breed: 52%; spread: 9%; slope-resistance: 60%; and road-gravity: 89%). All these three simulations were completed after approximately 2 hours and 30 minutes.

The SLEUTH simulations produce yearly graphical and statistical results since 1975 until 2025 based on the number of pixels that every year change within the different land-cover types generating in this way the continuous evolution of the landscape. It is also necessary to mention that the model produces two kinds of simulations: simulations of changes in the landscape and simulations related with urban growth types.

The main conclusions from the simulations, their statistics and analysis are that urban expansion principally affects the category agriculture, rangelands and grasslands, in second place forests are diminished by urban expansion and finally the category barrenlands suffer also development, especially the areas of the beaches, which presented an unprecedented urban growth unable to be matched by the SLEUTH simulation from 1974 to 2001 because only one formula (parameters calibration) was used for all 3 counties and census-tracts regardless of the differences at the micro level. On the other hand, wetlands are basically not affected by the urban expansion because they constitute protected areas and water cover (lakes, rivers and sea) is neither affected at all.

At the beginning (in 1974) of the normal trend simulation, urban areas constitute 157.51 Km^2 and for the simulation 2001 these areas growth to 269.46 Km^2. The net increment in urban land between 1974 and 2001 was 111.95 Km^2, and these areas will be 388.32 Km^2 in 2025, representing an increase of 116.9 Km^2. Because of this strong growth, urban land areas would occupy about 3.8318% of the total landscape by 2025 in relation with just 1.5542% in 1974 and 2.6589% in 2001.

The second scenario, smart growth provides an alternative growth strategy in which urban areas growth in a more compact way, increasing consequently its population density and decreasing the vegetated area and open space in the metro areas. Under this scenario, the projected urban area for year 2025 would be 290.03 Km^2 and the total increase from 2001 to 2025 will be just 18.61 Km^2 in 24 years, occupying 2.7437% of the entire surface.

The last scenario embodies a super sprawl growth strategy. This scenario simulates the spatial consequences of urban growth at a higher rate than normal encouraging spontaneous and edge growth, so development in isolated areas as well as around existing urban clusters will occur. All these will happen while maintaining the same demographic projections, consequently population densities will decrease as well as the urban areas will tend to be more diffused than normal. This design is based on the finding that the low-density urban use (mainly residential) tends to develop away from existing large urban facilities (Yang and Lo 2003). Under this scenario, the projected urban land for 2025 would be 449.51 Km^2, which implies a net increase in urban land of 178.09 Km^2 since 2001 (271.42 Km^2), occupying 4.4356% of the entire modeled area for year 2025.

Analyzing the maps and statistical tables of the types of urban growth, in the year 1974 (classified land-cover) urban areas constituted 157.51 Km^2 (175,007 pixels) and every year these values went up achieving urban areas for the simulation of the year 2001 the value of 269.51 Km^2 (299,453 pixels). Looking into the future, and according to the normal trend simulations, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and these values went up achieving urban areas for the simulation of the year 2025 the value of 388.06 Km^2 (431,178 pixels). In the case of the smart growth projections, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and these values went up achieving urban areas for the simulation of the year 2025 the value of 288.02 Km^2 (320,020 pixels). And analyzing the urban sprawl simulation, in the year 2001 (classified land-cover) urban areas constituted 271.42 Km^2 (301,581 pixels) and these values went up achieving urban areas for the simulation of the year 2025 the value of 449.96 Km^2 (499,958 pixels). In all simulations: past to present and the three different scenarios - projections, most of the growth in absolute and percentage was generated because of the edge and road-influenced growth, increasing the number of urban pixels especially in the periphery and inside the cities as well as along the major roads and highways, while the spread and breed growth constituted just a small amount of new urban growth that was generated in the rural areas of this region of analysis. The growth in urban land as projected under these three different scenarios would slowly change more and more the spatial form in the cities of these three counties with numerous edge cities developed throughout new areas. These changes using all three different scenarios are not really of any drastic magnitude at least until 2025; where a small metropolitan area would begin to emerge in the city of Pensacola plus its suburbs, presenting an urban development in direction towards the north and the west. This is related to the fact that the southern and eastern parts are surrounded by water. With these results, it is expected that all these simulations could add in the understanding of urban coastal dynamics of middle size cities and their surroundings and these results should be highlighted for local or regional planning considerations.

Land planning officials can expect that there will be the highest amount of growth around roads (road-gravity) and around the edges of current cities and inside existing urban clusters (breed). Investment in infrastructure especially for Pensacola and Fort Walton Beach is wise as the most growth will likely occur in these two cities and on their beaches for the next 20 years, if past patterns of growth continue into the future. These findings can be used to understand urban and population dynamics and finally to generate land planning policies in Escambia, Santa Rosa, and Okaloosa counties. Finally, it is necessary to indicate that these urbanization processes, which produce the expansion of cities are associated with internal growth (births – deaths) and migration flows from other areas of the United Sates (especially North-South flows) to towns along the beach, generating a high levels of urbanization along the coast line of North-West Florida.

In a similar way with the classified images, the other land-cover types (rangeland-agriculture, forest, wetlands and barrenlands) slightly decrease in surface during the 51 years of analysis (1974 to 2025). Most of the decrease in rangeland-agriculture, forests, and barrenlands were attributed to urban expansion, especially into numerous beaches inside Santa Rosa island and others. The category wetland was less affected by urbanization because it constitutes protected areas while water land-cover also remained constant in time.

After these simulations were generated, it was necessary to perform accuracy evaluations of the SLEUTH simulations as well, compare them first against the same 1,500 random sample points (ground-truth) used before to assess the accuracy of the classified land-cover images; and, finally these simulations were compared against the classified land-cover images (ground-truth).

Analyzing the accuracy evaluations of the SLEUTH simulations for 1986, 1992 and 2001 (there is not simulation for year 1974) against the 1,500 random sample points, it was possible to say that most errors occur between categories urban (1) and agriculture-rangeland (3) for all three simulations. It is possible that all these errors are the product of selecting the polygons for urban development in suburbs and residential areas from the classified land-cover 1974 (origin of the simulations), because using 30 m (900 m^2) resolution Landsat images makes difficult to differentiate small houses (less than 300 m^2) from its surroundings, generally yards, grasses and trees. Also, it is possible that the new urbanized pixels (from edge and road-influenced growth, and from spread and breed growth) during the process of the simulation were growing in areas of agriculture, rangeland and grasslands that did not match exactly the sample points obtained from the higher accuracy imagery. In the case of the accuracy of the simulation 1986, also some errors occurred between categories agriculture-rangeland (3) and forests (4). The same mistake in the selection of the urban areas from the classified land-cover 1974 (origin of the simulation) can explain the confusion in the classifier algorithm between agriculture-rangeland and forests in the simulation of 1986.

When the accuracy was assessed between the classified images and the simulations, three maps of conflicts were generated for a visual comparison that show in black color all the areas that do not match between the classified land-covers and the simulations, whereas the other land-covers that do match are maintained with their normal colors. These maps show really few disagreements (in black color) especially in areas of beaches and some wetlands where urban development was impossible to replicate through SLEUTH, demonstrating that this model really simulates reality with a high degree of certainty and confidence.

Analyzing the error matrices among simulations versus classified images, it was possible to conclude that most errors occur between categories urban=1 (truth) and agriculture-rangeland=3 (mapped) in all three simulations. The explanations about these conflicts are the same one mentioned before when the random points were compared against the simulated images.

Chapter 4 answers the question: what kind of results the SLEUTH model will produce if dasymetric densities are applied to these simulations? How accurate are these results? It is important to notice that most researchers use this CA model generally just to understand urban growth and changes in the landscapes; nevertheless, this investigation is an attempt to go beyond the traditional use of the SLEUTH model into a new field: demographics in space and time.

Therefore, in this Chapter, population density maps (choropleth and dasymetric) were elaborated and analyzed. Dasymetric is a cartographic technique based on satellite imagery and census-tracts, where accurate maps are made because population densities exist just inside the urbanized pixels (using medium-resolution images) of every census-tract. The spatial input data used for this analysis were the classified Landsat images and selected SLEUTH simulations every five years while the population statistics come from estimations based on Geolytics at the census-tract level and projections from the Florida Office of Demographic and Economic Research made at the county level. Additional demographic statistics were also obtained through the use of several formulas.

Analyzing the choropleth trend in just three main images from past (1970), present (2001) and future (2025), it is possible to say that in 1970 most census-tracts had population densities below 500 inhabitants per Km^2. Just the census-tracts of Pensacola, Milton, Fort Walton Beach and Niceville had choropleth densities above 500 inhabitants per Km^2. Therefore, some suburbs of Pensacola and Fort Walton Beach plus the cities of Milton and Niceville had densities between 500 and 1,000 inhabitants per Km^2. Some more central census-tracts in Pensacola and Fort Walton Beach had densities between 1,000 and 1,500 inhabitants per Km^2. And these densities are even higher into the most centric areas of Pensacola city, existing in 1970 census-tracts with 1,500 to 2,000 inhabitants per Km^2 and from 2,000 to 2,500 inhabitants per Km^2.

Thirty one years later, the image from the year 2001 shows the city of Pensacola with most census-tracts having densities between 500 and 1,000 inhabitants per Km^2. In Milton, the densities are between 500 and 1,000 inhabitants per Km^2. Fort Walton Beach is the city with the highest population density in the region, where many zones have values above 1,500 inhabitants per Km^2. The city of Florosa also presents values of 1,000 to 1,500 inhabitants per Km^2, while Oriole Beach, Valparaiso and Destin presented generally densities of 500 to 1,000 inhabitants per Km^2. Finally, as it was mentioned before, most census-tracts in these three counties present population densities below 500 inhabitants per Km^2, in a similar way as most past images.

Looking twenty four years into the future, in the year 2025 most censuses tracts in Pensacola will have densities between 1,000 to 1,500 inhabitants per Km^2. The main changes in this city will occur in the suburbs of Pensacola, while the downtown of this city still will decrease its densities. Here, some censuses tracts will diminish from into 500-1,000 inhabitants per Km^2 in 2025. In Milton and the southeast part of Crestview, the densities will be between 500 and 1,000 inhabitants per Km^2. Fort Walton Beach still will show higher densities than Pensacola, with most of its census-tracts above 1,000 inhabitants per Km^2, and even a census-tract in its northwest part will increase its density 3,500 inhabitants per Km^2 in 2020. These high densities of Fort Walton Beach are because the lack of lands due that the Eglin Air Force Base is surrounding this city as well as the city of Niceville. Finally, as it was mentioned before, most census-tracts corresponding to the rural areas of this region will present population densities below 500 inhabitants per Km^2.

Analyzing the dasymetric trend in just five main maps from past (classified image 1974), present (classified image 2001) and future (three maps from 2025 depicting normal trend, smart growth and urban sprawl), it is possible to say that in 1974 the city of Pensacola presented most census-tracts with dasymetric densities between 2,000 to 3,000 inhabitants per Km^2. Some census-tracts in the downtown area had densities of 4,000 to 5,000 and a few ones even greater than 5,000 inhabitants per Km^2. The density is lower in the suburbs (less than 2,000 inhabitants per Km^2). Fort Walton Beach has a similar pattern as Pensacola (high density in downtown and decreasing density in suburbs). Gulf Breeze also presents densities above 4,000 inhabitants per Km^2. Instead, the cities of Milton and Crestview showed very low population densities (less than 2,000 inhabitants per Km^2) while the densities were low on the beaches of Santa Rosa island and others because much of these areas in 1974 were just barren lands. Many rural areas also presented a rare phenomenon, showing very high population densities, but the reason is that Landsat images (medium-resolution at 30m) do not represent accurate the population density in rural areas where small houses (less than 300 m^2) are located on large pieces of land, presenting consequently many inaccuracies because urbanized pixels may be designated as grass or forest instead of urban and falsely low numbers of urban pixels increases population density.

In 2001, according to the classified Landsat image, the dasymetric densities in Pensacola City present some census-tracts with low densities, between 2,000-3,000 inhabitants per Km^2 while others are higher: 3,000-4,000 inhabitants per Km^2. Fort Walton Beach has a similar pattern as Pensacola (high density in downtown and decreasing density in suburbs). Instead, Gulf Breeze presents lower densities than the simulations, just between 1,000-2,000 inhabitants per Km^2. And the cities of Milton and Crestview have densities between 2,000-3,000 inhabitants per Km^2 or even less in some censuses tracts. Finally, the beaches of Santa Rosa island and others have densities above 3,000 inhabitants per Km^2. This classified image also shows a more accurate picture of the rural areas, with low densities with pixel values below 2,000 inhabitants per Km^2, representing reality in the way it is: higher densities in the cities and lower ones in the countryside.

Looking into the future, the smart growth simulation of 2025 will show very high densities because of constraints to urban growth since 2001. The downtowns of Pensacola and Fort Walton Beach will have many census-tracts with dasymetric densities above 4,000 inhabitants per Km^2, with many of them even above 5,000 inhabitants per Km^2 and just a few with densities below 2,000 inhabitants per Km^2. The suburbs of Pensacola also will present similar densities to the ones in the center of the city. Gulf Breeze and Navarre will present densities between 3,000 to 4,000 inhabitants per Km^2. The city of Milton will have a density between 3,000 and 4,000 inhabitants per Km^2 whereas the city of Crestview will present values between 2,000 and 4,000 inhabitants per Km^2 or even more. Finally, the densities in Santa Rosa island and other beaches will increase and they will present densities above 3,000 inhabitants per Km^2 and even more. The rural areas also will increase their densities and in 2025 they will have all census-tracts above 3,000 inhabitants per Km^2 again due to the smart growth policies, where not enough urban pixels are generated by spontaneous and new spreading center growth.

In the normal growth simulation of 2025, the downtowns of the cities of Pensacola and Fort Walton Beach will show most census-tracts with dasymetric densities between 2,000 to 3,000 inhabitants per Km^2, with a few census-tracts in these areas with densities above 4,000 inhabitants per Km^2. Some census-tracts in the suburbs of Pensacola will present similar densities to the ones in the center of the city. Gulf Breeze will present densities below 3,000 inhabitants per Km^2, an increase in relation with the normal simulation of 2020. The cities of Milton and Crestview will show population densities of until 3,000 inhabitants per Km^2. The densities will be between 2,000 to 3,000 inhabitants per Km^2 in Santa Rosa island, whereas the other beaches will present higher population densities (until 4,000 inhabitants per Km^2). Finally, the densities in the rural areas will be between 1,000 to 2,000 inhabitants per Km^2 in some zones, while other ones will presents dasymetric densities between 2,000 to 3,000 inhabitants per Km^2, which were generated by spontaneous and new spreading center growth.

And the SLEUTH simulation of 2025 will show a decrease in densities due to the urban sprawl policies. In the centers of the cities of Pensacola and Fort Walton Beach, most census-tracts will present densities between 1,000 to 2,000 inhabitants per Km^2 or even less than 1,000 inhabitants per Km^2 with few census-tracts between 2,000 to 3,000 inhabitants per Km^2. The suburbs of Pensacola also will present similar densities to the ones in the center of the city. Gulf

Breeze will present densities between 1,000 until 4,000 inhabitants per Km^2. The cities of Milton and Crestview will show population densities of until 2,000 inhabitants per Km^2 with few census-tracts above 3,000 inhabitants per Km^2. The densities are also below 2,000 inhabitants per Km^2 in Santa Rosa island and in the other beaches containing urban settlements. The rural areas will present in 2025 densities below 2,000 inhabitants per Km^2 matching reality with higher accuracy than before because the countryside in fact have densities lower than urban areas.

Finally, Chapter 6 is concerned with the accuracy of the results obtained from the censuses from the sky applied into past, present and future SLEUTH simulations. After dasymetric densities had been calculated and spatially represented, this same information about demographic data and urbanized surfaces is used to know the degree in which urban areas are predicting population statistics through a chronological series of linear regressions for the 110 census-tracts, where population becomes the dependent variable (Y) of urban areas (X). The input data for this linear regression model consist of two kinds of data: first, the count of the number of urbanized pixels in every census-tract obtained from urban land-cover through satellite image classification or SLEUTH simulation (spatial independent variable X); and second, the statistics about population for every census-tract obtained from censuses (Geolytics) and estimated or projected from known values (statistical dependent variable Y).

Analyzing correlations and linear regressions results in all 110 censuses tracts from the classified images, is possible to say that the image from 2001 shows the highest coefficients: R=77.8%, and between 60.6% (according to R^2) and 60.2% (considering adjusted R^2). The classified image 1992 also presents a high correlation coefficient (R=72.0%), but the coefficient of determination (R^2=51.8%) and adjusted coefficient of determination (adjusted R^2=51.4%) are a little bit lower.

The classified image of 1986 presents very similar statistics to the classified image from 1986 with a slightly smaller correlation coefficient (R=71.1%), and with similar coefficients of determination (R^2=50.6%) and adjusted coefficient of determination (adjusted R^2=50.2%). And the classified image 1974 presents among the group of all four classified images the smaller correlation coefficient (R=67.8%) and very poor values for the coefficient of determination (R^2=46.0%) and adjusted coefficient of determination (adjusted R^2=45.5%). The main reason why some of these classified images have higher R, R^2 and adjusted R^2 values than others, is because when their accuracy was assessed against 1,500 random sample points collected from high-resolution digital photographs, they also presented different Kappa index of agreement for their urban land-covers. In this context, the classified image 1974 had the lowest Kappa index for urban land-cover (87.89% using land-cover 1974 as the reference image and 78.77% using points 1974 as the reference image) whereas the classified image 2001 has the highest Kappa index for urban areas (93.30% using land-cover 2001 as the reference image and 85.79% using points 2001 as the reference image) and identically, the image from 1974 also has the lowest coefficients of correlation and determination while the image from 2001 shows the best correlation and regression results. Nevertheless, in the case of the classified images from 1986 and 1992, the results not necessarily match this pattern; instead according to the Kappa indexes, the correlation and regression values from the image of 1986 (91.28% using land-cover 1974 as the reference image and 84.36% using points 1974 as the reference image) are higher than expected in relation to the ones from the image of 1992 (84.37% using land-cover 1974 as the reference image and 79.56% using points 1974 as the reference image).

Among the group of the historical simulated images from 1975 until 2001, simulation 1980 has the highest correlation coefficient (R=73.5%), coefficient of determination (R^2=54.0%) and adjusted coefficient of determination (adjusted R^2=53.5%) between urban areas and population. The next best values present simulation 1985 with R=72.5%, R^2=52.6% and adjusted R^2=52.1%. Slightly lower values present simulation 1986, with R=71.5%, R^2=51.2% and adjusted R^2=50.7%. The rest of simulations present low values for their correlations and very poor statistics (below the threshold of 50%) for their coefficients of determinations and adjusted coefficient of determination. The main reason why these simulations present higher values than others can be explained because of small errors which accumulate over time through the simulation process from 1974 until 2001. These errors were already evaluated in Chapter 4 through error matrices and Kappa indexes of agreement, comparing the collected 1,500 sample points from high-resolution photographs against the SLEUTH simulations for years 1986, 1992 and 2001, not being possible to have Kappa indexes for all simulations. In this scenario, the closer in time (number of years) the simulation is from its beginning (year 1974), in general the higher will be its correlation and coefficient of determination; in the other hand, the farther away the simulation is from in time from its beginning in 1974, in general the lower will be its correlation and coefficient of determination.

Even if the values of the historical simulations are generally poor; nevertheless, the values of the simulations into the future projected from the last classified image of 2001 into year 2025 are quite high, with the highest coefficients for smart growth in 2010, whereas normal trend and urban sprawl simulations have astonishing their highest measures for year 2025. It is more difficult to explain based on solid proof of the behavior of the simulations into the future because of the lack of physical evidence (imagery). Nevertheless, because it was used a linear regression model, is possible that the coefficients of correlation and regression for the simulation based on smart growth trend will be higher near the beginning of the simulation process (year 2001) because this trend tends to just slightly increase the number of urbanized pixels, consequently increasing population densities and the differences in the cloud of points (represented by census-tracts) in relation with the regression line. These differences are more difficult to evaluate when the graphics are made of cumulative frequencies instead of raw values, as is the case in this dissertation; nevertheless, this differences are showed in the values of R, R^2 and adjusted R^2. Contrary to what happens with the smart growth trend, in the case of the normal trend and urban sprawl simulations both tend to increase in a moderate and faster speeds the numbers of urbanized pixels, consequently maintaining or diminishing population densities and the differences in the cloud of points (represented by census-tracts) in relation with the regression line as it can be verified in the values of R, R^2 and adjusted R^2 specially in the final years when the regressions were applied to the simulations 2025 using normal and sprawl trends.

It is important to evaluate the degree of accuracy not just spatially (through error matrices and Kappa indexes) but also demographically between the classified Landsat images and the SLEUTH simulations with the real, estimated and projected population data at the census-tract level. Therefore, in order to generate these comparisons it is necessary to use just the urban pixels (the only ones that contain population) within the census-tracts from the maps already generated in the classified images and SLEUTH simulations. This statistical technique is called Censuses from the Sky, and it consists of two steps: First, in applying a linear regression to a small sample compose of a few census-tracts (just 10 were selected in this particular case) containing the number of urbanized pixels (spatial independent variable *X*) and the demographic data (statistical dependent variable *Y*) to obtain the unknowns *a* and *b* coefficients. The second step consists of using these two coefficients into the allometric growth model to derive the population estimations. Finally, the actual or real population values are compared against the estimated population values that resulted from the application of the allometric growth model (censuses from the sky) using their differences in absolute and percentage values as well as the Root Mean Square Error (RMSE). This research compares estimated populations obtained in the censuses from the sky through the allometric growth model (logarithmic linear regression) against actual populations obtained through the dasymetric density method in Chapter 5, but if densities from these two methods will be compared as well, it will be possible to appreciate that always the linear regressions used in the censuses from the sky tend to smooth the density gaps among the different census-tracts, because depending on the urban configuration of the city in a certain moment of time (different zones, different residential densities, different heights of buildings within a census-tract and among them) is possible that in reality the best regression pattern for the cloud of points is not necessarily linear, but instead power, cubic or quadratic regressions.

The main idea behind this process also known as model calibration is to apply a linear regression to a small sample of censuses tracts (just 10 of them were selected: numbers 10, 20, 30, 40, 50, 60, 70, 80, 90 and 100) with their correspondence number of urbanized pixels as well as their demographic values, in order to obtain the unknowns a (y-intercept of the regression line or the value of Y when $X = 0$) and b coefficients (the slope of the regression line). As it was mentioned before, the input data for this linear regression model consist of two kinds of data: first, the count of the number of urbanized pixels in every census-tract obtained from urban land-cover through satellite image classification or SLEUTH simulation (spatial independent variable X); and second, the statistics about population for every census-tract obtained from censuses

(Geolytics) and estimated or projected from known values (statistical dependent variable *Y*). In these linear regression samples, what matters the most is to obtain the values of the *a* and *b* coefficients that later on will be used for the calculation of the allometric growth model.

The main conclusions from the results of the censuses from the sky indicate that the higher the surface of the urban areas (measured in Km^2), the higher is also their populations, with the exceptions of the classified Landsat images for years 1986, 1992 and 2001 with their respective simulations, because for every one of these mentioned years, both have exactly the same population values at the census-tract level as well as in their total sums. The same happens with the simulations made from 2005 until 2025, because for every one of the selected years (2005, 2010, 1015, 2020 and 2025), the smart growth, normal and urban sprawl trends have exactly the same population at the census-tract level and in their total sums, regardless of the amount of urbanized areas.

Also, it is very interested that the results from the future simulations (2005 until 2025) show small differences between the total values of the actual population in relation to the estimated population, while their total RMSE (measured at the census-tract level) indicates high levels of errors. The reason why this asymmetries occur is simply because when the values of the estimated population at the census-tract level are added together, sometimes they are lower and sometimes they are higher than the ones from the actual population, and by coincidence, at the end of the sum, the total value of the estimated population can be similar to the one obtained from the sum of the actual population; therefore RMSE is always the best measure to evaluate the accuracy of the census from the sky.

In addition, because population estimates depend on the amount of urbanized areas according to the allometric growth model, and actual populations in the linear regression analyses made at the beginning of this chapter constitute the dependent variable *Y* of urban areas (independent variable *X*), it is possible to compare the differences in absolute and percentage values between the Total results of the estimated versus the actual populations for the whole region (Escambia, Santa Rosa and Okaloosa counties) against the correlation (R) and regression coefficients (R^2 and adjusted R^2) from table 6.1 (a linear regression of all 110 census-tracts between urban areas and actual populations). Doing this comparison, is possible to notice that in some cases (especially with normal and urban sprawl simulations) the lower the regression indexes are between urban areas and actual populations, the higher the differences are between estimated and actual populations, and vice versa, being the reason for this anomalies, the same one already explained: the coincidence at the end of the sum of adding sometimes lower and sometimes higher estimated population values in relation to the total actual population. Finally, this pattern sometimes does not occur between the Root Mean Square Errors (RMSE) for the 100 census-tracts and the measures obtained through linear regression analysis (with the exceptions of classified and simulated images from 1980 to 1992), being in most cases these results totally different, this lack of coincidences between the results of these two tables (correlation, coefficient of determination in relation with RMSE) has to do with the way how the formulas were designed to calculate these indexes, being enough to say that even if the measurement of values from the cloud of points to the regression line is always the same, the calculation of these errors varies according to the formulas used, becoming a whole new statistical topic beyond the area of interest of this current research that should not be explained nor analyzed into deepest details. The pattern that is always present in the analysis of RMSE results is the fact that the closer the simulations are from their origins (year 1974 for historical simulations and year 2001 for future simulations), the lower are their RMSEs, and vice versa.

7.2. Recommendations

After this research was completed, it is possible to mention main recommendations made to other researches as well as urban planners, geographers, environmental scientists, etc.

This research shows with great graphical, statistical and explanatory detail the different processes of how the images were processed, edited, simulated and mapped. It is very important for a researcher to depict with abundant information step by step the classification process, the SLEUTH simulations, the Dasymetric maps and the Census from the sky. The reason why is fundamental to explain all these procedures is simply because most investigations just briefly talk about the methods used and after show the results, but the lack of this detailed methodology can easily generate many problems, complications and therefore, many hours are lost just trying to figure out how to solve this problems.

In this research, wetlands increased because of deltatron dynamics, while in reality they should have been static through time. It is important to modify the deltatron dynamics of SLEUTH because is based in random procedures and transition probabilities matrices that many times do not match the real processes of landscape evolution.

Knowing that the current research is based on three counties in northwest Florida, a region affected by continuous hurricanes, some researches may want to know why this investigation do not presents too much information or do not emphasizes on any of these weather related problems. The reason is simply because the structure of this dissertation consists on just four Landsat images that were acquired in dates without hurricanes (it will appear a big cloud in the whole image) or flooding. And even if Landsat images with 30m resolution will had been acquired after a hurricane, it will show flooded zones just for a some days or weeks, where urban areas simply will appear surrounded by water in the flooded zones, being impossible with this resolution to evaluate the magnitude of the damages at the building level, as usually is seen in photographs taken at lower altitude. Finally, this kind of images will generate just distortions for a long term comprehension of urban growth and landscape changes, possible showing after classification areas with urban pixels (in clusters or isolated) within big bodies of water or wetlands. Nevertheless, it is necessary to clarify that one or a time series of Landsat images can be used to assess the magnitude of natural phenomena damages in a city or region, but this kind of research is different from the main purpose of this dissertation.

This investigation also was not developed to show global warming effects. Nevertheless, the only possible conclusion about this topic is that from the classified images since 1974 until 2001, it has been impossible to determine any changes in sea levels, instead the water land-cover is almost unchanged during these 27 years and it seems that this trend will continue at least for many decades more.

It is very important to notice that the predictions made in this research concerning with urban growth and landscape changes have a good degree of accuracy among simulations versus real data (classified images) at least until year 2001, when they are tested spatially. Beyond this year and until 2025, the simulations are really tested through the degree of accuracy obtained using censuses from the sky, in other words demographically instead of spatially, because of the impossibility to obtain future images. The main recommendation in this topic related with accuracy is always to perform simulations that are as close as possible to reality, instead of simulations based on ideas or ideals of different authors that at the end misrepresent reality, generating instead unrealistic apocalyptic scenarios as for example the GNO 1,000 Friends of

Florida (Zwick and Carr 2006) which create a simulation with exaggerated amounts of urban land for year 2060.

This investigation should be considered as a planning tool that can be used for the local Governments of Escambia, Santa Rosa and Okaloosa counties as well as for the Planning Departments of Incorporated cities such as Pensacola. For planning or policy making, it is especially important the simulations with three different scenarios as well as the projected dasymetric densities. Finally, this research can be also used for real state purposes or demographic studies.

It is necessary to understand that the SLEUTH simulation is not always necessarily the final product of a research, but instead just another step in the understanding of the urban dynamics, that logically are triggered by population changes. It would be very interesting if dasymetric densities and censuses from the sky will be applied to already existing SLEUTH simulations.

GLOSSARY

Accuracy Evaluation is a process of accuracy verification between two images (one representing ground-truth and the other one representing the classified image) using a method called cross classification. This evaluation can be done also using a specific number of sample points (stratified, random or systematic) in order to determine the percentage of agreement between the classified image and its true sample point.

Allometric Growth Model is based on linear regression in order to make predictions about a single value: population in the "urban areas" within the census-tracts. Through this model (linear regression) is possible to find the line that most nearly fits the given data; and then, this equation is used to predict values for the data. The linear regression equation has been modified in the allometric growth model, using logarithms instead of real numbers.

ArcMap is a Geographic Information software package elaborated by ESRI to perform spatial analysis, manage large amounts of spatial data, and to produce cartographically appealing maps to aid in decision making.

Breed coefficient that acts on the spreading growth of new centers determining the likelihood of isolated pixels to become urbanized and begin their own growth cycle.

Calibration Process is a technique used in SLEUTH and it performs brute force Monte Carlo runs through the historical data using every combination of the model coefficient values indicated. Calibration requires many (often thousands) of single simulations of land-cover change.

Cellular Automaton consists in a regular uniform array with a discrete variable at each cell. The state of CA is completely specified by the values of the variables at each site. CA evolves in discrete time steps, with the value of a variable at one site being affected by the values of the variables at sites in its neighborhood on the previous time step.

Choropleth Mapping assumes that the population has a uniform distribution throughout the political-administrative area of analysis. Therefore, the different values of specific attributes (in this case population) are divided by the surface area of the different counties or census tracks, and then placed uniformly in each administrative region without considering the difference in the spatial distribution of how populated areas in reality are, generating biased estimates of population densities.

Brute Force Monte Carlo Runs is a method that involves calibrating the data in steps, sequentially narrowing the range of coefficient values and increasing the data resolution. The model chooses randomly several places where cells have the potential to become urbanized.

Dasymetric Mapping uses categorical ancillary data sets (e.g. land-cover) derived from remotely sensed data to improve the distribution of spatial phenomena, generating finer grained studies in social and physical sciences.

Deltatrons are semi independent agents with their own life cycles able to store pixel's information (in a delta space) about the different types of land-cover transitions and their respective aging processes (in the case of urban cells) in order to bring new changes in the landscape.

Digital Elevation Model (DEM) is a type of raster GIS layer that represents the world as a regular arrangement of locations. In a DEM, each cell has a value corresponding to its elevation.

The fact that locations are arranged regularly permits the raster GIS to infer many interesting associations among locations.

Dispersion coefficient which affects urban spontaneous growth and determines the dispersiveness of the distribution through randomly selecting the number of times a pixel can be selected for possible development.

Digital Orthoimagery Quarter Quadrangle (DOQQ) is a computer-generated image of an aerial photograph in which the image displacement caused by terrain relief and camera tilt has been removed. The DOQQ combines the image characteristics of the original photograph with the georeferenced qualities of a map.

Edge Growth this type of growth is the most common type of development and occurs at the edges of already urbanized clusters where according to the limitation of the slopes, new cells have a fixed probability to become urbanized in a process of expansion of developed cells spreading outward their urban characteristics if they present three or more urbanized neighbors within the 3×3 Moore neighborhood.

ERDAS Imagine is a Remote Sensing software package elaborated by Leica Geosystems designed specifically to process geospatial imagery and to extract specific data from images.

False Color Composite is a multispectral image with colors assigned arbitrarily to each of its three bands. Therefore FCI look different from True Color Composite images.

Gaussian Maximum Likelihood Classifier is a classifier algorithm used to improve the land-cover accuracy classification from satellite images and digital air photos assigning equal probabilities to each class.

Geographic Information Systems (GIS) are a group of software packages used in geographic analysis and digital cartography designed for capturing, storing, analyzing, managing and presenting data which is geospatially referenced.

Kappa Coefficients is a multivariate technique that measures the proportion of agreement between two datasets (in this case two images) after chance agreement is removed from consideration.

Landsat Multi Spectral Scanner (MSS) is an instrument placed on the Landsat satellites able to take images in an area of 180*180 Kms. The MSS image has 4 spectral bands and a spatial resolution of 79 meters.

Landsat Thematic Mapper (TM) is an instrument placed on the Landsat satellites able to take images in an area of 180×180 Kms. The MSS image has 7 spectral bands and a spatial resolution of 30 meters.

IDRISI is an integrated GIS and Image-processing software package elaborated by Clarke Labs that provides many modules for the analysis and display of digital spatial information. Tools for land planning, decision support, and risk analysis are included in this program for spatial statistics, surface analysis, and spatial modeling.

New Spreading Center Growth happens when cells have two or more non-urbanized cells within a 3×3 Moore Neighborhood and the slope is low, new pixels can become randomly urbanized, acquiring these cells immediately a fixed probability to become a new spreading center, where two of its neighbors are randomly chosen and also urbanized.

National Land-Cover Data (NLCD) 1992 was the first land-cover mapping project with a national scope, providing 21 different land-cover classes at the native 30-meter resolution of Landsat TM for the conterminous 48 states with an accuracy classification higher than 85%. The acquisition date was 1992, but cloud cover and other factors forced to use scenes from other years before because of a lack of useable.

Percentage of Agreement is computed by dividing the total correct (sum of the major diagonal) by the total number of pixels of the error matrix.

Photoshop is a software package elaborated by Adobe Perfect that consists of image-editing capabilities, which include enhanced color-correction, cloning and healing tools, different image effects, fully customizable paint settings, artistic brushes, and drawing tools.

Producer's accuracy relates to the probability that a reference sample (photo-interpreted land-cover class in this project) will be correctly mapped and measures the errors of omission (1 - producer's accuracy).

Road-gravity coefficient determines the distances and possibilities of urbanization in cells along the roads according to the pixels-roads distances and the dimensions of the image.

Road-influenced Growth because urbanization processes tend to follow lines of transportation, new cells randomly chosen are able to become developed along the transportation network.

Remote Sensing is the field of study of images taken from satellites, airplanes, etc and the ways how this images or photographs are processed.

Slope-resistance factor generates urban limitations to steeper or critical slopes, while making soft slopes suitable for urbanization.

Spontaneous Growth occurs outside the boundaries of a group of urbanized pixels, where new cells are randomly chosen to become urbanized anywhere on the landscape if they fall in a suitable location according to the slope values: if the slope is 0% the probabilities for a cell to become spontaneous urban is high, but if the slope is 20% or higher the probabilities for a cell to become spontaneous urbanized is zero.

Spread coefficient which determines the probability of new pixels becoming urbanized through a process of outward expansion that occurs in the edges of existing urbanized clusters;

SPSS is a statistical software package developed by SPSS, Inc. and it is used for statistical analyses, able to process cross tabulation frequencies, means, t-tests, ANOVA, correlation, regression methods, factor analysis and cluster analysis.

Supervised Classification is a method of image classification where the user needs to select areas in order to indicate what kind of spectral properties will be used in the selection of every land-cover category.

TIGER files are spatial vector files from the U.S. Census Bureau used in GIS that contain population datasets.

Spatial resolution refers to the Ground Sample Distance (GSD) of an image or in other words, how much of the earth's surface a single pixel covers.

Spectral resolution means how many bands and how narrow or wide these bands are in an image.

SLEUTH is a software package product developed by the US Geological Survey in collaboration with the Department of Geography, UC Santa Barbara that uses CA, terrain mapping and land-cover deltatron modeling to address urban growth and landscape changes.

User's accuracy indicates the probability that a sample from land-cover map actually matches what it is from the reference data (photo-interpreted land-cover class in this project) and measures the error of commission (1- use's accuracy).

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http://seamless.usgs.gov/website/seamless/products/1arc.asp

Escambia county GIS Data

http://data.geocomm.com/catalog/US/61093/2804/index.htm

Florida Clearinghouse

http://www.fgdl.org/

http://data.geocomm.com/

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Statistical - Demographic Data

Census Boundaries Maps

http://www.census.gov/geo/www/cob/index.html

Census Tiger Files Data

http://www.census.gov/geo/www/tiger/index.html

Census 2000 Basic Data

http://factfinder.census.gov/servlet/GCTTable?_bm=y&-

geo_id=04000US12&_box_head_nbr=GCT-PH1&-ds_name=DEC_2000_SF1_U&-format=ST-

Florida’s Office of Economic and Demographic Research http://edr.state.fl.us/population.htm

Historical Census-tract Data from Geolytics

http://www.geolytics.com/

Population Projections

http://www.census.gov/population/www/projections/popproj.html

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APPENDIX I: COORDINATES THAT ENCLOSE CLOUDS AND THEIR SHADOWS

Table A-I.1: Coordinates that enclose clouds and their shadows in Rectangles: Land-cover 1986

AOI	Upper Left X	Upper Left Y	Lower Right X	Lower Right Y
1	450204.13	3430370.65	450495.05	3430122.65
2	441662.43	3416010.48	441939.04	3415633.71
3	442468.43	3415280.79	442630.58	3415128.17
4	442826.12	3414937.41	443660.74	3413983.56
5	441896.12	3414112.33	442291.97	3413716.48
6	441810.27	3413549.56	442067.81	3413349.25
7	442816.58	3414966.02	443694.12	3413897.71
8	455643.28	3369522.23	457909.13	3368347.34
9	461042.17	3370864.96	462356.92	3369969.81
10	455643.28	3369522.23	457853.19	3368403.29
11	458552.52	3368599.11	462776.52	3365969.60
12	444062.25	3370025.75	445544.84	3369158.58
13	437991.99	3367256.38	457125.87	3354360.59
14	437991.99	3351115.66	444202.11	3348933.73
15	483591.65	3371485.11	484525.86	3370447.10
16	460202.96	3354612.35	461321.90	3353045.83
17	477504.58	3382711.74	479630.56	3380795.56
18	483784.63	3413468.62	484959.52	3412629.41
19	487477.13	3418503.85	495617.42	3412153.86
20	491589.24	3430952.06	492708.18	3429805.15
21	499086.14	3421720.80	507030.62	3414251.87
22	496065.00	3395733.41	499114.11	3394138.92
23	469210.43	3369578.18	472007.78	3367899.77
24	473042.80	3371396.46	473518.35	3370892.93
25	474749.19	3368990.74	475644.34	3368235.45
26	476903.15	3370221.57	477574.51	3369690.07
27	474665.26	3369018.71	475616.36	3368207.48
28	476427.60	3370277.52	477546.54	3369746.02
29	474245.66	3369046.68	475644.34	3368179.50
30	474357.56	3368627.08	482861.50	3362668.72
31	482973.40	3371452.40	484539.91	3370501.30
32	513940.07	3369522.23	520541.82	3367731.93
33	521660.76	3374193.81	526472.21	3369746.02
34	518247.99	3376403.72	519422.88	3375732.35
35	521968.47	3384012.51	524458.11	3383173.30
36	536151.04	3408153.65	537773.50	3407230.52
37	556767.52	3417189.09	558138.22	3416573.68
38	555368.84	3403258.28	558641.74	3402111.37
39	537158.09	3378166.05	537689.58	3377186.97
40	536179.01	3373522.44	541074.38	3371480.38
41	542025.48	3371844.03	543899.70	3370948.88
42	546417.32	3376487.64	548123.70	3375005.04
43	547676.13	3374725.30	549466.43	3373802.18
44	547592.21	3370613.20	548039.78	3370081.70
45	556711.57	3377998.21	559984.47	3376935.21
46	439452.21	3400358.39	461530.05	3388861.89
47	460557.71	3416830.97	468851.20	3414257.13
48	461515.50	3361778.45	469988.21	3356686.27
49	462029.00	3357114.18	463227.16	3355830.44
50	460274.55	3354461.11	461601.08	3353091.79
51	462157.37	3351551.29	463398.32	3349925.22
52	537442.44	3362039.18	545531.02	3351594.09

Table A-I.2: Coordinates that enclose clouds and their shadows in Rectangles: Land-cover 2001

AOI	Upper Left X	Upper Left Y	Lower Right X	Lower Right Y
1	438000.00	3431000.00	451140.00	3421670.00
2	475260.00	3426560.00	477780.00	3425480.00
3	480000.00	3428480.00	480900.00	3427700.00
4	474780.00	3424160.00	475740.00	3423260.00
5	469380.00	3406580.00	470040.00	3405680.00
6	490080.00	3431000.00	545040.00	3388940.00
7	474876.82	3424081.82	475551.53	3423407.11
8	476580.00	3385100.00	478920.00	3384440.00
9	483000.00	3375980.00	484140.00	3375080.00
10	483780.00	3373520.00	485040.00	3371240.00
11	529020.00	3385640.00	530040.00	3384800.00
12	538080.00	3384080.00	539160.00	3383360.00
13	549540.00	3388280.00	559380.00	3373280.00
14	491820.00	3358760.00	498780.00	3355040.00
15	493866.25	3415859.17	494442.01	3415475.32
16	559900.55	3347982.63	560000.00	3347990.00
17	437991.99	3348010.60	438000.00	3347990.00
18	438000.00	3431000.00	438075.91	3430868.14
19	482449.84	3353994.64	489923.51	3350050.20
20	463142.85	3349323.60	482657.44	3347974.18
21	497916.19	3356901.07	505389.86	3348285.59
22	508192.49	3359496.10	509541.90	3358458.09
23	537360.58	3353371.84	560010.00	3347990.00
24	538917.59	3356070.66	541201.21	3351711.02
25	553242.13	3359392.30	554072.54	3358146.68
26	557186.57	3358977.09	559885.40	3353994.64
27	485979.07	3355447.86	492829.94	3352749.03
28	495113.56	3357108.67	505493.66	3351295.82
29	497560.74	3411492.95	498376.41	3410581.32
30	499144.10	3411061.12	499527.94	3410533.34
31	500247.65	3416578.87	500871.39	3415907.15
32	500007.74	3413987.93	500487.55	3413556.11
33	500247.65	3411396.99	501015.33	3410725.26
34	531184.42	3409683.89	531599.62	3409112.98
35	503510.32	3429677.54	504086.08	3428909.85
36	504853.77	3429485.61	505141.65	3429053.79
37	504421.94	3427374.47	504805.79	3426990.63
38	502550.71	3416243.01	503462.34	3415331.38
39	502886.57	3412740.44	504805.79	3408997.96
40	491755.11	3399401.88	492618.76	3397770.54
41	495833.45	3399401.88	497272.86	3398778.13
42	501974.94	3398154.38	502694.65	3397578.62
43	495977.39	3395899.30	496601.13	3395323.54
44	500919.37	3395419.50	502118.88	3394459.89
45	506485.10	3428382.06	507060.87	3427902.26
46	504805.79	3421185.00	506916.93	3417250.60
47	506629.04	3414131.87	510131.62	3412740.44
48	507684.61	3411972.75	508020.48	3411636.89
49	506427.87	3411137.10	507362.08	3409164.89
50	508555.79	3404390.04	508971.00	3403974.83
51	507673.48	3398836.68	510735.61	3397642.97
52	513953.45	3431015.00	515406.66	3429302.28
53	513226.84	3426343.95	514264.85	3425357.84
54	513797.74	3420738.70	514472.45	3420323.49
55	511462.22	3408801.58	512188.83	3408126.88
56	513019.24	3408126.88	513642.04	3407244.57
57	511721.72	3405324.25	516652.27	3404545.74
58	516029.47	3403144.43	517690.28	3401172.21
59	519714.40	3401172.21	520233.41	3400757.00
60	516807.97	3424631.24	518728.29	3419960.19
61	518105.49	3418143.67	518780.19	3417365.17
62	520025.81	3410514.30	524333.55	3406985.06
63	523866.44	3401172.21	524541.15	3400238.00
64	514939.56	3431000.00	536478.27	3418714.58
65	536478.27	3431000.00	544989.95	3427589.57
66	531132.52	3420946.30	536530.17	3418766.48
67	519403.00	3410670.00	529575.50	3405998.95
68	523866.44	3401172.21	524644.95	3400186.10

APPENDIX II: CALIBRATION TABLES FOR SLEUTH

COARSE CALIBRATION

Table A-II.1: Scenarios of Sub Calibrations using high-performance computer for Coarse Calibration

MC = 5	Coefficient Settings (Values)				
	Diff	**Brd**	**Sprd**	**Slp**	**RG**
Subsets	start / step / stop	start / step / stop	start / step / stop	start / step / stop	start / step / stop
sub_cal1a.sh	1 – 1 – 1	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal1b.sh	1 – 1 – 1	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal1c.sh	1 – 1 – 1	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal1d.sh	1 – 1 – 1	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal1e.sh	1 – 1 – 1	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal1f.sh	1 – 1 – 1	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal2a.sh	20 – 1 – 20	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal2b.sh	20 – 1 – 20	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal2c.sh	20 – 1 – 20	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal2d.sh	20 – 1 – 20	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal2e.sh	20 – 1 – 20	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal2f.sh	20 – 1 – 20	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal3a.sh	40 – 1 – 40	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal3b.sh	40 – 1 – 40	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal3c.sh	40 – 1 – 40	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal3d.sh	40 – 1 – 40	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal3e.sh	40 – 1 – 40	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal3f.sh	40 – 1 – 40	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal4a.sh	60 – 1 – 60	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal4b.sh	60 – 1 – 60	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal4c.sh	60 – 1 – 60	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal4d.sh	60 – 1 – 60	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal4e.sh	60 – 1 – 60	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal4f.sh	60 – 1 – 60	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal5a.sh	80 – 1 – 80	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal5b.sh	80 – 1 – 80	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal5c.sh	80 – 1 – 80	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal5d.sh	80 – 1 – 80	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal5e.sh	80 – 1 – 80	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal5f.sh	80 – 1 – 80	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal6a.sh	100 – 1 – 100	1 – 1 – 1	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal6b.sh	100 – 1 – 100	20 – 1 – 20	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal6c.sh	100 – 1 – 100	40 – 1 – 40	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal6d.sh	100 – 1 – 100	60 – 1 – 60	0 – 20 – 100	0 – 20 – 100	0 – 20 – 100
sub_cal6e.sh	100 – 1 – 100	80 – 1 – 80	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
sub_cal6f.sh	100 – 1 – 100	100 – 1 – 100	0 – 20 - 100	0 – 20 - 100	0 – 20 - 100
Total # of simulations		**7,776**			

Note: SLEUTH was unable to run in parallel; therefore, the author of this dissertation plays the role of the Master processor and sends sub-calibrations to be processed in different nodes, using 36 processors for coarse calibration.

Table A-II.2: Coarse Calibration: 36 sub-scenarios with Monte Carlo = 5

Name of Calibration	Processor-node	# of Simulations	Time
sub_cal 1a	C3-29	216	23h 52’ 16.19’’
sub_cal 1b	C2-30	216	23h 53’ 30.72’’
sub_cal 1c	C1-24	216	23h 55’ 12.59’’
sub_cal 1d	C2-22	216	23h 57’ 11.23’’
sub_cal 1e	C3-03	216	25h 25’ 42.84’’
sub_cal 1f	C4-26	216	23h 52’ 37.45’’
sub_cal 2a	C4-28	216	24h 00’ 42.73’’
sub_cal 2b	C4-10	216	23h 52’ 10.28’’
sub_cal 2c	C3-22	216	26h 38’ 41.58’’
sub_cal 2d	C2-32	216	24h 25’ 34.86’’
sub_cal 2e	C3-28	216	24h 37’ 34.07’’
sub_cal 2f	C4-02	216	25h 22’ 02.48’’
sub_cal 3a	C2-14	216	24h 23’ 34.61’’
sub_cal 3b	C1-20	216	24h 48’ 46.19’’
sub_cal 3c	C1-26	216	25h 09’ 29.73’’
sub_cal 3d	C3-13	216	25h 22’ 55.70’’
sub_cal 3e	C1-25	216	24h 54’ 39.27’’
sub_cal 3f	C3-20	216	27h 13’ 45.59’’
sub_cal 4a	C2-13	216	24h 07’ 26.38’’
sub_cal 4b	C3-12	216	26h 04’ 16.89’’
sub_cal 4c	C4-18	216	25h 32’ 15.04’’
sub_cal 4d	C1-26	216	25h 48’ 56.71’’
sub_cal 4e	C3-11	216	25h 15’ 58.77’’
sub_cal 4f	C4-09	216	25h 53’ 31.91’’
sub_cal 5a	C2-18	216	23h 43’ 19.32’’
sub_cal 5b	C1-14	216	25h 11’ 13.20’’
sub_cal 5c	C1-19	216	24h 56’ 29.62’’
sub_cal 5d	C4-02	216	26h 08’ 42.91’’
sub_cal 5e	C4-23	216	26h 31’ 43.39’’
sub_cal 5f	C3-06	216	25h 53’ 35.21’’
sub_cal 6a	C4-18	216	24h 46’ 26.45’’
sub_cal 6b	C3-13	216	25h 27’ 13.74’’
sub_cal 6c	C4-23	216	25h 34’ 58.11’’
sub_cal 6d	C1-27	216	25h 20’ 05.18’’
sub_cal 6e	C2-23	216	24h 07’ 59.48’’
sub_cal 6f	C2-11	216	26h 34’ 30.17’’
TOTAL		**7,776**	**Max. time: 27h 13’ 45.59’’**

Note: Results were computed using http://www.csgnetwork.com/timescalc.html

RESULTS FROM COARSE CALIBRATION

THAT ARE BEING APPLIED FOR FINE CALIBRATION

The Highest Lee & Salee indexes (64.98 and 64.98) from the control_stats.log file are being chosen among 7,776 simulations made in coarse calibration.

Table A-II.3: Control Stats file for sub_Cal 1a

Runs	Product	Compare	Pop	Edges	Clusters	Cluster Size	Lee & Salee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch
32, 33, 34, 35	4.41	60.84	99.83	90.35	64.56	75.00	64.98	91.04	99.83	29.97	95.19	99.95	98.43

Diff	Brd	Sprd	Slp	RG
1	1	1	100	40-60-80-100

Note: Lee and Salee: a shape index, a measurement of spatial fit between the model's growth and the known urban extent for the control years.

Table A-II.4: Control Stats file for sub_Cal 1b

Runs	Product	Compare	Pop	Edges	Clusters	Cluster Size	Lee & Salee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch
33, 34, 35	6.92	60.85	99.77	90.08	62.90	75.00	64.98	90.53	99.77	48.67	95.44	99.91	98.43

Diff	Brd	Sprd	Slp	RG
1	20	1	100	60-80-100

Note: Lee and Salee shape index: a measurement of spatial fit between the model's growth and the known urban extent for the control years.

FINE CALIBRATION

Table A-II.5: Scenarios of sub-Calibrations in a high-performance computer for Fine Calibration

MC = 8	Coefficient Settings (Values)				
	Diff	Brd	Sprd	Slp	RG
Subsets	start – step – stop	start – step – stop	start – step – stop	start – step – stop	start – step – stop
sub_cal1a.sh	1 – 1 – 1	1 – 1 – 1	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1b.sh	1 – 1 – 1	5 – 1 – 5	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1c.sh	1 – 1 – 1	10 – 1 – 10	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1d.sh	1 – 1 – 1	15 – 1 – 15	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1e.sh	1 – 1 – 1	20 – 1 – 20	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1f.sh	1 – 1 – 1	25 – 1 – 25	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1g.sh	1 – 1 – 1	30 – 1 – 30	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1h.sh	1 – 1 – 1	35 – 1 – 35	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1i.sh	1 – 1 – 1	40 – 1 – 40	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2a.sh	5 – 1 – 5	1 – 1 – 1	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2b.sh	5 – 1 – 5	5 – 1 – 5	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2c.sh	5 – 1 – 5	10 – 1 – 10	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2d.sh	5 – 1 – 5	15 – 1 – 15	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2e.sh	5 – 1 – 5	20 – 1 – 20	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2f.sh	5 – 1 – 5	25 – 1 – 25	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2g.sh	5 – 1 – 5	30 – 1 – 30	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2h.sh	5 – 1 – 5	35 – 1 – 35	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal2i.sh	5 – 1 – 5	40 – 1 – 40	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3a.sh	10 – 1 – 10	1 – 1 – 1	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3b.sh	10 – 1 – 10	5 – 1 – 5	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3c.sh	10 – 1 – 10	10 – 1 – 10	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3d.sh	10 – 1 – 10	15 – 1 – 15	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3e.sh	10 – 1 – 10	20 – 1 – 20	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3f.sh	10 – 1 – 10	25 – 1 – 25	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3g.sh	10 – 1 – 10	30 – 1 – 30	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3h.sh	10 – 1 – 10	35 – 1 – 35	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal3h.sh	10 – 1 – 10	40 – 1 – 40	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4a.sh	15 – 1 – 15	1 – 1 – 1	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4b.sh	15 – 1 – 15	5 – 1 – 5	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4c.sh	15 – 1 – 15	10 – 1 – 10	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4d.sh	15 – 1 – 15	15 – 1 – 15	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4e.sh	15 – 1 – 15	20 – 1 – 20	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4f.sh	15 – 1 – 15	25 – 1 – 25	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4g.sh	15 – 1 – 15	30 – 1 – 30	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4h.sh	15 – 1 – 15	35 – 1 – 35	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal4i.sh	15 – 1 – 15	40 – 1 – 40	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5a.sh	20 – 1 – 20	1 – 1 – 1	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5b.sh	20 – 1 – 20	5 – 1 – 5	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5c.sh	20 – 1 – 20	10 – 1 – 10	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5d.sh	20 – 1 – 20	15 – 1 – 15	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5e.sh	20 – 1 – 20	20 – 1 – 20	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5f.sh	20 – 1 – 20	25 – 1 – 25	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5g.sh	20 – 1 – 20	30 – 1 – 30	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal5h.sh	20 – 1 – 20	35 – 1 – 35	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
sub_cal1i.sh	20 – 1 – 20	40 – 1 – 40	0 – 5 – 20	80 – 5 – 100	20 – 10 – 100
Total # of simulations	**10,125**				

Note: SLEUTH was unable to run in parallel; therefore, the author of this dissertation plays the role of the Master processor and sends sub-calibrations to be processed in different nodes, using 45 processors for fine calibration.

Table A-II.6: Fine Calibration: 45 sub-scenarios with Monte Carlo = 8

Name of Calibration	Processor-node	# of Simulations	Time
sub_cal 1a	C3-10	225	36h 47' 47.92''
sub_cal 1b	C4-27	225	39h 02' 37.86''
sub_cal 1c	C1-27	225	37h 06' 20.28''
sub_cal 1d	C2-18	225	36h 21' 35.40''
sub_cal 1e	C2-38	225	37h 24' 08.23''
sub_cal 1f	C2-32	225	37h 07' 55.75''
sub_cal 1g	C3-02	225	37h 37' 25.52''
sub_cal 1h	C2-15	225	37h 33' 26.27''
sub_cal 1i	C2-34	225	38h 19' 13.81''
sub_cal 2a	C3-13	225	39h 19' 01.97''
sub_cal 2b	C4-20	225	37h 19' 34.02''
sub_cal 2c	C3-21	225	37h 13' 45.00''
sub_cal 2d	C3-34	225	37h 08' 16.89''
sub_cal 2e	C3-01	225	37h 14' 07.53''
sub_cal 2f	C1-01	225	34h 44' 11.03''
sub_cal 2g	C4-10	225	36h 22' 32.12''
sub_cal 2h	C3-20	225	36h 51' 13.69''
sub_cal 2i	C4-12	225	37h 31' 24.17''
sub_cal 3a	C4-27	225	38h 55' 54.30''
sub_cal 3b	C2-16	225	37h 37' 27.09''
sub_cal 3c	C4-03	225	37h 09' 34.23''
sub_cal 3d	C1-22	225	37h 45' 01.62''
sub_cal 3e	C3-23	225	36h 51' 07.20''
sub_cal 3f	C3-15	225	37h 30' 44.84''
sub_cal 3g	C3-08	225	37h 46' 52.80''
sub_cal 3h	C4-17	225	37h 38' 45.48''
sub_cal 3i	C2-13	225	38h 51' 34.03''
sub_cal 4a	C3-03	225	37h 20' 44.05''
sub_cal 4b	C1-17	225	36h 53' 38.11''
sub_cal 4c	C1-10	225	36h 02' 29.81''
sub_cal 4d	C4-13	225	37h 43' 00.06''
sub_cal 4e	C4-23	225	39h 04' 56.27''
sub_cal 4f	C3-29	225	36h 50' 52.14''
sub_cal 4g	C2-30	225	37h 09' 58.78''
sub_cal 4h	C2-19	225	37h 04' 19.31''
sub_cal 4i	C4-09	225	37h 56' 19.80''
sub_cal 5a	C1-25	225	37h 08' 07.00''
sub_cal 5b	C3-05	225	36h 55'53.16''
sub_cal 5c	C3-11	225	36h 36' 40.72''
sub_cal 5d	C4-05	225	37h 30' 37.88''
sub_cal 5e	C1-16	225	36h 45' 30.39''
sub_cal 5f	C2-21	225	37h 58' 03.91''
sub_cal 5g	C3-33	225	37h 23' 45.73''
sub_cal 5h	C1-23	225	37h 56' 39.80''
sub_cal 5i	C4-18	225	39h 28' 07.05''
TOTAL		**10,125**	**Max. Time: 39h 28' 07.05''**

Note: Results were computed using http://www.csgnetwork.com/timescalc.html

RESULTS FROM FINE CALIBRATION

THAT ARE BEING APPLIED FOR FINAL CALIBRATION

The Highest Product (18.84) from the control_stats.log file

is being chosen among 10,125 simulations made in the fine calibration

Table A-II.7: Control Stats file for sub_Cal 3i

Runs	Product	Compare	Pop	Edges	Clusters	Cluster Size	Lee & Salee	Slope	%Urban	Xmean	Ymean	Rad	Fmatch
86, 87, 88, 89	18.84	85.05	100.00	86.48	59.38	96.43	59.51	84.66	100.00	94.94	95.62	100.00	97.82

Diff	Brd	Sprd	Slp	RG
10	40	5	100	70-80-90-100

Note: Product index consists on all other metrics multiplied together.

FINAL CALIBRATION

Table A-II.8: Scenarios of sub-Calibrations using high-performance computer for Final Calibration

MC = 10	Coefficient Settings (Values)				
	Diff	Brd	Sprd	Slp	RG
Subsets	start step stop	start step stop	start step stop	start step stop	start step stop
sub_cal1a.sh	10 – 1 – 10	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal1b.sh	10 – 1 – 10	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal1c.sh	10 – 1 – 10	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal1d.sh	10 – 1 – 10	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal1e.sh	10 – 1 – 10	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal1f.sh	10 – 1 – 10	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2a.sh	12 – 1 – 12	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2b.sh	12 – 1 – 12	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2c.sh	12 – 1 – 12	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2d.sh	12 – 1 – 12	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2e.sh	12 – 1 – 12	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal2f.sh	12 – 1 – 12	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3a.sh	14 – 1 – 14	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3b.sh	14 – 1 – 14	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3c.sh	14 – 1 – 14	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3d.sh	14 – 1 – 14	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3e.sh	14 – 1 – 14	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal3f.sh	14 – 1 – 14	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4a.sh	16 – 1 – 16	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4b.sh	16 – 1 – 16	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4c.sh	16 – 1 – 16	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4d.sh	16 – 1 – 16	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4e.sh	16 – 1 – 16	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal4f.sh	16 – 1 – 16	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5a.sh	18 – 1 – 18	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5b.sh	18 – 1 – 18	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5c.sh	18 – 1 – 18	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5d.sh	18 – 1 – 18	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5e.sh	18 – 1 – 18	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal5f.sh	18 – 1 – 18	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6a.sh	20 – 1 – 20	40 – 1 – 40	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6b.sh	20 – 1 – 20	42 – 1 – 42	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6c.sh	20 – 1 – 20	44 – 1 – 44	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6d.sh	20 – 1 – 20	46 – 1 – 46	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6e.sh	20 – 1 – 20	48 – 1 – 48	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
sub_cal6f.sh	20 – 1 – 20	50 – 1 – 50	5 – 1 – 10	90 – 2 – 100	70 – 10 – 100
Total # of simulations		**5,184**			

Note: SLEUTH was unable to run in parallel; therefore, the author of this dissertation plays the role of the Master processor and sends sub-calibrations to be processed in different nodes, using 36 processors for coarse calibration.

Table A-II.9: Final Calibration: 36 sub-scenarios with Monte Carlo = 10

Name of Calibration	Processor-node	# of Simulations	Time
sub_cal 1a	C3-32	144	30h 36’ 25.52’’
sub_cal 1b	C3-03	144	29h 54’ 04.37’’
sub_cal 1c	C4-13	144	30h 27’ 23.53’’
sub_cal 1d	C2-04	144	30h 36’ 44.54’’
sub_cal 1e	C1-22	144	31h 32’ 50.38’’
sub_cal 1f	C2-14	144	30h 14’ 52.90’’
sub_cal 2a	C2-17	144	31h 10’ 34.70’’
sub_cal 2b	C1-30	144	30h 32’ 57.02’’
sub_cal 2c	C4-04	144	29h 49’ 17.19’’
sub_cal 2d	C3-05	144	30h 27’ 05.70’’
sub_cal 2e	C4-20	144	30h 38’ 01.03’’
sub_cal 2f	C4-18	144	30h 48’ 32.47’’
sub_cal 3a	C2-34	144	30h 42’ 50.22’’
sub_cal 3b	C4-21	144	30h 37’ 52.27’’
sub_cal 3c	C2-16	144	30h 07’ 40.38’’
sub_cal 3d	C2-33	144	30h 56’ 39.68’’
sub_cal 3e	C1-11	144	28h 58’ 45.72’’
sub_cal 3f	C1-07	144	29h 13’ 24.68’’
sub_cal 4a	C4-14	144	29h 46’ 27.07’’
sub_cal 4b	C1-23	144	30h 52’ 32.53’’
sub_cal 4c	C3-11	144	30h 29’ 51.95’’
sub_cal 4d	C3-25	144	30h 11’ 08.37’’
sub_cal 4e	C4-03	144	30h 56’ 56.60’’
sub_cal 4f	C2-25	144	30h 27’ 02.79’’
sub_cal 5a	C2-34	144	31h 39’ 11.70’’
sub_cal 5b	C2-38	144	30h 20’ 23.78’’
sub_cal 5c	C4-20	144	31h 05’ 05.55’’
sub_cal 5d	C1-20	144	30h 29’ 59.95’’
sub_cal 5e	C1-22	144	31h 36’ 40.47’’
sub_cal 5f	C2-27	144	30h 28’ 44.65’’
sub_cal 6a	C3-09	144	29h 58’ 37.09’’
sub_cal 6b	C4-12	144	30h 59’ 12.91’’
sub_cal 6c	C3-33	144	30h 04’ 34.88’’
sub_cal 6d	C3-08	144	30h 37’ 13.53’’
sub_cal 6e	C3-22	144	30h 36’ 24.92’’
sub_cal 6f	C2-33	144	31h 13’ 40.44’’
TOTAL		**5,184**	**Max. Time: 31h 39’ 11.70’’**

Note: Results were computed using http://www.csgnetwork.com/timescalc.html

APPENDIX III: SLEUTH SIMULATIONS

Table A-III.1 and Figure A-III.1: 120 nodes of AMD dual processor single core Opteron 248

AMD Dual processor Single core Opteron 248	Hyper-transport bus technology: 800 Mhz per processor
Number of computing cores: 2 (1 core per processor)	RAM Memory per Processor: 4GB
Number of Processors per node: 2	L-2 CPU Cache size: 1 Mb
CPU Speed: 2.2GHZ x 2	Operating system: Red Hat Linux EL4 - 64-bit

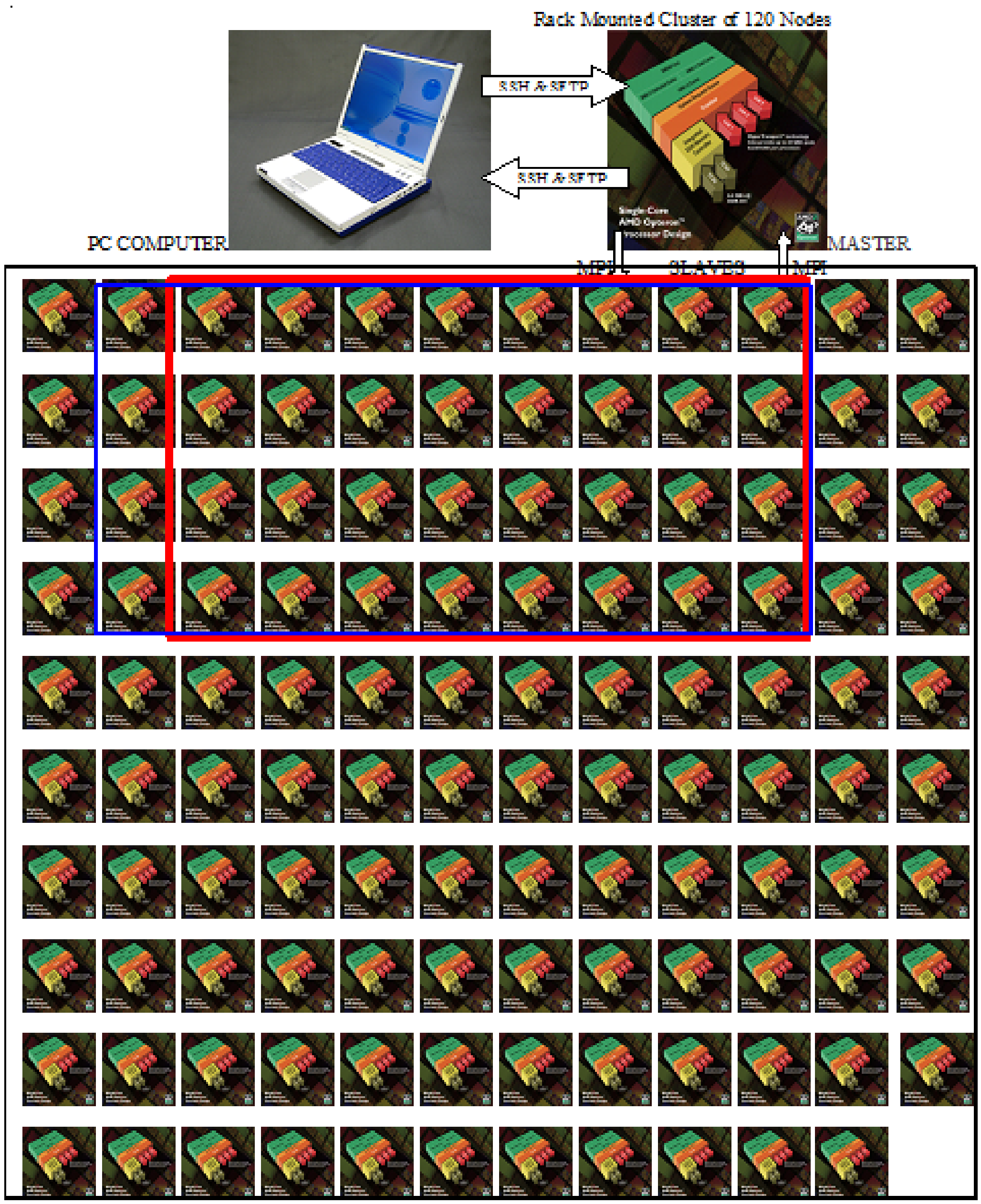


Table A-III.2 and Figure A-III.2: 39 Nodes of AMD Dual processor Dual core Opteron 275

AMD Dual processor Dual core Opteron 275	Hyper-transport bus technology: 1000 Mhz per processor
Number of computing cores: 4 (2 core per processor)	RAM Memory per Processor: 4GB
Number of Processors per node: 2	L-2 CPU Cache size: 1 Mb x 2
CPU Speed: 2.2GHZ x 4	Operating system: Red Hat Linux EL4 - 64-bit

Notes: Inside the red line are the maximum number of processor-nodes allowed to run = s32 or d16
Inside the blue line are the number of processor-nodes used to run the sub calibrations = 25-36

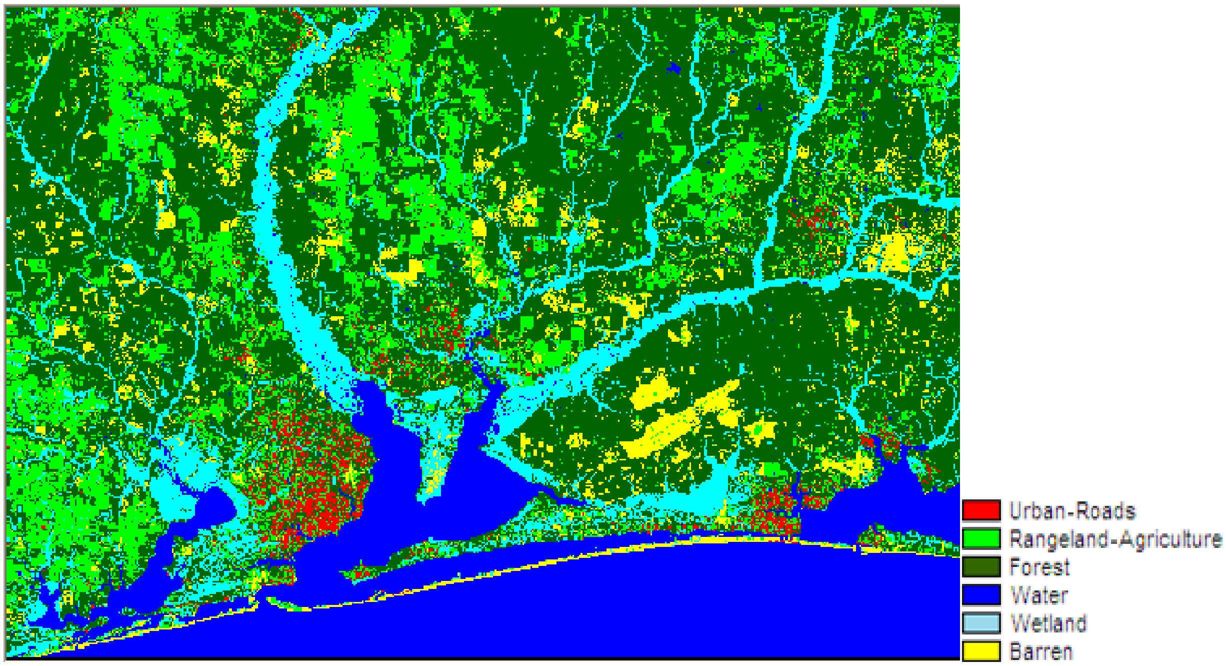


Figure A-III.3: Classified Landsat Image: Land-cover 1974

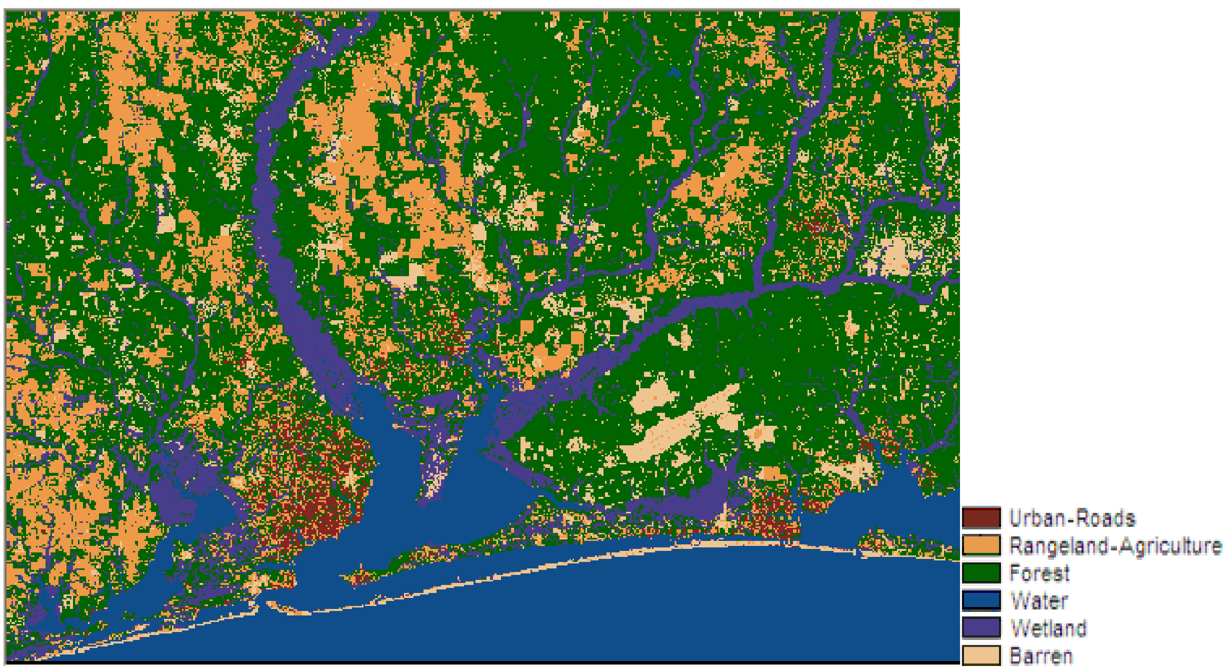


Figure A-III.4: SLEUTH Simulation: Land-cover 1975

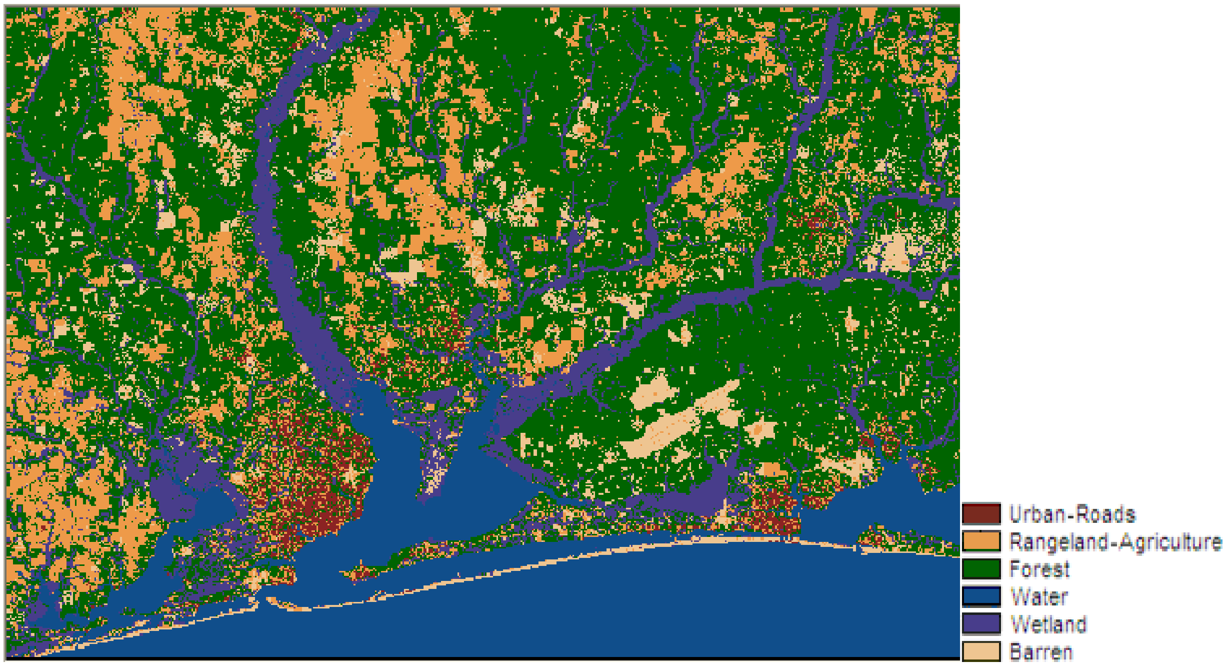


Figure A-III.5: SLEUTH Simulation: Land-cover 1980

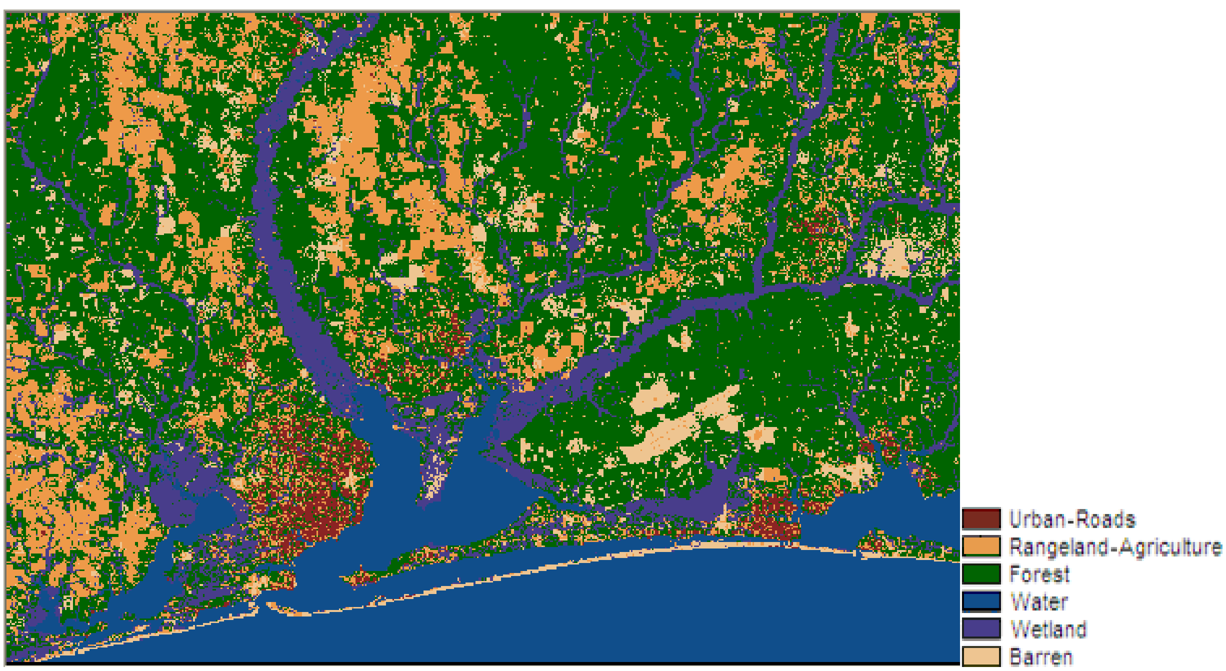


Figure A-III.6: SLEUTH Simulation: Land-cover 1985

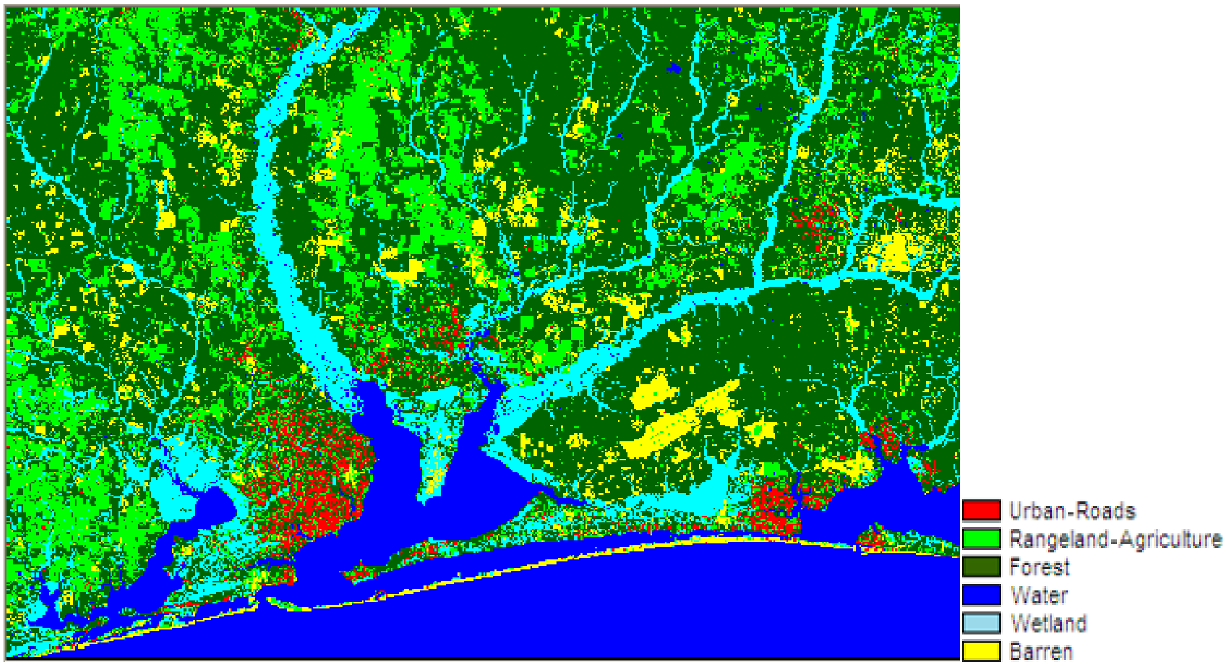


Figure A-III.7: Classified Landsat Image: Land-cover 1986

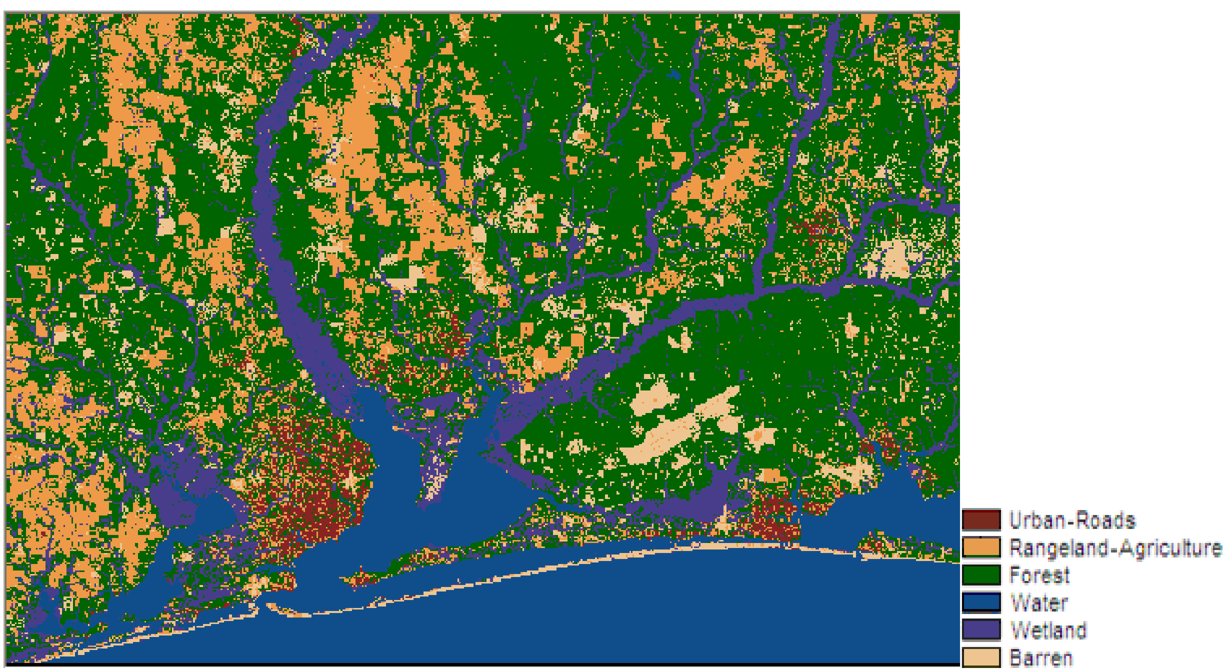


Figure A-III.8: SLEUTH Simulation: Land-cover 1986

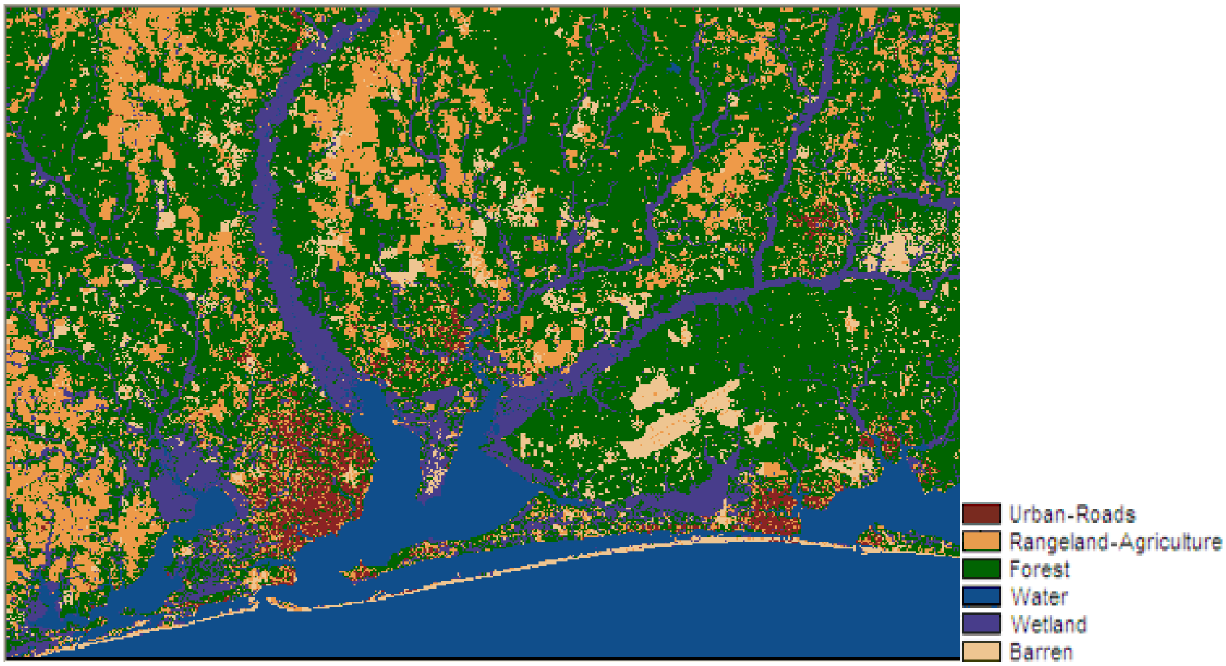


Figure A-III.9: SLEUTH Simulation: Land-cover 1990

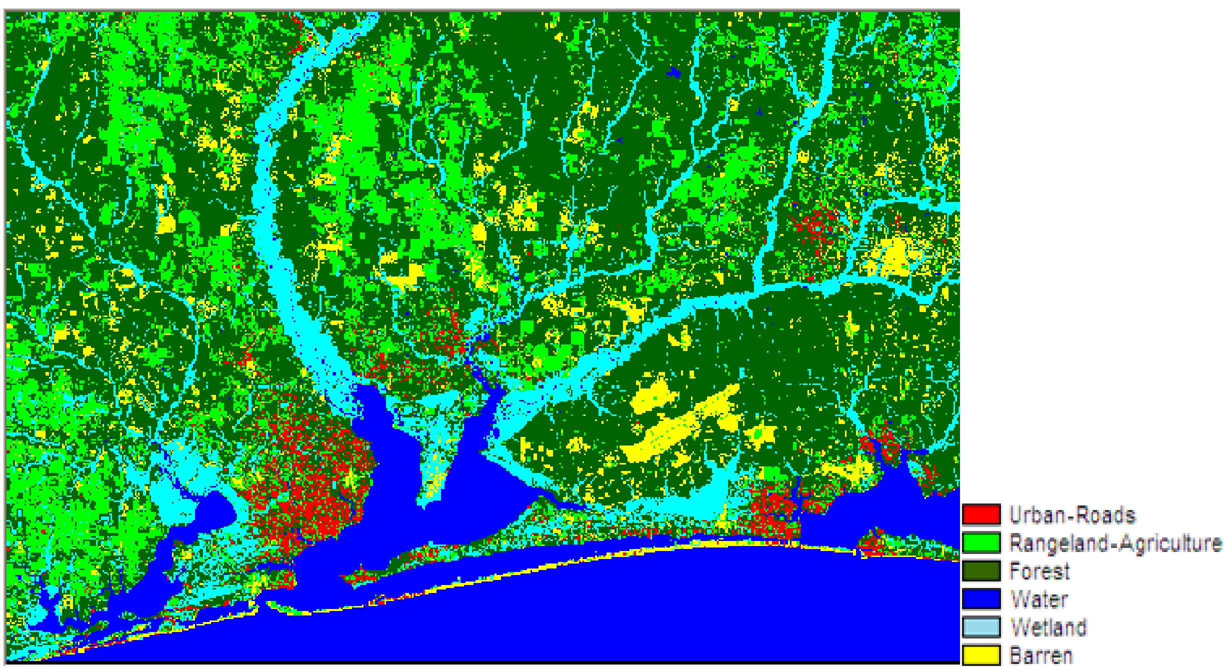


Figure A-III.10: Classified Landsat Image: Land-cover 1992

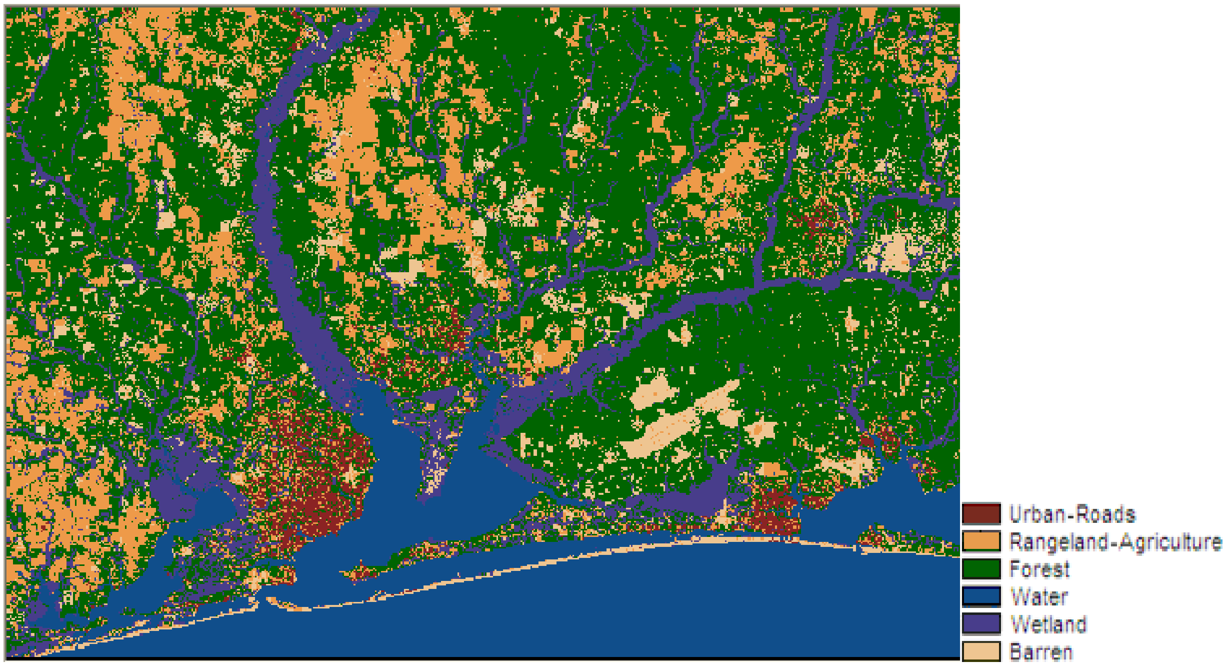


Figure A-III.11: SLEUTH Simulation: Land-cover 1992

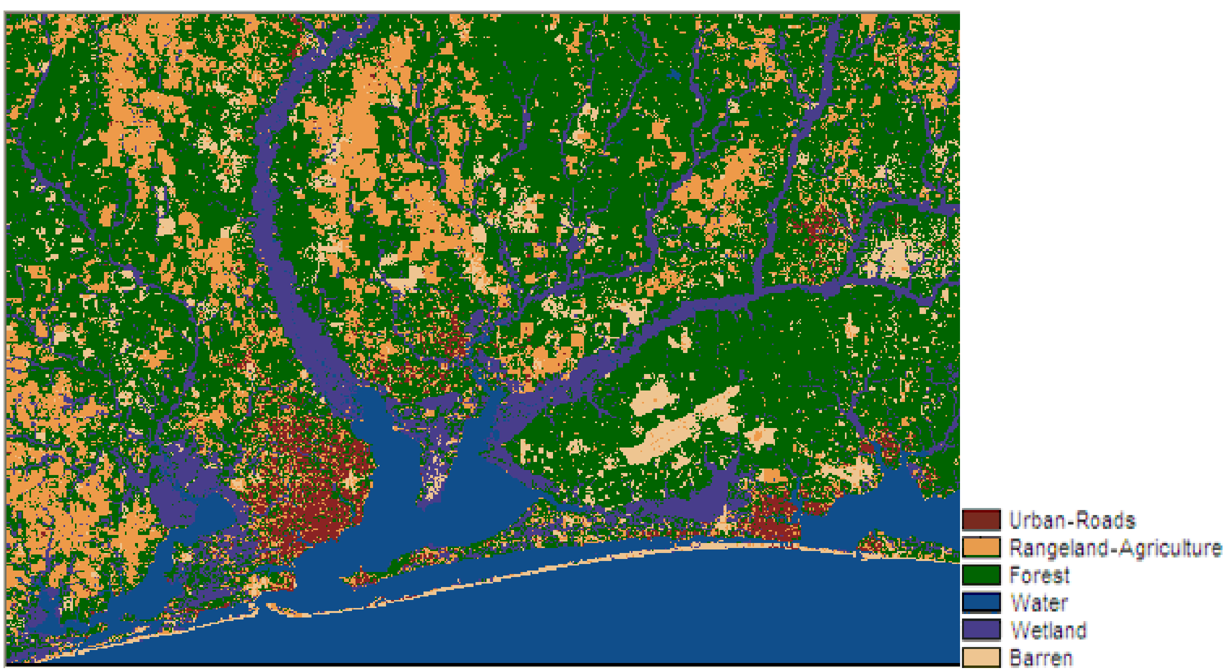


Figure A-III.12: SLEUTH Simulation: Land-cover 1995

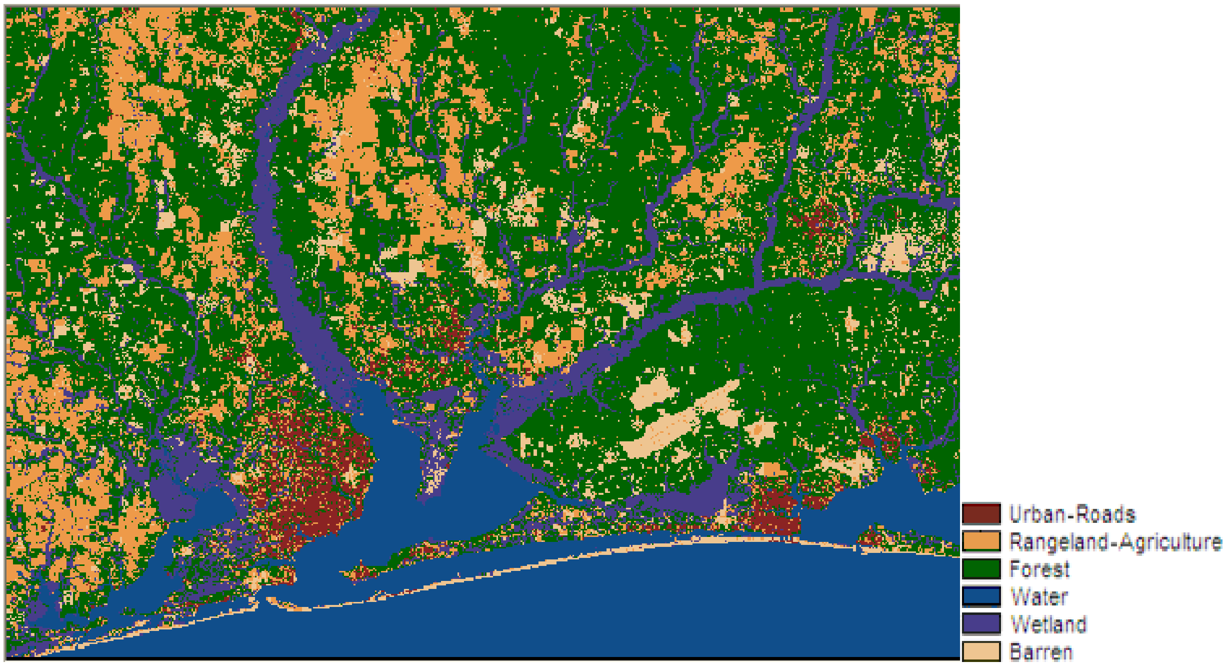


Figure A-III.13: SLEUTH Simulation: Land-cover 2000

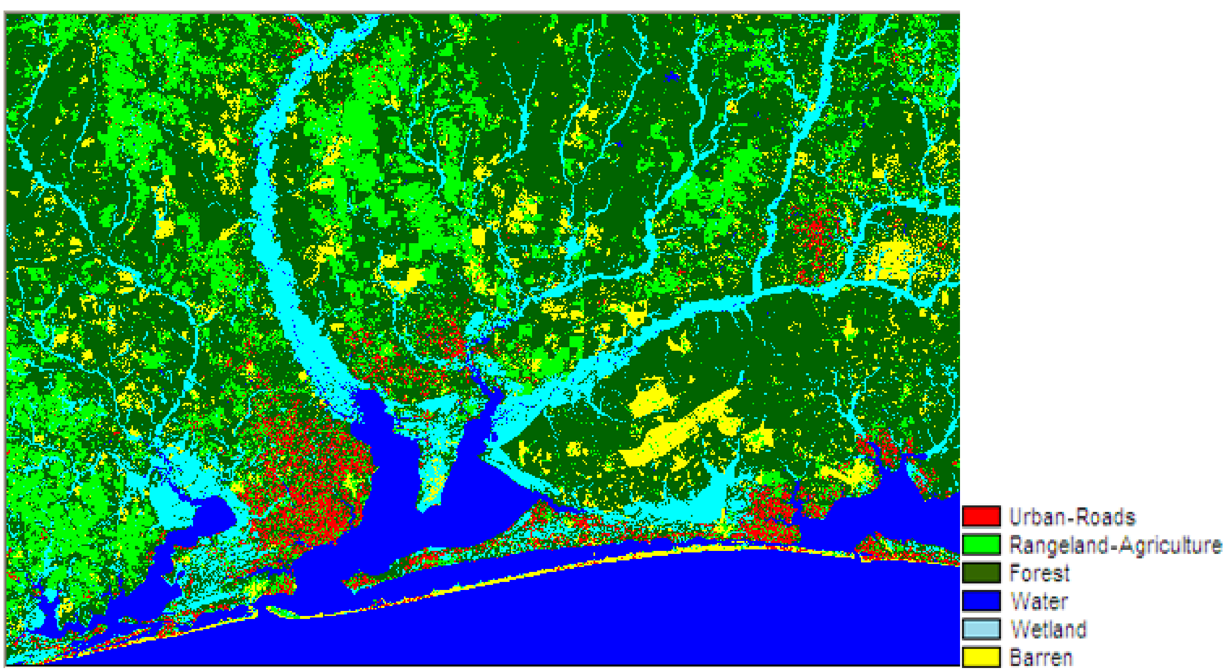


Figure A-III.14: Classified Landsat Image: Land-cover 2001

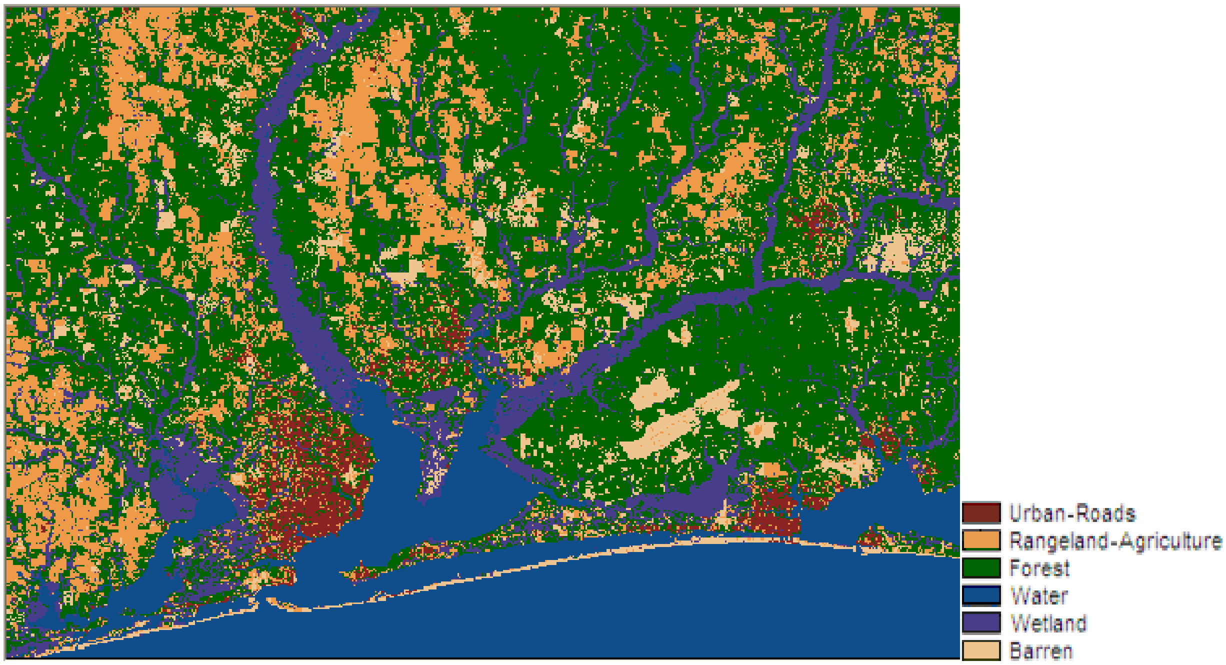


Figure A-III.15: SLEUTH Simulation: Land-cover 2001

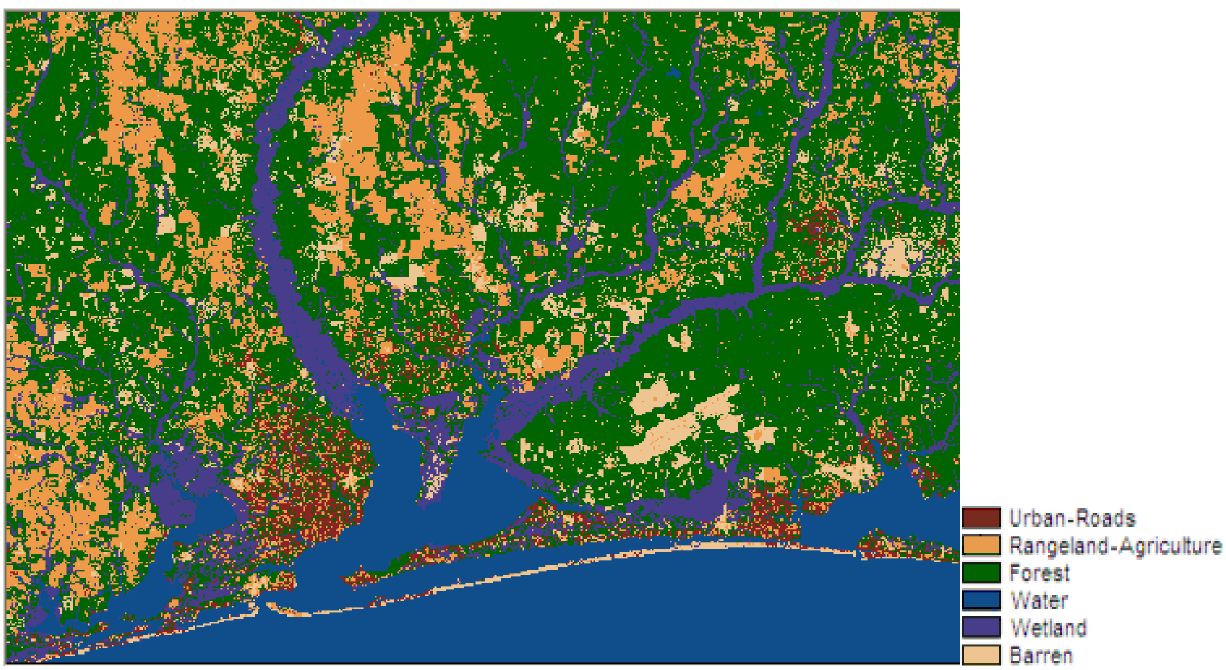


Figure A-III.16: SLEUTH Simulation: Land-cover 2005 Smart Growth

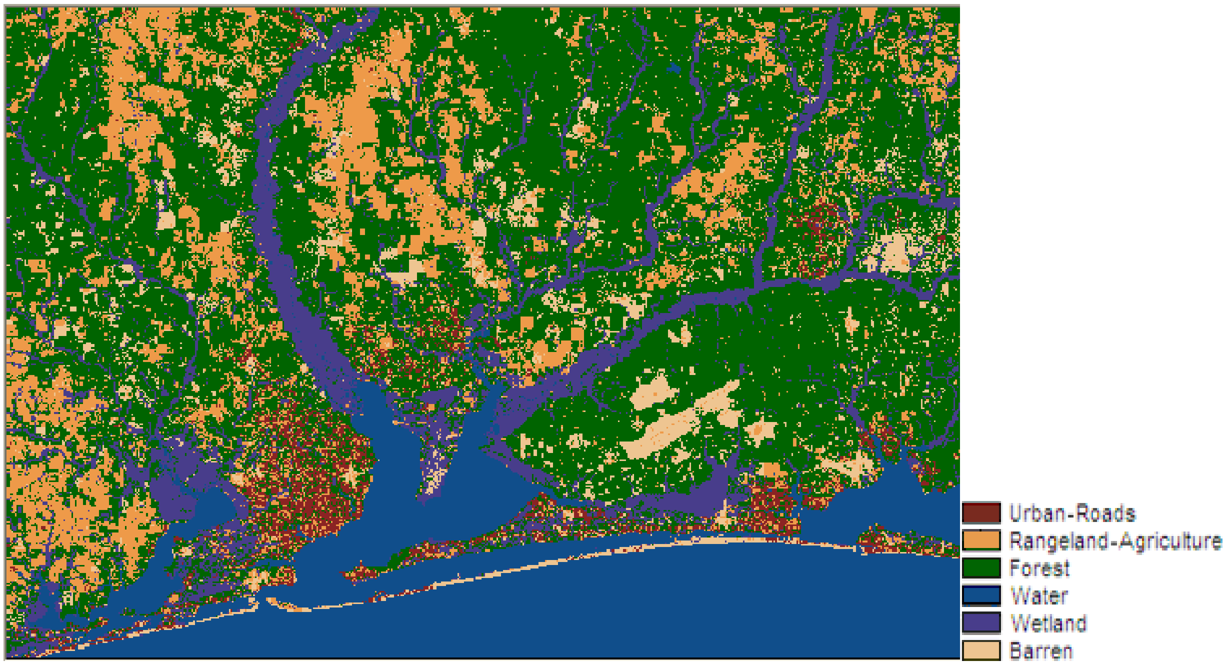


Figure A-III.17: SLEUTH Simulation: Land-cover 2005 Normal Trend

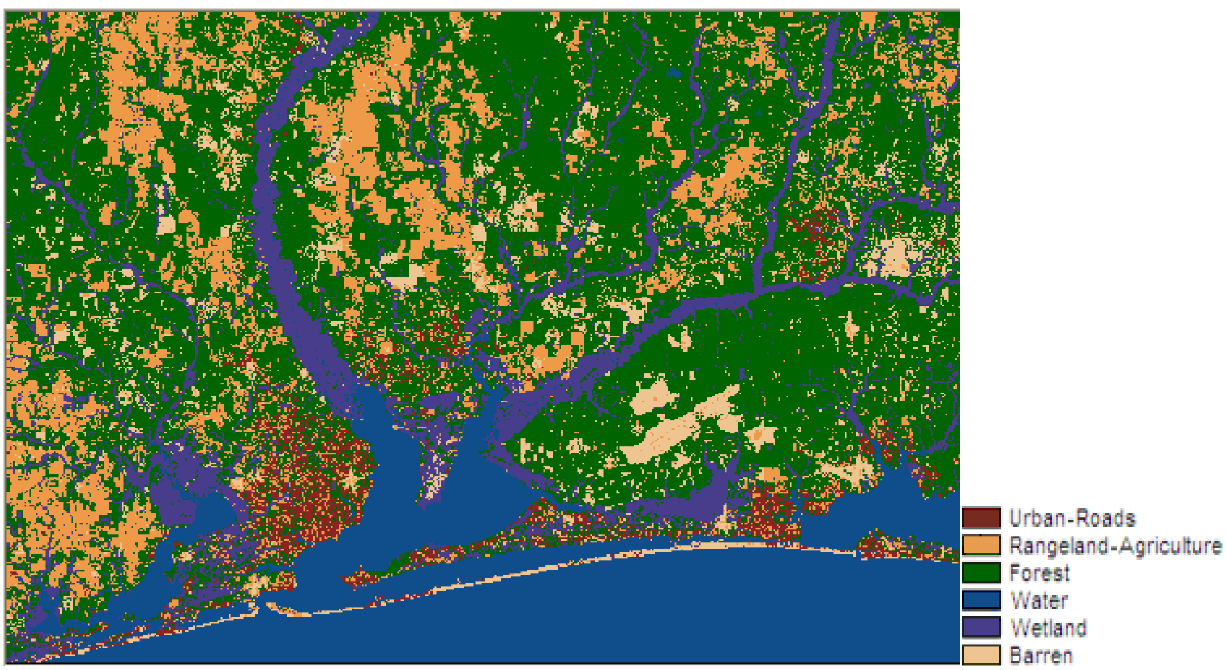


Figure A-III.18: SLEUTH Simulation: Land-cover 2005 Urban Sprawl

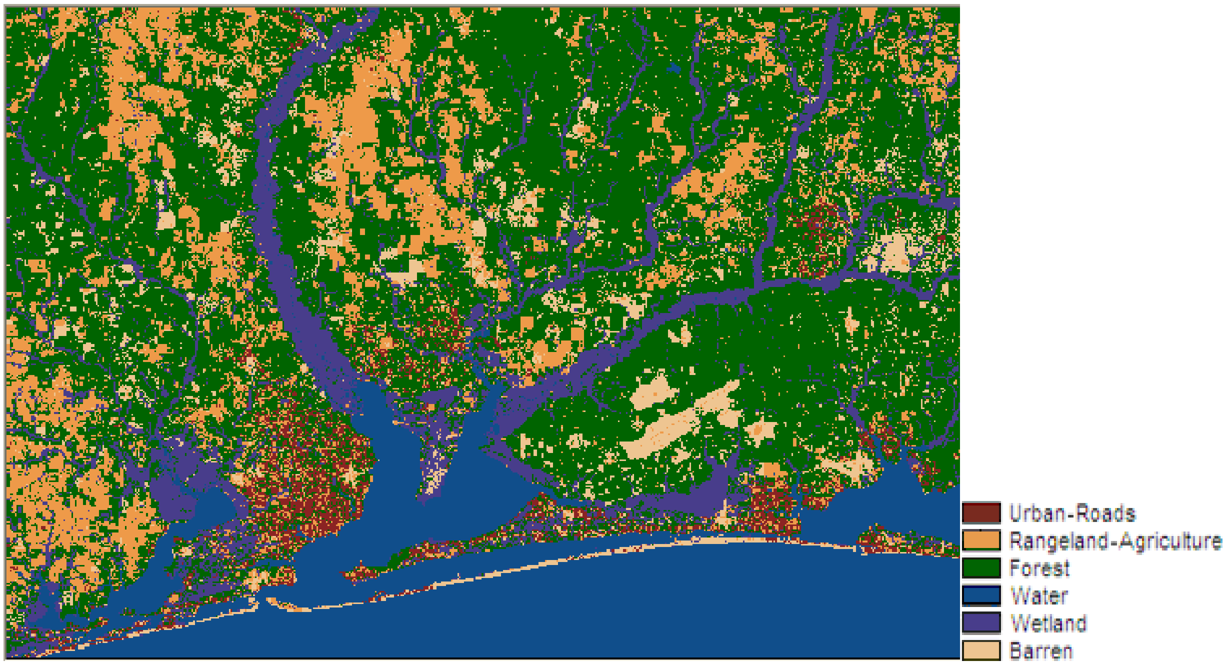


Figure A-III.19: SLEUTH Simulation: Land-cover 2010 Smart Growth

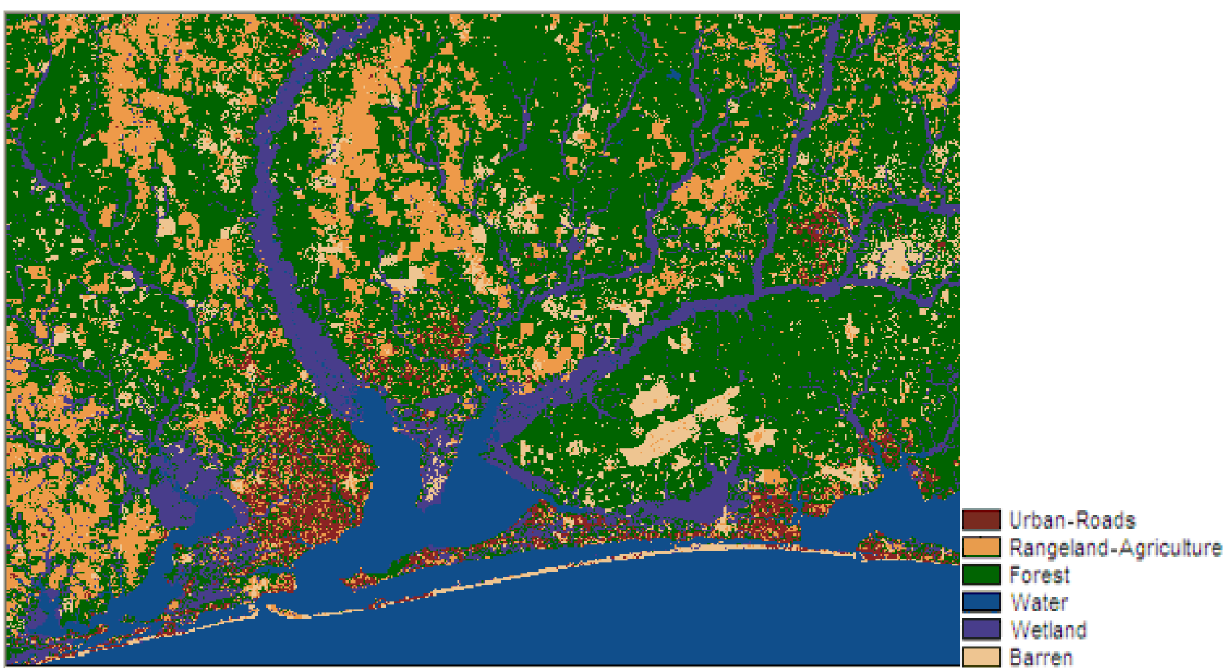


Figure A-III.20: SLEUTH Simulation: Land-cover 2010 Normal Trend

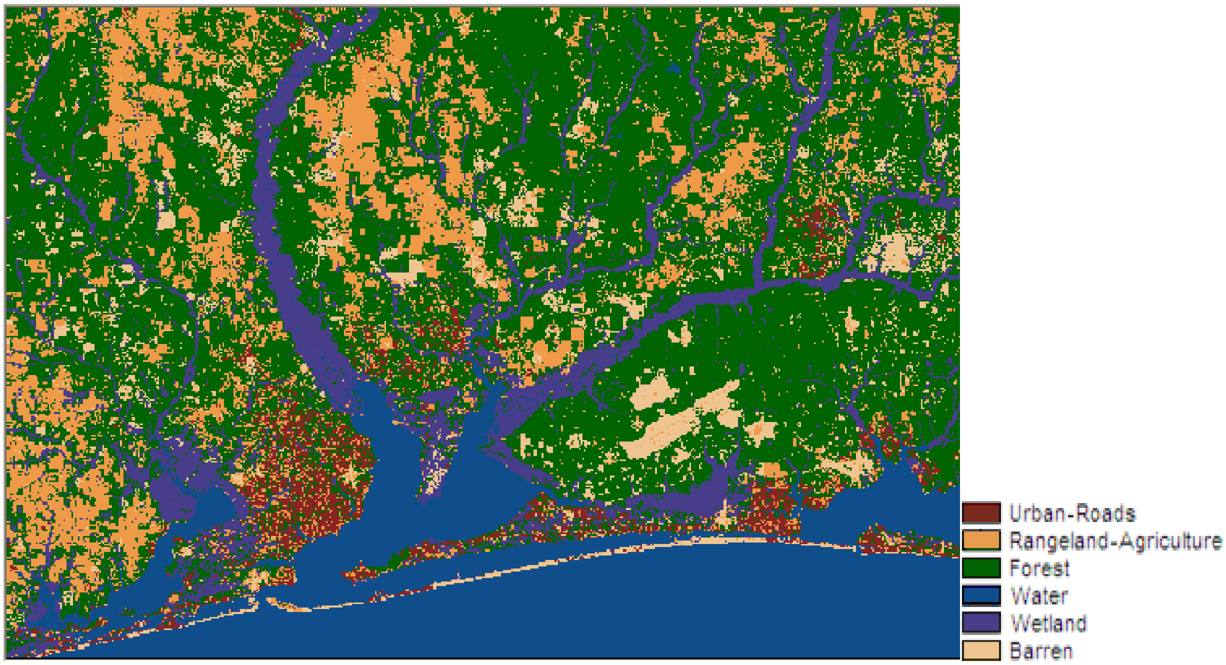


Figure A-III.21: SLEUTH Simulation: Land-cover 2010 Urban Sprawl

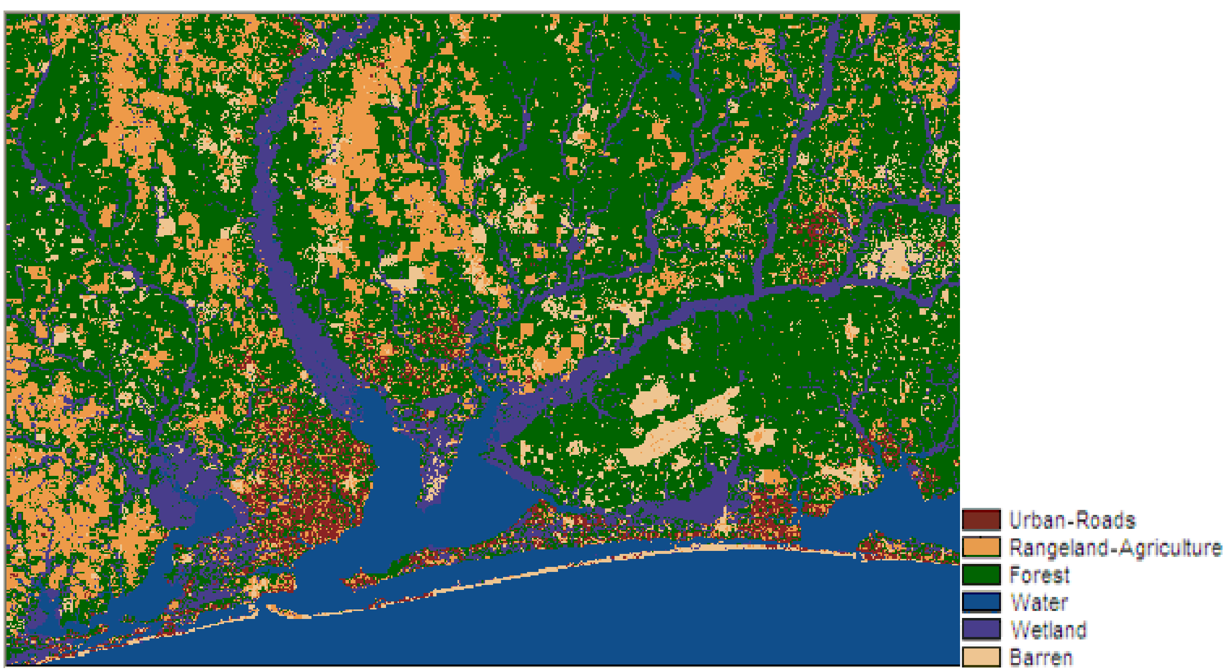


Figure A-III.22: SLEUTH Simulation: Land-cover 2015 Smart Growth

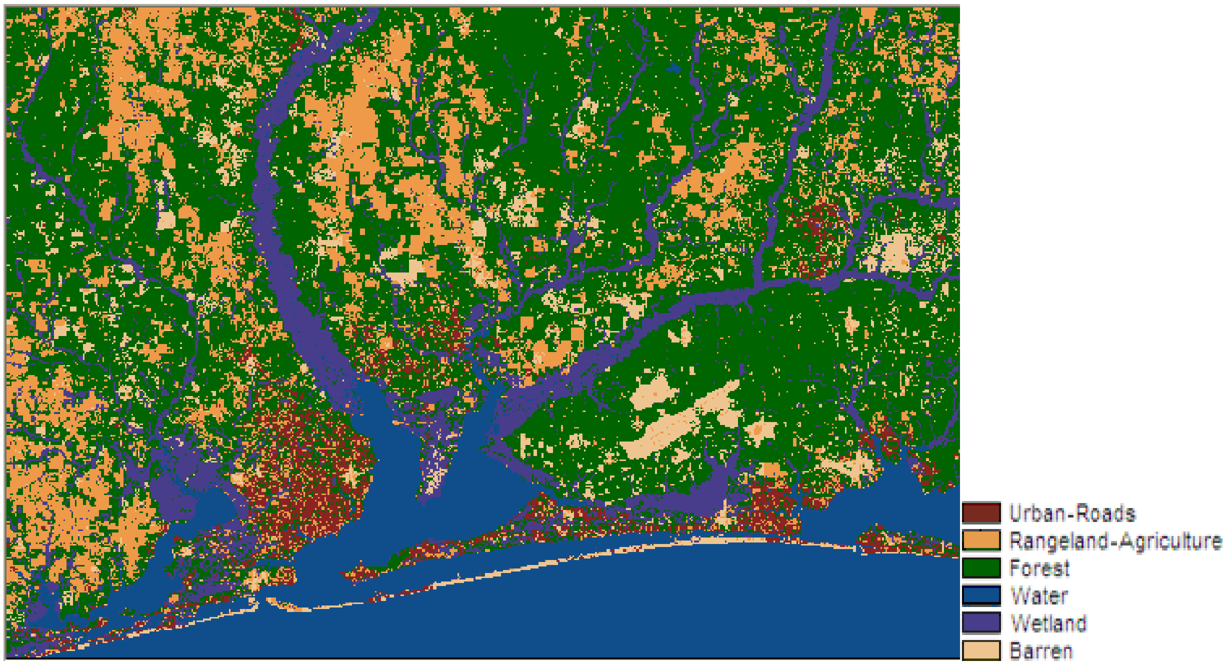


Figure A-III.23: SLEUTH Simulation: Land-cover 2015 Normal Trend

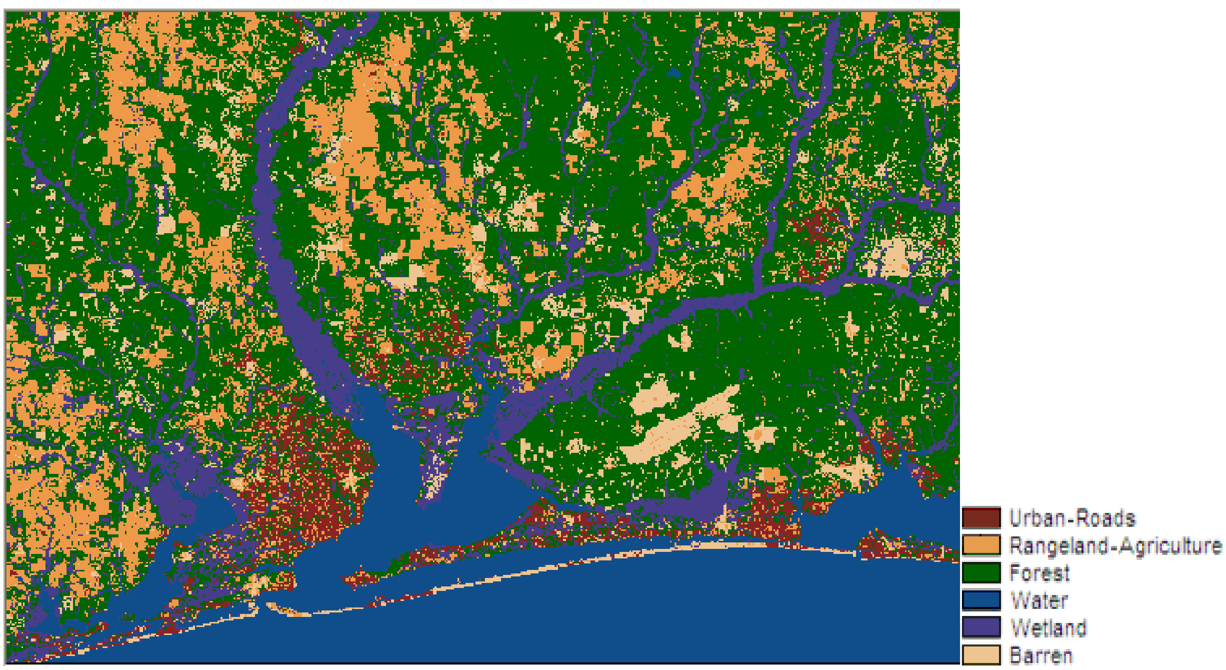


Figure A-III.24: SLEUTH Simulation: Land-cover 2015 Urban Sprawl

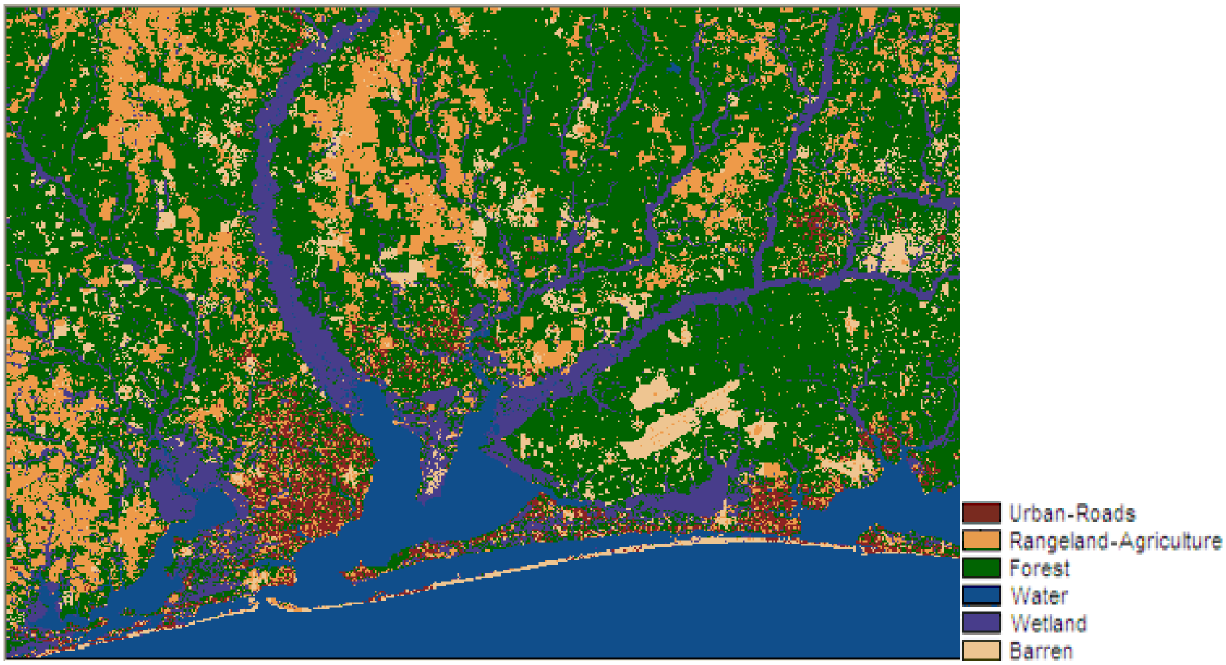


Figure A-III.25: SLEUTH Simulation: Land-cover 2020 Smart Growth

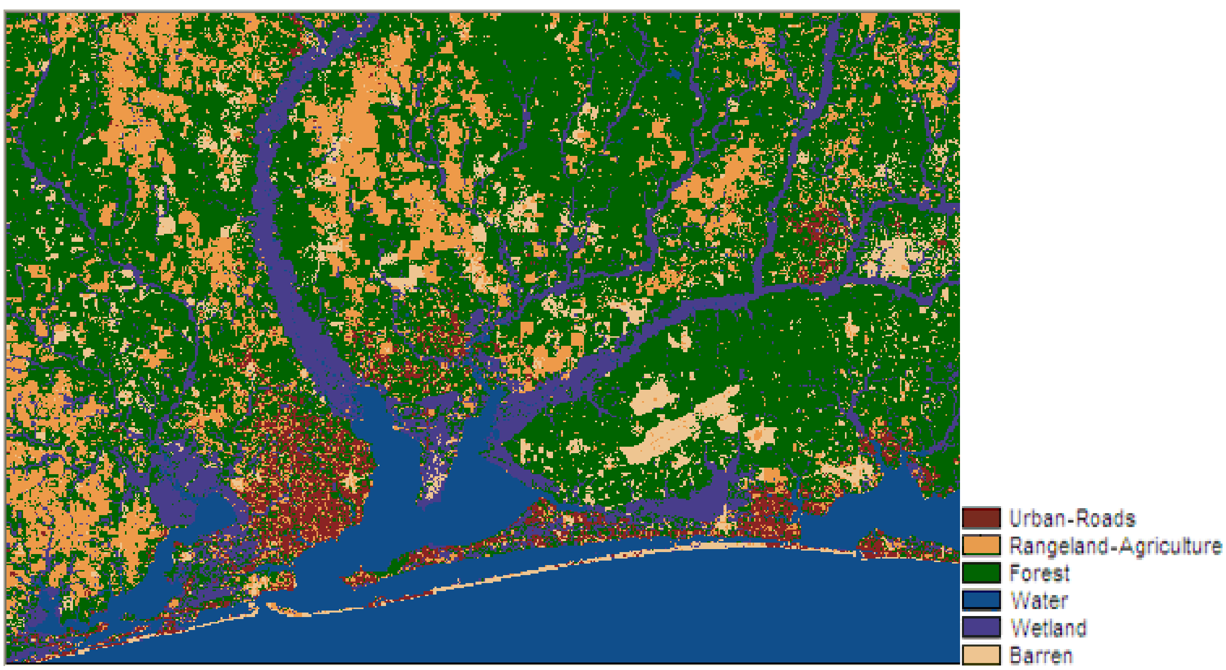


Figure A-III.26: SLEUTH Simulation: Land-cover 2020 Normal Trend

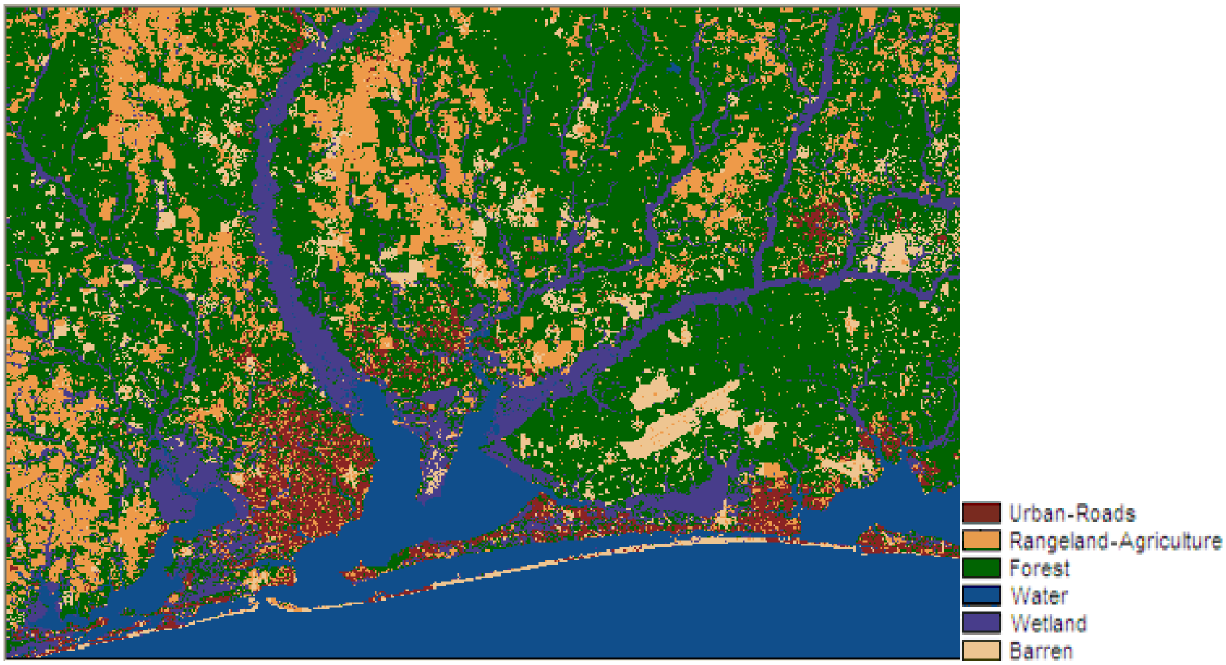


Figure A-III.27: SLEUTH Simulation: Land-cover 2020 Urban Sprawl

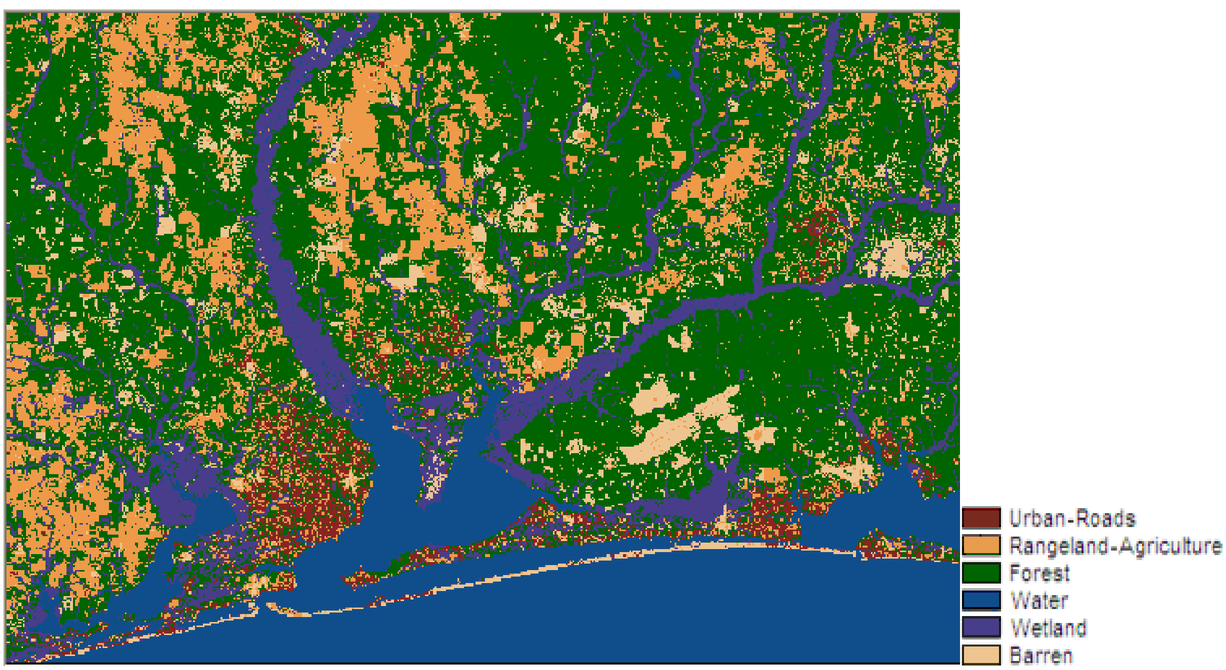


Figure A-III.28: SLEUTH Simulation: Land-cover 2025 Smart Growth

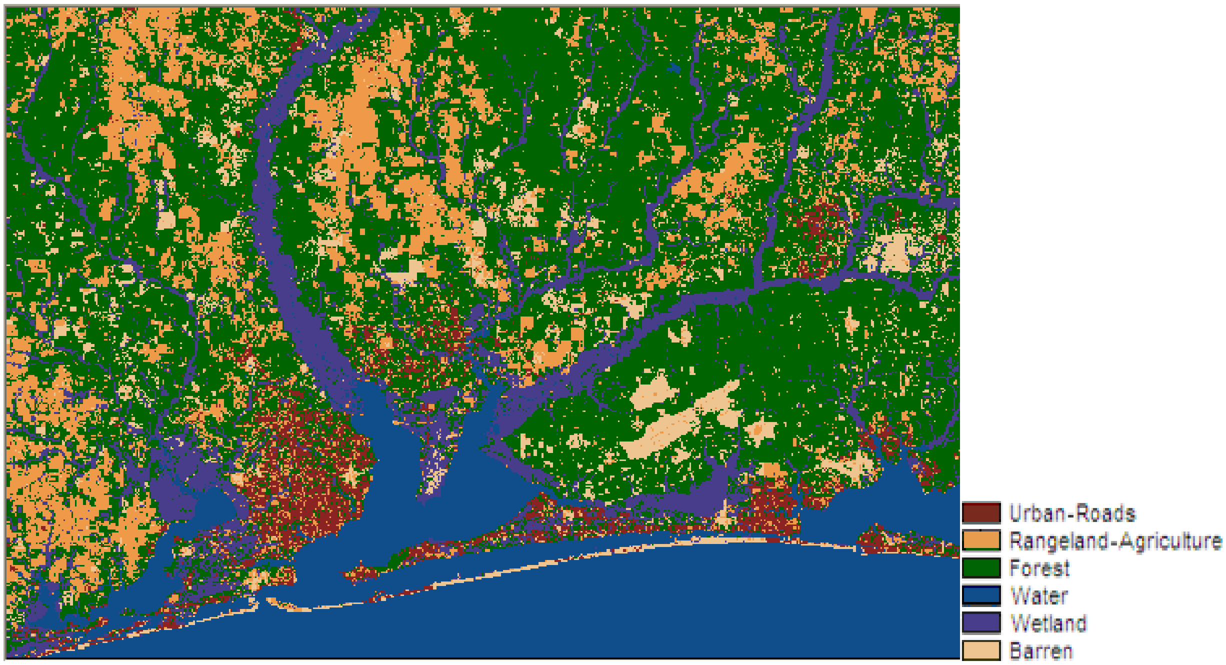


Figure A-III.29: SLEUTH Simulation: Land-cover 2025 Normal Trend

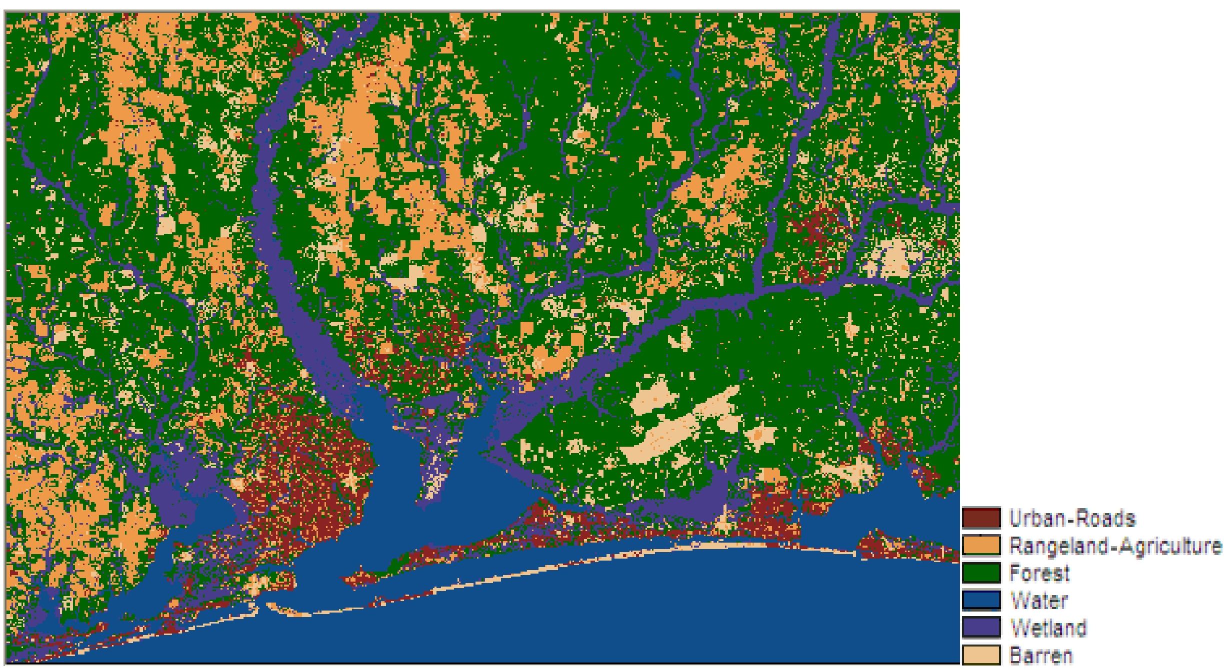


Figure A-III.30: SLEUTH Simulation: Land-cover 2025 Urban Sprawl

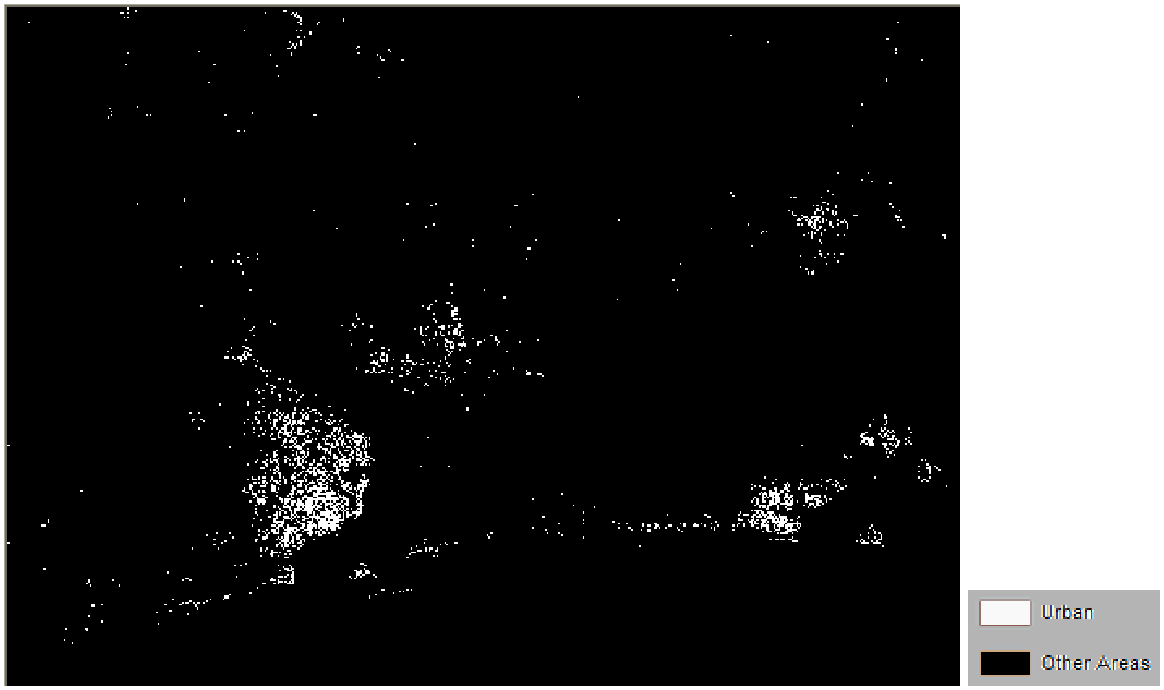


Figure A-III.31: Classified Landsat Image: Urban 1974

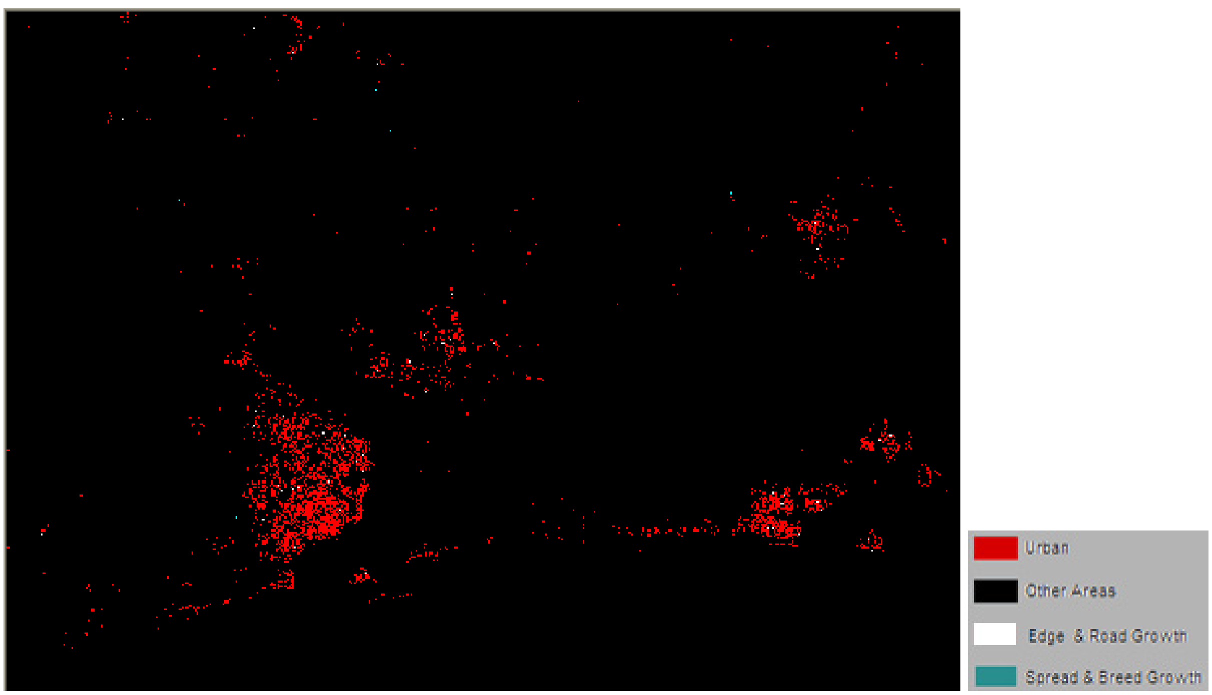


Figure A-III.32: SLEUTH Simulation: Urban 1975

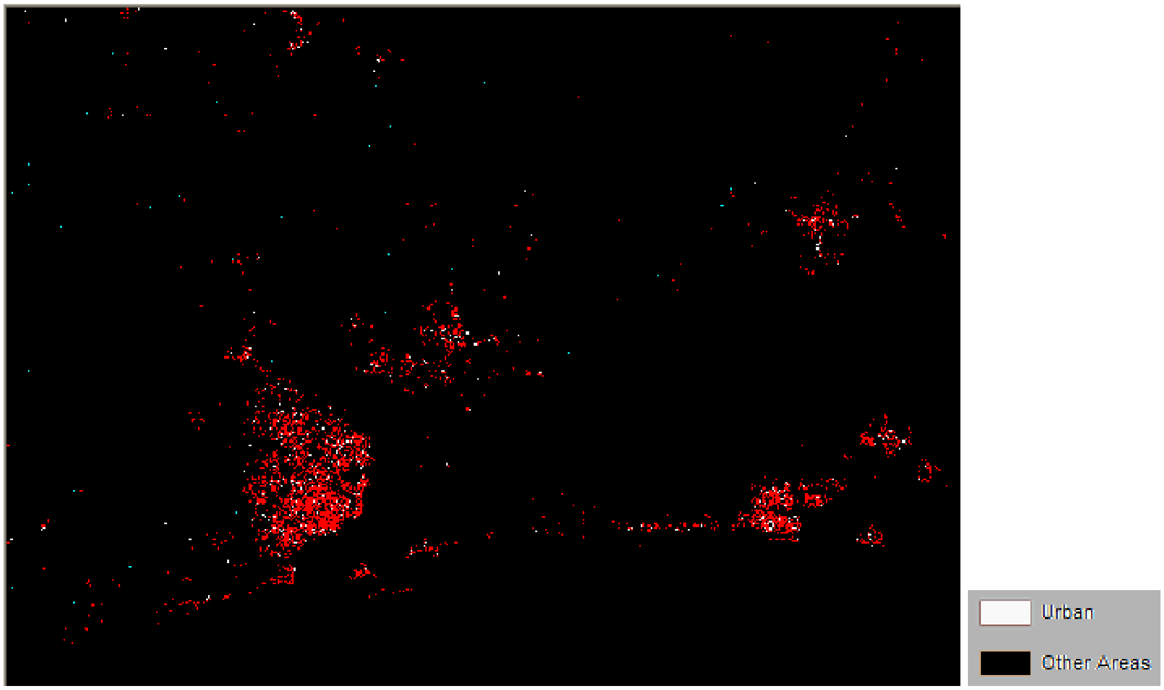


Figure A-III.33: SLEUTH Simulation: Urban 1980

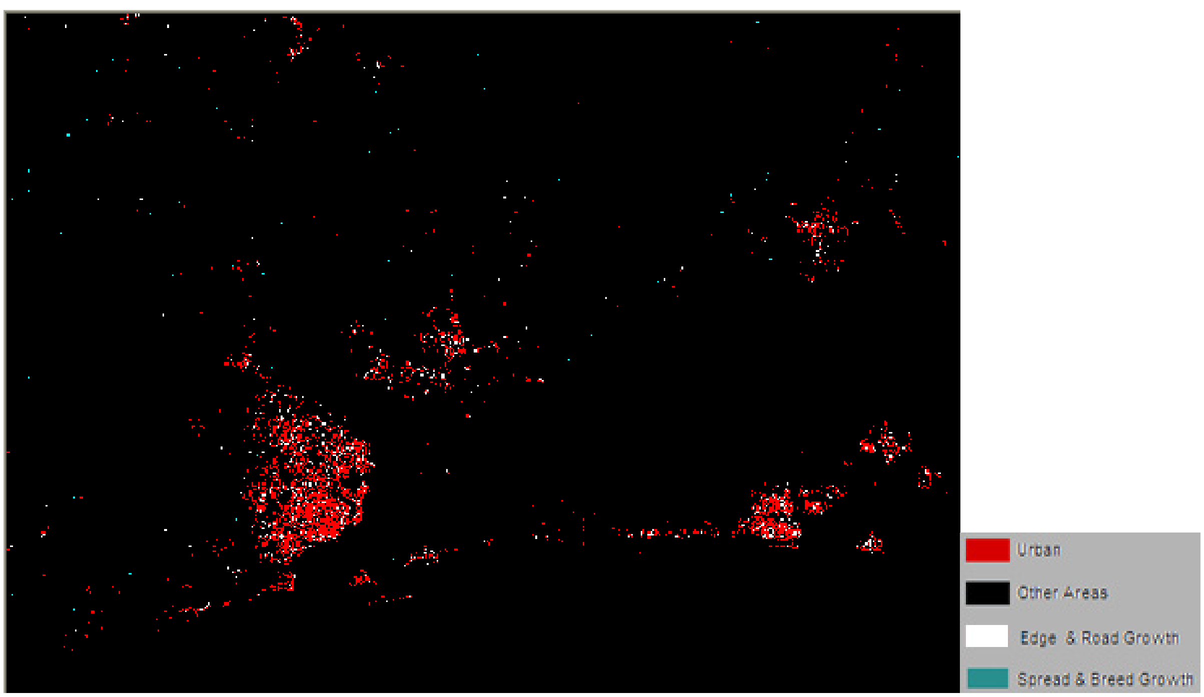


Figure A-III.34: SLEUTH Simulation: Urban 1985

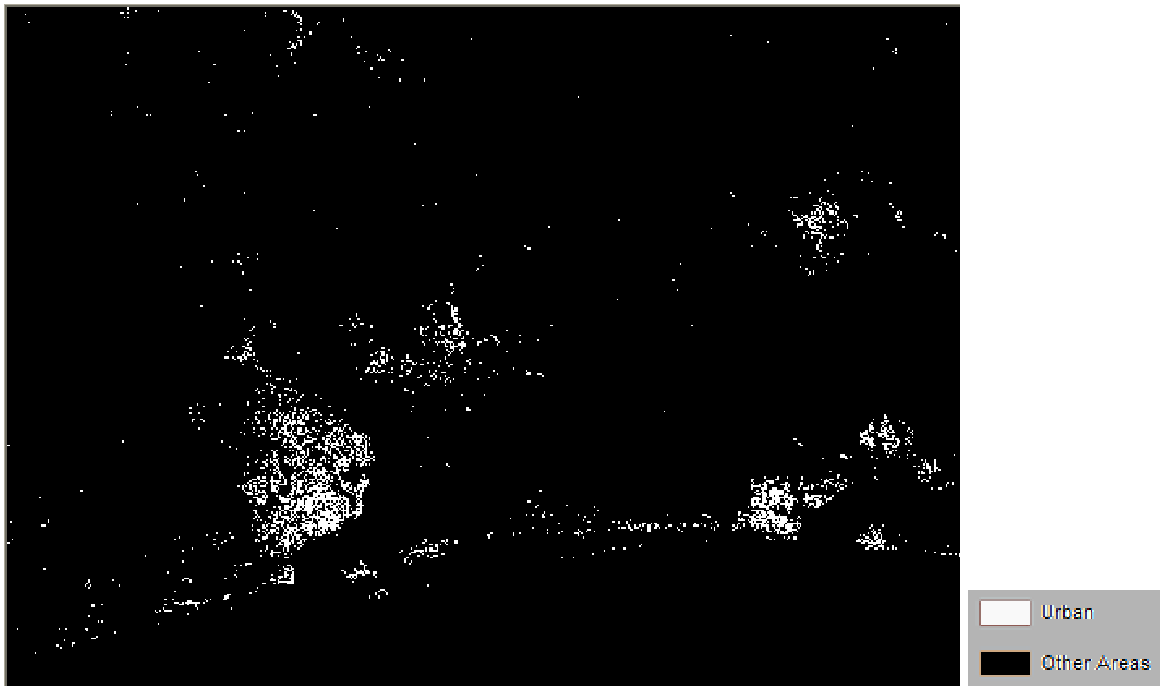


Figure A-III.35: Classified Landsat Image: Urban 1986

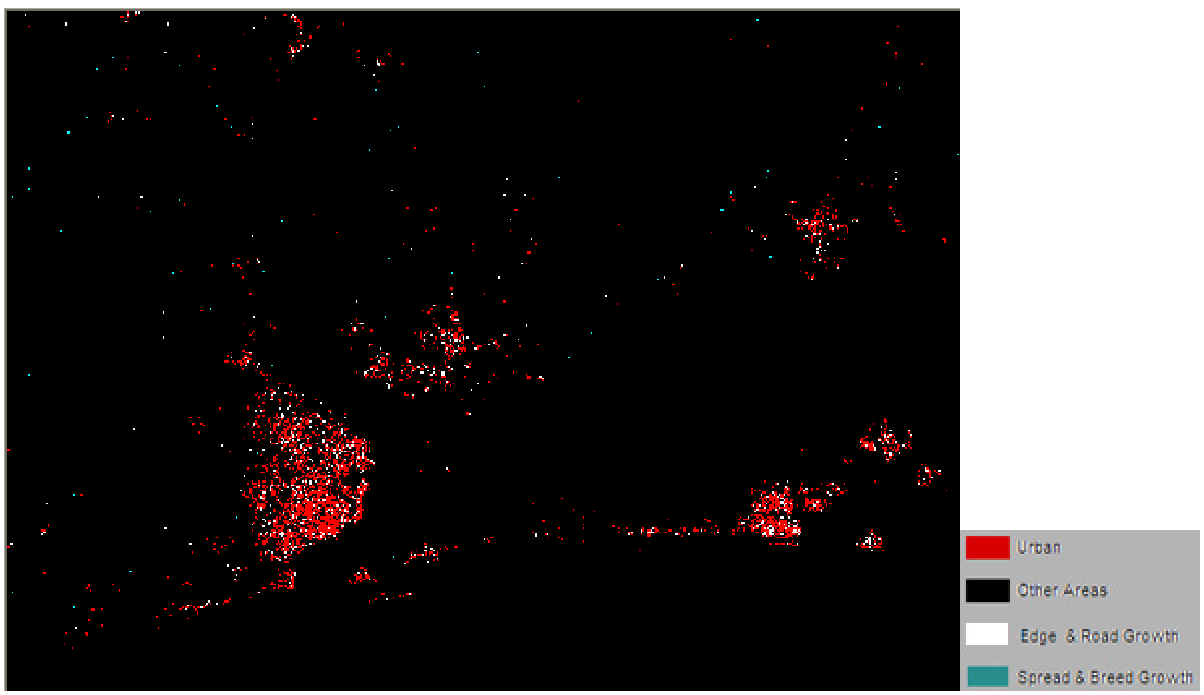


Figure A-III.36: SLEUTH Simulation: Urban 1986

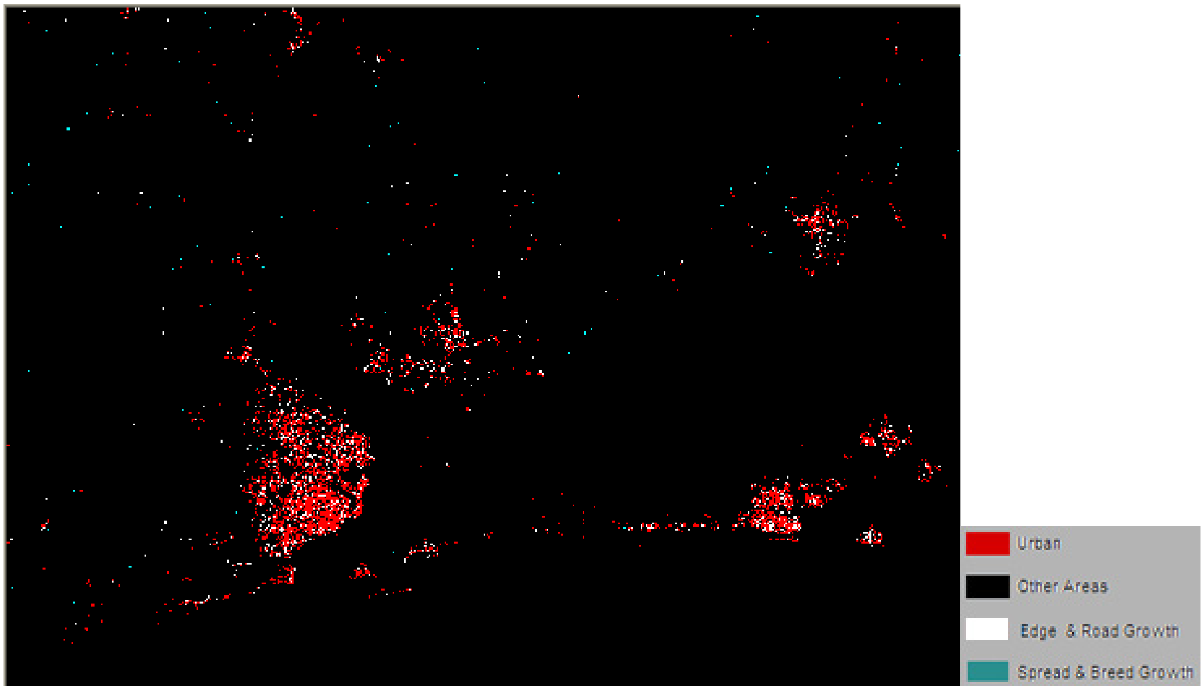


Figure A-III.37: SLEUTH Simulation: Urban 1990

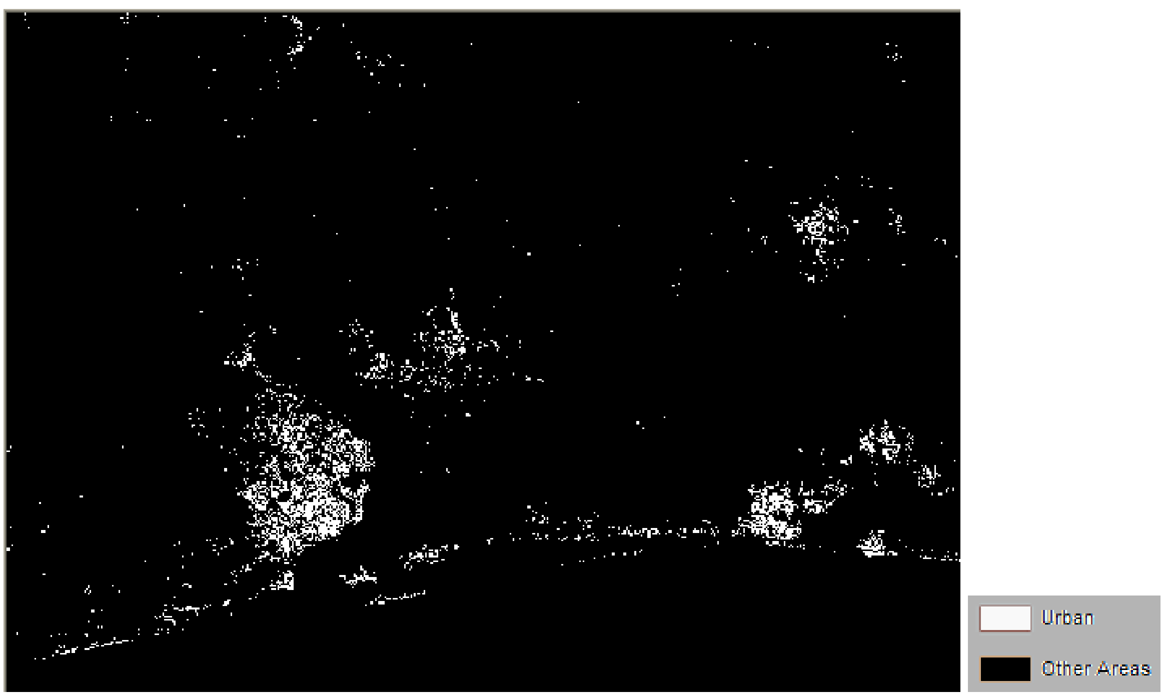


Figure A-III.38: Classified Landsat Image: Urban 1992

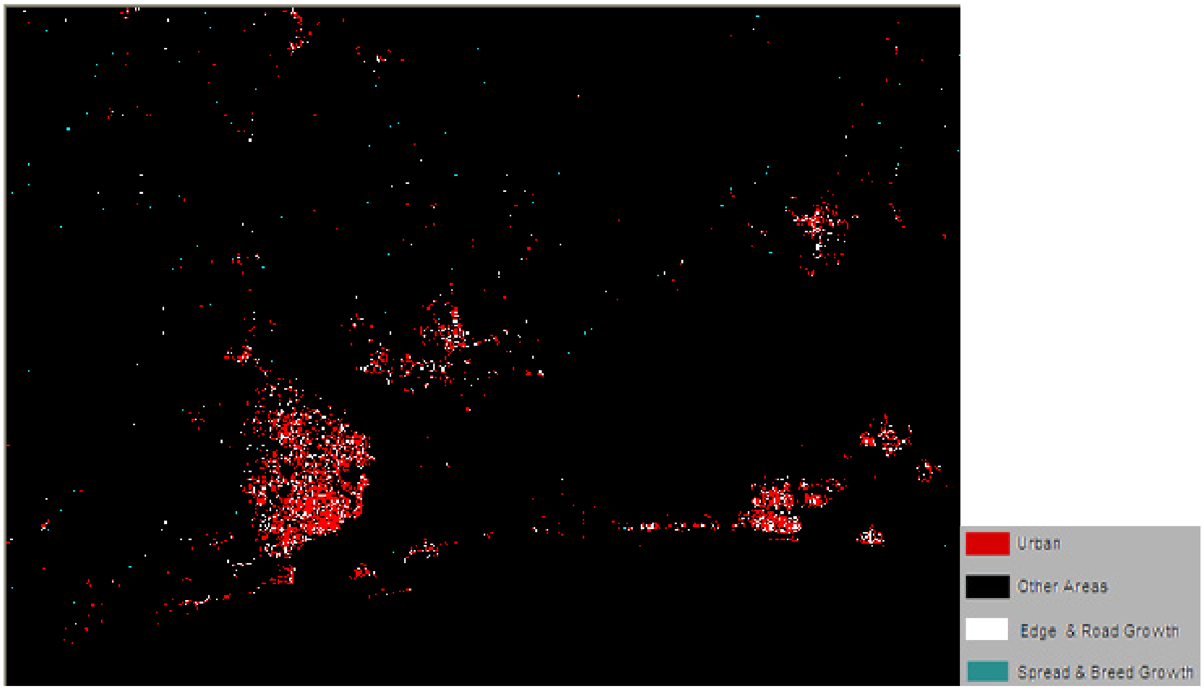


Figure A-III.39: SLEUTH Simulation: Urban 1992

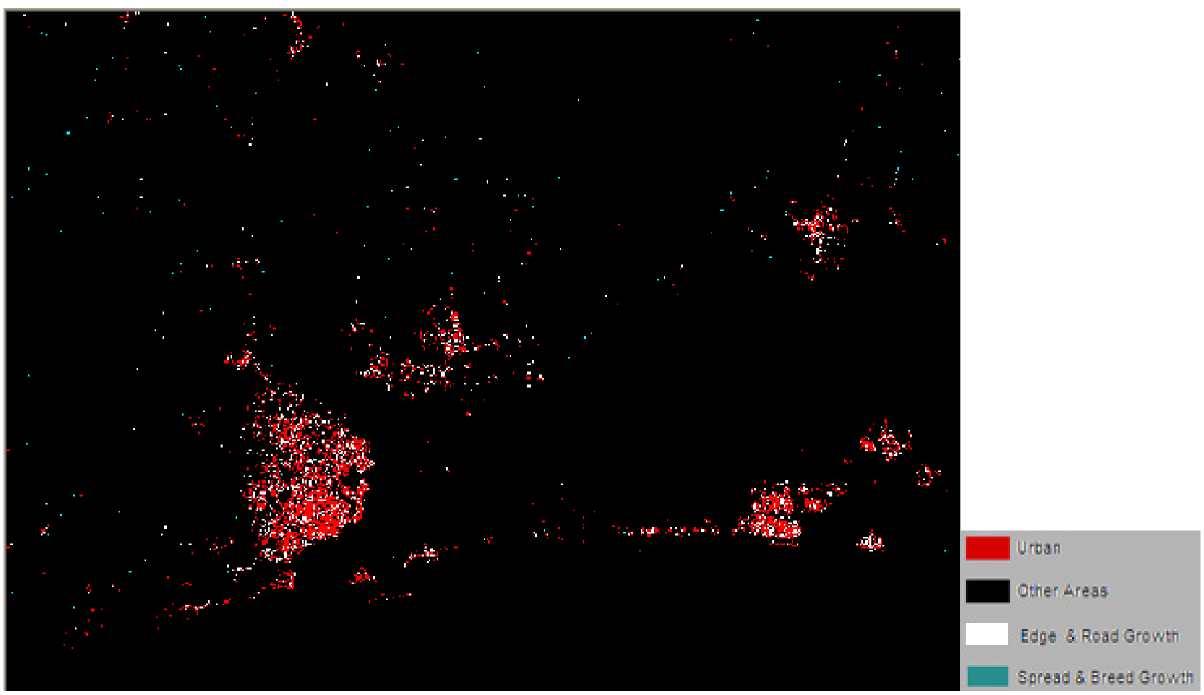


Figure A-III.40: SLEUTH Simulation: Urban 1995

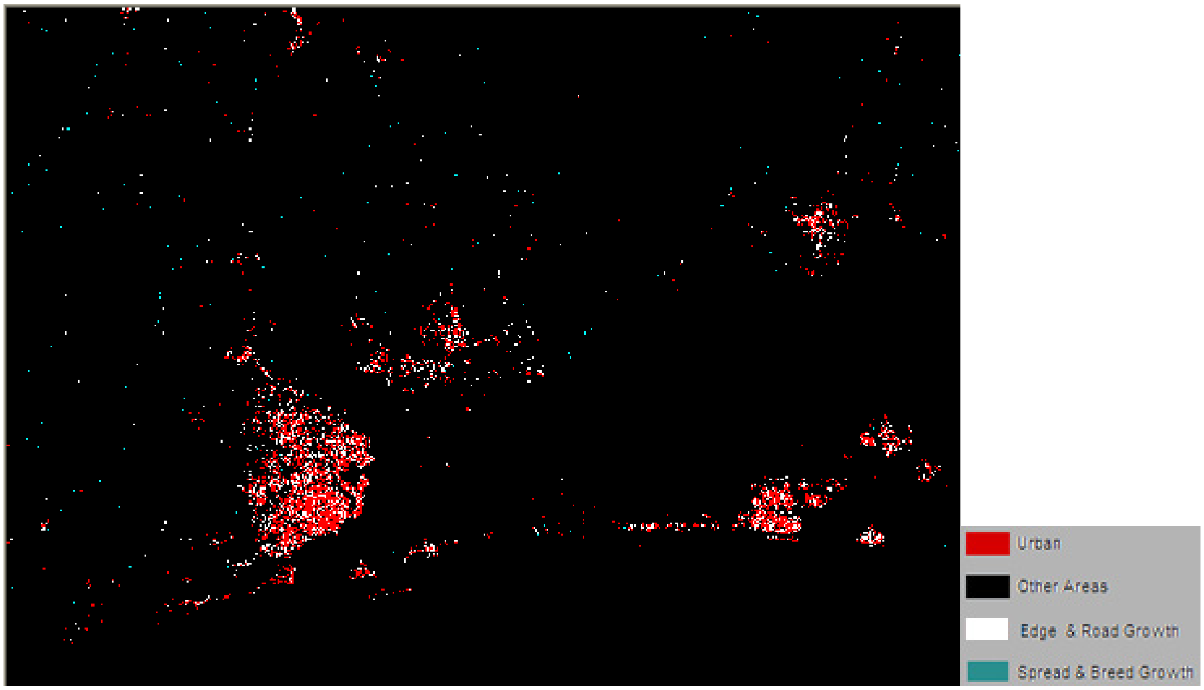


Figure A-III.41: SLEUTH Simulation: Urban 2000

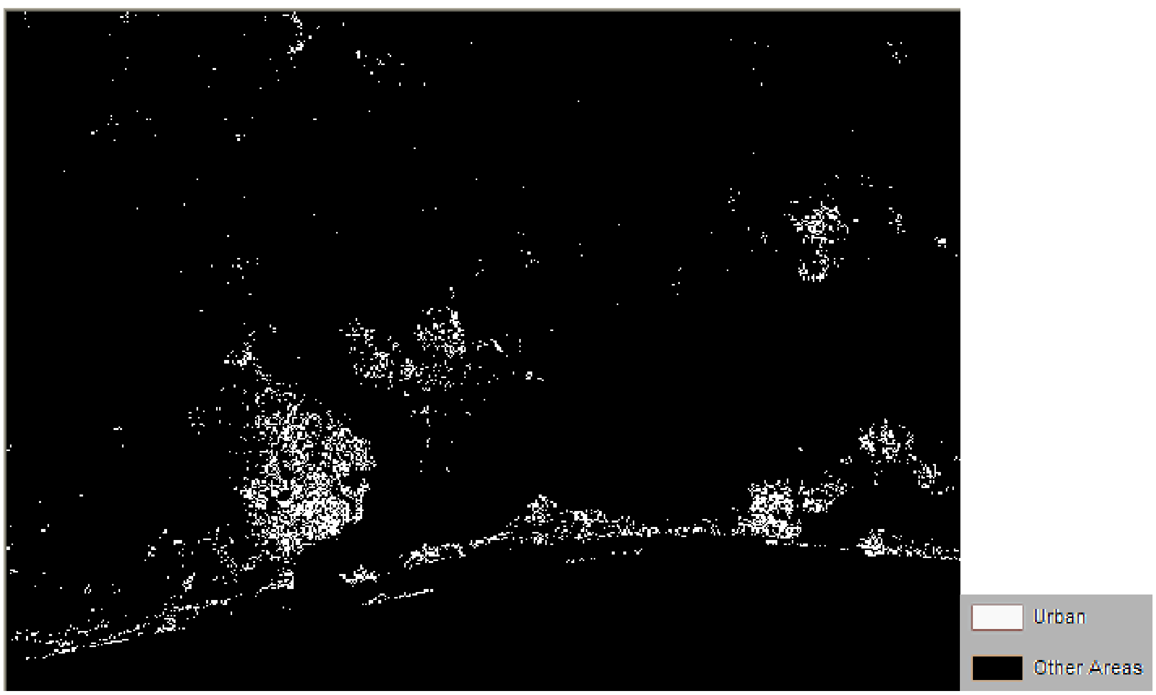


Figure A-III.42: Classified Landsat Image: Urban 2001

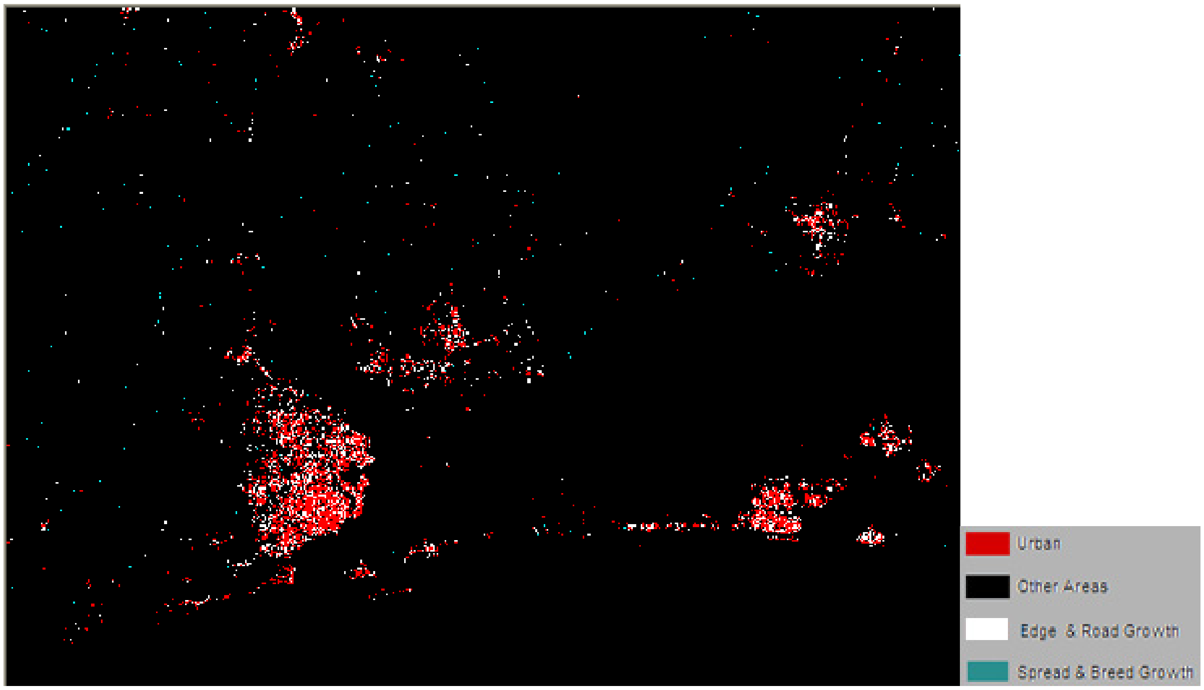


Figure A-III.43: SLEUTH Simulation: Urban 2001

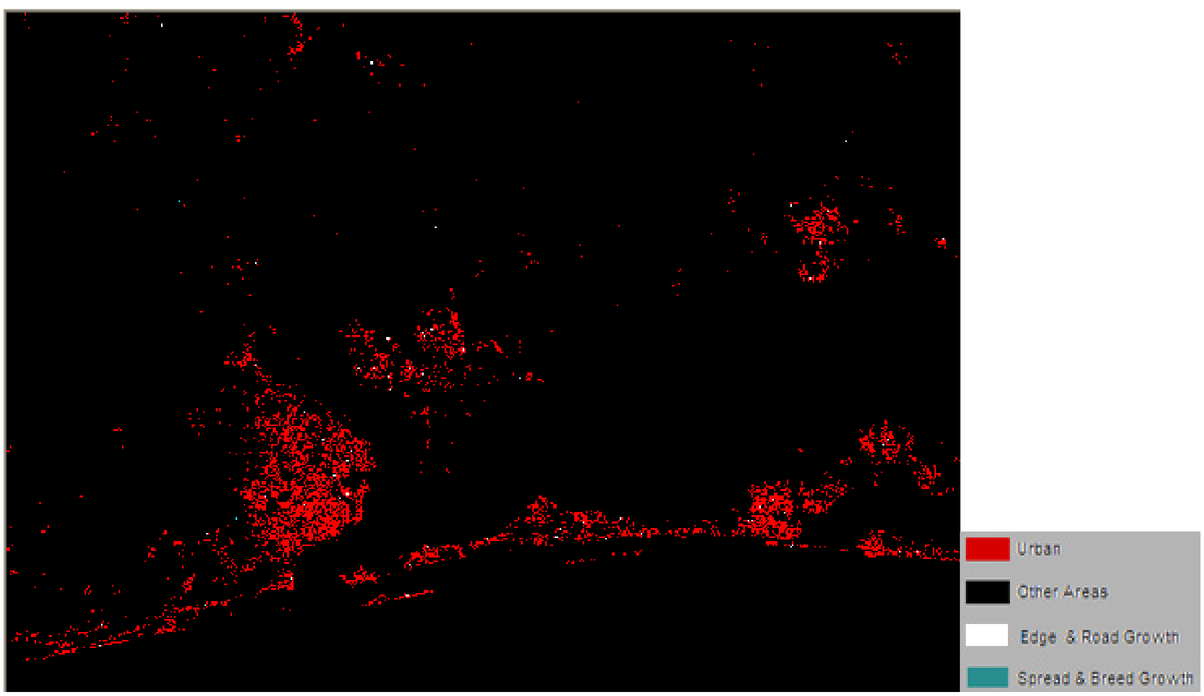


Figure A-III.44: SLEUTH Simulation: Urban 2005 Smart Growth

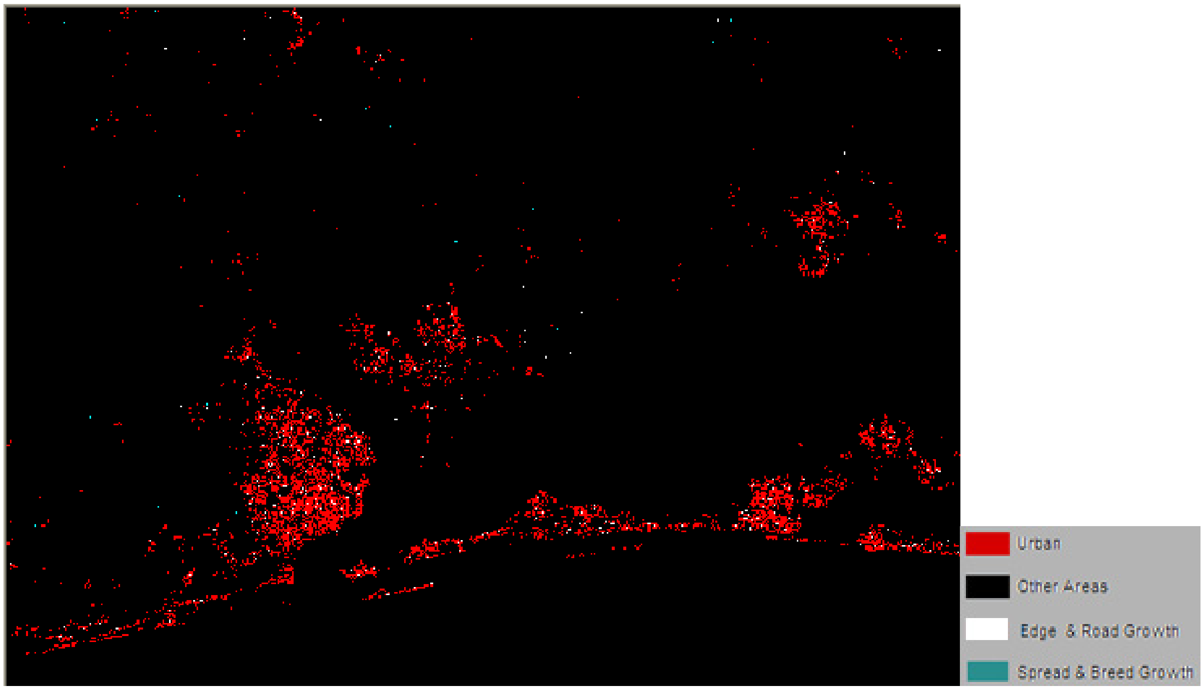


Figure A-III.45: SLEUTH Simulation: Urban 2005 Normal Trend

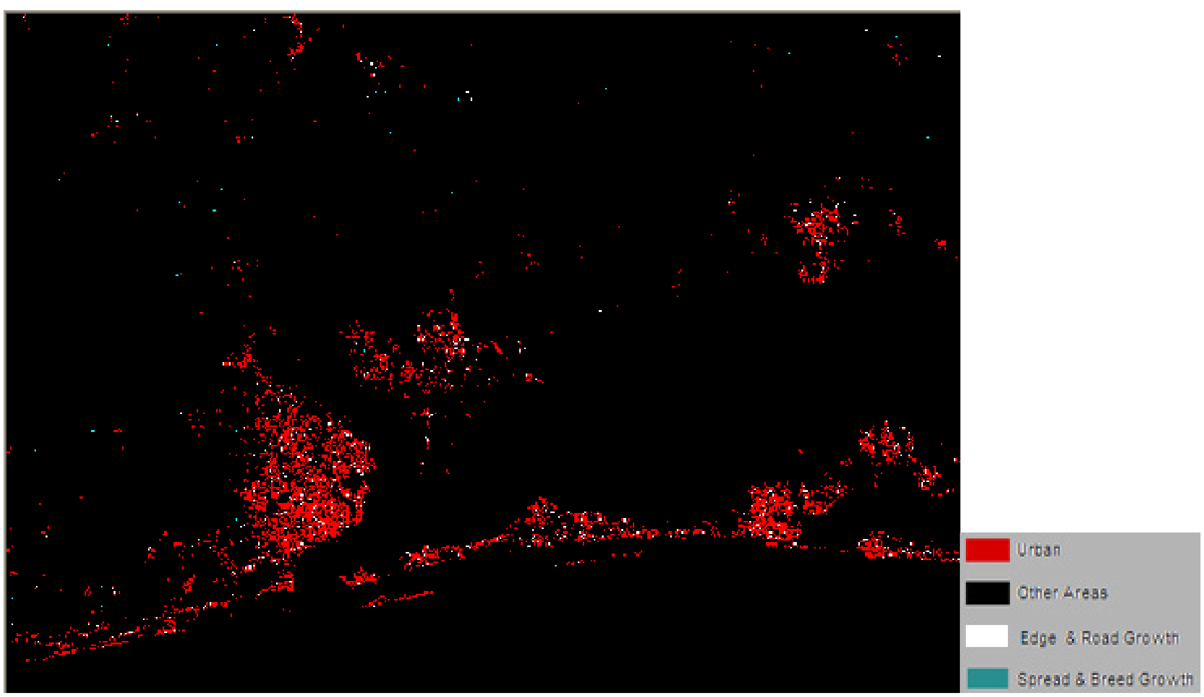


Figure A-III.46: SLEUTH Simulation: Urban 2005 Urban Sprawl

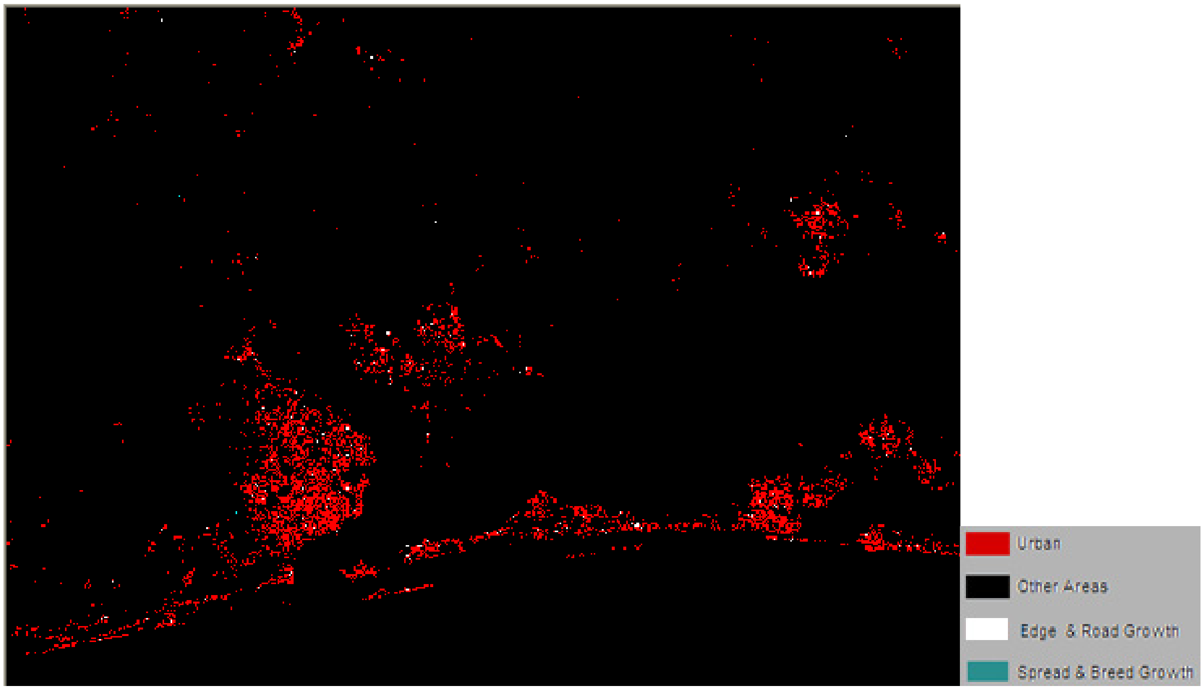


Figure A-III.47: SLEUTH Simulation: Urban 2010 Smart Growth

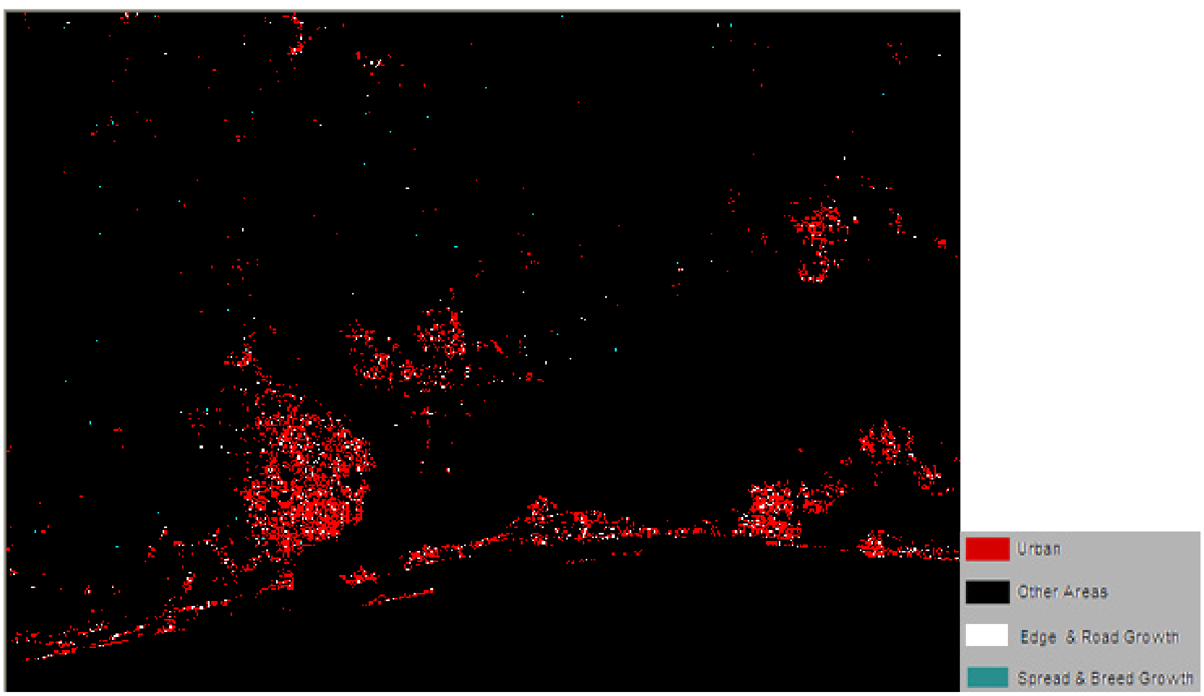


Figure A-III.48: SLEUTH Simulation: Urban 2010 Normal Trend

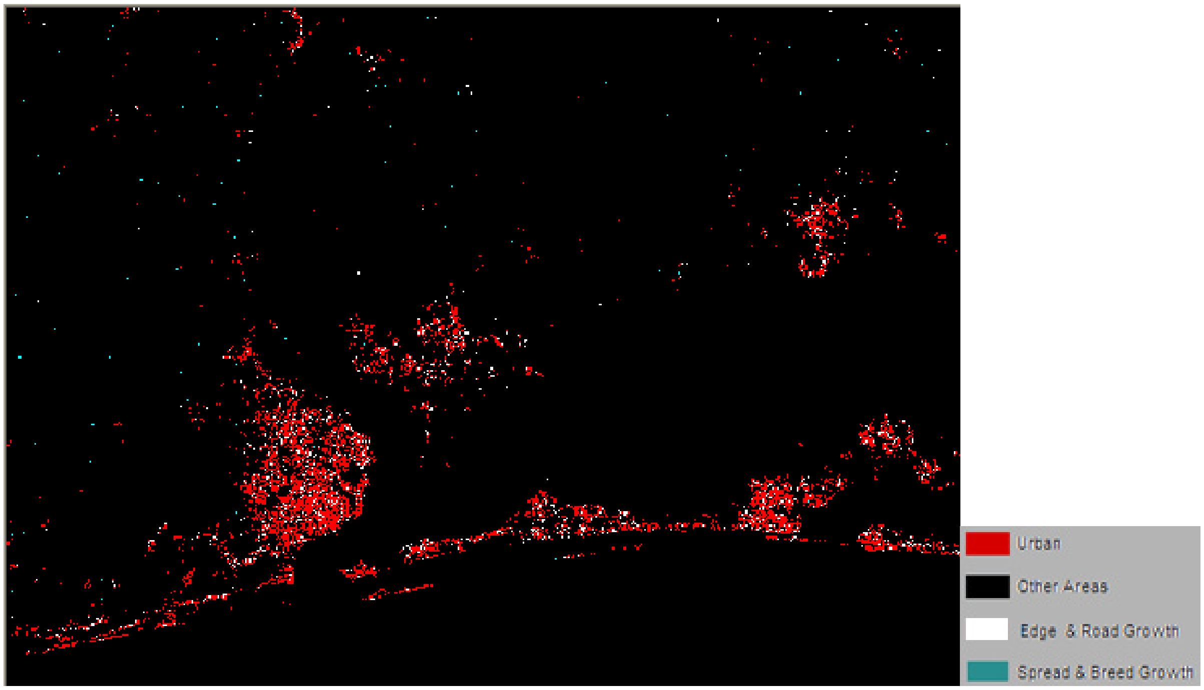


Figure A-III.49: SLEUTH Simulation: Urban 2010 Urban Sprawl

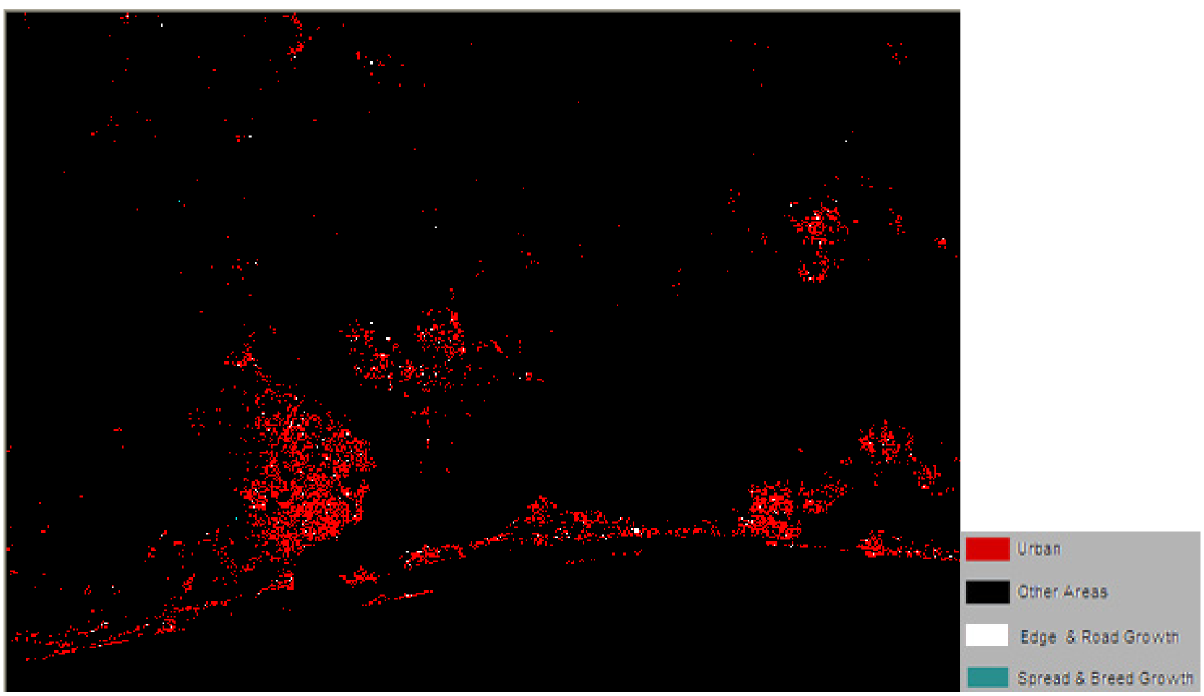


Figure A-III.50: SLEUTH Simulation: Urban 2015 Smart Growth

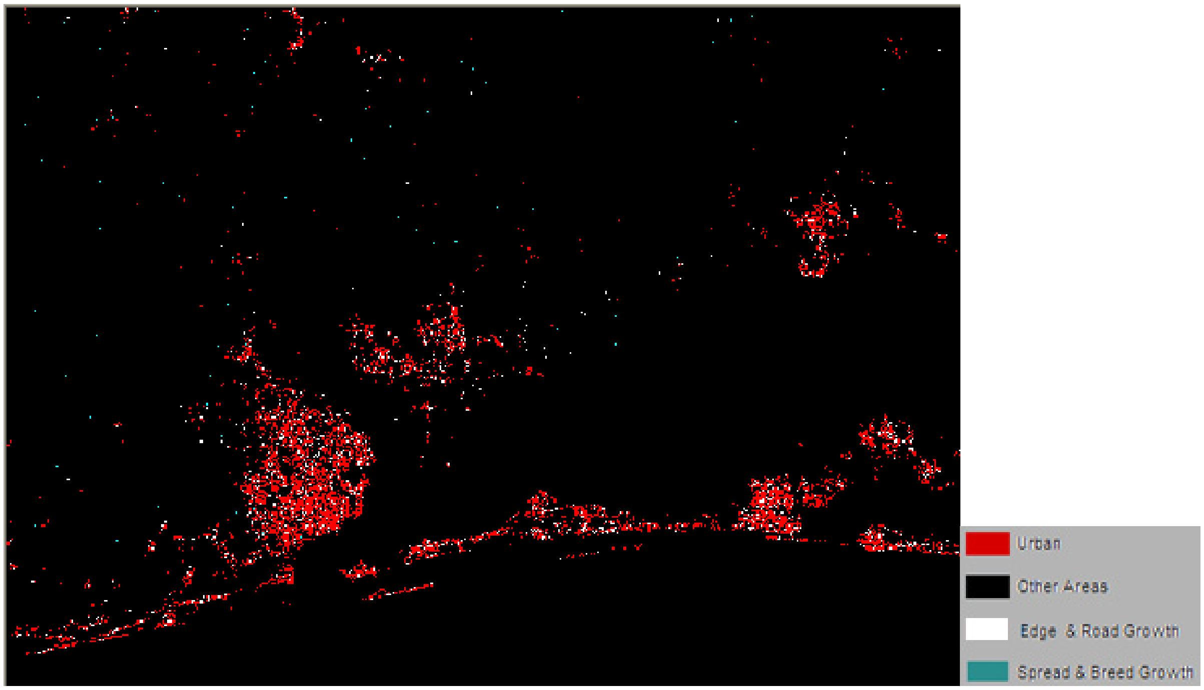


Figure A-III.51: SLEUTH Simulation: Urban 2015 Normal Trend

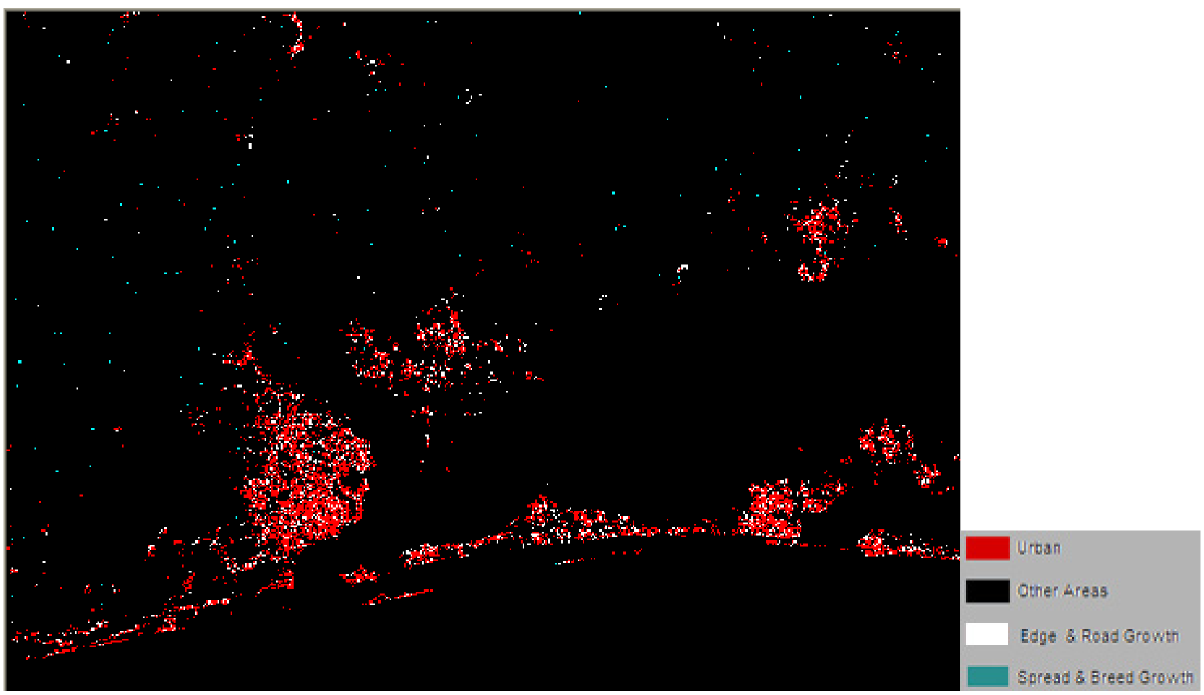


Figure A-III.52: SLEUTH Simulation: Urban 2015 Urban Sprawl

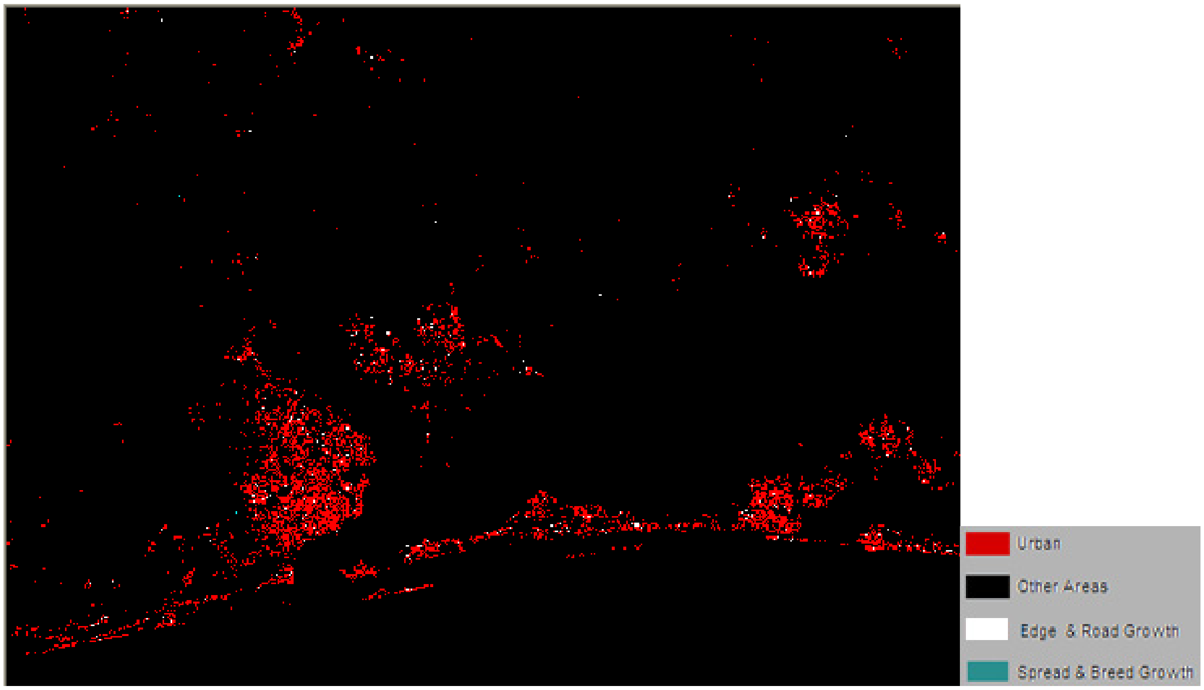


Figure A-III.53: SLEUTH Simulation: Urban 2020 Smart Growth

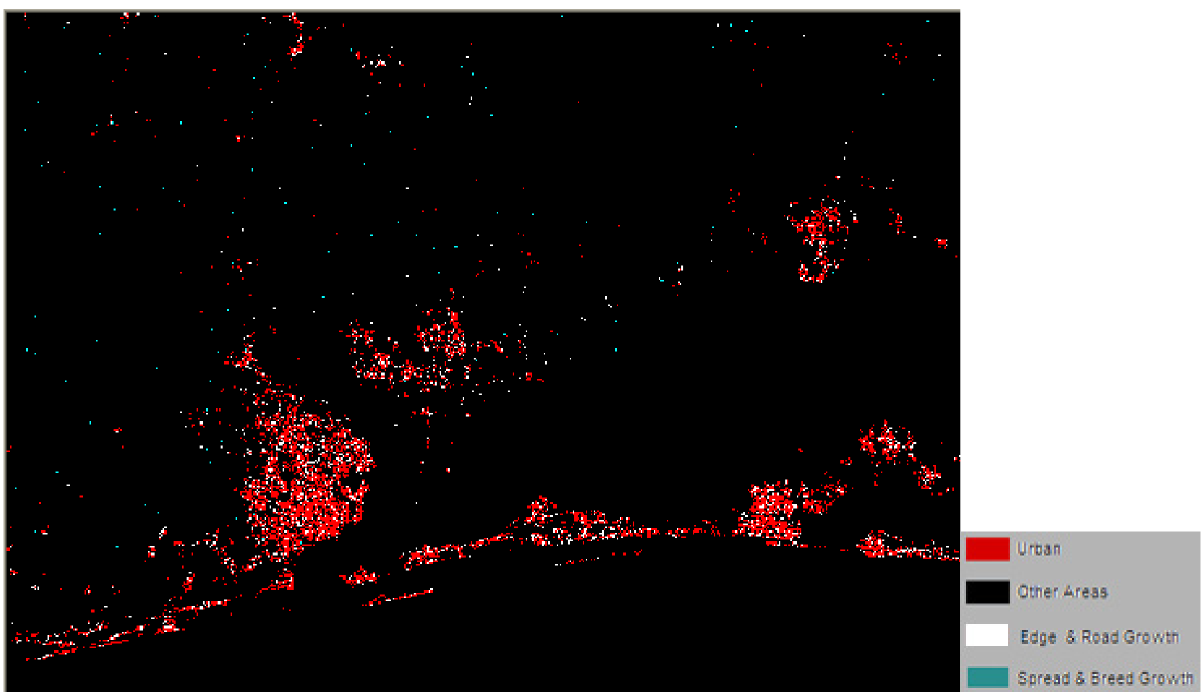


Figure A-III.54: SLEUTH Simulation: Urban 2020 Normal Trend

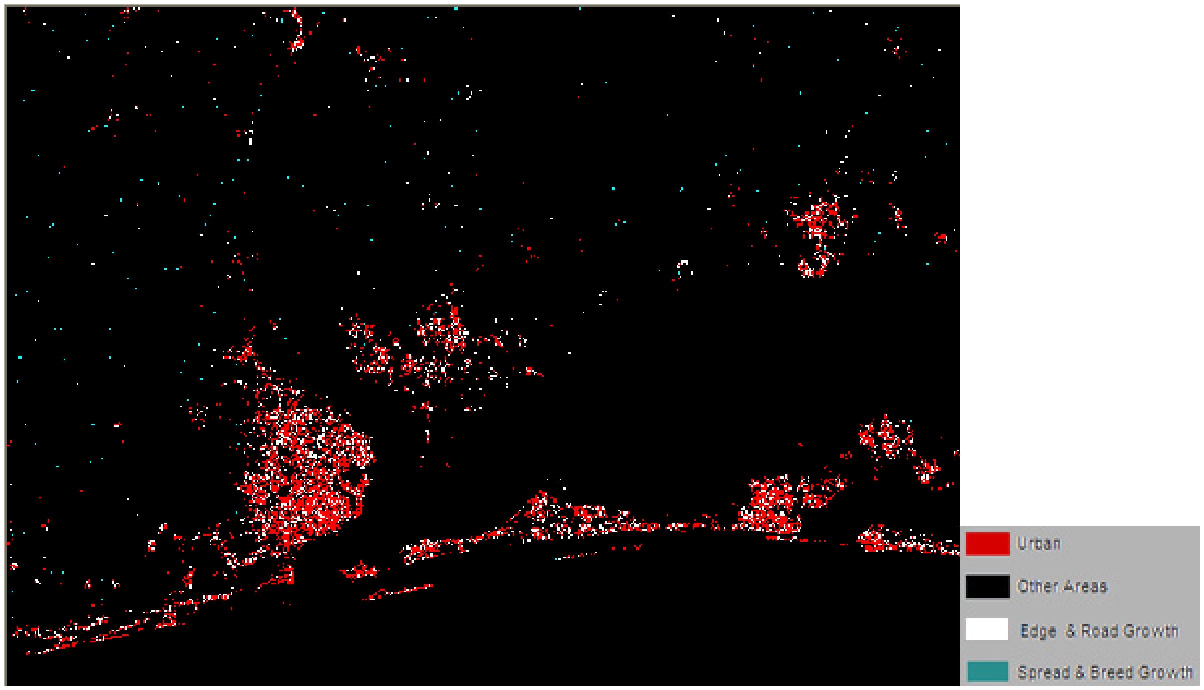


Figure A-III.55: SLEUTH Simulation: Urban 2020 Urban Sprawl

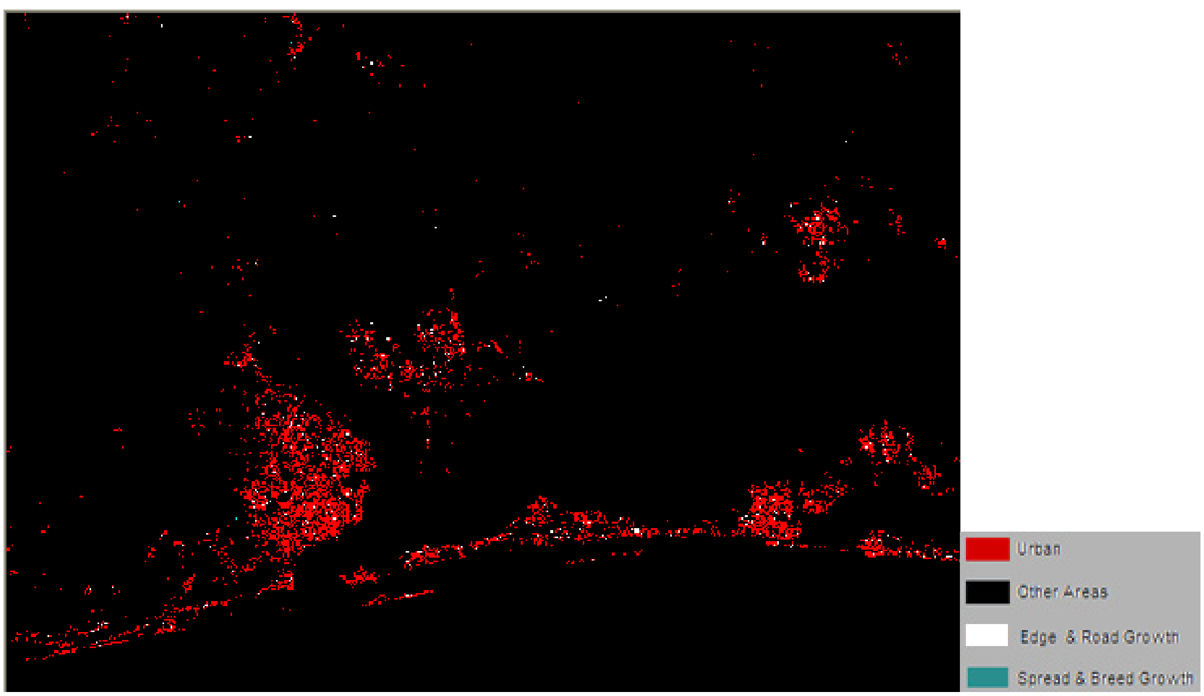


Figure A-III.56: SLEUTH Simulation: Urban 2025 Smart Growth

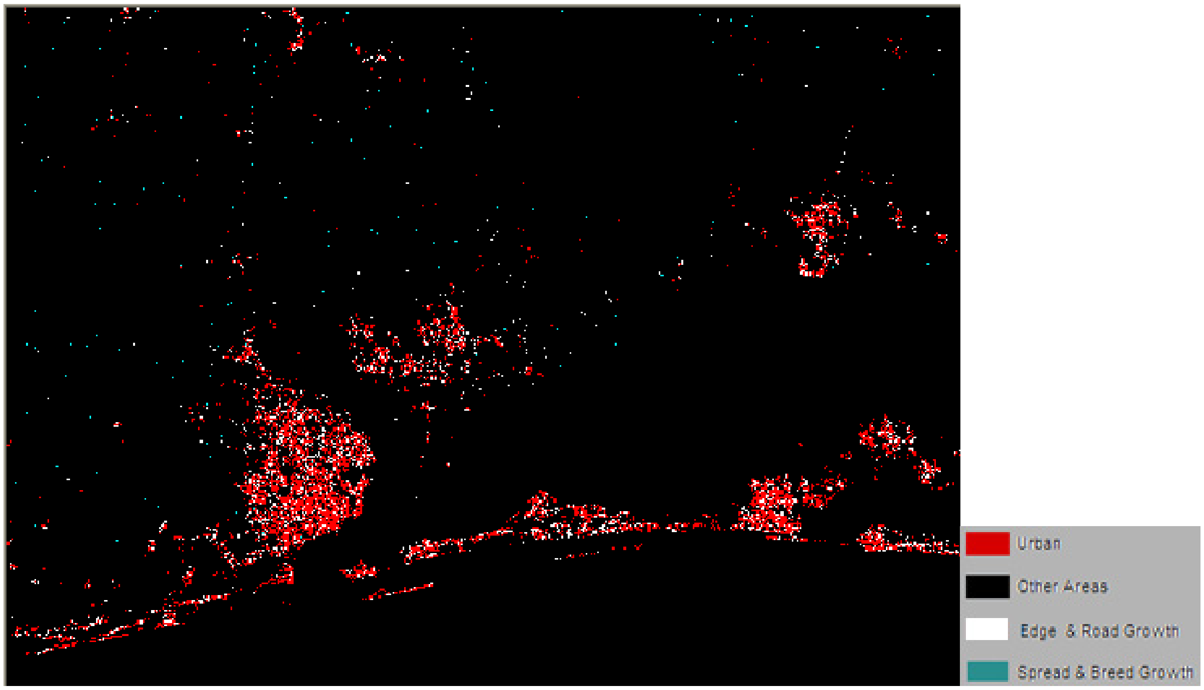


Figure A-III.57: SLEUTH Simulation: Urban 2025 Normal Trend

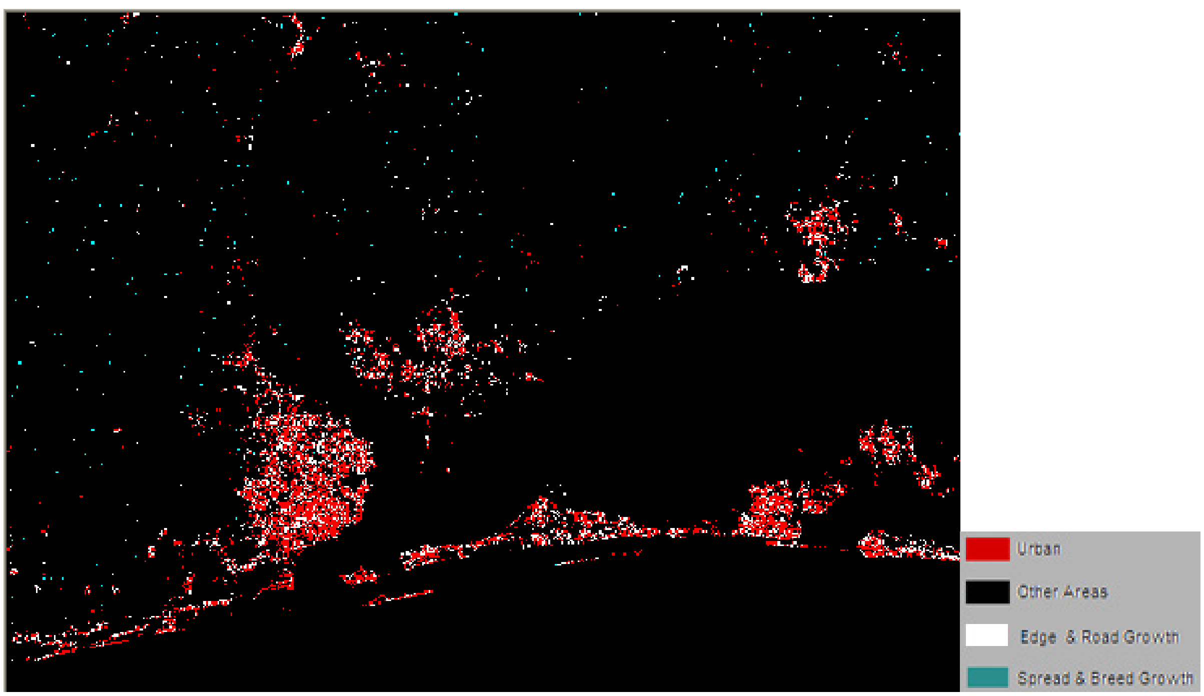


Figure A-III.58: SLEUTH Simulation: Urban 2025 Urban Sprawl

APPENDIX IV: CHOROPLETH AND DASYMETRIC FIGURES AND TABLES

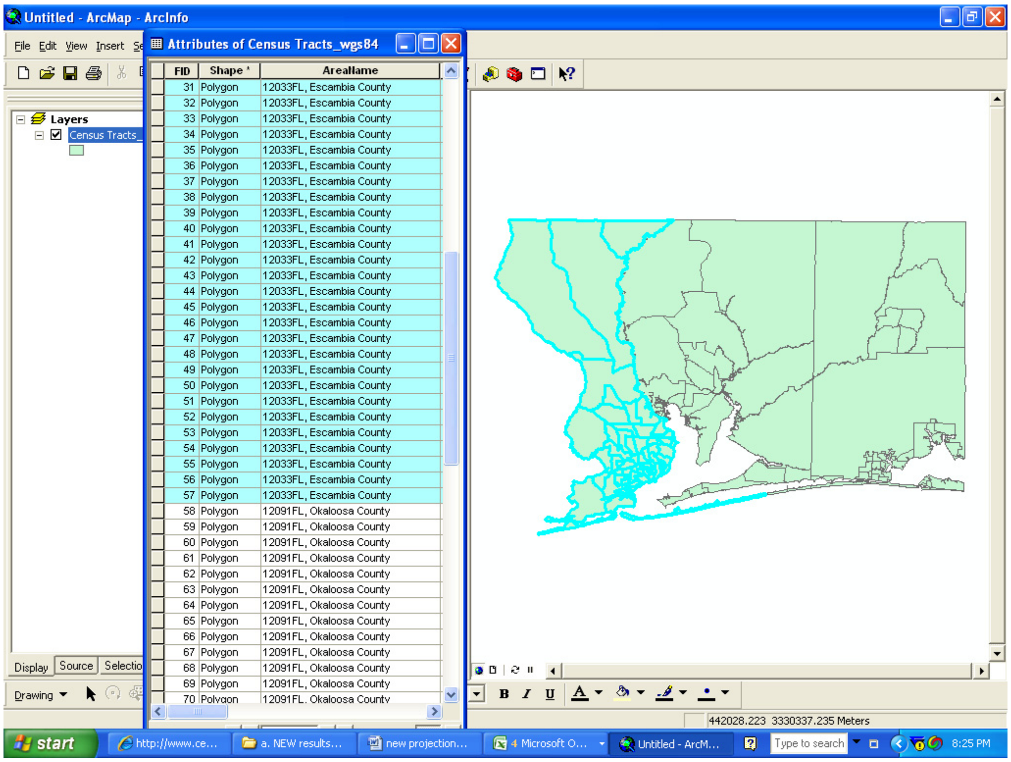


Figure A-IV.1: Selecting Census-tracts for Escambia county in ArcMap
Note: Census-tracts 0 to 57 from the Geolytics database correspond to Escambia county

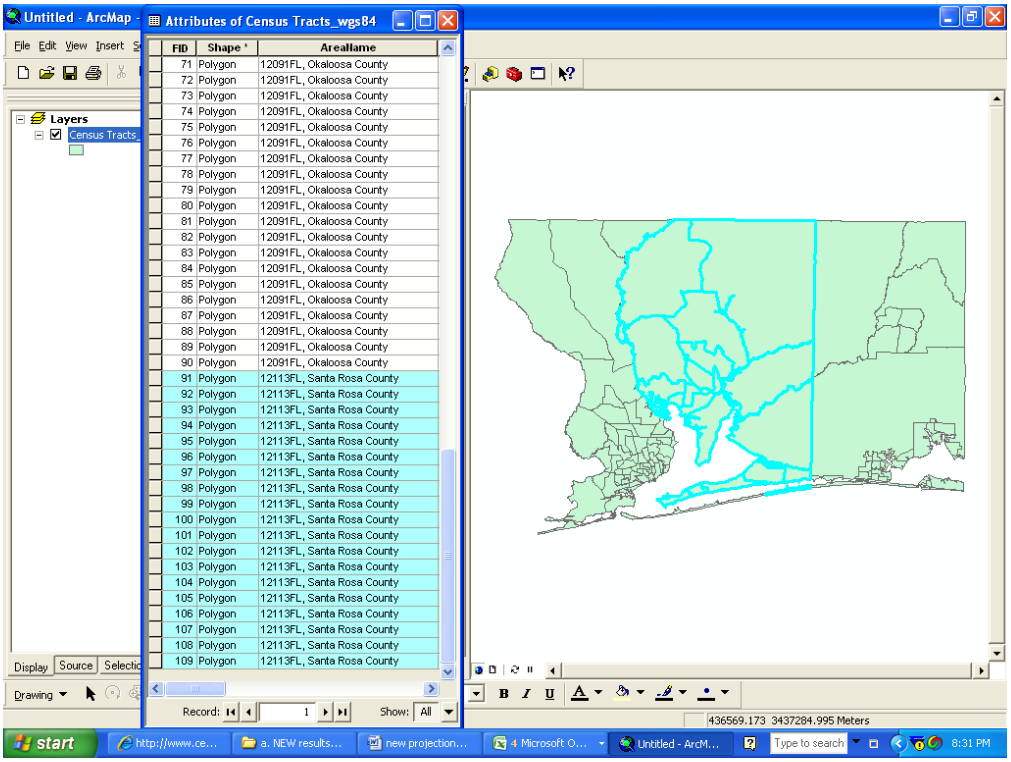


Figure A-IV.2: Selecting Census-tracts for Santa Rosa county in ArcMap

Note: Census-tracts 91 to 109 from the Geolytics database correspond to Santa Rosa county

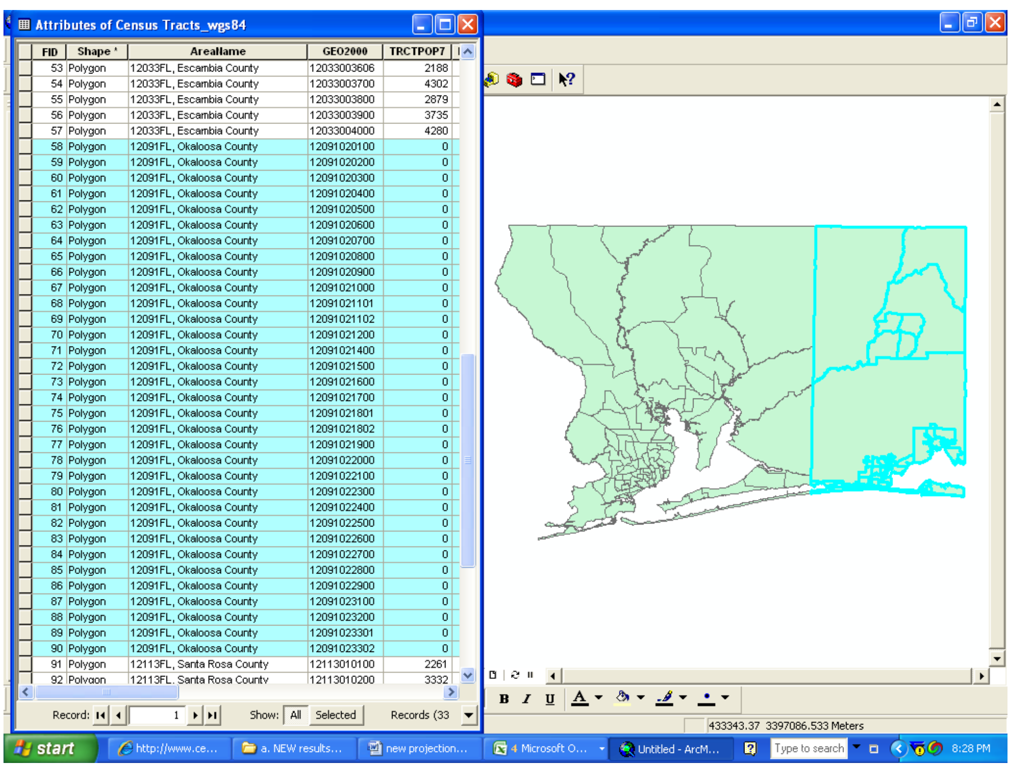


Figure A-IV.3: Selecting Census-tracts for Okaloosa county in ArcMap

Note: Census-tracts 58 to 90 from the Geolytics database correspond to Escambia county and they do not contain population data for the year 1970

Table A-IV.1: Population Data for Escambia Census-tracts according to Geolytics

Tracts	1970	1970 %	1980	1980 %	1990	1990 %	2000	2000 %
0	4,085	2.01	2,691	1.16	2,104	0.80	2,021	0.69
1	4,659	2.29	3,725	1.60	3,262	1.24	3,044	1.03
2	5,887	2.89	4,106	1.77	3,645	1.39	3,402	1.16
3	2,247	1.10	1,861	0.80	1,655	0.63	1,613	0.55
4	5,079	2.49	2,548	1.10	2,117	0.81	1,923	0.65
5	8,824	4.33	6,737	2.90	5,680	2.16	5,080	1.73
6	3,372	1.66	2,813	1.21	2,707	1.03	2,607	0.89
7	4,635	2.28	5,149	2.22	6,573	2.50	6,310	2.14
8	2,394	1.18	2,577	1.11	3,395	1.29	2,990	1.02
9	2,881	1.41	4,156	1.79	5,709	2.18	6,127	2.08
10	1,551	0.76	2,716	1.17	3,239	1.23	2,960	1.01
11	3,370	1.65	5,897	2.54	7,038	2.68	6,623	2.25
12	4,084	2.01	4,460	1.92	5,031	1.92	5,179	1.76
13	3,126	1.54	3,492	1.50	4,131	1.57	3,858	1.31
14	5,369	2.64	5,440	2.34	4,868	1.85	4,616	1.57
15	2,778	1.36	3,737	1.61	4,583	1.75	5,559	1.89
16	3,900	1.92	6,261	2.69	6,422	2.45	6,081	2.07
17	3,515	1.73	2,473	1.06	1,746	0.67	1,339	0.45
18	3,494	1.72	2,731	1.18	1,918	0.73	2,805	0.95
19	4,775	2.34	4,031	1.73	3,525	1.34	3,110	1.06
20	4,701	2.31	3,633	1.56	2,837	1.08	2,411	0.82
21	3,069	1.51	2,317	1.00	2,292	0.87	2,201	0.75
22	3,599	1.77	3,011	1.30	2,474	0.94	2,270	0.77
23	6,403	3.14	5,926	2.55	5,168	1.97	5,205	1.77
24	6,684	3.28	5,144	2.21	4,952	1.89	4,061	1.38
25	6,942	3.41	6,099	2.62	5,722	2.18	5,371	1.82
26	4,816	2.36	3,707	1.60	3,801	1.45	10,389	3.53
27	877	0.43	1,585	0.68	2,482	0.95	2,738	0.93
28	2,540	1.25	4,891	2.10	8,042	3.06	17,455	5.93
29	996	0.49	580	0.25	871	0.33	2,501	0.85
30	2,893	1.42	5,759	2.48	8,648	3.29	8,012	2.72
31	1,837	0.90	2,570	1.11	3,094	1.18	2,748	0.93
32	2,732	1.34	3,823	1.65	4,603	1.75	6,096	2.07
33	1,897	0.93	2,492	1.07	2,896	1.10	2,773	0.94
34	2,331	1.14	3,262	1.40	3,927	1.50	3,008	1.02
35	5,663	2.78	4,733	2.04	4,282	1.63	4,155	1.41
36	6,603	3.24	6,842	2.94	6,632	2.53	7,061	2.40
37	4,864	2.39	5,519	2.38	4,953	1.89	4,887	1.66
38	2,864	1.41	4,716	2.03	4,527	1.72	4,846	1.65
39	4,491	2.21	4,650	2.00	7,030	2.68	8,079	2.74
40	824	0.40	1,864	0.80	2,166	0.83	2,791	0.95
41	2,933	1.44	6,854	2.95	7,942	3.03	9,040	3.07
42	714	0.35	1,693	0.73	1,963	0.75	2,462	0.84
43	2,425	1.19	5,750	2.47	6,669	2.54	6,824	2.32
44	928	0.46	2,201	0.95	2,553	0.97	2,259	0.77
45	4,399	2.16	4,638	2.00	4,614	1.76	4,642	1.58
46	3,821	1.88	5,671	2.44	7,660	2.92	9,580	3.25
47	2,630	1.29	4,140	1.78	5,441	2.07	6,136	2.08
48	3,812	1.87	6,001	2.58	7,887	3.00	8,781	2.98
49	2,214	1.09	5,860	2.52	7,734	2.95	9,018	3.06
50	1,261	0.62	2,748	1.18	4,411	1.68	4,841	1.64
51	1,762	0.87	3,723	1.60	6,155	2.34	8,896	3.02
52	1,707	0.84	3,607	1.55	5,963	2.27	8,416	2.86
53	2,188	1.07	4,624	1.99	7,645	2.91	9,251	3.14
54	4,302	2.11	2,828	1.22	2,839	1.08	3,315	1.13
55	2,879	1.41	2,925	1.26	3,817	1.45	4,485	1.52
56	3,735	1.83	4,338	1.87	4,588	1.75	5,097	1.73
57	4,280	2.10	4,055	1.75	3,854	1.47	5,062	1.72
Total Pop. According to Geolytics	**203,641**	**100.00**	**232,380**	**100.00**	**262,482**	**100.00**	**294,410**	**100.00**
Pop. according to Florida's Office of Demographic and Economic Research	**205,334**		**233,794**		**262,798**		**294,410**	
Differences	**-1,693**	**-0.83**	**-1,414**	**-0.61**	**-316**	**-0.12**	**0**	**0.00**

Table A-IV.2: Population Data for Santa Rosa Census-tracts according to Geolytics

Tracts	1970	1970 %	1980	1980 %	1990	1990 %	2000	2000 %
91	2,261	5.97	2,712	4.83	2,599	3.17	3,612	3.07
92	3,332	8.80	3,983	7.09	3,953	4.83	4,132	3.51
93	1,085	2.87	1,820	3.24	3,365	4.11	6,611	5.61
94	4,477	11.83	2,436	4.34	2,269	2.77	2,227	1.89
95	2,153	5.69	4,634	8.25	6,449	7.87	8,075	6.86
96	1,436	3.79	3,092	5.50	4,302	5.25	6,056	5.14
97	6,459	17.06	6,436	11.45	6,520	7.96	6,093	5.17
98	1,421	3.75	2,599	4.63	3,923	4.79	4,902	4.16
99	1,717	4.54	3,331	5.93	4,988	6.09	8,136	6.91
100	892	2.36	2,046	3.64	3,112	3.80	3,595	3.05
101	1,113	2.94	2,126	3.78	3,234	3.95	3,142	2.67
102	1,947	5.14	3,374	6.00	5,133	6.27	6,750	5.73
103	1,175	3.10	4,056	7.22	5,806	7.09	10,120	8.60
104	262	0.69	841	1.50	1,367	1.67	3,714	3.15
105	1,411	3.73	2,591	4.61	7,041	8.59	8,738	7.42
106	786	2.08	1,451	2.58	3,678	4.49	9,740	8.27
107	707	1.87	1,298	2.31	3,528	4.31	7,532	6.40
108	1,028	2.72	1,887	3.36	5,128	6.26	8,903	7.56
109	4,190	11.07	5,478	9.75	5,530	6.75	5,665	4.81
Total Pop. According to Geolytics	**37,852**	**100.00**	**56,191**	**100.00**	**81,925**	**100.00**	**117,743**	**100.00**
Pop. according to Florida's Office of Demographic and Economic Research	**37,742**		**55,988**		**81,608**		**117,743**	
Differences	**110**	**0.29**	**203**	**0.36**	**317**	**0.39**	**0**	**0.00**

Table A-IV.3: Population Data for Okaloosa Census-tracts according to Geolytics

Tracts	1970	1970 %	1980	1980 %	1990	1990 %	2000	2000 %
58	No Data	---	4,376	3.98	5,210	3.62	6,742	3.95
59	No Data	---	1,547	1.41	1,645	1.14	1,799	1.06
60	No Data	---	2,903	2.64	5,172	3.60	8,493	4.98
61	No Data	---	3,676	3.34	4,895	3.40	5,529	3.24
62	No Data	---	4,000	3.64	5,005	3.48	5,472	3.21
63	No Data	---	2,098	1.91	2,827	1.97	5,364	3.15
64	No Data	---	2,176	1.98	3,847	2.68	7,760	4.55
65	No Data	---	3,074	2.80	5,946	4.14	5,376	3.15
66	No Data	---	2,109	1.92	3,331	2.32	4,575	2.68
67	No Data	---	1,470	1.34	7,272	5.06	9,663	5.67
68	No Data	---	2,633	2.40	3,191	2.22	3,308	1.94
69	No Data	---	5,570	5.07	6,751	4.70	7,261	4.26
70	No Data	---	6,858	6.24	5,296	3.68	7,494	4.40
71	No Data	---	6,854	6.24	7,464	5.19	7,325	4.30
72	No Data	---	5,938	5.40	7,154	4.98	7,918	4.64
73	No Data	---	1,995	1.82	2,170	1.51	1,844	1.08
74	No Data	---	2,916	2.65	2,932	2.04	2,649	1.55
75	No Data	---	1,770	1.61	3,973	2.76	5,299	3.11
76	No Data	---	1,872	1.70	4,200	2.92	5,115	3.00
77	No Data	---	4,471	4.07	5,376	3.74	6,305	3.70
78	No Data	---	6,814	6.20	7,342	5.11	7,006	4.11
79	No Data	---	3,376	3.07	3,303	2.30	3,212	1.88
80	No Data	---	2,123	1.93	2,145	1.49	2,339	1.37
81	No Data	---	4,392	4.00	4,127	2.87	4,043	2.37
82	No Data	---	4,552	4.14	4,454	3.10	4,088	2.40
83	No Data	---	2,542	2.31	2,933	2.04	2,874	1.69
84	No Data	---	4,117	3.75	3,740	2.60	3,694	2.17
85	No Data	---	1,470	1.34	2,385	1.66	2,040	1.20
86	No Data	---	3,775	3.43	4,340	3.02	4,164	2.44
87	No Data	---	2,994	2.72	5,239	3.64	7,434	4.36
88	No Data	---	1,537	1.40	2,031	1.41	1,825	1.07
89	No Data	---	2,470	2.25	5,102	3.55	9,292	5.45
90	No Data	---	1,441	1.31	2,978	2.07	3,196	1.87
Total Pop. According to Geolytics	No Data	**---**	**109,909**	**100.00**	**143,776**	**100.00**	**170,498**	**100.00**
Pop. according to Florida's Office of Demographic and Economic Research	**88,187**		**109,920**		**143,777**		**170,498**	
Differences	**---**	**0.0000**	**-11**	**-0.01**	**-1**	**0.00**	**0**	**0.00**

Table A-IV.4: Calculation of Population Growth Rates for Escambia Census-tracts

Tracts	Population 1970 Geolytics	annual growth rates 70-80	Population 1980 Geolytics	annual growth rates 80-90	Population 1990 Geolytics	annual growth rates 90-2000	Population 2000 Geolytics	average growth trend for projections	smoothing projections trends 70-2000
0	4,085	-4.09	2,691	-2.43	2,104	-0.40	2,021	-2.31	-0.54
1	4,659	-2.21	3,725	-1.32	3,262	-0.69	3,044	-1.41	-0.09
2	5,887	-3.54	4,106	-1.18	3,645	-0.69	3,402	-1.80	-0.28
3	2,247	-1.87	1,861	-1.17	1,655	-0.26	1,613	-1.10	0.07
4	5,079	-6.67	2,548	-1.84	2,117	-0.96	1,923	-3.15	-0.96
5	8,824	-2.66	6,737	-1.69	5,680	-1.11	5,080	-1.82	-0.29
6	3,372	-1.80	2,813	-0.38	2,707	-0.38	2,607	-0.85	0.19
7	4,635	1.06	5,149	2.47	6,573	-0.41	6,310	1.04	1.14
8	2,394	0.74	2,577	2.80	3,395	-1.26	2,990	0.76	1.00
9	2,881	3.73	4,156	3.23	5,709	0.71	6,127	2.56	1.90
10	1,551	5.76	2,716	1.78	3,239	-0.90	2,960	2.21	1.73
11	3,370	5.75	5,897	1.78	7,038	-0.61	6,623	2.31	1.77
12	4,084	0.88	4,460	1.21	5,031	0.29	5,179	0.80	1.02
13	3,126	1.11	3,492	1.69	4,131	-0.68	3,858	0.71	0.97
14	5,369	0.13	5,440	-1.10	4,868	-0.53	4,616	-0.50	0.37
15	2,778	3.01	3,737	2.06	4,583	1.95	5,559	2.34	1.79
16	3,900	4.85	6,261	0.25	6,422	-0.54	6,081	1.52	1.38
17	3,515	-3.46	2,473	-3.42	1,746	-2.62	1,339	-3.17	-0.96
18	3,494	-2.43	2,731	-3.47	1,918	3.87	2,805	-0.68	0.28
19	4,775	-1.68	4,031	-1.33	3,525	-1.24	3,110	-1.42	-0.09
20	4,701	-2.54	3,633	-2.44	2,837	-1.61	2,411	-2.20	-0.48
21	3,069	-2.77	2,317	-0.11	2,292	-0.40	2,201	-1.09	0.07
22	3,599	-1.77	3,011	-1.95	2,474	-0.86	2,270	-1.52	-0.14
23	6,403	-0.77	5,926	-1.36	5,168	0.07	5,205	-0.69	0.28
24	6,684	-2.58	5,144	-0.38	4,952	-1.96	4,061	-1.64	-0.20
25	6,942	-1.29	6,099	-0.64	5,722	-0.63	5,371	-0.85	0.19
26	4,816	-2.58	3,707	0.25	3,801	10.58	10,389	2.75	1.99
27	877	6.10	1,585	4.59	2,482	0.99	2,738	3.89	2.56
28	2,540	6.77	4,891	5.10	8,042	8.06	17,455	6.64	3.94
29	996	-5.26	580	4.15	871	11.12	2,501	3.34	2.29
30	2,893	7.13	5,759	4.15	8,648	-0.76	8,012	3.51	2.37
31	1,837	3.41	2,570	1.87	3,094	-1.18	2,748	1.37	1.30
32	2,732	3.42	3,823	1.87	4,603	2.85	6,096	2.71	1.97
33	1,897	2.77	2,492	1.51	2,896	-0.43	2,773	1.28	1.26
34	2,331	3.42	3,262	1.87	3,927	-2.63	3,008	0.89	1.06
35	5,663	-1.78	4,733	-1.00	4,282	-0.30	4,155	-1.03	0.11
36	6,603	0.36	6,842	-0.31	6,632	0.63	7,061	0.22	0.73
37	4,864	1.27	5,519	-1.08	4,953	-0.13	4,887	0.02	0.63
38	2,864	5.11	4,716	-0.41	4,527	0.68	4,846	1.80	1.52
39	4,491	0.35	4,650	4.22	7,030	1.40	8,079	1.99	1.61
40	824	8.51	1,864	1.51	2,166	2.57	2,791	4.20	2.72
41	2,933	8.86	6,854	1.48	7,942	1.30	9,040	3.88	2.56
42	714	9.02	1,693	1.49	1,963	2.29	2,462	4.27	2.75
43	2,425	9.02	5,750	1.49	6,669	0.23	6,824	3.58	2.41
44	928	9.02	2,201	1.49	2,553	-1.22	2,259	3.10	2.17
45	4,399	0.53	4,638	-0.05	4,614	0.06	4,642	0.18	0.71
46	3,821	4.03	5,671	3.05	7,660	2.26	9,580	3.11	2.18
47	2,630	4.64	4,140	2.77	5,441	1.21	6,136	2.87	2.06
48	3,812	4.64	6,001	2.77	7,887	1.08	8,781	2.83	2.03
49	2,214	10.22	5,860	2.81	7,734	1.55	9,018	4.86	3.05
50	1,261	8.10	2,748	4.85	4,411	0.93	4,841	4.63	2.93
51	1,762	7.77	3,723	5.16	6,155	3.75	8,896	5.56	3.40
52	1,707	7.77	3,607	5.16	5,963	3.51	8,416	5.48	3.36
53	2,188	7.77	4,624	5.16	7,645	1.93	9,251	4.95	3.09
54	4,302	-4.11	2,828	0.04	2,839	1.56	3,315	-0.84	0.20
55	2,879	0.16	2,925	2.70	3,817	1.63	4,485	1.49	1.37
56	3,735	1.51	4,338	0.56	4,588	1.06	5,097	1.04	1.14
57	4,280	-0.54	4,055	-0.51	3,854	2.76	5,062	0.57	0.90
total pop & growth rates	**203,641**	**1.33**	**232,380**	**1.23**	**262,482**	**1.15**	**294,410**	**1.24**	**1.24**

Table A-IV.5: Calculation of Population Growth Rates for Santa Rosa Census-tracts

Tracts	Population 1970 Geolytics	annual growth rates 70-80	Population 1980 Geolytics	annual growth rates 80-90	Population 1990 Geolytics	annual growth rates 90-2000	Population 2000 Geolytics	average growth trend 70-2000 for projections	smoothing projections trends 70-2000
91	2,261	1.84	2,691	-0.42	2,599	3.35	3,612	1.59	2.72
92	3,332	1.80	3,725	-0.08	3,953	0.44	4,132	0.72	2.29
93	1,085	5.31	4,106	6.34	3,365	6.99	6,611	6.21	5.03
94	4,477	-5.90	1,861	-0.71	2,269	-0.19	2,227	-2.27	0.79
95	2,153	7.97	2,548	3.36	6,449	2.27	8,075	4.53	4.19
96	1,436	7.97	6,737	3.36	4,302	3.48	6,056	4.94	4.40
97	6,459	-0.04	2,813	0.13	6,520	-0.68	6,093	-0.19	1.83
98	1,421	6.22	5,149	4.20	3,923	2.25	4,902	4.23	4.04
99	1,717	6.85	2,577	4.12	4,988	5.01	8,136	5.33	4.59
100	892	8.66	4,156	4.28	3,112	1.45	3,595	4.80	4.33
101	1,113	6.69	2,716	4.28	3,234	-0.29	3,142	3.56	3.71
102	1,947	5.65	5,897	4.29	5,133	2.78	6,750	4.24	4.05
103	1,175	13.19	4,460	3.65	5,806	5.71	10,120	7.52	5.69
104	262	12.37	3,492	4.98	1,367	10.51	3,714	9.29	6.57
105	1,411	6.27	5,440	10.51	7,041	2.18	8,738	6.32	5.09
106	786	6.32	3,737	9.75	3,678	10.23	9,740	8.77	6.31
107	707	6.26	6,261	10.52	3,528	7.88	7,532	8.22	6.04
108	1,028	6.26	2,473	10.51	5,128	5.67	8,903	7.48	5.67
109	4,190	2.72	2,731	0.09	5,530	0.24	5,665	1.02	2.44
total pop & growth rates	**37,852**	**4.03**	**73,570**	**3.84**	**81,925**	**3.69**	**117,743**	**3.86**	**3.86**

Table A-IV.6: Calculation of Population Growth Rates for Okaloosa Census-tracts

Tracts	Population 1970 Geolytics	annual growth rates 70-80	Population 1980 Geolytics	annual growth rates 80-90	Population 1990 Geolytics	annual growth rates 90-2000	Population 2000 Geolytics	average growth trend 70-2000 for projections	smoothing projections trends 70-2000
58	No Data	---	4,376	1.76	5,210	2.61	6,742	1.46	1.47
59	No Data	---	1,547	0.62	1,645	0.90	1,799	0.51	0.99
60	No Data	---	2,903	5.95	5,172	5.08	8,493	3.68	2.58
61	No Data	---	3,676	2.91	4,895	1.23	5,529	1.38	1.43
62	No Data	---	4,000	2.27	5,005	0.90	5,472	1.05	1.27
63	No Data	---	2,098	3.03	2,827	6.61	5,364	3.21	2.35
64	No Data	---	2,176	5.86	3,847	7.27	7,760	4.38	2.93
65	No Data	---	3,074	6.82	5,946	-1.00	5,376	1.94	1.71
66	No Data	---	2,109	4.68	3,331	3.22	4,575	2.63	2.06
67	No Data	---	1,470	17.34	7,272	2.88	9,663	6.74	4.11
68	No Data	---	2,633	1.94	3,191	0.36	3,308	0.77	1.12
69	No Data	---	5,570	1.94	6,751	0.73	7,261	0.89	1.19
70	No Data	---	6,858	-2.55	5,296	3.53	7,494	0.33	0.90
71	No Data	---	6,854	0.86	7,464	-0.19	7,325	0.22	0.85
72	No Data	---	5,938	1.88	7,154	1.02	7,918	0.97	1.22
73	No Data	---	1,995	0.84	2,170	-1.61	1,844	-0.26	0.61
74	No Data	---	2,916	0.05	2,932	-1.01	2,649	-0.32	0.58
75	No Data	---	1,770	8.42	3,973	2.92	5,299	3.78	2.63
76	No Data	---	1,872	8.42	4,200	1.99	5,115	3.47	2.47
77	No Data	---	4,471	1.86	5,376	1.61	6,305	1.16	1.32
78	No Data	---	6,814	0.75	7,342	-0.47	7,006	0.09	0.79
79	No Data	---	3,376	-0.22	3,303	-0.28	3,212	-0.17	0.66
80	No Data	---	2,123	0.10	2,145	0.87	2,339	0.32	0.90
81	No Data	---	4,392	-0.62	4,127	-0.21	4,043	-0.28	0.60
82	No Data	---	4,552	-0.22	4,454	-0.85	4,088	-0.36	0.56
83	No Data	---	2,542	1.44	2,933	-0.20	2,874	0.41	0.95
84	No Data	---	4,117	-0.96	3,740	-0.12	3,694	-0.36	0.56
85	No Data	---	1,470	4.96	2,385	-1.55	2,040	1.14	1.31
86	No Data	---	3,775	1.40	4,340	-0.41	4,164	0.33	0.91
87	No Data	---	2,994	5.75	5,239	3.56	7,434	3.11	2.29
88	No Data	---	1,537	2.83	2,031	-1.06	1,825	0.59	1.03
89	No Data	---	2,470	7.52	5,102	6.18	9,292	4.57	3.02
90	No Data	---	1,441	7.53	2,978	0.71	3,196	2.75	2.11
total pop & growth rates	**---**	**---**	**109,909**	**2.72**	**143,776**	**1.72**	**170,498**	**1.48**	**1.48**

Table A-IV.7: Historical Population Data for Escambia Census-tracts

Tracts	1970	1974	1975	1980	1985	1986	1990	1992	1995	2000	2001
0	4,119	3,743	3,548	2,707	2,457	2,402	2,107	2,071	2,068	2,021	1,992
1	4,698	4,607	4,454	3,748	3,599	3,558	3,266	3,192	3,160	3,044	3,015
2	5,936	5,517	5,260	4,131	3,994	3,954	3,649	3,567	3,532	3,402	3,362
3	2,266	2,253	2,186	1,872	1,812	1,794	1,657	1,634	1,639	1,613	1,600
4	5,121	4,180	3,855	2,564	2,398	2,359	2,120	2,061	2,024	1,923	1,888
5	8,897	8,569	8,246	6,778	6,387	6,292	5,687	5,512	5,388	5,080	5,020
6	3,400	3,391	3,292	2,830	2,848	2,843	2,710	2,666	2,664	2,607	2,589
7	4,674	5,218	5,216	5,180	6,001	6,160	6,581	6,470	6,459	6,310	6,326
8	2,414	2,662	2,652	2,593	3,051	3,142	3,399	3,284	3,195	2,990	2,993
9	2,905	3,595	3,690	4,181	5,023	5,195	5,716	5,747	5,932	6,127	6,188
10	1,564	2,089	2,187	2,733	3,060	3,120	3,243	3,157	3,106	2,960	2,984
11	3,398	4,538	4,750	5,933	6,646	6,777	7,046	6,900	6,848	6,623	6,681
12	4,118	4,567	4,557	4,487	4,887	4,956	5,037	5,022	5,120	5,179	5,185
13	3,152	3,527	3,527	3,513	3,918	3,992	4,136	4,044	4,004	3,858	3,861
14	5,414	5,829	5,772	5,473	5,313	5,264	4,874	4,780	4,754	4,616	4,592
15	2,801	3,373	3,437	3,760	4,269	4,365	4,589	4,728	5,063	5,559	5,608
16	3,932	5,077	5,267	6,299	6,544	6,573	6,430	6,304	6,268	6,081	6,110
17	3,544	3,305	3,154	2,488	2,147	2,077	1,748	1,643	1,533	1,339	1,314
18	3,523	3,424	3,303	2,748	2,364	2,287	1,920	2,055	2,327	2,805	2,788
19	4,815	4,824	4,690	4,056	3,892	3,847	3,529	3,411	3,321	3,110	3,080
20	4,740	4,587	4,419	3,655	3,316	3,241	2,840	2,725	2,623	2,411	2,378
21	3,095	2,967	2,852	2,331	2,378	2,380	2,295	2,256	2,253	2,201	2,183
22	3,629	3,623	3,519	3,029	2,818	2,769	2,477	2,413	2,377	2,270	2,247
23	6,456	6,708	6,582	5,962	5,714	5,647	5,174	5,136	5,202	5,205	5,173
24	6,740	6,511	6,271	5,175	5,210	5,200	4,958	4,722	4,497	4,061	4,017
25	7,000	7,125	6,954	6,136	6,098	6,071	5,729	5,607	5,560	5,371	5,334
26	4,856	4,692	4,519	3,730	3,874	3,891	3,806	4,618	6,306	10,389	10,502
27	884	1,196	1,256	1,595	2,045	2,142	2,485	2,512	2,615	2,738	2,783
28	2,561	3,552	3,754	4,921	6,465	6,807	8,052	9,328	11,888	17,455	17,983
29	1,004	869	814	584	733	765	872	1,069	1,481	2,501	2,536
30	2,917	4,099	4,346	5,794	7,276	7,592	8,658	8,451	8,349	8,012	8,130
31	1,852	2,265	2,317	2,586	2,909	2,969	3,098	2,998	2,924	2,748	2,759
32	2,755	3,369	3,447	3,846	4,328	4,417	4,609	4,834	5,314	6,096	6,162
33	1,913	2,282	2,319	2,507	2,772	2,819	2,899	2,849	2,842	2,773	2,783
34	2,350	2,874	2,941	3,282	3,692	3,768	3,932	3,694	3,447	3,008	3,013
35	5,710	5,699	5,534	4,762	4,648	4,610	4,287	4,224	4,231	4,155	4,123
36	6,658	7,232	7,178	6,884	6,953	6,945	6,640	6,665	6,864	7,061	7,050
37	4,904	5,522	5,531	5,553	5,398	5,350	4,959	4,902	4,935	4,887	4,874
38	2,888	3,766	3,917	4,745	4,769	4,759	4,532	4,555	4,698	4,846	4,876
39	4,528	4,917	4,880	4,678	5,895	6,155	7,038	7,175	7,560	8,079	8,137
40	831	1,228	1,319	1,875	2,073	2,108	2,169	2,262	2,466	2,791	2,841
41	2,957	4,428	4,771	6,896	7,612	7,740	7,952	8,090	8,499	9,040	9,190
42	720	1,084	1,170	1,703	1,881	1,912	1,965	2,039	2,205	2,462	2,507
43	2,445	3,682	3,973	5,785	6,389	6,497	6,677	6,649	6,766	6,824	6,927
44	936	1,409	1,521	2,214	2,446	2,487	2,556	2,472	2,409	2,259	2,288
45	4,436	4,851	4,823	4,666	4,774	4,781	4,620	4,585	4,642	4,642	4,634
46	3,853	4,822	4,963	5,706	6,797	7,018	7,669	7,952	8,593	9,580	9,702
47	2,652	3,397	3,517	4,165	4,895	5,040	5,448	5,532	5,796	6,136	6,207
48	3,844	4,924	5,098	6,038	7,096	7,306	7,896	7,998	8,348	8,781	8,880
49	2,232	3,511	3,831	5,896	6,943	7,152	7,743	7,916	8,377	9,018	9,211
50	1,271	1,852	1,981	2,765	3,589	3,770	4,416	4,460	4,635	4,841	4,939
51	1,777	2,556	2,727	3,746	4,934	5,198	6,162	6,578	7,423	8,896	9,117
52	1,721	2,476	2,642	3,629	4,781	5,036	5,970	6,343	7,107	8,416	8,622
53	2,206	3,174	3,386	4,652	6,129	6,457	7,654	7,884	8,436	9,251	9,453
54	4,338	3,938	3,733	2,845	2,924	2,931	2,842	2,907	3,077	3,315	3,292
55	2,903	3,129	3,099	2,943	3,446	3,546	3,822	3,913	4,150	4,485	4,506
56	3,766	4,279	4,296	4,364	4,604	4,638	4,594	4,651	4,851	5,097	5,110
57	4,316	4,525	4,451	4,080	4,081	4,068	3,859	4,040	4,431	5,062	5,063
TOTAL	**205,334**	**227,408**	**227,698**	**233,794**	**253,293**	**256,942**	**262,798**	**265,247**	**276,584**	**294,410**	**296,709**

Table A-IV.8: Population's Projections for Escambia Census-tracts

Tracts	2005	2010	2015	2020	2025
0	1,864	1,772	1,655	1,531	1,402
1	2,872	2,793	2,667	2,523	2,364
2	3,178	3,060	2,894	2,710	2,514
3	1,534	1,503	1,447	1,379	1,302
4	1,737	1,616	1,477	1,338	1,199
5	4,744	4,565	4,315	4,040	3,746
6	2,494	2,459	2,381	2,284	2,170
7	6,328	6,539	6,637	6,673	6,644
8	2,977	3,055	3,079	3,074	3,040
9	6,378	6,841	7,208	7,522	7,774
10	3,055	3,250	3,396	3,514	3,602
11	6,853	7,306	7,652	7,938	8,155
12	5,162	5,302	5,349	5,346	5,290
13	3,837	3,933	3,959	3,948	3,899
14	4,455	4,431	4,329	4,189	4,014
15	5,756	6,141	6,437	6,682	6,870
16	6,170	6,452	6,627	6,742	6,792
17	1,209	1,125	1,028	930	834
18	2,695	2,669	2,596	2,501	2,386
19	2,934	2,852	2,723	2,575	2,412
20	2,230	2,126	1,990	1,846	1,695
21	2,093	2,051	1,974	1,882	1,777
22	2,136	2,071	1,972	1,860	1,737
23	5,001	4,950	4,814	4,637	4,423
24	3,809	3,682	3,496	3,288	3,062
25	5,139	5,066	4,907	4,707	4,471
26	10,865	11,710	12,396	12,998	13,497
27	2,945	3,263	3,552	3,830	4,090
28	20,066	23,769	27,658	31,877	36,385
29	2,654	2,901	3,116	3,315	3,492
30	8,536	9,371	10,106	10,795	11,419
31	2,778	2,894	2,962	3,002	3,013
32	6,370	6,859	7,255	7,601	7,886
33	2,797	2,908	2,969	3,003	3,008
34	3,005	3,093	3,128	3,133	3,107
35	3,958	3,886	3,747	3,578	3,385
36	6,939	7,027	6,990	6,887	6,720
37	4,778	4,814	4,765	4,671	4,534
38	4,951	5,212	5,390	5,521	5,601
39	8,293	8,773	9,116	9,382	9,562
40	3,024	3,376	3,703	4,022	4,327
41	9,720	10,770	11,721	12,636	13,490
42	2,672	2,989	3,283	3,573	3,850
43	7,284	8,011	8,655	9,262	9,815
44	2,383	2,590	2,766	2,925	3,064
45	4,557	4,609	4,580	4,507	4,393
46	10,109	10,993	11,742	12,423	13,016
47	6,437	6,959	7,389	7,772	8,095
48	9,202	9,937	10,541	11,075	11,524
49	9,930	11,268	12,559	13,865	15,159
50	5,300	5,980	6,628	7,276	7,910
51	9,963	11,497	13,033	14,633	16,271
52	9,406	10,834	12,256	13,734	15,241
53	10,209	11,609	12,967	14,347	15,720
54	3,173	3,129	3,032	2,909	2,765
55	4,548	4,753	4,878	4,960	4,994
56	5,111	5,282	5,362	5,391	5,368
57	5,018	5,125	5,142	5,111	5,030
TOTAL	**303,623**	**323,801**	**340,395**	**355,672**	**369,307**

Table A-IV.9: Historical Population Data for Santa Rosa Census-tracts

Tracts	1970	1974	1975	1980	1985	1986	1990	1992	1995	2000	2001
91	2,254	2,947	2,855	2,702	2,675	2,671	2,589	2,816	3,113	3,612	3,658
92	3,322	4,338	4,200	3,969	3,998	4,006	3,938	4,046	4,108	4,132	4,167
93	1,082	1,609	1,616	1,813	2,490	2,659	3,352	3,908	4,791	6,611	6,846
94	4,464	4,313	3,828	2,427	2,369	2,359	2,260	2,293	2,285	2,227	2,213
95	2,147	3,512	3,628	4,617	5,505	5,710	6,424	6,844	7,334	8,075	8,296
96	1,432	2,343	2,420	3,081	3,672	3,809	4,285	4,674	5,186	6,056	6,234
97	6,440	7,842	7,442	6,413	6,527	6,554	6,495	6,526	6,408	6,093	6,118
98	1,417	2,178	2,209	2,590	3,215	3,362	3,908	4,161	4,457	4,902	5,029
99	1,712	2,692	2,748	3,319	4,104	4,289	4,969	5,581	6,472	8,136	8,390
100	889	1,491	1,551	2,039	2,540	2,659	3,100	3,250	3,400	3,595	3,698
101	1,110	1,734	1,768	2,118	2,640	2,763	3,221	3,262	3,241	3,142	3,213
102	1,941	2,923	2,948	3,362	4,190	4,385	5,113	5,501	5,982	6,750	6,925
103	1,172	2,299	2,500	4,041	4,886	5,083	5,784	6,583	7,787	10,120	10,546
104	261	498	538	838	1,079	1,137	1,362	1,694	2,288	3,714	3,903
105	1,407	2,166	2,198	2,582	4,295	4,770	7,014	7,459	7,971	8,738	9,054
106	784	1,209	1,228	1,446	2,323	2,562	3,664	4,535	6,077	9,740	10,209
107	705	1,085	1,101	1,293	2,152	2,390	3,514	4,166	5,235	7,532	7,875
108	1,025	1,578	1,601	1,880	3,128	3,474	5,108	5,810	6,864	8,903	9,276
109	4,178	5,645	5,520	5,458	5,546	5,567	5,509	5,637	5,690	5,665	5,722
TOTAL	**37,742**	**52,402**	**51,899**	**55,988**	**67,336**	**70,208**	**81,608**	**88,745**	**98,688**	**117,743**	**121,370**

Table A-IV.10: Population's Projections for Santa Rosa Census-tracts

Tracts	2005	2010	2015	2020	2025
91	3,826	4,069	4,135	4,113	4,010
92	4,286	4,463	4,441	4,325	4,129
93	7,827	9,305	10,570	11,750	12,807
94	2,146	2,076	1,919	1,737	1,540
95	9,185	10,490	11,448	12,226	12,801
96	6,955	8,020	8,837	9,529	10,075
97	6,179	6,292	6,122	5,830	5,443
98	5,535	6,275	6,797	7,206	7,490
99	9,432	10,979	12,212	13,293	14,186
100	4,115	4,730	5,194	5,582	5,882
101	3,491	3,895	4,152	4,332	4,431
102	7,623	8,645	9,368	9,933	10,327
103	12,359	15,155	17,758	20,362	22,892
104	4,729	6,045	7,385	8,827	10,346
105	10,372	12,363	14,081	15,693	17,149
106	12,250	15,471	18,669	22,046	25,525
107	9,352	11,660	13,890	16,193	18,509
108	10,864	13,310	15,583	17,853	20,054
109	5,918	6,208	6,222	6,103	5,869
TOTAL	**136,443**	**159,450**	**178,786**	**196,932**	**213,466**

Table A-IV.11: Historical Population Data for Okaloosa Census-tracts

Tracts	1970	1974	1975	1980	1985	1986	1990	1992	1995	2000	2001
58	3,511	4,121	4,077	4,376	5,038	5,155	5,210	5,423	5,907	6,742	6,841
59	1,241	1,457	1,441	1,547	1,684	1,704	1,645	1,655	1,715	1,799	1,817
60	2,329	2,734	2,705	2,903	4,082	4,348	5,172	5,647	6,606	8,493	8,713
61	2,949	3,462	3,425	3,676	4,474	4,629	4,895	4,958	5,185	5,529	5,608
62	3,209	3,767	3,727	4,000	4,720	4,854	5,005	5,037	5,216	5,472	5,542
63	1,683	1,976	1,955	2,098	2,569	2,661	2,827	3,177	3,881	5,364	5,490
64	1,746	2,049	2,027	2,176	3,048	3,244	3,847	4,377	5,446	7,760	7,988
65	2,466	2,895	2,864	3,074	4,503	4,835	5,946	5,760	5,635	5,376	5,468
66	1,692	1,986	1,965	2,109	2,794	2,940	3,331	3,509	3,891	4,575	4,669
67	1,179	1,384	1,370	1,470	3,432	4,047	7,272	7,610	8,355	9,663	10,061
68	2,113	2,480	2,453	2,633	3,058	3,135	3,191	3,177	3,238	3,308	3,345
69	4,469	5,245	5,189	5,571	6,470	6,632	6,751	6,771	6,979	7,261	7,348
70	5,503	6,458	6,389	6,859	6,370	6,243	5,296	5,612	6,279	7,494	7,562
71	5,499	6,455	6,386	6,855	7,550	7,657	7,464	7,350	7,370	7,325	7,388
72	4,764	5,592	5,532	5,939	6,877	7,045	7,154	7,217	7,502	7,918	8,015
73	1,601	1,879	1,859	1,995	2,196	2,227	2,170	2,076	1,994	1,844	1,855
74	2,340	2,746	2,717	2,916	3,087	3,106	2,932	2,840	2,778	2,649	2,665
75	1,420	1,667	1,649	1,770	2,792	3,042	3,973	4,161	4,573	5,299	5,439
76	1,502	1,763	1,744	1,872	2,952	3,217	4,200	4,319	4,620	5,115	5,242
77	3,587	4,210	4,166	4,471	5,173	5,298	5,376	5,487	5,803	6,305	6,388
78	5,467	6,417	6,348	6,815	7,466	7,564	7,342	7,190	7,149	7,006	7,062
79	2,709	3,179	3,145	3,376	3,526	3,538	3,303	3,247	3,247	3,212	3,233
80	1,703	1,999	1,978	2,123	2,253	2,268	2,145	2,157	2,233	2,339	2,360
81	3,524	4,136	4,092	4,392	4,497	4,494	4,127	4,063	4,071	4,043	4,068
82	3,652	4,287	4,241	4,552	4,755	4,771	4,454	4,328	4,253	4,088	4,111
83	2,040	2,394	2,368	2,542	2,882	2,939	2,933	2,887	2,894	2,874	2,901
84	3,303	3,877	3,836	4,117	4,145	4,129	3,740	3,688	3,705	3,694	3,715
85	1,179	1,384	1,370	1,470	1,973	2,082	2,385	2,285	2,199	2,040	2,067
86	3,029	3,555	3,517	3,775	4,272	4,356	4,340	4,255	4,237	4,164	4,202
87	2,402	2,820	2,789	2,994	4,173	4,437	5,239	5,555	6,220	7,434	7,605
88	1,233	1,447	1,432	1,537	1,864	1,927	2,031	1,965	1,919	1,825	1,844
89	1,982	2,326	2,301	2,470	3,738	4,040	5,102	5,687	6,863	9,292	9,574
90	1,156	1,357	1,343	1,441	2,181	2,358	2,978	2,986	3,075	3,196	3,264
TOTAL	**88,187**	**103,504**	**102,400**	**109,920**	**130,595**	**134,925**	**143,777**	**146,452**	**155,039**	**170,498**	**173,450**

Table A-IV.12: Population's Projections for Okaloosa Census-tracts

Tracts	2005	2010	2015	2020	2025
58	7,371	7,983	8,484	8,888	9,186
59	1,921	2,032	2,110	2,159	2,179
60	9,804	11,212	12,582	13,918	15,189
61	6,033	6,521	6,917	7,232	7,460
62	5,923	6,352	6,684	6,933	7,095
63	6,123	6,923	7,682	8,402	9,067
64	9,112	10,600	12,099	13,614	15,113
65	5,948	6,518	7,010	7,432	7,773
66	5,148	5,740	6,279	6,771	7,203
67	12,013	14,795	17,879	21,299	25,032
68	3,555	3,786	3,956	4,074	4,140
69	7,828	8,361	8,762	9,052	9,226
70	7,967	8,392	8,673	8,836	8,881
71	7,768	8,160	8,412	8,548	8,569
72	8,552	9,152	9,609	9,946	10,156
73	1,932	2,006	2,043	2,052	2,033
74	2,772	2,873	2,922	2,929	2,898
75	6,133	7,031	7,910	8,772	9,598
76	5,875	6,685	7,463	8,214	8,919
77	6,842	7,356	7,759	8,069	8,278
78	7,406	7,755	7,969	8,071	8,066
79	3,373	3,510	3,583	3,606	3,581
80	2,487	2,619	2,706	2,757	2,771
81	4,235	4,394	4,474	4,490	4,446
82	4,273	4,425	4,496	4,503	4,450
83	3,062	3,232	3,347	3,417	3,442
84	3,861	3,998	4,062	4,068	4,020
85	2,213	2,378	2,507	2,606	2,672
86	4,427	4,664	4,820	4,911	4,937
87	8,463	9,544	10,562	11,521	12,400
88	1,953	2,070	2,153	2,208	2,234
89	10,961	12,810	14,690	16,605	18,519
90	3,606	4,032	4,423	4,782	5,102
TOTAL	**188,939**	**207,905**	**225,028**	**240,683**	**254,631**

Table A-IV.13: Historical Growth Rates for Escambia Census-tracts

Tracts	1970-1974	1974-1975	1975-1980	1980-1985	1985-1986	1986-1990	1990-1992	1992-1995	1995-2000	2000-2001
0	-2.36	-5.21	-5.27	-1.92	-2.24	-3.22	-0.86	-0.05	-0.46	-1.43
1	-0.49	-3.32	-3.39	-0.81	-1.14	-2.12	-1.14	-0.34	-0.75	-0.95
2	-1.81	-4.66	-4.72	-0.67	-1.00	-1.99	-1.13	-0.33	-0.75	-1.18
3	-0.14	-2.97	-3.05	-0.65	-0.99	-1.97	-0.70	0.10	-0.32	-0.81
4	-4.95	-7.78	-7.83	-1.33	-1.63	-2.64	-1.40	-0.60	-1.02	-1.82
5	-0.93	-3.77	-3.85	-1.18	-1.49	-2.50	-1.55	-0.76	-1.17	-1.18
6	-0.07	-2.92	-2.98	0.13	-0.18	-1.19	-0.82	-0.03	-0.43	-0.69
7	2.79	-0.04	-0.14	2.99	2.65	1.67	-0.85	-0.06	-0.47	0.25
8	2.47	-0.38	-0.45	3.31	2.98	1.99	-1.71	-0.91	-1.32	0.10
9	5.47	2.64	2.53	3.74	3.42	2.42	0.27	1.06	0.65	1.00
10	7.50	4.69	4.56	2.29	1.96	0.97	-1.33	-0.54	-0.96	0.81
11	7.50	4.67	4.55	2.30	1.97	0.98	-1.04	-0.25	-0.67	0.88
12	2.62	-0.22	-0.31	1.72	1.41	0.41	-0.15	0.65	0.23	0.12
13	2.85	0.00	-0.08	2.21	1.89	0.89	-1.12	-0.33	-0.74	0.08
14	1.86	-0.98	-1.06	-0.59	-0.92	-1.91	-0.97	-0.18	-0.59	-0.52
15	4.76	1.90	1.81	2.57	2.25	1.26	1.50	2.31	1.89	0.88
16	6.60	3.74	3.64	0.77	0.44	-0.55	-0.98	-0.19	-0.60	0.48
17	-1.73	-4.57	-4.63	-2.91	-3.26	-4.22	-3.05	-2.28	-2.67	-1.87
18	-0.71	-3.53	-3.61	-2.97	-3.26	-4.28	3.46	4.23	3.81	-0.61
19	0.05	-2.78	-2.86	-0.82	-1.16	-2.13	-1.69	-0.89	-1.30	-0.96
20	-0.82	-3.66	-3.73	-1.93	-2.26	-3.25	-2.05	-1.26	-1.67	-1.37
21	-1.05	-3.88	-3.95	0.40	0.08	-0.91	-0.85	-0.04	-0.47	-0.82
22	-0.04	-2.87	-2.95	-1.43	-1.74	-2.75	-1.30	-0.50	-0.92	-1.01
23	0.96	-1.88	-1.96	-0.85	-1.17	-2.16	-0.37	0.43	0.01	-0.61
24	-0.86	-3.69	-3.77	0.13	-0.19	-1.18	-2.41	-1.61	-2.02	-1.08
25	0.44	-2.40	-2.47	-0.12	-0.44	-1.44	-1.07	-0.28	-0.69	-0.69
26	-0.86	-3.69	-3.76	0.76	0.44	-0.55	10.15	10.94	10.50	1.09
27	7.85	5.02	4.89	5.10	4.74	3.78	0.54	1.35	0.92	1.64
28	8.52	5.69	5.56	5.61	5.29	4.29	7.63	8.42	7.98	3.02
29	-3.55	-6.33	-6.43	4.65	4.37	3.33	10.72	11.48	11.05	1.40
30	8.88	6.03	5.92	4.66	4.34	3.34	-1.20	-0.40	-0.82	1.47
31	5.16	2.30	2.22	2.38	2.06	1.07	-1.63	-0.83	-1.23	0.40
32	5.16	2.32	2.21	2.39	2.06	1.07	2.41	3.21	2.78	1.08
33	4.51	1.62	1.57	2.03	1.70	0.70	-0.87	-0.08	-0.49	0.36
34	5.16	2.33	2.22	2.38	2.06	1.07	-3.07	-2.28	-2.69	0.17
35	-0.05	-2.90	-2.96	-0.48	-0.82	-1.80	-0.74	0.06	-0.36	-0.77
36	2.09	-0.75	-0.83	0.20	-0.12	-1.12	0.19	0.99	0.57	-0.16
37	3.01	0.16	0.08	-0.56	-0.89	-1.88	-0.58	0.22	-0.20	-0.27
38	6.86	4.01	3.91	0.10	-0.21	-1.21	0.25	1.04	0.62	0.62
39	2.08	-0.75	-0.84	4.73	4.41	3.41	0.97	1.76	1.34	0.72
40	10.26	7.41	7.29	2.03	1.69	0.72	2.12	2.92	2.51	1.79
41	10.62	7.75	7.65	2.00	1.68	0.68	0.86	1.66	1.24	1.66
42	10.77	7.93	7.80	2.01	1.65	0.69	1.87	2.64	2.23	1.83
43	10.78	7.90	7.80	2.01	1.69	0.69	-0.21	0.58	0.17	1.51
44	10.77	7.95	7.80	2.01	1.68	0.69	-1.66	-0.86	-1.28	1.28
45	2.26	-0.58	-0.66	0.46	0.15	-0.85	-0.38	0.41	0.00	-0.17
46	5.77	2.92	2.83	3.56	3.25	2.24	1.83	2.62	2.20	1.27
47	6.39	3.53	3.44	3.28	2.96	1.97	0.77	1.57	1.15	1.16
48	6.39	3.53	3.44	3.28	2.96	1.96	0.64	1.44	1.02	1.13
49	11.99	9.11	9.01	3.32	3.01	2.00	1.11	1.90	1.49	2.14
50	9.87	6.97	6.90	5.36	5.04	4.03	0.50	1.29	0.87	2.02
51	9.51	6.69	6.56	5.66	5.35	4.34	3.32	4.11	3.69	2.48
52	9.52	6.70	6.55	5.67	5.33	4.35	3.08	3.86	3.44	2.45
53	9.52	6.68	6.56	5.67	5.35	4.34	1.49	2.28	1.86	2.18
54	-2.39	-5.21	-5.29	0.55	0.24	-0.77	1.14	1.91	1.50	-0.69
55	1.89	-0.96	-1.03	3.21	2.90	1.89	1.18	1.98	1.56	0.47
56	3.24	0.40	0.31	1.08	0.74	-0.24	0.62	1.41	0.99	0.26
57	1.19	-1.64	-1.73	0.00	-0.32	-1.31	2.32	3.13	2.70	0.02
TOTAL	**2.59**	**0.13**	**0.53**	**1.62**	**1.44**	**0.57**	**0.46**	**1.40**	**1.26**	**0.78**

Table A-IV.14: Projected Growth Rates for Escambia Census-tracts

Tracts	2001-2005	2005-2010	2010-2015	2015-2020	2020-2025
0	-1.65	-1.01	-1.36	-1.55	-1.75
1	-1.21	-0.56	-0.92	-1.10	-1.29
2	-1.40	-0.75	-1.11	-1.31	-1.49
3	-1.05	-0.41	-0.76	-0.96	-1.14
4	-2.06	-1.43	-1.78	-1.96	-2.17
5	-1.40	-0.77	-1.12	-1.31	-1.50
6	-0.93	-0.28	-0.64	-0.83	-1.02
7	0.01	0.66	0.30	0.11	-0.09
8	-0.13	0.52	0.16	-0.03	-0.22
9	0.76	1.41	1.05	0.86	0.66
10	0.59	1.25	0.88	0.69	0.50
11	0.64	1.29	0.93	0.74	0.54
12	-0.11	0.54	0.18	-0.01	-0.21
13	-0.16	0.50	0.13	-0.06	-0.25
14	-0.75	-0.11	-0.46	-0.66	-0.85
15	0.65	1.30	0.95	0.75	0.56
16	0.24	0.90	0.54	0.34	0.15
17	-2.06	-1.43	-1.79	-1.98	-2.16
18	-0.84	-0.19	-0.55	-0.74	-0.94
19	-1.21	-0.57	-0.92	-1.11	-1.30
20	-1.59	-0.95	-1.31	-1.49	-1.69
21	-1.05	-0.40	-0.76	-0.95	-1.14
22	-1.26	-0.62	-0.97	-1.16	-1.36
23	-0.84	-0.20	-0.56	-0.75	-0.94
24	-1.32	-0.68	-1.03	-1.22	-1.41
25	-0.93	-0.29	-0.64	-0.83	-1.02
26	0.85	1.51	1.15	0.95	0.76
27	1.42	2.07	1.71	1.52	1.32
28	2.78	3.45	3.08	2.88	2.68
29	1.14	1.80	1.44	1.25	1.05
30	1.23	1.88	1.52	1.33	1.13
31	0.17	0.82	0.47	0.27	0.07
32	0.83	1.49	1.13	0.94	0.74
33	0.13	0.78	0.42	0.23	0.03
34	-0.07	0.58	0.23	0.03	-0.17
35	-1.02	-0.37	-0.73	-0.92	-1.10
36	-0.40	0.25	-0.11	-0.30	-0.49
37	-0.50	0.15	-0.20	-0.40	-0.59
38	0.38	1.03	0.67	0.48	0.29
39	0.48	1.13	0.77	0.58	0.38
40	1.57	2.23	1.87	1.67	1.47
41	1.41	2.07	1.71	1.51	1.32
42	1.61	2.27	1.89	1.71	1.50
43	1.26	1.92	1.56	1.36	1.17
44	1.02	1.68	1.32	1.12	0.93
45	-0.42	0.23	-0.13	-0.32	-0.51
46	1.03	1.69	1.33	1.13	0.94
47	0.91	1.57	1.21	1.02	0.82
48	0.89	1.55	1.19	0.99	0.80
49	1.90	2.56	2.19	2.00	1.80
50	1.78	2.44	2.08	1.88	1.69
51	2.24	2.91	2.54	2.34	2.14
52	2.20	2.87	2.50	2.30	2.10
53	1.94	2.60	2.24	2.04	1.84
54	-0.92	-0.28	-0.63	-0.82	-1.01
55	0.23	0.89	0.52	0.33	0.14
56	0.00	0.66	0.30	0.11	-0.09
57	-0.22	0.42	0.07	-0.12	-0.32
TOTAL	**0.58**	**1.30**	**1.00**	**0.88**	**0.76**

Table A-IV.15: Historical Growth Rates for Santa Rosa Census-tracts

Tracts	1970-1974	1974-1975	1975-1980	1980-1985	1985-1986	1986-1990	1990-1992	1992-1995	1995-2000	2000-2001
91	6.93	-3.12	-1.10	-0.20	-0.15	-0.78	4.29	3.40	3.02	1.27
92	6.90	-3.18	-1.13	0.15	0.20	-0.43	1.36	0.51	0.12	0.85
93	10.43	0.44	2.33	6.55	6.79	5.96	7.98	7.03	6.65	3.55
94	-0.86	-11.25	-8.71	-0.48	-0.42	-1.07	0.73	-0.12	-0.51	-0.63
95	13.09	3.30	4.94	3.58	3.72	2.99	3.22	2.33	1.94	2.74
96	13.10	3.29	4.95	3.57	3.73	2.99	4.44	3.53	3.15	2.94
97	5.05	-5.10	-2.93	0.35	0.41	-0.23	0.24	-0.61	-1.00	0.41
98	11.35	1.42	3.23	4.42	4.57	3.83	3.19	2.32	1.92	2.59
99	11.98	2.08	3.85	4.34	4.51	3.75	5.98	5.06	4.68	3.12
100	13.80	4.02	5.62	4.49	4.69	3.91	2.39	1.52	1.12	2.87
101	11.80	1.96	3.68	4.50	4.66	3.91	0.63	-0.22	-0.62	2.26
102	10.78	0.86	2.66	4.50	4.65	3.91	3.72	2.83	2.45	2.59
103	18.35	8.74	10.08	3.87	4.03	3.28	6.68	5.76	5.38	4.21
104	17.53	8.03	9.27	5.19	5.38	4.62	11.52	10.54	10.17	5.09
105	11.39	1.48	3.27	10.71	11.06	10.12	3.12	2.24	1.85	3.62
106	11.44	1.57	3.32	9.95	10.29	9.36	11.25	10.25	9.89	4.82
107	11.38	1.47	3.27	10.73	11.06	10.12	8.88	7.91	7.55	4.55
108	11.39	1.46	3.27	10.72	11.06	10.12	6.65	5.71	5.34	4.19
109	7.81	-2.21	-0.23	0.32	0.38	-0.26	1.16	0.31	-0.09	1.01
TOTAL	**8.55**	**-0.96**	**1.53**	**3.76**	**4.27**	**3.83**	**4.28**	**3.60**	**3.59**	**3.08**

Table A-IV.16: Projected Growth Rates for Santa Rosa Census-tracts

Tracts	2001-2005	2005-2010	2010-2015	2015-2020	2020-2025
91	1.13	1.24	0.32	-0.11	-0.51
92	0.71	0.81	-0.10	-0.53	-0.92
93	3.40	3.52	2.58	2.14	1.74
94	-0.77	-0.66	-1.56	-1.97	-2.38
95	2.58	2.69	1.76	1.32	0.92
96	2.77	2.89	1.96	1.52	1.12
97	0.25	0.36	-0.55	-0.97	-1.36
98	2.43	2.54	1.61	1.18	0.78
99	2.97	3.08	2.15	1.71	1.31
100	2.71	2.82	1.89	1.45	1.05
101	2.10	2.21	1.29	0.85	0.45
102	2.43	2.55	1.62	1.18	0.78
103	4.05	4.16	3.22	2.77	2.37
104	4.92	5.03	4.09	3.63	3.23
105	3.46	3.57	2.64	2.19	1.79
106	4.66	4.78	3.83	3.38	2.97
107	4.39	4.51	3.56	3.12	2.71
108	4.03	4.14	3.20	2.76	2.35
109	0.85	0.96	0.05	-0.39	-0.78
TOTAL	**2.97**	**3.17**	**2.32**	**1.95**	**1.63**

Table A-IV.17: Historical Growth Rates for Okaloosa Census-tracts

Tracts	1970-1974	1974-1975	1975-1980	1980-1985	1985-1986	1986-1990	1990-1992	1992-1995	1995-2000	2000-2001
58	4.09	-1.07	1.43	2.86	2.32	0.27	2.02	2.89	2.68	1.47
59	4.09	-1.10	1.43	1.71	1.19	-0.88	0.30	1.19	0.96	1.00
60	4.09	-1.06	1.42	7.05	6.52	4.43	4.49	5.37	5.15	2.59
61	4.09	-1.07	1.42	4.01	3.46	1.41	0.64	1.50	1.29	1.43
62	4.09	-1.06	1.42	3.37	2.84	0.77	0.32	1.17	0.96	1.28
63	4.09	-1.06	1.42	4.13	3.58	1.52	6.01	6.90	6.69	2.35
64	4.08	-1.07	1.43	6.97	6.43	4.35	6.67	7.56	7.34	2.94
65	4.09	-1.07	1.43	7.93	7.37	5.31	-1.58	-0.73	-0.94	1.71
66	4.09	-1.06	1.42	5.79	5.23	3.17	2.64	3.50	3.29	2.05
67	4.09	-1.01	1.42	18.48	17.92	15.78	2.30	3.16	2.95	4.12
68	4.09	-1.09	1.43	3.04	2.52	0.44	-0.22	0.64	0.43	1.12
69	4.08	-1.07	1.43	3.04	2.50	0.45	0.15	1.01	0.80	1.20
70	4.08	-1.07	1.43	-1.47	-1.99	-4.03	2.94	3.81	3.60	0.91
71	4.09	-1.07	1.43	1.95	1.42	-0.64	-0.77	0.09	-0.12	0.86
72	4.09	-1.07	1.43	2.98	2.44	0.38	0.44	1.30	1.09	1.23
73	4.08	-1.06	1.42	1.94	1.41	-0.65	-2.19	-1.33	-1.55	0.60
74	4.08	-1.06	1.42	1.15	0.62	-1.43	-1.58	-0.73	-0.95	0.60
75	4.09	-1.08	1.43	9.54	8.95	6.90	2.34	3.20	2.99	2.64
76	4.09	-1.08	1.43	9.54	8.98	6.89	1.41	2.27	2.06	2.48
77	4.08	-1.05	1.42	2.96	2.42	0.37	1.03	1.88	1.67	1.32
78	4.09	-1.08	1.43	1.84	1.31	-0.74	-1.04	-0.19	-0.40	0.80
79	4.08	-1.07	1.43	0.87	0.34	-1.70	-0.85	0.00	-0.22	0.65
80	4.09	-1.05	1.42	1.20	0.67	-1.38	0.28	1.16	0.93	0.90
81	4.08	-1.06	1.43	0.47	-0.07	-2.11	-0.78	0.07	-0.14	0.62
82	4.09	-1.07	1.43	0.88	0.34	-1.70	-1.42	-0.58	-0.79	0.56
83	4.08	-1.09	1.43	2.54	1.98	-0.05	-0.79	0.08	-0.14	0.94
84	4.09	-1.06	1.42	0.14	-0.39	-2.44	-0.70	0.15	-0.06	0.57
85	4.09	-1.01	1.42	6.06	5.52	3.46	-2.12	-1.27	-1.49	1.32
86	4.08	-1.07	1.43	2.50	1.97	-0.09	-0.98	-0.14	-0.35	0.91
87	4.09	-1.10	1.43	6.87	6.33	4.24	2.97	3.84	3.63	2.30
88	4.08	-1.04	1.43	3.93	3.38	1.32	-1.64	-0.79	-1.00	1.04
89	4.08	-1.07	1.43	8.64	8.08	6.01	5.58	6.47	6.25	3.03
90	4.09	-1.03	1.42	8.64	8.12	6.01	0.13	0.98	0.77	2.13
TOTAL	**4.09**	**-1.07**	**1.43**	**3.51**	**3.32**	**1.60**	**0.93**	**1.92**	**1.92**	**1.73**

Note: Geolytics Population Data from the decade 1970 to1980 did not exist for Okaloosa county,
therefore the calculated growth rates are similar for all census-tracts of this county in the decade of the 70’s

Table A-IV.18: Projected Growth Rates for Okaloosa Census-tracts

Tracts	2001-2005	2005-2010	2010-2015	2015-2020	2020-2025
58	1.88	1.61	1.22	0.93	0.66
59	1.40	1.13	0.76	0.46	0.18
60	2.99	2.72	2.33	2.04	1.76
61	1.84	1.57	1.19	0.89	0.62
62	1.68	1.41	1.02	0.73	0.46
63	2.77	2.49	2.10	1.81	1.54
64	3.35	3.07	2.68	2.39	2.11
65	2.13	1.85	1.47	1.18	0.90
66	2.47	2.20	1.81	1.52	1.24
67	4.53	4.25	3.86	3.56	3.28
68	1.53	1.27	0.88	0.59	0.32
69	1.59	1.33	0.94	0.65	0.38
70	1.31	1.04	0.66	0.37	0.10
71	1.26	0.99	0.61	0.32	0.05
72	1.63	1.37	0.98	0.69	0.42
73	1.02	0.75	0.37	0.09	-0.19
74	0.99	0.72	0.34	0.05	-0.21
75	3.05	2.77	2.38	2.09	1.82
76	2.89	2.62	2.23	1.94	1.66
77	1.73	1.46	1.07	0.79	0.51
78	1.20	0.93	0.55	0.25	-0.01
79	1.07	0.80	0.41	0.13	-0.14
80	1.32	1.04	0.66	0.37	0.10
81	1.01	0.74	0.36	0.07	-0.20
82	0.97	0.70	0.32	0.03	-0.24
83	1.36	1.09	0.70	0.41	0.15
84	0.97	0.70	0.32	0.03	-0.24
85	1.72	1.45	1.06	0.78	0.50
86	1.31	1.05	0.66	0.37	0.11
87	2.71	2.43	2.05	1.75	1.48
88	1.45	1.17	0.79	0.51	0.23
89	3.44	3.17	2.78	2.48	2.21
90	2.52	2.26	1.87	1.57	1.30
TOTAL	**2.16**	**1.93**	**1.60**	**1.35**	**1.13**

Table A-IV.19: Choropleth Densities of Escambia county in the 70's

Tract ID	1970			1974			1975		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
0	4,119	2.40	1,718	3,743	2.40	1,561	3,548	2.40	1,479
1	4,698	4.60	1,021	4,607	4.60	1,001	4,454	4.60	968
2	5,936	2.01	2,957	5,517	2.01	2,749	5,260	2.01	2,621
3	2,266	1.24	1,826	2,253	1.24	1,815	2,186	1.24	1,761
4	5,121	1.74	2,935	4,180	1.74	2,396	3,855	1.74	2,210
5	8,897	5.45	1,632	8,569	5.45	1,572	8,246	5.45	1,513
6	3,400	2.26	1,501	3,391	2.26	1,497	3,292	2.26	1,454
7	4,674	5.87	796	5,218	5.87	889	5,216	5.87	888
8	2,414	2.22	1,085	2,662	2.22	1,197	2,652	2.22	1,192
9	2,905	10.92	266	3,595	10.92	329	3,690	10.92	338
10	1,564	2.69	581	2,089	2.69	777	2,187	2.69	813
11	3,398	5.30	641	4,538	5.30	856	4,750	5.30	896
12	4,118	6.86	600	4,567	6.86	665	4,557	6.86	664
13	3,152	4.79	658	3,527	4.79	736	3,527	4.79	736
14	5,414	3.77	1,437	5,829	3.77	1,547	5,772	3.77	1,532
15	2,801	4.45	630	3,373	4.45	759	3,437	4.45	773
16	3,932	10.93	360	5,077	10.93	464	5,267	10.93	482
17	3,544	1.61	2,207	3,305	1.61	2,058	3,154	1.61	1,964
18	3,523	2.30	1,531	3,424	2.30	1,488	3,303	2.30	1,435
19	4,815	4.64	1,039	4,824	4.64	1,040	4,690	4.64	1,012
20	4,740	2.09	2,272	4,587	2.09	2,199	4,419	2.09	2,118
21	3,095	1.77	1,752	2,967	1.77	1,680	2,852	1.77	1,615
22	3,629	2.97	1,224	3,623	2.97	1,222	3,519	2.97	1,187
23	6,456	5.07	1,275	6,708	5.07	1,324	6,582	5.07	1,299
24	6,740	3.16	2,135	6,511	3.16	2,063	6,271	3.16	1,987
25	7,000	6.02	1,162	7,125	6.02	1,183	6,954	6.02	1,155
26	4,856	20.80	233	4,692	20.80	226	4,519	20.80	217
27	884	18.74	47	1,196	18.74	64	1,256	18.74	67
28	2,561	86.78	30	3,552	86.78	41	3,754	86.78	43
29	1,004	10.81	93	869	10.81	80	814	10.81	75
30	2,917	19.23	152	4,099	19.23	213	4,346	19.23	226
31	1,852	2.74	676	2,265	2.74	827	2,317	2.74	846
32	2,755	4.83	570	3,369	4.83	697	3,447	4.83	713
33	1,913	1.74	1,098	2,282	1.74	1,310	2,319	1.74	1,331
34	2,350	3.35	702	2,874	3.35	858	2,941	3.35	878
35	5,710	3.72	1,534	5,699	3.72	1,531	5,534	3.72	1,487
36	6,658	6.17	1,079	7,232	6.17	1,172	7,178	6.17	1,163
37	4,904	3.98	1,231	5,522	3.98	1,386	5,531	3.98	1,389
38	2,888	9.27	312	3,766	9.27	406	3,917	9.27	423
39	4,528	12.41	365	4,917	12.41	396	4,880	12.41	393
40	831	12.57	66	1,228	12.57	98	1,319	12.57	105
41	2,957	15.37	192	4,428	15.37	288	4,771	15.37	311
42	720	16.79	43	1,084	16.79	65	1,170	16.79	70
43	2,445	7.68	318	3,682	7.68	479	3,973	7.68	517
44	936	2.30	406	1,409	2.30	612	1,521	2.30	661
45	4,436	10.34	429	4,851	10.34	469	4,823	10.34	466
46	3,853	14.62	263	4,822	14.62	330	4,963	14.62	339
47	2,652	10.07	263	3,397	10.07	337	3,517	10.07	349
48	3,844	6.01	640	4,924	6.01	820	5,098	6.01	849
49	2,232	137.01	16	3,511	137.01	26	3,831	137.01	28
50	1,271	95.95	13	1,852	95.95	19	1,981	95.95	21
51	1,777	32.47	55	2,556	32.47	79	2,727	32.47	84
52	1,721	15.32	112	2,476	15.32	162	2,642	15.32	173
53	2,206	26.85	82	3,174	26.85	118	3,386	26.85	126
54	4,338	17.74	245	3,938	17.74	222	3,733	17.74	210
55	2,903	481.19	6	3,129	481.19	7	3,099	481.19	6
56	3,766	405.45	9	4,279	405.45	11	4,296	405.45	11
57	4,316	96.09	45	4,525	96.09	47	4,451	96.09	46
Total	**205,334**	**1715.49**	**120**	**227,408**	**1715.49**	**133**	**227,694**	**1715.49**	**133**

Table A-IV.20: Choropleth Densities of Escambia county in the 80's

Tract ID	1980			1985			1986		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
0	2,707	2.40	1,129	2,457	2.40	1,025	2,402	2.40	1,002
1	3,748	4.60	815	3,599	4.60	782	3,558	4.60	773
2	4,131	2.01	2,058	3,994	2.01	1,990	3,954	2.01	1,970
3	1,872	1.24	1,508	1,812	1.24	1,460	1,794	1.24	1,445
4	2,564	1.74	1,470	2,398	1.74	1,374	2,359	1.74	1,352
5	6,778	5.45	1,244	6,387	5.45	1,172	6,292	5.45	1,154
6	2,830	2.26	1,250	2,848	2.26	1,258	2,843	2.26	1,255
7	5,180	5.87	882	6,001	5.87	1,022	6,160	5.87	1,049
8	2,593	2.22	1,166	3,051	2.22	1,372	3,142	2.22	1,412
9	4,181	10.92	383	5,023	10.92	460	5,195	10.92	476
10	2,733	2.69	1,016	3,060	2.69	1,138	3,120	2.69	1,160
11	5,933	5.30	1,120	6,646	5.30	1,254	6,777	5.30	1,279
12	4,487	6.86	654	4,887	6.86	712	4,956	6.86	722
13	3,513	4.79	733	3,918	4.79	818	3,992	4.79	833
14	5,473	3.77	1,452	5,313	3.77	1,410	5,264	3.77	1,397
15	3,760	4.45	846	4,269	4.45	960	4,365	4.45	982
16	6,299	10.93	576	6,544	10.93	599	6,573	10.93	601
17	2,488	1.61	1,549	2,147	1.61	1,337	2,077	1.61	1,293
18	2,748	2.30	1,194	2,364	2.30	1,027	2,287	2.30	994
19	4,056	4.64	875	3,892	4.64	839	3,847	4.64	830
20	3,655	2.09	1,752	3,316	2.09	1,589	3,241	2.09	1,553
21	2,331	1.77	1,320	2,378	1.77	1,346	2,380	1.77	1,348
22	3,029	2.97	1,021	2,818	2.97	950	2,769	2.97	934
23	5,962	5.07	1,177	5,714	5.07	1,128	5,647	5.07	1,115
24	5,175	3.16	1,640	5,210	3.16	1,651	5,200	3.16	1,647
25	6,136	6.02	1,019	6,098	6.02	1,013	6,071	6.02	1,008
26	3,730	20.80	179	3,874	20.80	186	3,891	20.80	187
27	1,595	18.74	85	2,045	18.74	109	2,142	18.74	114
28	4,921	86.78	57	6,465	86.78	74	6,807	86.78	78
29	584	10.81	54	733	10.81	68	765	10.81	71
30	5,794	19.23	301	7,276	19.23	378	7,592	19.23	395
31	2,586	2.74	944	2,909	2.74	1,062	2,969	2.74	1,084
32	3,846	4.83	796	4,328	4.83	896	4,417	4.83	914
33	2,507	1.74	1,439	2,772	1.74	1,591	2,819	1.74	1,618
34	3,282	3.35	980	3,692	3.35	1,103	3,768	3.35	1,125
35	4,762	3.72	1,280	4,648	3.72	1,249	4,610	3.72	1,239
36	6,884	6.17	1,115	6,953	6.17	1,127	6,945	6.17	1,125
37	5,553	3.98	1,394	5,398	3.98	1,355	5,350	3.98	1,343
38	4,745	9.27	512	4,769	9.27	515	4,759	9.27	514
39	4,678	12.41	377	5,895	12.41	475	6,155	12.41	496
40	1,875	12.57	149	2,073	12.57	165	2,108	12.57	168
41	6,896	15.37	449	7,612	15.37	495	7,740	15.37	504
42	1,703	16.79	101	1,881	16.79	112	1,912	16.79	114
43	5,785	7.68	753	6,389	7.68	832	6,497	7.68	846
44	2,214	2.30	961	2,446	2.30	1,062	2,487	2.30	1,080
45	4,666	10.34	451	4,774	10.34	462	4,781	10.34	462
46	5,706	14.62	390	6,797	14.62	465	7,018	14.62	480
47	4,165	10.07	414	4,895	10.07	486	5,040	10.07	501
48	6,038	6.01	1,005	7,096	6.01	1,182	7,306	6.01	1,216
49	5,896	137.01	43	6,943	137.01	51	7,152	137.01	52
50	2,765	95.95	29	3,589	95.95	37	3,770	95.95	39
51	3,746	32.47	115	4,934	32.47	152	5,198	32.47	160
52	3,629	15.32	237	4,781	15.32	312	5,036	15.32	329
53	4,652	26.85	173	6,129	26.85	228	6,457	26.85	240
54	2,845	17.74	160	2,924	17.74	165	2,931	17.74	165
55	2,943	481.19	6	3,446	481.19	7	3,546	481.19	7
56	4,364	405.45	11	4,604	405.45	11	4,638	405.45	11
57	4,080	96.09	42	4,081	96.09	42	4,068	96.09	42
Total	**233,797**	**1715.49**	**136**	**253,295**	**1715.49**	**148**	**256,939**	**1715.49**	**150**

Table A-IV.21: Choropleth Densities of Escambia county in the 90's and earlier 2000's

Tract	1990			1992			1995			2000			2001		
ID	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
0	2,107	2.40	879	2,071	2.40	864	2,068	2.40	862	2,021	2.40	843	1,992	2.40	831
1	3,266	4.60	710	3,192	4.60	694	3,160	4.60	687	3,044	4.60	662	3,015	4.60	655
2	3,649	2.01	1,818	3,567	2.01	1,777	3,532	2.01	1,760	3,402	2.01	1,695	3,362	2.01	1,675
3	1,657	1.24	1,335	1,634	1.24	1,316	1,639	1.24	1,320	1,613	1.24	1,300	1,600	1.24	1,289
4	2,120	1.74	1,215	2,061	1.74	1,181	2,024	1.74	1,160	1,923	1.74	1,102	1,888	1.74	1,082
5	5,687	5.45	1,043	5,512	5.45	1,011	5,388	5.45	989	5,080	5.45	932	5,020	5.45	921
6	2,710	2.26	1,197	2,666	2.26	1,177	2,664	2.26	1,176	2,607	2.26	1,151	2,589	2.26	1,143
7	6,581	5.87	1,121	6,470	5.87	1,102	6,459	5.87	1,100	6,310	5.87	1,075	6,326	5.87	1,077
8	3,399	2.22	1,528	3,284	2.22	1,476	3,195	2.22	1,436	2,990	2.22	1,344	2,993	2.22	1,345
9	5,716	10.92	524	5,747	10.92	526	5,932	10.92	543	6,127	10.92	561	6,188	10.92	567
10	3,243	2.69	1,206	3,157	2.69	1,174	3,106	2.69	1,155	2,960	2.69	1,100	2,984	2.69	1,109
11	7,046	5.30	1,330	6,900	5.30	1,302	6,848	5.30	1,292	6,623	5.30	1,250	6,681	5.30	1,261
12	5,037	6.86	734	5,022	6.86	732	5,120	6.86	746	5,179	6.86	754	5,185	6.86	755
13	4,136	4.79	863	4,044	4.79	844	4,004	4.79	836	3,858	4.79	805	3,861	4.79	806
14	4,874	3.77	1,293	4,780	3.77	1,268	4,754	3.77	1,262	4,616	3.77	1,225	4,592	3.77	1,219
15	4,589	4.45	1,032	4,728	4.45	1,063	5,063	4.45	1,139	5,559	4.45	1,250	5,608	4.45	1,261
16	6,430	10.93	588	6,304	10.93	577	6,268	10.93	573	6,081	10.93	556	6,110	10.93	559
17	1,748	1.61	1,088	1,643	1.61	1,023	1,533	1.61	955	1,339	1.61	834	1,314	1.61	818
18	1,920	2.30	834	2,055	2.30	893	2,327	2.30	1,011	2,805	2.30	1,219	2,788	2.30	1,212
19	3,529	4.64	761	3,411	4.64	736	3,321	4.64	716	3,110	4.64	671	3,080	4.64	664
20	2,840	2.09	1,361	2,725	2.09	1,306	2,623	2.09	1,257	2,411	2.09	1,156	2,378	2.09	1,140
21	2,295	1.77	1,299	2,256	1.77	1,277	2,253	1.77	1,276	2,201	1.77	1,246	2,183	1.77	1,236
22	2,477	2.97	835	2,413	2.97	814	2,377	2.97	802	2,270	2.97	765	2,247	2.97	758
23	5,174	5.07	1,021	5,136	5.07	1,014	5,202	5.07	1,027	5,205	5.07	1,028	5,173	5.07	1,021
24	4,958	3.16	1,571	4,722	3.16	1,496	4,497	3.16	1,425	4,061	3.16	1,287	4,017	3.16	1,273
25	5,729	6.02	951	5,607	6.02	931	5,560	6.02	923	5,371	6.02	892	5,334	6.02	886
26	3,806	20.80	183	4,618	20.80	222	6,306	20.80	303	10,389	20.80	499	10,502	20.80	505
27	2,485	18.74	133	2,512	18.74	134	2,615	18.74	140	2,738	18.74	146	2,783	18.74	149
28	8,052	86.78	93	9,328	86.78	107	11,888	86.78	137	17,455	86.78	201	17,983	86.78	207
29	872	10.81	81	1,069	10.81	99	1,481	10.81	137	2,501	10.81	231	2,536	10.81	235
30	8,658	19.23	450	8,451	19.23	439	8,349	19.23	434	8,012	19.23	417	8,130	19.23	423
31	3,098	2.74	1,131	2,998	2.74	1,095	2,924	2.74	1,068	2,748	2.74	1,003	2,759	2.74	1,007
32	4,609	4.83	954	4,834	4.83	1,000	5,314	4.83	1,100	6,096	4.83	1,261	6,162	4.83	1,275
33	2,899	1.74	1,664	2,849	1.74	1,635	2,842	1.74	1,631	2,773	1.74	1,592	2,783	1.74	1,597
34	3,932	3.35	1,174	3,694	3.35	1,103	3,447	3.35	1,029	3,008	3.35	898	3,013	3.35	900
35	4,287	3.72	1,152	4,224	3.72	1,135	4,231	3.72	1,137	4,155	3.72	1,116	4,123	3.72	1,108
36	6,640	6.17	1,076	6,665	6.17	1,080	6,864	6.17	1,112	7,061	6.17	1,144	7,050	6.17	1,142
37	4,959	3.98	1,245	4,902	3.98	1,231	4,935	3.98	1,239	4,887	3.98	1,227	4,874	3.98	1,224
38	4,532	9.27	489	4,555	9.27	492	4,698	9.27	507	4,846	9.27	523	4,876	9.27	526
39	7,038	12.41	567	7,175	12.41	578	7,560	12.41	609	8,079	12.41	651	8,137	12.41	656
40	2,169	12.57	173	2,262	12.57	180	2,466	12.57	196	2,791	12.57	222	2,841	12.57	226
41	7,952	15.37	518	8,090	15.37	527	8,499	15.37	553	9,040	15.37	588	9,190	15.37	598
42	1,965	16.79	117	2,039	16.79	121	2,205	16.79	131	2,462	16.79	147	2,507	16.79	149
43	6,677	7.68	869	6,649	7.68	866	6,766	7.68	881	6,824	7.68	888	6,927	7.68	902
44	2,556	2.30	1,110	2,472	2.30	1,073	2,409	2.30	1,046	2,259	2.30	981	2,288	2.30	994
45	4,620	10.34	447	4,585	10.34	443	4,642	10.34	449	4,642	10.34	449	4,634	10.34	448
46	7,669	14.62	524	7,952	14.62	544	8,593	14.62	588	9,580	14.62	655	9,702	14.62	663
47	5,448	10.07	541	5,532	10.07	550	5,796	10.07	576	6,136	10.07	610	6,207	10.07	617
48	7,896	6.01	1,315	7,998	6.01	1,332	8,348	6.01	1,390	8,781	6.01	1,462	8,880	6.01	1,479
49	7,743	137.01	57	7,916	137.01	58	8,377	137.01	61	9,018	137.01	66	9,211	137.01	67
50	4,416	95.95	46	4,460	95.95	46	4,635	95.95	48	4,841	95.95	50	4,939	95.95	51
51	6,162	32.47	190	6,578	32.47	203	7,423	32.47	229	8,896	32.47	274	9,117	32.47	281
52	5,970	15.32	390	6,343	15.32	414	7,107	15.32	464	8,416	15.32	549	8,622	15.32	563
53	7,654	26.85	285	7,884	26.85	294	8,436	26.85	314	9,251	26.85	345	9,453	26.85	352
54	2,842	17.74	160	2,907	17.74	164	3,077	17.74	173	3,315	17.74	187	3,292	17.74	186
55	3,822	481.19	8	3,913	481.19	8	4,150	481.19	9	4,485	481.19	9	4,506	481.19	9
56	4,594	405.45	11	4,651	405.45	11	4,851	405.45	12	5,097	405.45	13	5,110	405.45	13
57	3,859	96.09	40	4,040	96.09	42	4,431	96.09	46	5,062	96.09	53	5,063	96.09	53
Total	**262,798**	**1715.49**	**153**	**265,252**	**1715.49**	**155**	**276,582**	**1715.49**	**161**	**294,410**	**1715.49**	**172**	**296,708**	**1715.49**	**173**

Table A-IV.22: Projections of Choropleth Densities for Escambia county in 2005-2025

Tract ID	2005			2010			2015			2020			2025		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
0	1,864	2.40	777	1,772	2.40	739	1,655	2.40	690	1,531	2.40	638	1,402	2.40	585
1	2,872	4.60	624	2,793	4.60	607	2,667	4.60	580	2,523	4.60	548	2,364	4.60	514
2	3,178	2.01	1,583	3,060	2.01	1,525	2,894	2.01	1,442	2,710	2.01	1,350	2,514	2.01	1,252
3	1,534	1.24	1,236	1,503	1.24	1,211	1,447	1.24	1,166	1,379	1.24	1,111	1,302	1.24	1,049
4	1,737	1.74	996	1,616	1.74	926	1,477	1.74	847	1,338	1.74	767	1,199	1.74	687
5	4,744	5.45	870	4,565	5.45	838	4,315	5.45	792	4,040	5.45	741	3,746	5.45	687
6	2,494	2.26	1,101	2,459	2.26	1,086	2,381	2.26	1,051	2,284	2.26	1,009	2,170	2.26	958
7	6,328	5.87	1,078	6,539	5.87	1,114	6,637	5.87	1,130	6,673	5.87	1,136	6,644	5.87	1,132
8	2,977	2.22	1,338	3,055	2.22	1,373	3,079	2.22	1,384	3,074	2.22	1,382	3,040	2.22	1,367
9	6,378	10.92	584	6,841	10.92	627	7,208	10.92	660	7,522	10.92	689	7,774	10.92	712
10	3,055	2.69	1,136	3,250	2.69	1,208	3,396	2.69	1,263	3,514	2.69	1,306	3,602	2.69	1,339
11	6,853	5.30	1,293	7,306	5.30	1,379	7,652	5.30	1,444	7,938	5.30	1,498	8,155	5.30	1,539
12	5,162	6.86	752	5,302	6.86	772	5,349	6.86	779	5,346	6.86	779	5,290	6.86	771
13	3,837	4.79	801	3,933	4.79	821	3,959	4.79	826	3,948	4.79	824	3,899	4.79	814
14	4,455	3.77	1,182	4,431	3.77	1,176	4,329	3.77	1,149	4,189	3.77	1,112	4,014	3.77	1,065
15	5,756	4.45	1,295	6,141	4.45	1,381	6,437	4.45	1,448	6,682	4.45	1,503	6,870	4.45	1,545
16	6,170	10.93	564	6,452	10.93	590	6,627	10.93	606	6,742	10.93	617	6,792	10.93	621
17	1,209	1.61	753	1,125	1.61	701	1,028	1.61	640	930	1.61	579	834	1.61	519
18	2,695	2.30	1,171	2,669	2.30	1,160	2,596	2.30	1,128	2,501	2.30	1,087	2,386	2.30	1,037
19	2,934	4.64	633	2,852	4.64	615	2,723	4.64	587	2,575	4.64	555	2,412	4.64	520
20	2,230	2.09	1,069	2,126	2.09	1,019	1,990	2.09	954	1,846	2.09	885	1,695	2.09	812
21	2,093	1.77	1,185	2,051	1.77	1,161	1,974	1.77	1,118	1,882	1.77	1,066	1,777	1.77	1,006
22	2,136	2.97	720	2,071	2.97	698	1,972	2.97	665	1,860	2.97	627	1,737	2.97	586
23	5,001	5.07	987	4,950	5.07	977	4,814	5.07	950	4,637	5.07	915	4,423	5.07	873
24	3,809	3.16	1,207	3,682	3.16	1,167	3,496	3.16	1,108	3,288	3.16	1,042	3,062	3.16	970
25	5,139	6.02	853	5,066	6.02	841	4,907	6.02	815	4,707	6.02	782	4,471	6.02	742
26	10,865	20.80	522	11,710	20.80	563	12,396	20.80	596	12,998	20.80	625	13,497	20.80	649
27	2,945	18.74	157	3,263	18.74	174	3,552	18.74	190	3,830	18.74	204	4,090	18.74	218
28	20,066	86.78	231	23,769	86.78	274	27,658	86.78	319	31,877	86.78	367	36,385	86.78	419
29	2,654	10.81	245	2,901	10.81	268	3,116	10.81	288	3,315	10.81	307	3,492	10.81	323
30	8,536	19.23	444	9,371	19.23	487	10,106	19.23	525	10,795	19.23	561	11,419	19.23	594
31	2,778	2.74	1,014	2,894	2.74	1,057	2,962	2.74	1,082	3,002	2.74	1,096	3,013	2.74	1,100
32	6,370	4.83	1,318	6,859	4.83	1,419	7,255	4.83	1,501	7,601	4.83	1,573	7,886	4.83	1,632
33	2,797	1.74	1,606	2,908	1.74	1,669	2,969	1.74	1,704	3,003	1.74	1,724	3,008	1.74	1,727
34	3,005	3.35	897	3,093	3.35	924	3,128	3.35	934	3,133	3.35	936	3,107	3.35	928
35	3,958	3.72	1,064	3,886	3.72	1,044	3,747	3.72	1,007	3,578	3.72	961	3,385	3.72	910
36	6,939	6.17	1,124	7,027	6.17	1,139	6,990	6.17	1,133	6,887	6.17	1,116	6,720	6.17	1,089
37	4,778	3.98	1,200	4,814	3.98	1,209	4,765	3.98	1,196	4,671	3.98	1,173	4,534	3.98	1,138
38	4,951	9.27	534	5,212	9.27	563	5,390	9.27	582	5,521	9.27	596	5,601	9.27	605
39	8,293	12.41	668	8,773	12.41	707	9,116	12.41	734	9,382	12.41	756	9,562	12.41	770
40	3,024	12.57	241	3,376	12.57	269	3,703	12.57	295	4,022	12.57	320	4,327	12.57	344
41	9,720	15.37	633	10,770	15.37	701	11,721	15.37	763	12,636	15.37	822	13,490	15.37	878
42	2,672	16.79	159	2,989	16.79	178	3,283	16.79	196	3,573	16.79	213	3,850	16.79	229
43	7,284	7.68	948	8,011	7.68	1,043	8,655	7.68	1,127	9,262	7.68	1,206	9,815	7.68	1,278
44	2,383	2.30	1,035	2,590	2.30	1,125	2,766	2.30	1,201	2,925	2.30	1,270	3,064	2.30	1,331
45	4,557	10.34	441	4,609	10.34	446	4,580	10.34	443	4,507	10.34	436	4,393	10.34	425
46	10,109	14.62	691	10,993	14.62	752	11,742	14.62	803	12,423	14.62	849	13,016	14.62	890
47	6,437	10.07	639	6,959	10.07	691	7,389	10.07	734	7,772	10.07	772	8,095	10.07	804
48	9,202	6.01	1,532	9,937	6.01	1,655	10,541	6.01	1,755	11,075	6.01	1,844	11,524	6.01	1,919
49	9,930	137.01	72	11,268	137.01	82	12,559	137.01	92	13,865	137.01	101	15,159	137.01	111
50	5,300	95.95	55	5,980	95.95	62	6,628	95.95	69	7,276	95.95	76	7,910	95.95	82
51	9,963	32.47	307	11,497	32.47	354	13,033	32.47	401	14,633	32.47	451	16,271	32.47	501
52	9,406	15.32	614	10,834	15.32	707	12,256	15.32	800	13,734	15.32	897	15,241	15.32	995
53	10,209	26.85	380	11,609	26.85	432	12,967	26.85	483	14,347	26.85	534	15,720	26.85	585
54	3,173	17.74	179	3,129	17.74	176	3,032	17.74	171	2,909	17.74	164	2,765	17.74	156
55	4,548	481.19	9	4,753	481.19	10	4,878	481.19	10	4,960	481.19	10	4,994	481.19	10
56	5,111	405.45	13	5,282	405.45	13	5,362	405.45	13	5,391	405.45	13	5,368	405.45	13
57	5,018	96.09	52	5,125	96.09	53	5,142	96.09	54	5,111	96.09	53	5,030	96.09	52
Total	**303,621**	**1715.49**	**177**	**323,801**	**1715.49**	**189**	**340,396**	**1715.49**	**198**	**355,673**	**1715.49**	**207**	**369,305**	**1715.49**	**215**

Table A-IV.23: Choropleth Densities of Santa Rosa county in the 70's

Tract ID	1970			1974			1975		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
91	2,254	834.68	3	2,947	834.68	4	2,855	834.68	3
92	3,322	396.13	8	4,338	396.13	11	4,200	396.13	11
93	1,082	205.01	5	1,609	205.01	8	1,616	205.01	8
94	4,464	209.81	21	4,313	209.81	21	3,828	209.81	18
95	2,147	34.58	62	3,512	34.58	102	3,628	34.58	105
96	1,432	66.75	21	2,343	66.75	35	2,420	66.75	36
97	6,440	10.49	614	7,842	10.49	748	7,442	10.49	710
98	1,417	95.32	15	2,178	95.32	23	2,209	95.32	23
99	1,712	61.96	28	2,692	61.96	43	2,748	61.96	44
100	889	18.22	49	1,491	18.22	82	1,551	18.22	85
101	1,110	11.55	96	1,734	11.55	150	1,768	11.55	153
102	1,941	26.90	72	2,923	26.90	109	2,948	26.90	110
103	1,172	244.95	5	2,299	244.95	9	2,500	244.95	10
104	261	297.82	1	498	297.82	2	538	297.82	2
105	1,407	10.25	137	2,166	10.25	211	2,198	10.25	215
106	784	43.29	18	1,209	43.29	28	1,228	43.29	28
107	705	25.17	28	1,085	25.17	43	1,101	25.17	44
108	1,025	28.65	36	1,578	28.65	55	1,601	28.65	56
109	4,178	12.31	339	5,645	12.31	459	5,520	12.31	448
Total	**37,742**	**2633.83**	**14**	**52,402**	**2633.83**	**20**	**51,899**	**2633.83**	**20**

Table A-IV.24: Choropleth Densities of Santa Rosa county in the 80's

Tract ID	1980			1985			1986		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
91	2,702	834.68	3	2,675	834.68	3	2,671	834.68	3
92	3,969	396.13	10	3,998	396.13	10	4,006	396.13	10
93	1,813	205.01	9	2,490	205.01	12	2,659	205.01	13
94	2,427	209.81	12	2,369	209.81	11	2,359	209.81	11
95	4,617	34.58	134	5,505	34.58	159	5,710	34.58	165
96	3,081	66.75	46	3,672	66.75	55	3,809	66.75	57
97	6,413	10.49	612	6,527	10.49	622	6,554	10.49	625
98	2,590	95.32	27	3,215	95.32	34	3,362	95.32	35
99	3,319	61.96	54	4,104	61.96	66	4,289	61.96	69
100	2,039	18.22	112	2,540	18.22	139	2,659	18.22	146
101	2,118	11.55	183	2,640	11.55	229	2,763	11.55	239
102	3,362	26.90	125	4,190	26.90	156	4,385	26.90	163
103	4,041	244.95	16	4,886	244.95	20	5,083	244.95	21
104	838	297.82	3	1,079	297.82	4	1,137	297.82	4
105	2,582	10.25	252	4,295	10.25	419	4,770	10.25	466
106	1,446	43.29	33	2,323	43.29	54	2,562	43.29	59
107	1,293	25.17	51	2,152	25.17	86	2,390	25.17	95
108	1,880	28.65	66	3,128	28.65	109	3,474	28.65	121
109	5,458	12.31	443	5,546	12.31	451	5,567	12.31	452
Total	**55,988**	**2633.83**	**21**	**67,334**	**2633.83**	**26**	**70,209**	**2633.83**	**27**

Table A-IV.25: Choropleth Densities of Santa Rosa county in the 90's and earlier 2000's

Tract ID	1990			1992			1995			2000			2001		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
91	2,589	834.68	3	2,816	834.68	3	3,113	834.68	4	3,612	834.68	4	3,658	834.68	4
92	3,938	396.13	10	4,046	396.13	10	4,108	396.13	10	4,132	396.13	10	4,167	396.13	11
93	3,352	205.01	16	3,908	205.01	19	4,791	205.01	23	6,611	205.01	32	6,846	205.01	33
94	2,260	209.81	11	2,293	209.81	11	2,285	209.81	11	2,227	209.81	11	2,213	209.81	11
95	6,424	34.58	186	6,844	34.58	198	7,334	34.58	212	8,075	34.58	234	8,296	34.58	240
96	4,285	66.75	64	4,674	66.75	70	5,186	66.75	78	6,056	66.75	91	6,234	66.75	93
97	6,495	10.49	619	6,526	10.49	622	6,408	10.49	611	6,093	10.49	581	6,118	10.49	583
98	3,908	95.32	41	4,161	95.32	44	4,457	95.32	47	4,902	95.32	51	5,029	95.32	53
99	4,969	61.96	80	5,581	61.96	90	6,472	61.96	104	8,136	61.96	131	8,390	61.96	135
100	3,100	18.22	170	3,250	18.22	178	3,400	18.22	187	3,595	18.22	197	3,698	18.22	203
101	3,221	11.55	279	3,262	11.55	282	3,241	11.55	281	3,142	11.55	272	3,213	11.55	278
102	5,113	26.90	190	5,501	26.90	204	5,982	26.90	222	6,750	26.90	251	6,925	26.90	257
103	5,784	244.95	24	6,583	244.95	27	7,787	244.95	32	10,120	244.95	41	10,546	244.95	43
104	1,362	297.82	5	1,694	297.82	6	2,288	297.82	8	3,714	297.82	12	3,903	297.82	13
105	7,014	10.25	685	7,459	10.25	728	7,971	10.25	778	8,738	10.25	853	9,054	10.25	884
106	3,664	43.29	85	4,535	43.29	105	6,077	43.29	140	9,740	43.29	225	10,209	43.29	236
107	3,514	25.17	140	4,166	25.17	166	5,235	25.17	208	7,532	25.17	299	7,875	25.17	313
108	5,108	28.65	178	5,810	28.65	203	6,864	28.65	240	8,903	28.65	311	9,276	28.65	324
109	5,509	12.31	448	5,637	12.31	458	5,690	12.31	462	5,665	12.31	460	5,722	12.31	465
Total	**81,609**	**2633.83**	**31**	**88,746**	**2633.83**	**34**	**98,689**	**2633.83**	**37**	**117,743**	**2633.83**	**45**	**121,372**	**2633.83**	**46**

Table A-IV.26: Projections of Choropleth Densities for Santa Rosa county in 2005-2025

Tract ID	2005			2010			2015			2020			2025		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
91	3,826	834.68	5	4,069	834.68	5	4,135	834.68	5	4,113	834.68	5	4,010	834.68	5
92	4,286	396.13	11	4,463	396.13	11	4,441	396.13	11	4,325	396.13	11	4,129	396.13	10
93	7,827	205.01	38	9,305	205.01	45	10,570	205.01	52	11,750	205.01	57	12,807	205.01	62
94	2,146	209.81	10	2,076	209.81	10	1,919	209.81	9	1,737	209.81	8	1,540	209.81	7
95	9,185	34.58	266	10,490	34.58	303	11,448	34.58	331	12,226	34.58	354	12,801	34.58	370
96	6,955	66.75	104	8,020	66.75	120	8,837	66.75	132	9,529	66.75	143	10,075	66.75	151
97	6,179	10.49	589	6,292	10.49	600	6,122	10.49	584	5,830	10.49	556	5,443	10.49	519
98	5,535	95.32	58	6,275	95.32	66	6,797	95.32	71	7,206	95.32	76	7,490	95.32	79
99	9,432	61.96	152	10,979	61.96	177	12,212	61.96	197	13,293	61.96	215	14,186	61.96	229
100	4,115	18.22	226	4,730	18.22	260	5,194	18.22	285	5,582	18.22	306	5,882	18.22	323
101	3,491	11.55	302	3,895	11.55	337	4,152	11.55	359	4,332	11.55	375	4,431	11.55	384
102	7,623	26.90	283	8,645	26.90	321	9,368	26.90	348	9,933	26.90	369	10,327	26.90	384
103	12,359	244.95	50	15,155	244.95	62	17,758	244.95	72	20,362	244.95	83	22,892	244.95	93
104	4,729	297.82	16	6,045	297.82	20	7,385	297.82	25	8,827	297.82	30	10,346	297.82	35
105	10,372	10.25	1,012	12,363	10.25	1,207	14,081	10.25	1,374	15,693	10.25	1,532	17,149	10.25	1,674
106	12,250	43.29	283	15,471	43.29	357	18,669	43.29	431	22,046	43.29	509	25,525	43.29	590
107	9,352	25.17	372	11,660	25.17	463	13,890	25.17	552	16,193	25.17	643	18,509	25.17	735
108	10,864	28.65	379	13,310	28.65	465	15,583	28.65	544	17,853	28.65	623	20,054	28.65	700
109	5,918	12.31	481	6,208	12.31	504	6,222	12.31	506	6,103	12.31	496	5,869	12.31	477
Total	**136,444**	**2633.83**	**52**	**159,451**	**2633.83**	**61**	**178,783**	**2633.83**	**68**	**196,933**	**2633.83**	**75**	**213,465**	**2633.83**	**81**

Table A-IV.27: Choropleth Densities of Okaloosa county in the 70's

Tract ID	1970			1974			1975		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
58	3,511	656.87	5	4,121	656.87	6	4,077	656.87	6
59	1,241	222.09	6	1,457	222.09	7	1,441	222.09	6
60	2,329	290.72	8	2,734	290.72	9	2,705	290.72	9
61	2,949	26.58	111	3,462	26.58	130	3,425	26.58	129
62	3,209	23.02	139	3,767	23.02	164	3,727	23.02	162
63	1,683	48.67	35	1,976	48.67	41	1,955	48.67	40
64	1,746	25.66	68	2,049	25.66	80	2,027	25.66	79
65	2,466	947.64	3	2,895	947.64	3	2,864	947.64	3
66	1,692	15.02	113	1,986	15.02	132	1,965	15.02	131
67	1,179	10.29	115	1,384	10.29	134	1,370	10.29	133
68	2,113	5.04	419	2,480	5.04	492	2,453	5.04	487
69	4,469	6.68	669	5,245	6.68	785	5,189	6.68	776
70	5,503	33.00	167	6,458	33.00	196	6,389	33.00	194
71	5,499	7.41	742	6,455	7.41	871	6,386	7.41	862
72	4,764	6.17	773	5,592	6.17	907	5,532	6.17	897
73	1,601	2.29	699	1,879	2.29	821	1,859	2.29	812
74	2,340	3.48	672	2,746	3.48	789	2,717	3.48	781
75	1,420	2.64	538	1,667	2.64	632	1,649	2.64	625
76	1,502	3.38	444	1,763	3.38	522	1,744	3.38	516
77	3,587	6.04	594	4,210	6.04	697	4,166	6.04	690
78	5,467	4.07	1,342	6,417	4.07	1,575	6,348	4.07	1,558
79	2,709	2.06	1,314	3,179	2.06	1,542	3,145	2.06	1,526
80	1,703	2.20	773	1,999	2.20	907	1,978	2.20	898
81	3,524	3.46	1,019	4,136	3.46	1,196	4,092	3.46	1,183
82	3,652	3.76	971	4,287	3.76	1,139	4,241	3.76	1,127
83	2,040	2.47	826	2,394	2.47	969	2,368	2.47	959
84	3,303	3.05	1,084	3,877	3.05	1,272	3,836	3.05	1,259
85	1,179	1.11	1,059	1,384	1.11	1,243	1,370	1.11	1,230
86	3,029	5.45	555	3,555	5.45	652	3,517	5.45	645
87	2,402	6.80	353	2,820	6.80	415	2,789	6.80	410
88	1,233	17.72	70	1,447	17.72	82	1,432	17.72	81
89	1,982	23.06	86	2,326	23.06	101	2,301	23.06	100
90	1,156	5.34	216	1,357	5.34	254	1,343	5.34	251
Total	**88,187**	**2423.26**	**36**	**103,504**	**2423.26**	**43**	**102,400**	**2423.26**	**42**

Table A-IV.28: Choropleth Densities of Okaloosa county in the 80's

Tract ID	1980			1985			1986		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
58	4,077	656.87	6	5,038	656.87	8	5,155	656.87	8
59	1,441	222.09	6	1,684	222.09	8	1,704	222.09	8
60	2,705	290.72	9	4,082	290.72	14	4,348	290.72	15
61	3,425	26.58	129	4,474	26.58	168	4,629	26.58	174
62	3,727	23.02	162	4,720	23.02	205	4,854	23.02	211
63	1,955	48.67	40	2,569	48.67	53	2,661	48.67	55
64	2,027	25.66	79	3,048	25.66	119	3,244	25.66	126
65	2,864	947.64	3	4,503	947.64	5	4,835	947.64	5
66	1,965	15.02	131	2,794	15.02	186	2,940	15.02	196
67	1,370	10.29	133	3,432	10.29	333	4,047	10.29	393
68	2,453	5.04	487	3,058	5.04	607	3,135	5.04	622
69	5,189	6.68	776	6,470	6.68	968	6,632	6.68	992
70	6,389	33.00	194	6,370	33.00	193	6,243	33.00	189
71	6,386	7.41	862	7,550	7.41	1,019	7,657	7.41	1,033
72	5,532	6.17	897	6,877	6.17	1,115	7,045	6.17	1,143
73	1,859	2.29	812	2,196	2.29	959	2,227	2.29	973
74	2,717	3.48	781	3,087	3.48	887	3,106	3.48	892
75	1,649	2.64	625	2,792	2.64	1,058	3,042	2.64	1,153
76	1,744	3.38	516	2,952	3.38	873	3,217	3.38	952
77	4,166	6.04	690	5,173	6.04	856	5,298	6.04	877
78	6,348	4.07	1,558	7,466	4.07	1,832	7,564	4.07	1,856
79	3,145	2.06	1,526	3,526	2.06	1,711	3,538	2.06	1,716
80	1,978	2.20	898	2,253	2.20	1,022	2,268	2.20	1,029
81	4,092	3.46	1,183	4,497	3.46	1,300	4,494	3.46	1,299
82	4,241	3.76	1,127	4,755	3.76	1,264	4,771	3.76	1,268
83	2,368	2.47	959	2,882	2.47	1,167	2,939	2.47	1,190
84	3,836	3.05	1,259	4,145	3.05	1,360	4,129	3.05	1,355
85	1,370	1.11	1,230	1,973	1.11	1,771	2,082	1.11	1,869
86	3,517	5.45	645	4,272	5.45	783	4,356	5.45	799
87	2,789	6.80	410	4,173	6.80	614	4,437	6.80	652
88	1,432	17.72	81	1,864	17.72	105	1,927	17.72	109
89	2,301	23.06	100	3,738	23.06	162	4,040	23.06	175
90	1,343	5.34	251	2,181	5.34	408	2,358	5.34	441
Total	**102,400**	**2423.26**	**42**	**130,594**	**2423.26**	**54**	**134,922**	**2423.26**	**56**

Table A-IV.29: Choropleth Densities of Okaloosa county in the 90's and earlier 2000's

Tract ID	1990			1992			1995			2000			2001		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
58	5,210	656.87	8	5,423	656.87	8	5,907	656.87	9	6,742	656.87	10	6,841	656.87	10
59	1,645	222.09	7	1,655	222.09	7	1,715	222.09	8	1,799	222.09	8	1,817	222.09	8
60	5,172	290.72	18	5,647	290.72	19	6,606	290.72	23	8,493	290.72	29	8,713	290.72	30
61	4,895	26.58	184	4,958	26.58	187	5,185	26.58	195	5,529	26.58	208	5,608	26.58	211
62	5,005	23.02	217	5,037	23.02	219	5,216	23.02	227	5,472	23.02	238	5,542	23.02	241
63	2,827	48.67	58	3,177	48.67	65	3,881	48.67	80	5,364	48.67	110	5,490	48.67	113
64	3,847	25.66	150	4,377	25.66	171	5,446	25.66	212	7,760	25.66	302	7,988	25.66	311
65	5,946	947.64	6	5,760	947.64	6	5,635	947.64	6	5,376	947.64	6	5,468	947.64	6
66	3,331	15.02	222	3,509	15.02	234	3,891	15.02	259	4,575	15.02	305	4,669	15.02	311
67	7,272	10.29	707	7,610	10.29	739	8,355	10.29	812	9,663	10.29	939	10,061	10.29	978
68	3,191	5.04	633	3,177	5.04	630	3,238	5.04	642	3,308	5.04	656	3,345	5.04	663
69	6,751	6.68	1,010	6,771	6.68	1,013	6,979	6.68	1,044	7,261	6.68	1,086	7,348	6.68	1,099
70	5,296	33.00	160	5,612	33.00	170	6,279	33.00	190	7,494	33.00	227	7,562	33.00	229
71	7,464	7.41	1,007	7,350	7.41	992	7,370	7.41	995	7,325	7.41	988	7,388	7.41	997
72	7,154	6.17	1,160	7,217	6.17	1,171	7,502	6.17	1,217	7,918	6.17	1,284	8,015	6.17	1,300
73	2,170	2.29	948	2,076	2.29	907	1,994	2.29	871	1,844	2.29	805	1,855	2.29	810
74	2,932	3.48	842	2,840	3.48	816	2,778	3.48	798	2,649	3.48	761	2,665	3.48	766
75	3,973	2.64	1,506	4,161	2.64	1,577	4,573	2.64	1,733	5,299	2.64	2,008	5,439	2.64	2,061
76	4,200	3.38	1,243	4,319	3.38	1,278	4,620	3.38	1,367	5,115	3.38	1,513	5,242	3.38	1,551
77	5,376	6.04	890	5,487	6.04	908	5,803	6.04	961	6,305	6.04	1,044	6,388	6.04	1,058
78	7,342	4.07	1,802	7,190	4.07	1,765	7,149	4.07	1,755	7,006	4.07	1,719	7,062	4.07	1,733
79	3,303	2.06	1,602	3,247	2.06	1,575	3,247	2.06	1,575	3,212	2.06	1,558	3,233	2.06	1,569
80	2,145	2.20	973	2,157	2.20	979	2,233	2.20	1,013	2,339	2.20	1,061	2,360	2.20	1,071
81	4,127	3.46	1,193	4,063	3.46	1,174	4,071	3.46	1,177	4,043	3.46	1,169	4,068	3.46	1,176
82	4,454	3.76	1,184	4,328	3.76	1,150	4,253	3.76	1,130	4,088	3.76	1,086	4,111	3.76	1,093
83	2,933	2.47	1,187	2,887	2.47	1,169	2,894	2.47	1,171	2,874	2.47	1,163	2,901	2.47	1,174
84	3,740	3.05	1,227	3,688	3.05	1,210	3,705	3.05	1,216	3,694	3.05	1,212	3,715	3.05	1,219
85	2,385	1.11	2,141	2,285	1.11	2,052	2,199	1.11	1,974	2,040	1.11	1,832	2,067	1.11	1,856
86	4,340	5.45	796	4,255	5.45	780	4,237	5.45	777	4,164	5.45	764	4,202	5.45	770
87	5,239	6.80	770	5,555	6.80	817	6,220	6.80	915	7,434	6.80	1,093	7,605	6.80	1,118
88	2,031	17.72	115	1,965	17.72	111	1,919	17.72	108	1,825	17.72	103	1,844	17.72	104
89	5,102	23.06	221	5,687	23.06	247	6,863	23.06	298	9,292	23.06	403	9,574	23.06	415
90	2,978	5.34	557	2,986	5.34	559	3,075	5.34	575	3,196	5.34	598	3,264	5.34	611
Total	**143,776**	**2423.26**	**59**	**146,456**	**2423.26**	**60**	**155,038**	**2423.26**	**64**	**170,498**	**2423.26**	**70**	**173,450**	**2423.26**	**72**

Table A-IV.30: Projections of Choropleth Densities for Okaloosa county in 2005-2025

Tract ID	2005			2010			2015			2020			2025		
	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit	Pop	Area	Densit
58	7,371	656.87	11	7,983	656.87	12	8,484	656.87	13	8,888	656.87	14	9,186	656.87	14
59	1,921	222.09	9	2,032	222.09	9	2,110	222.09	10	2,159	222.09	10	2,179	222.09	10
60	9,804	290.72	34	11,212	290.72	39	12,582	290.72	43	13,918	290.72	48	15,189	290.72	52
61	6,033	26.58	227	6,521	26.58	245	6,917	26.58	260	7,232	26.58	272	7,460	26.58	281
62	5,923	23.02	257	6,352	23.02	276	6,684	23.02	290	6,933	23.02	301	7,095	23.02	308
63	6,123	48.67	126	6,923	48.67	142	7,682	48.67	158	8,402	48.67	173	9,067	48.67	186
64	9,112	25.66	355	10,600	25.66	413	12,099	25.66	472	13,614	25.66	531	15,113	25.66	589
65	5,948	947.64	6	6,518	947.64	7	7,010	947.64	7	7,432	947.64	8	7,773	947.64	8
66	5,148	15.02	343	5,740	15.02	382	6,279	15.02	418	6,771	15.02	451	7,203	15.02	480
67	12,013	10.29	1,167	14,795	10.29	1,438	17,879	10.29	1,737	21,299	10.29	2,070	25,032	10.29	2,432
68	3,555	5.04	705	3,786	5.04	751	3,956	5.04	785	4,074	5.04	808	4,140	5.04	821
69	7,828	6.68	1,171	8,361	6.68	1,251	8,762	6.68	1,311	9,052	6.68	1,354	9,226	6.68	1,380
70	7,967	33.00	241	8,392	33.00	254	8,673	33.00	263	8,836	33.00	268	8,881	33.00	269
71	7,768	7.41	1,048	8,160	7.41	1,101	8,412	7.41	1,135	8,548	7.41	1,153	8,569	7.41	1,156
72	8,552	6.17	1,387	9,152	6.17	1,484	9,609	6.17	1,558	9,946	6.17	1,613	10,156	6.17	1,647
73	1,932	2.29	844	2,006	2.29	876	2,043	2.29	892	2,052	2.29	896	2,033	2.29	888
74	2,772	3.48	796	2,873	3.48	826	2,922	3.48	840	2,929	3.48	842	2,898	3.48	833
75	6,133	2.64	2,324	7,031	2.64	2,665	7,910	2.64	2,998	8,772	2.64	3,325	9,598	2.64	3,638
76	5,875	3.38	1,738	6,685	3.38	1,978	7,463	3.38	2,208	8,214	3.38	2,430	8,919	3.38	2,639
77	6,842	6.04	1,133	7,356	6.04	1,218	7,759	6.04	1,284	8,069	6.04	1,336	8,278	6.04	1,370
78	7,406	4.07	1,818	7,755	4.07	1,903	7,969	4.07	1,956	8,071	4.07	1,981	8,066	4.07	1,980
79	3,373	2.06	1,636	3,510	2.06	1,703	3,583	2.06	1,738	3,606	2.06	1,749	3,581	2.06	1,737
80	2,487	2.20	1,129	2,619	2.20	1,188	2,706	2.20	1,228	2,757	2.20	1,251	2,771	2.20	1,257
81	4,235	3.46	1,224	4,394	3.46	1,270	4,474	3.46	1,293	4,490	3.46	1,298	4,446	3.46	1,285
82	4,273	3.76	1,136	4,425	3.76	1,176	4,496	3.76	1,195	4,503	3.76	1,197	4,450	3.76	1,183
83	3,062	2.47	1,239	3,232	2.47	1,308	3,347	2.47	1,355	3,417	2.47	1,383	3,442	2.47	1,393
84	3,861	3.05	1,267	3,998	3.05	1,312	4,062	3.05	1,333	4,068	3.05	1,335	4,020	3.05	1,319
85	2,213	1.11	1,987	2,378	1.11	2,135	2,507	1.11	2,251	2,606	1.11	2,340	2,672	1.11	2,399
86	4,427	5.45	812	4,664	5.45	855	4,820	5.45	884	4,911	5.45	900	4,937	5.45	905
87	8,463	6.80	1,244	9,544	6.80	1,403	10,562	6.80	1,553	11,521	6.80	1,694	12,400	6.80	1,823
88	1,953	17.72	110	2,070	17.72	117	2,153	17.72	121	2,208	17.72	125	2,234	17.72	126
89	10,961	23.06	475	12,810	23.06	555	14,690	23.06	637	16,605	23.06	720	18,519	23.06	803
90	3,606	5.34	675	4,032	5.34	754	4,423	5.34	828	4,782	5.34	895	5,102	5.34	955
Total	**188,940**	**2423.26**	**78**	**207,909**	**2423.26**	**86**	**225,027**	**2423.26**	**93**	**240,685**	**2423.26**	**99**	**254,635**	**2423.26**	**105**

Table A-IV.31: Dasymetric Densities of Escambia county in the 70's

Tract ID	Real 1974				Sim 1975			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	3,743	1,872	1.68	2,222	3,548	1,899	1.71	2,076
1	4,607	2,952	2.66	1,734	4,454	2,997	2.70	1,651
2	5,517	1,440	1.30	4,257	5,260	1,449	1.30	4,033
3	2,253	774	0.70	3,234	2,186	783	0.70	3,102
4	4,180	1,503	1.35	3,090	3,855	1,503	1.35	2,850
5	8,569	3,546	3.19	2,685	8,246	3,618	3.26	2,532
6	3,391	1,044	0.94	3,609	3,292	1,062	0.96	3,444
7	5,218	2,493	2.24	2,326	5,216	2,529	2.28	2,292
8	2,662	1,224	1.10	2,416	2,652	1,224	1.10	2,407
9	3,595	2,196	1.98	1,819	3,690	2,232	2.01	1,837
10	2,089	882	0.79	2,632	2,187	900	0.81	2,700
11	4,538	2,754	2.48	1,831	4,750	2,799	2.52	1,886
12	4,567	2,880	2.59	1,762	4,557	2,916	2.62	1,736
13	3,527	2,178	1.96	1,799	3,527	2,232	2.01	1,756
14	5,829	1,926	1.73	3,363	5,772	1,980	1.78	3,239
15	3,373	2,358	2.12	1,589	3,437	2,385	2.15	1,601
16	5,077	3,132	2.82	1,801	5,267	3,186	2.87	1,837
17	3,305	1,269	1.14	2,894	3,154	1,287	1.16	2,723
18	3,424	1,512	1.36	2,516	3,303	1,530	1.38	2,399
19	4,824	2,772	2.49	1,934	4,690	2,790	2.51	1,868
20	4,587	1,422	1.28	3,584	4,419	1,449	1.30	3,389
21	2,967	1,125	1.01	2,930	2,852	1,152	1.04	2,751
22	3,623	1,467	1.32	2,744	3,519	1,503	1.35	2,601
23	6,708	2,610	2.35	2,856	6,582	2,673	2.41	2,736
24	6,511	1,647	1.48	4,392	6,271	1,656	1.49	4,208
25	7,125	1,764	1.59	4,488	6,954	1,764	1.59	4,380
26	4,692	2,466	2.22	2,114	4,519	2,484	2.24	2,021
27	1,196	405	0.36	3,281	1,256	450	0.41	3,101
28	3,552	2,241	2.02	1,761	3,754	2,259	2.03	1,846
29	869	243	0.22	3,973	814	252	0.23	3,589
30	4,099	1,323	1.19	3,443	4,346	1,368	1.23	3,530
31	2,265	675	0.61	3,728	2,317	693	0.62	3,715
32	3,369	1,071	0.96	3,495	3,447	1,080	0.97	3,546
33	2,282	702	0.63	3,612	2,319	711	0.64	3,624
34	2,874	756	0.68	4,224	2,941	765	0.69	4,272
35	5,699	1,485	1.34	4,264	5,534	1,521	1.37	4,043
36	7,232	1,872	1.68	4,292	7,178	1,917	1.73	4,160
37	5,522	1,206	1.09	5,088	5,531	1,215	1.09	5,058
38	3,766	1,683	1.51	2,486	3,917	1,719	1.55	2,532
39	4,917	2,862	2.58	1,909	4,880	2,916	2.62	1,859
40	1,228	657	0.59	2,077	1,319	693	0.62	2,115
41	4,428	2,565	2.31	1,918	4,771	2,565	2.31	2,067
42	1,084	396	0.36	3,042	1,170	405	0.36	3,210
43	3,682	2,043	1.84	2,003	3,973	2,061	1.85	2,142
44	1,409	738	0.66	2,121	1,521	747	0.67	2,262
45	4,851	2,763	2.49	1,951	4,823	2,817	2.54	1,902
46	4,822	3,267	2.94	1,640	4,963	3,321	2.99	1,660
47	3,397	2,664	2.40	1,417	3,517	2,736	2.46	1,428
48	4,924	3,006	2.71	1,820	5,098	3,024	2.72	1,873
49	3,511	1,935	1.74	2,016	3,831	1,989	1.79	2,140
50	1,852	639	0.58	3,220	1,981	675	0.61	3,261
51	2,556	2,475	2.23	1,147	2,727	2,520	2.27	1,202
52	2,476	2,277	2.05	1,208	2,642	2,367	2.13	1,240
53	3,174	1,800	1.62	1,959	3,386	1,863	1.68	2,019
54	3,938	1,251	1.13	3,498	3,733	1,278	1.15	3,246
55	3,129	954	0.86	3,644	3,099	1,035	0.93	3,327
56	4,279	1,215	1.09	3,913	4,296	1,260	1.13	3,788
57	4,525	1,359	1.22	3,700	4,451	1,395	1.26	3,545
Total	**227,408**	**101,736**	**91.56**	**2,484**	**227,694**	**103,599**	**93.24**	**2,442**

Table A-IV.32: Dasymetric Densities of Escambia county in the 80's

Tract ID	Sim 1980				Sim 1985				Real 1986				Sim 1986			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	2,707	1,989	1.79	1,512	2,457	2,115	1.90	1,291	2,402	1,935	1.74	1,379	2,402	2,115	1.90	1,262
1	3,748	3,231	2.91	1,289	3,599	3,492	3.14	1,145	3,558	3,132	2.82	1,262	3,558	3,510	3.16	1,126
2	4,131	1,485	1.34	3,091	3,994	1,611	1.45	2,755	3,954	1,467	1.32	2,995	3,954	1,629	1.47	2,697
3	1,872	855	0.77	2,433	1,812	936	0.84	2,151	1,794	846	0.76	2,356	1,794	945	0.85	2,109
4	2,564	1,557	1.40	1,830	2,398	1,620	1.46	1,645	2,359	1,512	1.36	1,734	2,359	1,620	1.46	1,618
5	6,778	3,996	3.60	1,885	6,387	4,239	3.82	1,674	6,292	3,618	3.26	1,932	6,292	4,284	3.86	1,632
6	2,830	1,134	1.02	2,773	2,848	1,215	1.09	2,604	2,843	1,143	1.03	2,764	2,843	1,242	1.12	2,543
7	5,180	2,754	2.48	2,090	6,001	2,979	2.68	2,238	6,160	2,637	2.37	2,596	6,160	3,024	2.72	2,263
8	2,593	1,341	1.21	2,148	3,051	1,395	1.26	2,430	3,142	1,251	1.13	2,791	3,142	1,440	1.30	2,424
9	4,181	2,421	2.18	1,919	5,023	2,727	2.45	2,047	5,195	2,430	2.19	2,375	5,195	2,772	2.49	2,082
10	2,733	999	0.90	3,040	3,060	1,053	0.95	3,229	3,120	1,026	0.92	3,379	3,120	1,062	0.96	3,264
11	5,933	3,087	2.78	2,135	6,646	3,438	3.09	2,148	6,777	2,961	2.66	2,543	6,777	3,483	3.13	2,162
12	4,487	3,222	2.90	1,547	4,887	3,456	3.11	1,571	4,956	3,222	2.90	1,709	4,956	3,483	3.13	1,581
13	3,513	2,421	2.18	1,612	3,918	2,673	2.41	1,629	3,992	2,439	2.20	1,819	3,992	2,727	2.45	1,627
14	5,473	2,187	1.97	2,781	5,313	2,340	2.11	2,523	5,264	2,052	1.85	2,850	5,264	2,394	2.15	2,443
15	3,760	2,628	2.37	1,590	4,269	2,826	2.54	1,678	4,365	2,529	2.28	1,918	4,365	2,880	2.59	1,684
16	6,299	3,618	3.26	1,934	6,544	3,987	3.59	1,824	6,573	3,672	3.30	1,989	6,573	4,068	3.66	1,795
17	2,488	1,350	1.22	2,048	2,147	1,440	1.30	1,657	2,077	1,287	1.16	1,793	2,077	1,449	1.30	1,593
18	2,748	1,638	1.47	1,864	2,364	1,755	1.58	1,497	2,287	1,611	1.45	1,577	2,287	1,773	1.60	1,433
19	4,056	3,042	2.74	1,481	3,892	3,258	2.93	1,327	3,847	2,880	2.59	1,484	3,847	3,348	3.01	1,277
20	3,655	1,575	1.42	2,578	3,316	1,665	1.50	2,213	3,241	1,485	1.34	2,425	3,241	1,674	1.51	2,151
21	2,331	1,269	1.14	2,041	2,378	1,368	1.23	1,931	2,380	1,278	1.15	2,069	2,380	1,395	1.26	1,896
22	3,029	1,728	1.56	1,948	2,818	1,944	1.75	1,611	2,769	1,548	1.39	1,988	2,769	1,971	1.77	1,561
23	5,962	2,952	2.66	2,244	5,714	3,123	2.81	2,033	5,647	2,754	2.48	2,278	5,647	3,177	2.86	1,975
24	5,175	1,818	1.64	3,163	5,210	2,025	1.82	2,859	5,200	1,692	1.52	3,415	5,200	2,052	1.85	2,816
25	6,136	2,025	1.82	3,367	6,098	2,259	2.03	2,999	6,071	1,656	1.49	4,073	6,071	2,286	2.06	2,951
26	3,730	2,601	2.34	1,593	3,874	2,736	2.46	1,573	3,891	3,024	2.72	1,430	3,891	2,790	2.51	1,550
27	1,595	486	0.44	3,647	2,045	522	0.47	4,353	2,142	675	0.61	3,526	2,142	540	0.49	4,407
28	4,921	2,448	2.20	2,234	6,465	2,664	2.40	2,696	6,807	3,591	3.23	2,106	6,807	2,754	2.48	2,746
29	584	261	0.23	2,486	733	288	0.26	2,828	765	306	0.28	2,778	765	288	0.26	2,951
30	5,794	1,530	1.38	4,208	7,276	1,728	1.56	4,678	7,592	1,809	1.63	4,663	7,592	1,764	1.59	4,782
31	2,586	783	0.70	3,670	2,909	945	0.85	3,420	2,969	1,026	0.92	3,215	2,969	954	0.86	3,458
32	3,846	1,224	1.10	3,491	4,328	1,323	1.19	3,635	4,417	1,656	1.49	2,964	4,417	1,377	1.24	3,564
33	2,507	828	0.75	3,364	2,772	936	0.84	3,291	2,819	864	0.78	3,625	2,819	954	0.86	3,283
34	3,282	846	0.76	4,310	3,692	900	0.81	4,558	3,768	855	0.77	4,897	3,768	936	0.84	4,473
35	4,762	1,692	1.52	3,127	4,648	1,872	1.68	2,759	4,610	1,728	1.56	2,964	4,610	1,908	1.72	2,685
36	6,884	2,187	1.97	3,497	6,953	2,358	2.12	3,276	6,945	2,034	1.83	3,794	6,945	2,412	2.17	3,199
37	5,553	1,350	1.22	4,570	5,398	1,575	1.42	3,808	5,350	1,440	1.30	4,128	5,350	1,602	1.44	3,711
38	4,745	1,980	1.78	2,663	4,769	2,142	1.93	2,474	4,759	1,962	1.77	2,695	4,759	2,196	1.98	2,408
39	4,678	3,312	2.98	1,569	5,895	3,753	3.38	1,745	6,155	3,285	2.96	2,082	6,155	3,852	3.47	1,775
40	1,875	819	0.74	2,544	2,073	936	0.84	2,461	2,108	837	0.75	2,798	2,108	963	0.87	2,432
41	6,896	2,835	2.55	2,703	7,612	3,204	2.88	2,640	7,740	3,366	3.03	2,555	7,740	3,249	2.92	2,647
42	1,703	441	0.40	4,291	1,881	477	0.43	4,382	1,912	630	0.57	3,372	1,912	477	0.43	4,454
43	5,785	2,322	2.09	2,768	6,389	2,547	2.29	2,787	6,497	2,610	2.35	2,766	6,497	2,574	2.32	2,805
44	2,214	837	0.75	2,939	2,446	963	0.87	2,822	2,487	738	0.66	3,744	2,487	972	0.87	2,843
45	4,666	3,204	2.88	1,618	4,774	3,681	3.31	1,441	4,781	3,321	2.99	1,600	4,781	3,816	3.43	1,392
46	5,706	3,915	3.52	1,619	6,797	4,482	4.03	1,685	7,018	3,996	3.60	1,951	7,018	4,572	4.11	1,706
47	4,165	3,087	2.78	1,499	4,895	3,384	3.05	1,607	5,040	2,997	2.70	1,869	5,040	3,438	3.09	1,629
48	6,038	3,294	2.96	2,037	7,096	3,600	3.24	2,190	7,306	3,258	2.93	2,492	7,306	3,690	3.32	2,200
49	5,896	2,223	2.00	2,947	6,943	2,520	2.27	3,061	7,152	2,421	2.18	3,282	7,152	2,565	2.31	3,098
50	2,765	756	0.68	4,064	3,589	873	0.79	4,568	3,770	873	0.79	4,798	3,770	900	0.81	4,654
51	3,746	2,835	2.55	1,468	4,934	3,141	2.83	1,745	5,198	2,790	2.51	2,070	5,198	3,213	2.89	1,798
52	3,629	2,736	2.46	1,474	4,781	3,033	2.73	1,751	5,036	2,853	2.57	1,961	5,036	3,051	2.75	1,834
53	4,652	2,142	1.93	2,413	6,129	2,412	2.17	2,823	6,457	2,142	1.93	3,349	6,457	2,475	2.23	2,899
54	2,845	1,422	1.28	2,223	2,924	1,557	1.40	2,087	2,931	1,629	1.47	1,999	2,931	1,611	1.45	2,022
55	2,943	1,206	1.09	2,711	3,446	1,386	1.25	2,763	3,546	981	0.88	4,016	3,546	1,458	1.31	2,702
56	4,364	1,539	1.39	3,151	4,604	1,746	1.57	2,930	4,638	1,431	1.29	3,601	4,638	1,809	1.63	2,849
57	4,080	1,530	1.38	2,963	4,081	1,746	1.57	2,597	4,068	1,602	1.44	2,821	4,068	1,791	1.61	2,524
Total	**233,797**	**114,993**	**103.49**	**2,259**	**253,295**	**126,369**	**113.73**	**2,227**	**256,939**	**116,793**	**105.11**	**2,444**	**256,939**	**128,754**	**115.88**	**2,217**

Table A-IV.33: Dasymetric Densities of Escambia county in the 90's

Tract ID	Sim 1990				Real 1992				Sim 1992				Sim 1995			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	2,107	2,160	1.94	1,084	2,071	1,881	1.69	1,223	2,071	2,196	1.98	1,048	2,068	2,232	2.01	1,029
1	3,266	3,654	3.29	993	3,192	2,970	2.67	1,194	3,192	3,726	3.35	952	3,160	3,861	3.47	909
2	3,649	1,710	1.54	2,371	3,567	1,485	1.34	2,669	3,567	1,773	1.60	2,235	3,532	1,791	1.61	2,191
3	1,657	999	0.90	1,843	1,634	900	0.81	2,017	1,634	1,017	0.92	1,785	1,639	1,035	0.93	1,760
4	2,120	1,656	1.49	1,422	2,061	1,413	1.27	1,621	2,061	1,692	1.52	1,353	2,024	1,728	1.56	1,301
5	5,687	4,482	4.03	1,410	5,512	3,780	3.40	1,620	5,512	4,563	4.11	1,342	5,388	4,671	4.20	1,282
6	2,710	1,341	1.21	2,245	2,666	1,143	1.03	2,592	2,666	1,377	1.24	2,151	2,664	1,449	1.30	2,043
7	6,581	3,303	2.97	2,214	6,470	2,745	2.47	2,619	6,470	3,366	3.03	2,136	6,459	3,474	3.13	2,066
8	3,399	1,512	1.36	2,498	3,284	1,278	1.15	2,855	3,284	1,557	1.40	2,344	3,195	1,611	1.45	2,204
9	5,716	2,916	2.62	2,178	5,747	2,466	2.22	2,589	5,747	3,015	2.71	2,118	5,932	3,159	2.84	2,086
10	3,243	1,152	1.04	3,128	3,157	1,026	0.92	3,419	3,157	1,179	1.06	2,975	3,106	1,224	1.10	2,820
11	7,046	3,672	3.30	2,132	6,900	2,952	2.66	2,597	6,900	3,798	3.42	2,019	6,848	3,906	3.52	1,948
12	5,037	3,672	3.30	1,524	5,022	3,357	3.02	1,662	5,022	3,753	3.38	1,487	5,120	3,897	3.51	1,460
13	4,136	2,880	2.59	1,596	4,044	2,358	2.12	1,906	4,044	2,961	2.66	1,518	4,004	3,087	2.78	1,441
14	4,874	2,538	2.28	2,134	4,780	2,079	1.87	2,555	4,780	2,619	2.36	2,028	4,754	2,691	2.42	1,963
15	4,589	3,015	2.71	1,691	4,728	2,646	2.38	1,985	4,728	3,141	2.83	1,673	5,063	3,303	2.97	1,703
16	6,430	4,428	3.99	1,613	6,304	4,212	3.79	1,663	6,304	4,617	4.16	1,517	6,268	4,869	4.38	1,430
17	1,748	1,512	1.36	1,285	1,643	1,251	1.13	1,459	1,643	1,512	1.36	1,207	1,533	1,557	1.40	1,094
18	1,920	1,881	1.69	1,134	2,055	1,629	1.47	1,402	2,055	1,908	1.72	1,197	2,327	1,971	1.77	1,312
19	3,529	3,573	3.22	1,097	3,411	2,934	2.64	1,292	3,411	3,690	3.32	1,027	3,321	3,816	3.43	967
20	2,840	1,719	1.55	1,836	2,725	1,512	1.36	2,002	2,725	1,755	1.58	1,725	2,623	1,836	1.65	1,587
21	2,295	1,485	1.34	1,717	2,256	1,287	1.16	1,948	2,256	1,521	1.37	1,648	2,253	1,620	1.46	1,545
22	2,477	2,097	1.89	1,312	2,413	1,710	1.54	1,568	2,413	2,214	1.99	1,211	2,377	2,367	2.13	1,116
23	5,174	3,312	2.98	1,736	5,136	2,970	2.67	1,921	5,136	3,429	3.09	1,664	5,202	3,582	3.22	1,614
24	4,958	2,232	2.01	2,468	4,722	1,854	1.67	2,830	4,722	2,331	2.10	2,251	4,497	2,385	2.15	2,095
25	5,729	2,484	2.24	2,563	5,607	1,944	1.75	3,205	5,607	2,565	2.31	2,429	5,560	2,862	2.58	2,159
26	3,806	2,862	2.58	1,478	4,618	3,510	3.16	1,462	4,618	2,898	2.61	1,771	6,306	2,970	2.67	2,359
27	2,485	612	0.55	4,512	2,512	1,701	1.53	1,641	2,512	630	0.57	4,430	2,615	693	0.62	4,193
28	8,052	3,006	2.71	2,976	9,328	4,950	4.46	2,094	9,328	3,132	2.82	3,309	11,888	3,312	2.98	3,988
29	872	288	0.26	3,364	1,069	378	0.34	3,142	1,069	324	0.29	3,666	1,481	333	0.30	4,942
30	8,658	2,016	1.81	4,772	8,451	2,736	2.46	3,432	8,451	2,106	1.90	4,459	8,349	2,277	2.05	4,074
31	3,098	1,026	0.92	3,355	2,998	1,593	1.43	2,091	2,998	1,071	0.96	3,110	2,924	1,179	1.06	2,756
32	4,609	1,530	1.38	3,347	4,834	1,962	1.77	2,738	4,834	1,611	1.45	3,334	5,314	1,746	1.57	3,382
33	2,899	1,053	0.95	3,059	2,849	936	0.84	3,382	2,849	1,116	1.00	2,837	2,842	1,161	1.04	2,720
34	3,932	963	0.87	4,537	3,694	1,278	1.15	3,212	3,694	990	0.89	4,146	3,447	1,062	0.96	3,606
35	4,287	2,097	1.89	2,271	4,224	1,998	1.80	2,349	4,224	2,241	2.02	2,094	4,231	2,367	2.13	1,986
36	6,640	2,646	2.38	2,788	6,665	2,646	2.38	2,799	6,665	2,790	2.51	2,654	6,864	2,997	2.70	2,545
37	4,959	1,755	1.58	3,140	4,902	1,530	1.38	3,560	4,902	1,818	1.64	2,996	4,935	1,944	1.75	2,821
38	4,532	2,358	2.12	2,136	4,555	2,322	2.09	2,180	4,555	2,394	2.15	2,114	4,698	2,565	2.31	2,035
39	7,038	4,140	3.73	1,889	7,175	4,041	3.64	1,973	7,175	4,302	3.87	1,853	7,560	4,545	4.09	1,848
40	2,169	1,053	0.95	2,289	2,262	1,026	0.92	2,450	2,262	1,152	1.04	2,182	2,466	1,215	1.09	2,255
41	7,952	3,564	3.21	2,479	8,090	4,158	3.74	2,162	8,090	3,735	3.36	2,407	8,499	4,014	3.61	2,353
42	1,965	486	0.44	4,492	2,039	774	0.70	2,927	2,039	540	0.49	4,195	2,205	540	0.49	4,537
43	6,677	2,808	2.53	2,642	6,649	3,537	3.18	2,089	6,649	2,934	2.64	2,518	6,766	3,141	2.83	2,393
44	2,556	1,053	0.95	2,697	2,472	1,035	0.93	2,654	2,472	1,125	1.01	2,441	2,409	1,197	1.08	2,236
45	4,620	4,131	3.72	1,243	4,585	3,753	3.38	1,357	4,585	4,365	3.93	1,167	4,642	4,698	4.23	1,098
46	7,669	5,067	4.56	1,682	7,952	4,374	3.94	2,020	7,952	5,292	4.76	1,670	8,593	5,679	5.11	1,681
47	5,448	3,744	3.37	1,617	5,532	3,555	3.20	1,729	5,532	3,861	3.47	1,592	5,796	4,041	3.64	1,594
48	7,896	3,852	3.47	2,278	7,998	3,312	2.98	2,683	7,998	3,978	3.58	2,234	8,348	4,176	3.76	2,221
49	7,743	2,754	2.48	3,124	7,916	2,664	2.40	3,302	7,916	2,826	2.54	3,112	8,377	3,069	2.76	3,033
50	4,416	990	0.89	4,956	4,460	1,404	1.26	3,530	4,460	1,008	0.91	4,916	4,635	1,080	0.97	4,769
51	6,162	3,465	3.12	1,976	6,578	3,096	2.79	2,361	6,578	3,690	3.32	1,981	7,423	4,005	3.60	2,059
52	5,970	3,384	3.05	1,960	6,343	3,393	3.05	2,077	6,343	3,573	3.22	1,973	7,107	3,789	3.41	2,084
53	7,654	2,844	2.56	2,990	7,884	2,754	2.48	3,181	7,884	3,060	2.75	2,863	8,436	3,231	2.91	2,901
54	2,842	1,908	1.72	1,655	2,907	1,890	1.70	1,709	2,907	1,962	1.77	1,646	3,077	2,142	1.93	1,596
55	3,822	1,737	1.56	2,445	3,913	1,071	0.96	4,060	3,913	1,854	1.67	2,345	4,150	2,079	1.87	2,218
56	4,594	2,079	1.87	2,455	4,651	1,359	1.22	3,803	4,651	2,205	1.98	2,344	4,851	2,421	2.18	2,226
57	3,859	1,935	1.74	2,216	4,040	1,710	1.54	2,625	4,040	1,998	1.80	2,247	4,431	2,196	1.98	2,242
Total	**262,798**	**138,591**	**124.73**	**2,107**	**265,252**	**132,228**	**119.01**	**2,229**	**265,252**	**143,856**	**129.47**	**2,049**	**276,582**	**151,848**	**136.66**	**2,024**

Table A-IV.34: Dasymetric Densities of Escambia county in the 2000's

Tract ID	Sim 2000				Real 2001				Sim 2001			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	2,021	2,304	2.07	975	1,992	1,818	1.64	1,217	1,992	2,322	2.09	953
1	3,044	3,960	3.56	854	3,015	2,988	2.69	1,121	3,015	4,005	3.60	836
2	3,402	1,872	1.68	2,019	3,362	1,440	1.30	2,594	3,362	1,890	1.70	1,976
3	1,613	1,143	1.03	1,568	1,600	846	0.76	2,101	1,600	1,152	1.04	1,543
4	1,923	1,791	1.61	1,193	1,888	1,440	1.30	1,457	1,888	1,800	1.62	1,165
5	5,080	4,896	4.41	1,153	5,020	3,618	3.26	1,542	5,020	4,932	4.44	1,131
6	2,607	1,539	1.39	1,882	2,589	1,125	1.01	2,557	2,589	1,539	1.39	1,869
7	6,310	3,789	3.41	1,850	6,326	2,700	2.43	2,603	6,326	3,816	3.43	1,842
8	2,990	1,665	1.50	1,995	2,993	1,206	1.09	2,758	2,993	1,674	1.51	1,987
9	6,127	3,447	3.10	1,975	6,188	2,457	2.21	2,798	6,188	3,537	3.18	1,944
10	2,960	1,296	1.17	2,538	2,984	1,008	0.91	3,289	2,984	1,323	1.19	2,506
11	6,623	4,140	3.73	1,778	6,681	2,943	2.65	2,522	6,681	4,212	3.79	1,762
12	5,179	4,194	3.77	1,372	5,185	3,123	2.81	1,845	5,185	4,230	3.81	1,362
13	3,858	3,312	2.98	1,294	3,861	2,295	2.07	1,869	3,861	3,366	3.03	1,275
14	4,616	2,925	2.63	1,753	4,592	1,935	1.74	2,637	4,592	2,934	2.64	1,739
15	5,559	3,429	3.09	1,801	5,608	2,538	2.28	2,455	5,608	3,465	3.12	1,798
16	6,081	5,310	4.78	1,272	6,110	4,212	3.79	1,612	6,110	5,382	4.84	1,261
17	1,339	1,602	1.44	929	1,314	1,215	1.09	1,202	1,314	1,611	1.45	906
18	2,805	2,106	1.90	1,480	2,788	1,584	1.43	1,956	2,788	2,115	1.90	1,465
19	3,110	4,023	3.62	859	3,080	2,754	2.48	1,243	3,080	4,077	3.67	839
20	2,411	1,899	1.71	1,411	2,378	1,485	1.34	1,779	2,378	1,935	1.74	1,365
21	2,201	1,683	1.51	1,453	2,183	1,242	1.12	1,953	2,183	1,701	1.53	1,426
22	2,270	2,565	2.31	983	2,247	1,638	1.47	1,524	2,247	2,610	2.35	957
23	5,205	3,870	3.48	1,494	5,173	2,826	2.54	2,034	5,173	3,942	3.55	1,458
24	4,061	2,565	2.31	1,759	4,017	1,746	1.57	2,556	4,017	2,619	2.36	1,704
25	5,371	3,141	2.83	1,900	5,334	1,890	1.70	3,136	5,334	3,195	2.88	1,855
26	10,389	3,069	2.76	3,761	10,502	3,744	3.37	3,117	10,502	3,096	2.79	3,769
27	2,738	774	0.70	3,931	2,783	2,304	2.07	1,342	2,783	783	0.70	3,949
28	17,455	3,582	3.22	5,414	17,983	10,170	9.15	1,965	17,983	3,681	3.31	5,428
29	2,501	369	0.33	7,531	2,536	909	0.82	3,100	2,536	378	0.34	7,454
30	8,012	2,565	2.31	3,471	8,130	3,267	2.94	2,765	8,130	2,619	2.36	3,449
31	2,748	1,314	1.18	2,324	2,759	1,377	1.24	2,226	2,759	1,341	1.21	2,286
32	6,096	1,962	1.77	3,452	6,162	1,881	1.69	3,640	6,162	2,034	1.83	3,366
33	2,773	1,341	1.21	2,298	2,783	900	0.81	3,436	2,783	1,386	1.25	2,231
34	3,008	1,170	1.05	2,857	3,013	1,242	1.12	2,695	3,013	1,179	1.06	2,840
35	4,155	2,646	2.38	1,745	4,123	1,836	1.65	2,495	4,123	2,700	2.43	1,697
36	7,061	3,267	2.94	2,401	7,050	2,340	2.11	3,348	7,050	3,321	2.99	2,359
37	4,887	2,088	1.88	2,601	4,874	1,503	1.35	3,603	4,874	2,133	1.92	2,539
38	4,846	2,745	2.47	1,962	4,876	2,412	2.17	2,246	4,876	2,826	2.54	1,917
39	8,079	5,094	4.58	1,762	8,137	5,004	4.50	1,807	8,137	5,211	4.69	1,735
40	2,791	1,449	1.30	2,140	2,841	1,152	1.04	2,740	2,841	1,458	1.31	2,165
41	9,040	4,509	4.06	2,228	9,190	4,482	4.03	2,278	9,190	4,590	4.13	2,225
42	2,462	594	0.53	4,605	2,507	900	0.81	3,095	2,507	630	0.57	4,422
43	6,824	3,429	3.09	2,211	6,927	3,186	2.87	2,416	6,927	3,474	3.13	2,216
44	2,259	1,251	1.13	2,006	2,288	1,035	0.93	2,456	2,288	1,278	1.15	1,989
45	4,642	5,292	4.76	975	4,634	3,924	3.53	1,312	4,634	5,400	4.86	953
46	9,580	6,210	5.59	1,714	9,702	4,167	3.75	2,587	9,702	6,291	5.66	1,714
47	6,136	4,464	4.02	1,527	6,207	3,249	2.92	2,123	6,207	4,572	4.11	1,508
48	8,781	4,437	3.99	2,199	8,880	3,087	2.78	3,196	8,880	4,500	4.05	2,193
49	9,018	3,411	3.07	2,938	9,211	2,853	2.57	3,587	9,211	3,483	3.13	2,938
50	4,841	1,305	1.17	4,122	4,939	1,296	1.17	4,234	4,939	1,332	1.20	4,120
51	8,896	4,311	3.88	2,293	9,117	4,482	4.03	2,260	9,117	4,437	3.99	2,283
52	8,416	4,293	3.86	2,178	8,622	3,753	3.38	2,553	8,622	4,392	3.95	2,181
53	9,251	3,564	3.21	2,884	9,453	3,096	2.79	3,393	9,453	3,627	3.26	2,896
54	3,315	2,412	2.17	1,527	3,292	2,313	2.08	1,581	3,292	2,457	2.21	1,489
55	4,485	2,601	2.34	1,916	4,506	1,350	1.22	3,709	4,506	2,709	2.44	1,848
56	5,097	2,844	2.56	1,991	5,110	1,512	1.36	3,755	5,110	2,925	2.63	1,941
57	5,062	2,439	2.20	2,306	5,063	1,872	1.68	3,005	5,063	2,475	2.23	2,273
Total	**294,410**	**165,267**	**148.74**	**1,979**	**296,708**	**140,670**	**126.60**	**2,344**	**296,708**	**168,102**	**151.29**	**1,961**

Table A-IV.35: Projections of Dasymetric Densities for Escambia county in 2005

Tract ID	Sim 2005 smart				Sim 2005 normal				Sim 2005 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	1,864	1,845	1.66	1,123	1,864	1,908	1.72	1,085	1,864	1,926	1.73	1,075
1	2,872	2,997	2.70	1,065	2,872	3,123	2.81	1,022	2,872	3,204	2.88	996
2	3,178	1,449	1.30	2,437	3,178	1,476	1.33	2,392	3,178	1,485	1.34	2,378
3	1,534	882	0.79	1,932	1,534	873	0.79	1,952	1,534	918	0.83	1,857
4	1,737	1,467	1.32	1,316	1,737	1,485	1.34	1,300	1,737	1,485	1.34	1,300
5	4,744	3,681	3.31	1,432	4,744	3,744	3.37	1,408	4,744	3,933	3.54	1,340
6	2,494	1,152	1.04	2,405	2,494	1,215	1.09	2,281	2,494	1,269	1.14	2,184
7	6,328	2,754	2.48	2,553	6,328	2,934	2.64	2,396	6,328	2,961	2.66	2,375
8	2,977	1,224	1.10	2,702	2,977	1,260	1.13	2,625	2,977	1,278	1.15	2,588
9	6,378	2,538	2.28	2,792	6,378	2,601	2.34	2,725	6,378	2,655	2.39	2,669
10	3,055	1,026	0.92	3,308	3,055	1,062	0.96	3,196	3,055	1,143	1.03	2,970
11	6,853	3,006	2.71	2,533	6,853	3,096	2.79	2,459	6,853	3,249	2.92	2,344
12	5,162	3,195	2.88	1,795	5,162	3,294	2.96	1,741	5,162	3,357	3.02	1,709
13	3,837	2,331	2.10	1,829	3,837	2,421	2.18	1,761	3,837	2,484	2.24	1,716
14	4,455	1,971	1.77	2,511	4,455	2,034	1.83	2,434	4,455	2,052	1.85	2,412
15	5,756	2,583	2.32	2,476	5,756	2,592	2.33	2,467	5,756	2,619	2.36	2,442
16	6,170	4,266	3.84	1,607	6,170	4,500	4.05	1,523	6,170	4,689	4.22	1,462
17	1,209	1,242	1.12	1,082	1,209	1,305	1.17	1,029	1,209	1,305	1.17	1,029
18	2,695	1,611	1.45	1,859	2,695	1,647	1.48	1,818	2,695	1,629	1.47	1,838
19	2,934	2,817	2.54	1,157	2,934	2,934	2.64	1,111	2,934	2,925	2.63	1,115
20	2,230	1,485	1.34	1,669	2,230	1,530	1.38	1,619	2,230	1,584	1.43	1,564
21	2,093	1,251	1.13	1,859	2,093	1,287	1.16	1,807	2,093	1,377	1.24	1,689
22	2,136	1,656	1.49	1,433	2,136	1,710	1.54	1,388	2,136	1,746	1.57	1,359
23	5,001	2,844	2.56	1,954	5,001	2,943	2.65	1,888	5,001	3,051	2.75	1,821
24	3,809	1,764	1.59	2,399	3,809	1,836	1.65	2,305	3,809	1,917	1.73	2,208
25	5,139	1,935	1.74	2,951	5,139	1,953	1.76	2,924	5,139	2,034	1.83	2,807
26	10,865	3,771	3.39	3,201	10,865	3,825	3.44	3,156	10,865	3,852	3.47	3,134
27	2,945	2,322	2.09	1,409	2,945	2,439	2.20	1,342	2,945	2,547	2.29	1,285
28	20,066	10,377	9.34	2,149	20,066	10,953	9.86	2,036	20,066	11,106	10.00	2,008
29	2,654	936	0.84	3,151	2,654	954	0.86	3,091	2,654	990	0.89	2,979
30	8,536	3,348	3.01	2,833	8,536	3,447	3.10	2,752	8,536	3,564	3.21	2,661
31	2,778	1,422	1.28	2,171	2,778	1,449	1.30	2,130	2,778	1,512	1.36	2,041
32	6,370	1,917	1.73	3,692	6,370	1,998	1.80	3,542	6,370	2,007	1.81	3,527
33	2,797	918	0.83	3,385	2,797	963	0.87	3,227	2,797	972	0.87	3,197
34	3,005	1,242	1.12	2,688	3,005	1,269	1.14	2,631	3,005	1,260	1.13	2,650
35	3,958	1,854	1.67	2,372	3,958	1,881	1.69	2,338	3,958	2,016	1.81	2,181
36	6,939	2,367	2.13	3,257	6,939	2,457	2.21	3,138	6,939	2,502	2.25	3,082
37	4,778	1,521	1.37	3,490	4,778	1,593	1.43	3,333	4,778	1,620	1.46	3,277
38	4,951	2,439	2.20	2,255	4,951	2,592	2.33	2,122	4,951	2,619	2.36	2,100
39	8,293	5,193	4.67	1,774	8,293	5,319	4.79	1,732	8,293	5,535	4.98	1,665
40	3,024	1,179	1.06	2,850	3,024	1,269	1.14	2,648	3,024	1,269	1.14	2,648
41	9,720	4,608	4.15	2,344	9,720	4,842	4.36	2,230	9,720	4,914	4.42	2,198
42	2,672	909	0.82	3,266	2,672	954	0.86	3,112	2,672	945	0.85	3,142
43	7,284	3,339	3.01	2,424	7,284	3,384	3.05	2,392	7,284	3,591	3.23	2,254
44	2,383	1,035	0.93	2,558	2,383	1,107	1.00	2,392	2,383	1,107	1.00	2,392
45	4,557	4,059	3.65	1,247	4,557	4,248	3.82	1,192	4,557	4,302	3.87	1,177
46	10,109	4,275	3.85	2,627	10,109	4,608	4.15	2,438	10,109	4,671	4.20	2,405
47	6,437	3,330	3.00	2,148	6,437	3,465	3.12	2,064	6,437	3,573	3.22	2,002
48	9,202	3,132	2.82	3,265	9,202	3,204	2.88	3,191	9,202	3,429	3.09	2,982
49	9,930	2,916	2.62	3,784	9,930	3,051	2.75	3,616	9,930	3,159	2.84	3,493
50	5,300	1,323	1.19	4,451	5,300	1,332	1.20	4,421	5,300	1,377	1.24	4,277
51	9,963	4,554	4.10	2,431	9,963	4,698	4.23	2,356	9,963	4,878	4.39	2,269
52	9,406	3,843	3.46	2,720	9,406	4,032	3.63	2,592	9,406	4,338	3.90	2,409
53	10,209	3,159	2.84	3,591	10,209	3,285	2.96	3,453	10,209	3,375	3.04	3,361
54	3,173	2,358	2.12	1,495	3,173	2,466	2.22	1,430	3,173	2,637	2.37	1,337
55	4,548	1,386	1.25	3,646	4,548	1,431	1.29	3,531	4,548	1,566	1.41	3,227
56	5,111	1,575	1.42	3,606	5,111	1,638	1.47	3,467	5,111	1,773	1.60	3,203
57	5,018	1,899	1.71	2,936	5,018	1,971	1.77	2,829	5,018	2,079	1.87	2,682
Total	**303,621**	**143,478**	**129.13**	**2,351**	**303,621**	**148,887**	**134.00**	**2,266**	**303,621**	**153,360**	**138.02**	**2,200**

Table A-IV.36: Projections of Dasymetric Densities for Escambia county in 2010

Tract ID	Sim 2010 smart				Sim 2010 normal				Sim 2010 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	1,772	1,881	1.69	1,047	1,772	1,980	1.78	994	1,772	2,007	1.81	981
1	2,793	3,015	2.71	1,029	2,793	3,285	2.96	945	2,793	3,411	3.07	910
2	3,060	1,449	1.30	2,346	3,060	1,539	1.39	2,209	3,060	1,575	1.42	2,159
3	1,503	900	0.81	1,856	1,503	945	0.85	1,767	1,503	1,008	0.91	1,657
4	1,616	1,467	1.32	1,224	1,616	1,521	1.37	1,181	1,616	1,611	1.45	1,115
5	4,565	3,699	3.33	1,371	4,565	4,014	3.61	1,264	4,565	4,284	3.86	1,184
6	2,459	1,170	1.05	2,335	2,459	1,305	1.17	2,094	2,459	1,386	1.25	1,971
7	6,539	2,772	2.49	2,621	6,539	3,132	2.82	2,320	6,539	3,321	2.99	2,188
8	3,055	1,224	1.10	2,773	3,055	1,323	1.19	2,566	3,055	1,350	1.22	2,514
9	6,841	2,583	2.32	2,943	6,841	2,736	2.46	2,778	6,841	2,934	2.64	2,591
10	3,250	1,053	0.95	3,429	3,250	1,179	1.06	3,063	3,250	1,278	1.15	2,826
11	7,306	3,015	2.71	2,692	7,306	3,240	2.92	2,505	7,306	3,510	3.16	2,313
12	5,302	3,240	2.92	1,818	5,302	3,447	3.10	1,709	5,302	3,582	3.22	1,645
13	3,933	2,349	2.11	1,860	3,933	2,565	2.31	1,704	3,933	2,754	2.48	1,587
14	4,431	1,998	1.80	2,464	4,431	2,178	1.96	2,260	4,431	2,367	2.13	2,080
15	6,141	2,601	2.34	2,623	6,141	2,727	2.45	2,502	6,141	2,826	2.54	2,414
16	6,452	4,293	3.86	1,670	6,452	4,824	4.34	1,486	6,452	5,265	4.74	1,362
17	1,125	1,251	1.13	999	1,125	1,368	1.23	914	1,125	1,377	1.24	908
18	2,669	1,611	1.45	1,841	2,669	1,728	1.56	1,716	2,669	1,701	1.53	1,743
19	2,852	2,826	2.54	1,121	2,852	3,177	2.86	997	2,852	3,294	2.96	962
20	2,126	1,485	1.34	1,591	2,126	1,647	1.48	1,434	2,126	1,710	1.54	1,381
21	2,051	1,260	1.13	1,809	2,051	1,413	1.27	1,613	2,051	1,458	1.31	1,563
22	2,071	1,674	1.51	1,375	2,071	1,782	1.60	1,291	2,071	1,899	1.71	1,212
23	4,950	2,880	2.59	1,910	4,950	3,060	2.75	1,797	4,950	3,249	2.92	1,693
24	3,682	1,773	1.60	2,307	3,682	1,935	1.74	2,114	3,682	2,079	1.87	1,968
25	5,066	1,944	1.75	2,896	5,066	2,052	1.85	2,743	5,066	2,313	2.08	2,434
26	11,710	3,771	3.39	3,450	11,710	3,879	3.49	3,354	11,710	3,915	3.52	3,323
27	3,263	2,358	2.12	1,538	3,263	2,610	2.35	1,389	3,263	2,754	2.48	1,316
28	23,769	10,449	9.40	2,528	23,769	11,763	10.59	2,245	23,769	12,582	11.32	2,099
29	2,901	945	0.85	3,411	2,901	1,080	0.97	2,985	2,901	1,134	1.02	2,842
30	9,371	3,357	3.02	3,102	9,371	3,744	3.37	2,781	9,371	4,050	3.65	2,571
31	2,894	1,431	1.29	2,247	2,894	1,566	1.41	2,053	2,894	1,665	1.50	1,931
32	6,859	1,944	1.75	3,920	6,859	2,187	1.97	3,485	6,859	2,187	1.97	3,485
33	2,908	918	0.83	3,520	2,908	1,044	0.94	3,095	2,908	1,062	0.96	3,042
34	3,093	1,251	1.13	2,747	3,093	1,287	1.16	2,670	3,093	1,296	1.17	2,652
35	3,886	1,881	1.69	2,295	3,886	1,998	1.80	2,161	3,886	2,169	1.95	1,991
36	7,027	2,403	2.16	3,249	7,027	2,619	2.36	2,981	7,027	2,844	2.56	2,745
37	4,814	1,539	1.39	3,476	4,814	1,701	1.53	3,145	4,814	1,692	1.52	3,161
38	5,212	2,466	2.22	2,348	5,212	2,736	2.46	2,117	5,212	2,853	2.57	2,030
39	8,773	5,265	4.74	1,851	8,773	5,706	5.14	1,708	8,773	6,201	5.58	1,572
40	3,376	1,197	1.08	3,134	3,376	1,395	1.26	2,689	3,376	1,413	1.27	2,655
41	10,770	4,653	4.19	2,572	10,770	5,112	4.60	2,341	10,770	5,517	4.97	2,169
42	2,989	918	0.83	3,618	2,989	1,017	0.92	3,266	2,989	1,044	0.94	3,181
43	8,011	3,366	3.03	2,644	8,011	3,726	3.35	2,389	8,011	3,915	3.52	2,274
44	2,590	1,035	0.93	2,780	2,590	1,179	1.06	2,441	2,590	1,224	1.10	2,351
45	4,609	4,095	3.69	1,251	4,609	4,626	4.16	1,107	4,609	4,824	4.34	1,062
46	10,993	4,338	3.90	2,816	10,993	4,986	4.49	2,450	10,993	5,355	4.82	2,281
47	6,959	3,384	3.05	2,285	6,959	3,753	3.38	2,060	6,959	4,077	3.67	1,897
48	9,937	3,159	2.84	3,495	9,937	3,483	3.13	3,170	9,937	3,699	3.33	2,985
49	11,268	2,925	2.63	4,280	11,268	3,285	2.96	3,811	11,268	3,591	3.23	3,486
50	5,980	1,341	1.21	4,955	5,980	1,449	1.30	4,586	5,980	1,539	1.39	4,317
51	11,497	4,581	4.12	2,789	11,497	5,085	4.58	2,512	11,497	5,526	4.97	2,312
52	10,834	3,870	3.48	3,111	10,834	4,383	3.94	2,746	10,834	4,914	4.42	2,450
53	11,609	3,240	2.92	3,981	11,609	3,564	3.21	3,619	11,609	3,816	3.43	3,380
54	3,129	2,376	2.14	1,463	3,129	2,682	2.41	1,296	3,129	2,907	2.62	1,196
55	4,753	1,395	1.26	3,786	4,753	1,746	1.57	3,025	4,753	2,061	1.85	2,562
56	5,282	1,602	1.44	3,663	5,282	1,881	1.69	3,120	5,282	2,151	1.94	2,728
57	5,125	1,926	1.73	2,957	5,125	2,160	1.94	2,636	5,125	2,412	2.17	2,361
Total	**323,801**	**144,792**	**130.31**	**2,485**	**323,801**	**159,534**	**143.58**	**2,255**	**323,801**	**169,938**	**152.94**	**2,117**

Table A-IV.37: Projections of Dasymetric Densities for Escambia county in 2015

Tract ID	Sim 2015 smart				Sim 2015 normal				Sim 2015 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	1,655	1,881	1.69	978	1,655	2,052	1.85	896	1,655	2,124	1.91	866
1	2,667	3,024	2.72	980	2,667	3,366	3.03	880	2,667	3,609	3.25	821
2	2,894	1,467	1.32	2,192	2,894	1,584	1.43	2,030	2,894	1,665	1.50	1,931
3	1,447	909	0.82	1,769	1,447	981	0.88	1,639	1,447	1,062	0.96	1,514
4	1,477	1,476	1.33	1,112	1,477	1,548	1.39	1,060	1,477	1,656	1.49	991
5	4,315	3,708	3.34	1,293	4,315	4,176	3.76	1,148	4,315	4,509	4.06	1,063
6	2,381	1,197	1.08	2,210	2,381	1,422	1.28	1,860	2,381	1,512	1.36	1,750
7	6,637	2,790	2.51	2,643	6,637	3,321	2.99	2,221	6,637	3,681	3.31	2,003
8	3,079	1,242	1.12	2,755	3,079	1,350	1.22	2,534	3,079	1,440	1.30	2,376
9	7,208	2,583	2.32	3,101	7,208	2,925	2.63	2,738	7,208	3,213	2.89	2,493
10	3,396	1,062	0.96	3,553	3,396	1,260	1.13	2,995	3,396	1,404	1.26	2,688
11	7,652	3,042	2.74	2,795	7,652	3,420	3.08	2,486	7,652	3,834	3.45	2,218
12	5,349	3,249	2.92	1,829	5,349	3,618	3.26	1,643	5,349	3,996	3.60	1,487
13	3,959	2,358	2.12	1,866	3,959	2,691	2.42	1,635	3,959	2,934	2.64	1,499
14	4,329	2,007	1.81	2,397	4,329	2,340	2.11	2,056	4,329	2,565	2.31	1,875
15	6,437	2,601	2.34	2,750	6,437	2,853	2.57	2,507	6,437	3,042	2.74	2,351
16	6,627	4,338	3.90	1,697	6,627	5,211	4.69	1,413	6,627	5,850	5.27	1,259
17	1,028	1,260	1.13	907	1,028	1,413	1.27	808	1,028	1,404	1.26	814
18	2,596	1,611	1.45	1,790	2,596	1,791	1.61	1,611	2,596	1,836	1.65	1,571
19	2,723	2,880	2.59	1,051	2,723	3,348	3.01	904	2,723	3,528	3.18	858
20	1,990	1,512	1.36	1,462	1,990	1,719	1.55	1,286	1,990	1,854	1.67	1,193
21	1,974	1,278	1.15	1,716	1,974	1,440	1.30	1,523	1,974	1,557	1.40	1,409
22	1,972	1,710	1.54	1,281	1,972	1,890	1.70	1,159	1,972	2,034	1.83	1,077
23	4,814	2,907	2.62	1,840	4,814	3,285	2.96	1,628	4,814	3,501	3.15	1,528
24	3,496	1,800	1.62	2,158	3,496	2,052	1.85	1,893	3,496	2,205	1.98	1,762
25	4,907	1,980	1.78	2,754	4,907	2,187	1.97	2,493	4,907	2,448	2.20	2,227
26	12,396	3,780	3.40	3,644	12,396	3,951	3.56	3,486	12,396	3,996	3.60	3,447
27	3,552	2,412	2.17	1,636	3,552	2,745	2.47	1,438	3,552	2,934	2.64	1,345
28	27,658	10,530	9.48	2,918	27,658	12,573	11.32	2,444	27,658	13,959	12.56	2,202
29	3,116	954	0.86	3,629	3,116	1,188	1.07	2,914	3,116	1,305	1.17	2,653
30	10,106	3,393	3.05	3,309	10,106	4,086	3.68	2,748	10,106	4,626	4.16	2,427
31	2,962	1,440	1.30	2,285	2,962	1,755	1.58	1,875	2,962	1,872	1.68	1,758
32	7,255	1,962	1.77	4,109	7,255	2,340	2.11	3,445	7,255	2,367	2.13	3,406
33	2,969	927	0.83	3,559	2,969	1,107	1.00	2,980	2,969	1,116	1.00	2,956
34	3,128	1,251	1.13	2,778	3,128	1,305	1.17	2,663	3,128	1,323	1.19	2,627
35	3,747	1,899	1.71	2,192	3,747	2,097	1.89	1,985	3,747	2,304	2.07	1,807
36	6,990	2,421	2.18	3,208	6,990	2,853	2.57	2,722	6,990	3,132	2.82	2,480
37	4,765	1,548	1.39	3,420	4,765	1,755	1.58	3,017	4,765	1,836	1.65	2,884
38	5,390	2,511	2.26	2,385	5,390	2,916	2.62	2,054	5,390	3,222	2.90	1,859
39	9,116	5,337	4.80	1,898	9,116	6,111	5.50	1,657	9,116	6,831	6.15	1,483
40	3,703	1,197	1.08	3,437	3,703	1,485	1.34	2,771	3,703	1,548	1.39	2,658
41	11,721	4,707	4.24	2,767	11,721	5,535	4.98	2,353	11,721	6,084	5.48	2,141
42	3,283	918	0.83	3,974	3,283	1,071	0.96	3,406	3,283	1,170	1.05	3,118
43	8,655	3,402	3.06	2,827	8,655	3,951	3.56	2,434	8,655	4,356	3.92	2,208
44	2,766	1,044	0.94	2,944	2,766	1,215	1.09	2,529	2,766	1,332	1.20	2,307
45	4,580	4,113	3.70	1,237	4,580	4,986	4.49	1,021	4,580	5,472	4.92	930
46	11,742	4,410	3.97	2,958	11,742	5,364	4.83	2,432	11,742	6,075	5.47	2,148
47	7,389	3,447	3.10	2,382	7,389	4,032	3.63	2,036	7,389	4,527	4.07	1,814
48	10,541	3,204	2.88	3,656	10,541	3,672	3.30	3,190	10,541	4,032	3.63	2,905
49	12,559	2,952	2.66	4,727	12,559	3,492	3.14	3,996	12,559	3,969	3.57	3,516
50	6,628	1,359	1.22	5,419	6,628	1,521	1.37	4,842	6,628	1,755	1.58	4,196
51	13,033	4,626	4.16	3,130	13,033	5,562	5.01	2,604	13,033	6,084	5.48	2,380
52	12,256	3,933	3.54	3,462	12,256	4,788	4.31	2,844	12,256	5,526	4.97	2,464
53	12,967	3,258	2.93	4,422	12,967	3,933	3.54	3,663	12,967	4,275	3.85	3,370
54	3,032	2,412	2.17	1,397	3,032	2,916	2.62	1,155	3,032	3,213	2.89	1,049
55	4,878	1,413	1.27	3,836	4,878	2,007	1.81	2,701	4,878	2,565	2.31	2,113
56	5,362	1,620	1.46	3,678	5,362	2,151	1.94	2,770	5,362	2,763	2.49	2,156
57	5,142	1,953	1.76	2,925	5,142	2,349	2.11	2,432	5,142	2,709	2.44	2,109
Total	**340,396**	**146,205**	**131.58**	**2,587**	**340,396**	**170,055**	**153.05**	**2,224**	**340,396**	**186,741**	**168.07**	**2,025**

Table A-IV.38: Projections of Dasymetric Densities for Escambia county in 2020

Tract ID	Sim 2020 smart				Sim 2020 normal				Sim 2020 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	1,531	1,890	1.70	900	1,531	2,124	1.91	801	1,531	2,196	1.98	775
1	2,523	3,060	2.75	916	2,523	3,492	3.14	803	2,523	3,717	3.35	754
2	2,710	1,476	1.33	2,040	2,710	1,656	1.49	1,818	2,710	1,719	1.55	1,752
3	1,379	909	0.82	1,686	1,379	1,026	0.92	1,493	1,379	1,116	1.00	1,373
4	1,338	1,476	1.33	1,007	1,338	1,593	1.43	933	1,338	1,701	1.53	874
5	4,040	3,753	3.38	1,196	4,040	4,374	3.94	1,026	4,040	4,680	4.21	959
6	2,284	1,224	1.10	2,073	2,284	1,512	1.36	1,678	2,284	1,629	1.47	1,558
7	6,673	2,835	2.55	2,615	6,673	3,564	3.21	2,080	6,673	3,969	3.57	1,868
8	3,074	1,251	1.13	2,730	3,074	1,359	1.22	2,513	3,074	1,557	1.40	2,194
9	7,522	2,592	2.33	3,224	7,522	3,114	2.80	2,684	7,522	3,465	3.12	2,412
10	3,514	1,071	0.96	3,646	3,514	1,368	1.23	2,854	3,514	1,584	1.43	2,465
11	7,938	3,069	2.76	2,874	7,938	3,609	3.25	2,444	7,938	4,095	3.69	2,154
12	5,346	3,258	2.93	1,823	5,346	3,870	3.48	1,535	5,346	4,401	3.96	1,350
13	3,948	2,412	2.17	1,819	3,948	2,808	2.53	1,562	3,948	3,240	2.92	1,354
14	4,189	2,025	1.82	2,298	4,189	2,475	2.23	1,881	4,189	2,790	2.51	1,668
15	6,682	2,601	2.34	2,854	6,682	2,988	2.69	2,485	6,682	3,276	2.95	2,266
16	6,742	4,446	4.00	1,685	6,742	5,607	5.05	1,336	6,742	6,309	5.68	1,187
17	930	1,260	1.13	820	930	1,431	1.29	722	930	1,431	1.29	722
18	2,501	1,629	1.47	1,706	2,501	1,845	1.66	1,506	2,501	1,890	1.70	1,470
19	2,575	2,907	2.62	984	2,575	3,591	3.23	797	2,575	3,708	3.34	772
20	1,846	1,512	1.36	1,357	1,846	1,746	1.57	1,175	1,846	1,926	1.73	1,065
21	1,882	1,296	1.17	1,614	1,882	1,566	1.41	1,335	1,882	1,656	1.49	1,263
22	1,860	1,719	1.55	1,202	1,860	1,962	1.77	1,053	1,860	2,151	1.94	961
23	4,637	2,934	2.64	1,756	4,637	3,447	3.10	1,495	4,637	3,681	3.31	1,400
24	3,288	1,818	1.64	2,010	3,288	2,178	1.96	1,677	3,288	2,286	2.06	1,598
25	4,707	1,998	1.80	2,618	4,707	2,349	2.11	2,226	4,707	2,619	2.36	1,997
26	12,998	3,807	3.43	3,794	12,998	4,005	3.60	3,606	12,998	4,068	3.66	3,550
27	3,830	2,439	2.20	1,745	3,830	2,898	2.61	1,468	3,830	3,132	2.82	1,359
28	31,877	10,656	9.59	3,324	31,877	13,383	12.04	2,647	31,877	15,300	13.77	2,315
29	3,315	963	0.87	3,825	3,315	1,260	1.13	2,923	3,315	1,530	1.38	2,407
30	10,795	3,447	3.10	3,480	10,795	4,455	4.01	2,692	10,795	5,148	4.63	2,330
31	3,002	1,440	1.30	2,316	3,002	1,890	1.70	1,765	3,002	2,052	1.85	1,626
32	7,601	1,971	1.77	4,285	7,601	2,583	2.32	3,270	7,601	2,610	2.35	3,236
33	3,003	936	0.84	3,565	3,003	1,197	1.08	2,788	3,003	1,197	1.08	2,788
34	3,133	1,251	1.13	2,783	3,133	1,323	1.19	2,631	3,133	1,350	1.22	2,579
35	3,578	1,917	1.73	2,074	3,578	2,205	1.98	1,803	3,578	2,457	2.21	1,618
36	6,887	2,421	2.18	3,161	6,887	3,024	2.72	2,530	6,887	3,366	3.03	2,273
37	4,671	1,575	1.42	3,295	4,671	1,890	1.70	2,746	4,671	1,953	1.76	2,657
38	5,521	2,520	2.27	2,434	5,521	3,123	2.81	1,964	5,521	3,564	3.21	1,721
39	9,382	5,409	4.87	1,927	9,382	6,597	5.94	1,580	9,382	7,515	6.76	1,387
40	4,022	1,206	1.09	3,706	4,022	1,557	1.40	2,870	4,022	1,701	1.53	2,627
41	12,636	4,725	4.25	2,971	12,636	5,886	5.30	2,385	12,636	6,651	5.99	2,111
42	3,573	927	0.83	4,283	3,573	1,143	1.03	3,473	3,573	1,287	1.16	3,085
43	9,262	3,429	3.09	3,001	9,262	4,311	3.88	2,387	9,262	4,734	4.26	2,174
44	2,925	1,053	0.95	3,086	2,925	1,269	1.14	2,561	2,925	1,386	1.25	2,345
45	4,507	4,140	3.73	1,210	4,507	5,301	4.77	945	4,507	5,931	5.34	844
46	12,423	4,455	4.01	3,098	12,423	5,823	5.24	2,370	12,423	6,660	5.99	2,073
47	7,772	3,483	3.13	2,479	7,772	4,347	3.91	1,987	7,772	4,806	4.33	1,797
48	11,075	3,231	2.91	3,809	11,075	3,942	3.55	3,122	11,075	4,320	3.89	2,849
49	13,865	2,970	2.67	5,187	13,865	3,771	3.39	4,085	13,865	4,482	4.03	3,437
50	7,276	1,377	1.24	5,871	7,276	1,674	1.51	4,829	7,276	2,043	1.84	3,957
51	14,633	4,707	4.24	3,454	14,633	6,021	5.42	2,700	14,633	6,840	6.16	2,377
52	13,734	4,059	3.65	3,760	13,734	5,211	4.69	2,928	13,734	5,994	5.39	2,546
53	14,347	3,303	2.97	4,826	14,347	4,284	3.86	3,721	14,347	4,824	4.34	3,305
54	2,909	2,457	2.21	1,316	2,909	3,078	2.77	1,050	2,909	3,501	3.15	923
55	4,960	1,422	1.28	3,876	4,960	2,322	2.09	2,373	4,960	3,276	2.95	1,682
56	5,391	1,638	1.47	3,657	5,391	2,538	2.28	2,360	5,391	3,438	3.09	1,742
57	5,111	2,007	1.81	2,830	5,111	2,637	2.37	2,154	5,111	3,195	2.88	1,777
Total	**355,673**	**147,762**	**132.99**	**2,675**	**355,673**	**181,602**	**163.44**	**2,176**	**355,673**	**203,103**	**182.79**	**1,946**

Table A-IV.39: Projections of Dasymetric Densities for Escambia county in 2025

Tract ID	Sim 2025 smart				Sim 2025 normal				Sim 2025 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
0	1,402	1,890	1.70	824	1,402	2,178	1.96	715	1,402	2,223	2.00	701
1	2,364	3,078	2.77	853	2,364	3,609	3.25	728	2,364	3,789	3.41	693
2	2,514	1,485	1.34	1,881	2,514	1,683	1.51	1,660	2,514	1,800	1.62	1,552
3	1,302	909	0.82	1,591	1,302	1,098	0.99	1,318	1,302	1,134	1.02	1,276
4	1,199	1,485	1.34	897	1,199	1,611	1.45	827	1,199	1,728	1.56	771
5	3,746	3,762	3.39	1,106	3,746	4,563	4.11	912	3,746	4,788	4.31	869
6	2,170	1,233	1.11	1,955	2,170	1,566	1.41	1,540	2,170	1,719	1.55	1,403
7	6,644	2,880	2.59	2,563	6,644	3,834	3.45	1,925	6,644	4,149	3.73	1,779
8	3,040	1,251	1.13	2,700	3,040	1,395	1.26	2,421	3,040	1,584	1.43	2,132
9	7,774	2,610	2.35	3,309	7,774	3,267	2.94	2,644	7,774	3,699	3.33	2,335
10	3,602	1,080	0.97	3,706	3,602	1,476	1.33	2,712	3,602	1,719	1.55	2,328
11	8,155	3,123	2.81	2,901	8,155	3,771	3.39	2,403	8,155	4,311	3.88	2,102
12	5,290	3,276	2.95	1,794	5,290	4,158	3.74	1,414	5,290	4,716	4.24	1,246
13	3,899	2,430	2.19	1,783	3,899	3,006	2.71	1,441	3,899	3,411	3.07	1,270
14	4,014	2,043	1.84	2,183	4,014	2,646	2.38	1,686	4,014	3,015	2.71	1,479
15	6,870	2,610	2.35	2,925	6,870	3,096	2.79	2,466	6,870	3,420	3.08	2,232
16	6,792	4,482	4.03	1,684	6,792	5,994	5.39	1,259	6,792	6,957	6.26	1,085
17	834	1,269	1.14	730	834	1,476	1.33	628	834	1,449	1.30	640
18	2,386	1,638	1.47	1,619	2,386	1,899	1.71	1,396	2,386	1,917	1.73	1,383
19	2,412	2,925	2.63	916	2,412	3,861	3.47	694	2,412	4,032	3.63	665
20	1,695	1,521	1.37	1,238	1,695	1,809	1.63	1,041	1,695	1,962	1.77	960
21	1,777	1,305	1.17	1,513	1,777	1,602	1.44	1,232	1,777	1,710	1.54	1,155
22	1,737	1,764	1.59	1,094	1,737	2,007	1.81	962	1,737	2,259	2.03	854
23	4,423	2,934	2.64	1,675	4,423	3,627	3.26	1,355	4,423	3,924	3.53	1,252
24	3,062	1,827	1.64	1,862	3,062	2,322	2.09	1,465	3,062	2,358	2.12	1,443
25	4,471	1,998	1.80	2,486	4,471	2,493	2.24	1,993	4,471	2,763	2.49	1,798
26	13,497	3,825	3.44	3,921	13,497	4,059	3.65	3,695	13,497	4,104	3.69	3,654
27	4,090	2,457	2.21	1,850	4,090	2,970	2.67	1,530	4,090	3,213	2.89	1,414
28	36,385	10,737	9.66	3,765	36,385	14,607	13.15	2,768	36,385	16,614	14.95	2,433
29	3,492	981	0.88	3,955	3,492	1,368	1.23	2,836	3,492	1,764	1.59	2,200
30	11,419	3,483	3.13	3,643	11,419	4,824	4.34	2,630	11,419	5,589	5.03	2,270
31	3,013	1,449	1.30	2,310	3,013	2,016	1.81	1,661	3,013	2,178	1.96	1,537
32	7,886	1,989	1.79	4,405	7,886	2,718	2.45	3,224	7,886	2,826	2.54	3,101
33	3,008	936	0.84	3,571	3,008	1,305	1.17	2,561	3,008	1,332	1.20	2,509
34	3,107	1,251	1.13	2,760	3,107	1,359	1.22	2,540	3,107	1,395	1.26	2,475
35	3,385	1,926	1.73	1,953	3,385	2,340	2.11	1,607	3,385	2,574	2.32	1,461
36	6,720	2,448	2.20	3,050	6,720	3,150	2.84	2,370	6,720	3,555	3.20	2,100
37	4,534	1,584	1.43	3,180	4,534	1,962	1.77	2,568	4,534	2,052	1.85	2,455
38	5,601	2,556	2.30	2,435	5,601	3,411	3.07	1,824	5,601	3,996	3.60	1,557
39	9,562	5,436	4.89	1,954	9,562	7,236	6.51	1,468	9,562	8,046	7.24	1,320
40	4,327	1,242	1.12	3,871	4,327	1,683	1.51	2,857	4,327	1,917	1.73	2,508
41	13,490	4,761	4.28	3,148	13,490	6,246	5.62	2,400	13,490	7,155	6.44	2,095
42	3,850	936	0.84	4,570	3,850	1,206	1.09	3,547	3,850	1,440	1.30	2,971
43	9,815	3,429	3.09	3,180	9,815	4,545	4.09	2,399	9,815	5,058	4.55	2,156
44	3,064	1,053	0.95	3,233	3,064	1,323	1.19	2,573	3,064	1,458	1.31	2,335
45	4,393	4,176	3.76	1,169	4,393	5,616	5.05	869	4,393	6,381	5.74	765
46	13,016	4,527	4.07	3,195	13,016	6,345	5.71	2,279	13,016	7,461	6.71	1,938
47	8,095	3,528	3.18	2,549	8,095	4,734	4.26	1,900	8,095	5,409	4.87	1,663
48	11,524	3,240	2.92	3,952	11,524	4,149	3.73	3,086	11,524	4,617	4.16	2,773
49	15,159	2,997	2.70	5,620	15,159	4,158	3.74	4,051	15,159	5,040	4.54	3,342
50	7,910	1,386	1.25	6,341	7,910	1,935	1.74	4,542	7,910	2,313	2.08	3,800
51	16,271	4,734	4.26	3,819	16,271	6,399	5.76	2,825	16,271	7,587	6.83	2,383
52	15,241	4,131	3.72	4,099	15,241	5,760	5.18	2,940	15,241	6,669	6.00	2,539
53	15,720	3,321	2.99	5,259	15,720	4,644	4.18	3,761	15,720	5,418	4.88	3,224
54	2,765	2,493	2.24	1,232	2,765	3,321	2.99	925	2,765	3,915	3.52	785
55	4,994	1,449	1.30	3,829	4,994	2,736	2.46	2,028	4,994	4,230	3.81	1,312
56	5,368	1,647	1.48	3,621	5,368	2,907	2.62	2,052	5,368	4,428	3.99	1,347
57	5,030	2,016	1.81	2,772	5,030	2,853	2.57	1,959	5,030	3,573	3.22	1,564
Total	**369,305**	**148,932**	**134.04**	**2,755**	**369,305**	**193,932**	**174.54**	**2,116**	**369,305**	**219,843**	**197.86**	**1,867**

Table A-IV.40: Dasymetric Densities of Santa Rosa county in the 70's

Tract ID	Real 1974				Sim 1975			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	2,947	792	0.71	4,134	2,855	855	0.77	3,710
92	4,338	1,179	1.06	4,088	4,200	1,206	1.09	3,870
93	1,609	468	0.42	3,820	1,616	477	0.43	3,764
94	4,313	837	0.75	5,725	3,828	864	0.78	4,923
95	3,512	1,998	1.80	1,953	3,628	2,025	1.82	1,991
96	2,343	981	0.88	2,654	2,420	1,017	0.92	2,644
97	7,842	3,564	3.21	2,445	7,442	3,636	3.27	2,274
98	2,178	972	0.87	2,490	2,209	990	0.89	2,479
99	2,692	1,539	1.39	1,944	2,748	1,602	1.44	1,906
100	1,491	945	0.85	1,753	1,551	972	0.87	1,773
101	1,734	1,305	1.17	1,476	1,768	1,332	1.20	1,475
102	2,923	2,160	1.94	1,504	2,948	2,214	1.99	1,479
103	2,299	1,611	1.45	1,586	2,500	1,674	1.51	1,659
104	498	153	0.14	3,617	538	486	0.44	1,230
105	2,166	1,368	1.23	1,759	2,198	1,413	1.27	1,728
106	1,209	1,116	1.00	1,204	1,228	1,125	1.01	1,213
107	1,085	855	0.77	1,410	1,101	873	0.79	1,401
108	1,578	621	0.56	2,823	1,601	630	0.57	2,824
109	5,645	1,314	1.18	4,773	5,520	1,341	1.21	4,574
Total	**52,402**	**23,778**	**21.40**	**2,449**	**51,899**	**24,732**	**22.26**	**2,332**

Table A-IV.41: Dasymetric Densities of Santa Rosa county in the 80's

Tract ID	Sim 1980				Sim 1985				Real 1986				Sim 1986			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	2,702	999	0.90	3,005	2,675	1,152	1.04	2,580	2,671	702	0.63	4,228	2,671	1,179	1.06	2,517
92	3,969	1,431	1.29	3,082	3,998	1,755	1.58	2,531	4,006	1,575	1.42	2,826	4,006	1,836	1.65	2,424
93	1,813	540	0.49	3,730	2,490	693	0.62	3,992	2,659	621	0.56	4,758	2,659	765	0.69	3,862
94	2,427	945	0.85	2,854	2,369	1,008	0.91	2,611	2,359	630	0.57	4,160	2,359	1,044	0.94	2,511
95	4,617	2,349	2.11	2,184	5,505	2,610	2.35	2,344	5,710	2,421	2.18	2,621	5,710	2,682	2.41	2,366
96	3,081	1,206	1.09	2,839	3,672	1,386	1.25	2,944	3,809	1,206	1.09	3,509	3,809	1,404	1.26	3,014
97	6,413	4,068	3.66	1,752	6,527	4,374	3.94	1,658	6,554	4,167	3.75	1,748	6,554	4,446	4.00	1,638
98	2,590	1,116	1.00	2,579	3,215	1,296	1.17	2,756	3,362	1,251	1.13	2,986	3,362	1,341	1.21	2,786
99	3,319	1,755	1.58	2,101	4,104	2,025	1.82	2,252	4,289	2,025	1.82	2,353	4,289	2,043	1.84	2,333
100	2,039	1,215	1.09	1,865	2,540	1,395	1.26	2,023	2,659	1,053	0.95	2,806	2,659	1,458	1.31	2,026
101	2,118	1,503	1.35	1,566	2,640	1,701	1.53	1,724	2,763	1,611	1.45	1,906	2,763	1,737	1.56	1,767
102	3,362	2,466	2.22	1,515	4,190	2,799	2.52	1,663	4,385	2,700	2.43	1,805	4,385	2,835	2.55	1,719
103	4,041	2,061	1.85	2,179	4,886	2,430	2.19	2,234	5,083	2,430	2.19	2,324	5,083	2,502	2.25	2,257
104	838	513	0.46	1,815	1,079	513	0.46	2,337	1,137	396	0.36	3,190	1,137	540	0.49	2,340
105	2,582	1,539	1.39	1,864	4,295	1,701	1.53	2,806	4,770	2,313	2.08	2,291	4,770	1,728	1.56	3,067
106	1,446	1,161	1.04	1,384	2,323	1,188	1.07	2,173	2,562	2,484	2.24	1,146	2,562	1,188	1.07	2,396
107	1,293	999	0.90	1,438	2,152	1,053	0.95	2,271	2,390	1,656	1.49	1,604	2,390	1,071	0.96	2,480
108	1,880	693	0.62	3,014	3,128	801	0.72	4,339	3,474	1,269	1.14	3,042	3,474	801	0.72	4,819
109	5,458	1,521	1.37	3,987	5,546	1,746	1.57	3,529	5,567	2,187	1.97	2,828	5,567	1,764	1.59	3,507
Total	**55,988**	**28,080**	**25.27**	**2,215**	**67,334**	**31,626**	**28.46**	**2,366**	**70,209**	**32,697**	**29.43**	**2,386**	**70,209**	**32,364**	**29.13**	**2,410**

Table A-IV.42: Dasymetric Densities of Santa Rosa county in the 90's

Tract ID	Sim 1990				Real 1992				Sim 1992				Sim 1995			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	2,589	1,476	1.33	1,949	2,816	729	0.66	4,292	2,816	1,692	1.52	1,849	3,113	1,899	1.71	1,821
92	3,938	1,971	1.77	2,220	4,046	1,638	1.47	2,745	4,046	2,079	1.87	2,162	4,108	2,259	2.03	2,021
93	3,352	909	0.82	4,097	3,908	882	0.79	4,923	3,908	954	0.86	4,552	4,791	1,080	0.97	4,929
94	2,260	1,125	1.01	2,232	2,293	522	0.47	4,881	2,293	1,179	1.06	2,161	2,285	1,323	1.19	1,919
95	6,424	2,943	2.65	2,425	6,844	2,448	2.20	3,106	6,844	3,051	2.75	2,492	7,334	3,321	2.99	2,454
96	4,285	1,503	1.35	3,168	4,674	1,242	1.12	4,181	4,674	1,611	1.45	3,224	5,186	1,764	1.59	3,267
97	6,495	4,779	4.30	1,510	6,526	4,203	3.78	1,725	6,526	4,878	4.39	1,486	6,408	5,157	4.64	1,381
98	3,908	1,458	1.31	2,978	4,161	1,314	1.18	3,519	4,161	1,521	1.37	3,040	4,457	1,665	1.50	2,974
99	4,969	2,106	1.90	2,622	5,581	2,781	2.50	2,230	5,581	2,178	1.96	2,847	6,472	2,304	2.07	3,121
100	3,100	1,611	1.45	2,138	3,250	1,242	1.12	2,907	3,250	1,683	1.51	2,146	3,400	1,809	1.63	2,088
101	3,221	1,926	1.73	1,858	3,262	1,728	1.56	2,097	3,262	2,043	1.84	1,774	3,241	2,142	1.93	1,681
102	5,113	3,141	2.83	1,809	5,501	2,790	2.51	2,191	5,501	3,294	2.96	1,856	5,982	3,546	3.19	1,874
103	5,784	2,916	2.62	2,204	6,583	2,565	2.31	2,852	6,583	3,087	2.78	2,369	7,787	3,420	3.08	2,530
104	1,362	567	0.51	2,669	1,694	459	0.41	4,101	1,694	594	0.53	3,169	2,288	594	0.53	4,280
105	7,014	1,854	1.67	4,204	7,459	2,466	2.22	3,361	7,459	1,971	1.77	4,205	7,971	2,115	1.90	4,188
106	3,664	1,260	1.13	3,231	4,535	3,807	3.43	1,324	4,535	1,305	1.17	3,861	6,077	1,341	1.21	5,035
107	3,514	1,179	1.06	3,312	4,166	2,079	1.87	2,226	4,166	1,233	1.11	3,754	5,235	1,305	1.17	4,457
108	5,108	891	0.80	6,370	5,810	1,557	1.40	4,146	5,810	900	0.81	7,173	6,864	1,035	0.93	7,369
109	5,509	1,962	1.77	3,120	5,637	2,223	2.00	2,818	5,637	2,070	1.86	3,026	5,690	2,160	1.94	2,927
Total	**81,609**	**35,577**	**32.02**	**2,549**	**88,746**	**36,675**	**33.01**	**2,689**	**88,746**	**37,323**	**33.59**	**2,642**	**98,689**	**40,239**	**36.22**	**2,725**

Table A-IV.43: Dasymetric Densities of Santa Rosa county in the 2000's

Tract ID	Sim 2000				Real 2001				Sim 2001			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	3,612	2,187	1.97	1,835	3,658	1,098	0.99	3,702	3,658	2,286	2.06	1,778
92	4,132	2,727	2.45	1,684	4,167	1,791	1.61	2,585	4,167	2,817	2.54	1,644
93	6,611	1,260	1.13	5,830	6,846	1,926	1.73	3,949	6,846	1,296	1.17	5,869
94	2,227	1,584	1.43	1,562	2,213	594	0.53	4,140	2,213	1,620	1.46	1,518
95	8,075	3,753	3.38	2,391	8,296	3,654	3.29	2,523	8,296	3,825	3.44	2,410
96	6,056	2,016	1.81	3,338	6,234	1,683	1.51	4,116	6,234	2,079	1.87	3,332
97	6,093	5,517	4.97	1,227	6,118	4,041	3.64	1,682	6,118	5,553	5.00	1,224
98	4,902	1,782	1.60	3,056	5,029	2,511	2.26	2,225	5,029	1,800	1.62	3,104
99	8,136	2,646	2.38	3,416	8,390	4,032	3.63	2,312	8,390	2,700	2.43	3,453
100	3,595	2,079	1.87	1,921	3,698	2,034	1.83	2,020	3,698	2,115	1.90	1,943
101	3,142	2,394	2.15	1,458	3,213	1,953	1.76	1,828	3,213	2,457	2.21	1,453
102	6,750	3,951	3.56	1,898	6,925	3,366	3.03	2,286	6,925	4,050	3.65	1,900
103	10,120	4,131	3.72	2,722	10,546	2,997	2.70	3,910	10,546	4,257	3.83	2,753
104	3,714	621	0.56	6,645	3,903	1,404	1.26	3,089	3,903	621	0.56	6,983
105	8,738	2,313	2.08	4,198	9,054	3,672	3.30	2,740	9,054	2,385	2.15	4,218
106	9,740	1,485	1.34	7,288	10,209	10,008	9.01	1,133	10,209	1,512	1.36	7,502
107	7,532	1,422	1.28	5,885	7,875	5,517	4.97	1,586	7,875	1,449	1.30	6,039
108	8,903	1,197	1.08	8,264	9,276	5,490	4.94	1,877	9,276	1,260	1.13	8,180
109	5,665	2,385	2.15	2,639	5,722	2,772	2.49	2,294	5,722	2,430	2.19	2,616
Total	**117,743**	**45,450**	**40.91**	**2,878**	**121,372**	**60,543**	**54.49**	**2,227**	**121,372**	**46,512**	**41.86**	**2,899**

Table A-IV.44: Projections of Dasymetric Densities for Santa Rosa county in 2005

Tract ID	Sim 2005 smart				Sim 2005 normal				Sim 2005 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	3,826	1,125	1.01	3,779	3,826	1,269	1.14	3,350	3,826	1,260	1.13	3,374
92	4,286	1,854	1.67	2,569	4,286	1,989	1.79	2,394	4,286	2,151	1.94	2,214
93	7,827	1,962	1.77	4,433	7,827	2,079	1.87	4,183	7,827	2,241	2.02	3,881
94	2,146	603	0.54	3,954	2,146	648	0.58	3,680	2,146	702	0.63	3,397
95	9,185	3,789	3.41	2,693	9,185	3,996	3.60	2,554	9,185	4,203	3.78	2,428
96	6,955	1,764	1.59	4,381	6,955	1,809	1.63	4,272	6,955	1,944	1.75	3,975
97	6,179	4,113	3.70	1,669	6,179	4,257	3.83	1,613	6,179	4,464	4.02	1,538
98	5,535	2,592	2.33	2,373	5,535	2,790	2.51	2,204	5,535	2,907	2.62	2,116
99	9,432	4,149	3.73	2,526	9,432	4,302	3.87	2,436	9,432	4,473	4.03	2,343
100	4,115	2,088	1.88	2,190	4,115	2,169	1.95	2,108	4,115	2,241	2.02	2,040
101	3,491	2,034	1.83	1,907	3,491	2,079	1.87	1,866	3,491	2,151	1.94	1,803
102	7,623	3,474	3.13	2,438	7,623	3,681	3.31	2,301	7,623	3,807	3.43	2,225
103	12,359	3,069	2.76	4,474	12,359	3,393	3.05	4,047	12,359	3,411	3.07	4,026
104	4,729	1,494	1.34	3,517	4,729	1,584	1.43	3,317	4,729	1,548	1.39	3,394
105	10,372	3,753	3.38	3,071	10,372	3,924	3.53	2,937	10,372	4,068	3.66	2,833
106	12,250	10,359	9.32	1,314	12,250	10,728	9.66	1,269	12,250	11,241	10.12	1,211
107	9,352	5,760	5.18	1,804	9,352	6,003	5.40	1,731	9,352	6,156	5.54	1,688
108	10,864	5,634	5.07	2,143	10,864	5,985	5.39	2,017	10,864	6,174	5.56	1,955
109	5,918	2,817	2.54	2,334	5,918	2,979	2.68	2,207	5,918	3,042	2.74	2,162
Total	**136,444**	**62,433**	**56.19**	**2,428**	**136,444**	**65,664**	**59.10**	**2,309**	**136,444**	**68,184**	**61.37**	**2,223**

Table A-IV.45: Projections of Dasymetric Densities for Santa Rosa county in 2010

Tract ID	Sim 2010 smart				Sim 2010 normal				Sim 2010 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	4,069	1,134	1.02	3,987	4,069	1,602	1.44	2,822	4,069	1,584	1.43	2,854
92	4,463	1,872	1.68	2,649	4,463	2,295	2.07	2,161	4,463	2,655	2.39	1,868
93	9,305	1,980	1.78	5,222	9,305	2,349	2.11	4,401	9,305	2,619	2.36	3,948
94	2,076	603	0.54	3,825	2,076	738	0.66	3,126	2,076	1,026	0.92	2,248
95	10,490	3,852	3.47	3,026	10,490	4,365	3.93	2,670	10,490	4,788	4.31	2,434
96	8,020	1,782	1.60	5,001	8,020	2,034	1.83	4,381	8,020	2,223	2.00	4,009
97	6,292	4,158	3.74	1,681	6,292	4,536	4.08	1,541	6,292	4,977	4.48	1,405
98	6,275	2,664	2.40	2,617	6,275	3,258	2.93	2,140	6,275	3,294	2.96	2,117
99	10,979	4,185	3.77	2,915	10,979	4,698	4.23	2,597	10,979	5,004	4.50	2,438
100	4,730	2,133	1.92	2,464	4,730	2,430	2.19	2,163	4,730	2,601	2.34	2,021
101	3,895	2,061	1.85	2,100	3,895	2,178	1.96	1,987	3,895	2,367	2.13	1,828
102	8,645	3,510	3.16	2,737	8,645	4,131	3.72	2,325	8,645	4,635	4.17	2,072
103	15,155	3,114	2.80	5,407	15,155	3,888	3.50	4,331	15,155	4,167	3.75	4,041
104	6,045	1,548	1.39	4,339	6,045	1,791	1.61	3,750	6,045	1,881	1.69	3,571
105	12,363	3,798	3.42	3,617	12,363	4,275	3.85	3,213	12,363	4,734	4.26	2,902
106	15,471	10,512	9.46	1,635	15,471	11,835	10.65	1,452	15,471	12,807	11.53	1,342
107	11,660	5,859	5.27	2,211	11,660	6,552	5.90	1,977	11,660	7,155	6.44	1,811
108	13,310	5,697	5.13	2,596	13,310	6,498	5.85	2,276	13,310	7,182	6.46	2,059
109	6,208	2,844	2.56	2,425	6,208	3,150	2.84	2,190	6,208	3,339	3.01	2,066
Total	**159,451**	**63,306**	**56.98**	**2,799**	**159,451**	**72,603**	**65.34**	**2,440**	**159,451**	**79,038**	**71.13**	**2,242**

Table A-IV.46: Projections of Dasymetric Densities for Santa Rosa county in 2015

Tract ID	Sim 2015 smart				Sim 2015 normal				Sim 2015 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	4,135	1,152	1.04	3,988	4,135	1,845	1.66	2,490	4,135	1,989	1.79	2,310
92	4,441	1,926	1.73	2,562	4,441	2,529	2.28	1,951	4,441	3,240	2.92	1,523
93	10,570	2,025	1.82	5,800	10,570	2,574	2.32	4,563	10,570	3,051	2.75	3,849
94	1,919	612	0.55	3,484	1,919	855	0.77	2,494	1,919	1,269	1.14	1,680
95	11,448	3,861	3.47	3,294	11,448	4,752	4.28	2,677	11,448	5,391	4.85	2,359
96	8,837	1,791	1.61	5,482	8,837	2,223	2.00	4,417	8,837	2,682	2.41	3,661
97	6,122	4,221	3.80	1,612	6,122	4,824	4.34	1,410	6,122	5,409	4.87	1,258
98	6,797	2,736	2.46	2,760	6,797	3,600	3.24	2,098	6,797	3,924	3.53	1,925
99	12,212	4,257	3.83	3,187	12,212	5,103	4.59	2,659	12,212	5,499	4.95	2,468
100	5,194	2,142	1.93	2,694	5,194	2,664	2.40	2,166	5,194	3,069	2.76	1,880
101	4,152	2,106	1.90	2,191	4,152	2,358	2.12	1,956	4,152	2,583	2.32	1,786
102	9,368	3,555	3.20	2,928	9,368	4,500	4.05	2,313	9,368	5,319	4.79	1,957
103	17,758	3,150	2.84	6,264	17,758	4,482	4.03	4,402	17,758	5,094	4.58	3,873
104	7,385	1,575	1.42	5,210	7,385	1,953	1.76	4,202	7,385	2,223	2.00	3,691
105	14,081	3,825	3.44	4,090	14,081	4,779	4.30	3,274	14,081	5,400	4.86	2,897
106	18,669	10,692	9.62	1,940	18,669	12,924	11.63	1,605	18,669	14,580	13.12	1,423
107	13,890	5,922	5.33	2,606	13,890	7,101	6.39	2,173	13,890	8,244	7.42	1,872
108	15,583	5,814	5.23	2,978	15,583	7,038	6.33	2,460	15,583	8,181	7.36	2,116
109	6,222	2,862	2.58	2,416	6,222	3,429	3.09	2,016	6,222	3,654	3.29	1,892
Total	**178,783**	**64,224**	**57.80**	**3,093**	**178,783**	**79,533**	**71.58**	**2,498**	**178,783**	**90,801**	**81.72**	**2,188**

Table A-IV.47: Projections of Dasymetric Densities for Santa Rosa county in 2020

Tract ID	Sim 2020 smart				Sim 2020 normal				Sim 2020 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	4,113	1,170	1.05	3,906	4,113	2,142	1.93	2,134	4,113	2,547	2.29	1,794
92	4,325	1,980	1.78	2,427	4,325	2,880	2.59	1,669	4,325	4,014	3.61	1,197
93	11,750	2,088	1.88	6,253	11,750	2,871	2.58	4,547	11,750	3,546	3.19	3,682
94	1,737	612	0.55	3,154	1,737	999	0.90	1,932	1,737	1,692	1.52	1,141
95	12,226	3,915	3.52	3,470	12,226	5,175	4.66	2,625	12,226	6,039	5.44	2,249
96	9,529	1,827	1.64	5,795	9,529	2,475	2.23	4,278	9,529	3,141	2.83	3,371
97	5,830	4,266	3.84	1,518	5,830	5,022	4.52	1,290	5,830	5,742	5.17	1,128
98	7,206	2,772	2.49	2,888	7,206	4,077	3.67	1,964	7,206	4,374	3.94	1,831
99	13,293	4,293	3.86	3,440	13,293	5,535	4.98	2,668	13,293	6,102	5.49	2,421
100	5,582	2,169	1.95	2,859	5,582	2,862	2.58	2,167	5,582	3,510	3.16	1,767
101	4,332	2,106	1.90	2,286	4,332	2,556	2.30	1,883	4,332	2,916	2.62	1,651
102	9,933	3,663	3.30	3,013	9,933	4,941	4.45	2,234	9,933	6,201	5.58	1,780
103	20,362	3,213	2.89	7,042	20,362	5,112	4.60	4,426	20,362	6,255	5.63	3,617
104	8,827	1,584	1.43	6,192	8,827	2,151	1.94	4,560	8,827	2,574	2.32	3,810
105	15,693	3,942	3.55	4,423	15,693	5,157	4.64	3,381	15,693	5,778	5.20	3,018
106	22,046	10,791	9.71	2,270	22,046	14,040	12.64	1,745	22,046	16,308	14.68	1,502
107	16,193	6,003	5.40	2,997	16,193	7,857	7.07	2,290	16,193	9,207	8.29	1,954
108	17,853	5,940	5.35	3,340	17,853	7,686	6.92	2,581	17,853	9,018	8.12	2,200
109	6,103	2,880	2.59	2,355	6,103	3,681	3.31	1,842	6,103	3,942	3.55	1,720
Total	**196,933**	**65,214**	**58.69**	**3,355**	**196,933**	**87,219**	**78.50**	**2,509**	**196,933**	**102,906**	**92.62**	**2,126**

Table A-IV.48: Projections of Dasymetric Densities for Santa Rosa county in 2025

Tract ID	Sim 2025 smart				Sim 2025 normal				Sim 2025 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
91	4,010	1,179	1.06	3,779	4,010	2,583	2.32	1,725	4,010	3,204	2.88	1,391
92	4,129	1,980	1.78	2,317	4,129	3,213	2.89	1,428	4,129	4,932	4.44	930
93	12,807	2,133	1.92	6,671	12,807	3,222	2.90	4,417	12,807	4,131	3.72	3,445
94	1,540	621	0.56	2,755	1,540	1,260	1.13	1,358	1,540	2,340	2.11	731
95	12,801	3,978	3.58	3,575	12,801	5,607	5.05	2,537	12,801	6,831	6.15	2,082
96	10,075	1,872	1.68	5,980	10,075	2,727	2.45	4,105	10,075	3,663	3.30	3,056
97	5,443	4,293	3.86	1,409	5,443	5,337	4.80	1,133	5,443	6,021	5.42	1,004
98	7,490	2,826	2.54	2,945	7,490	4,527	4.07	1,838	7,490	4,932	4.44	1,687
99	14,186	4,320	3.89	3,649	14,186	5,823	5.24	2,707	14,186	6,831	6.15	2,307
100	5,882	2,178	1.96	3,001	5,882	3,105	2.79	2,105	5,882	3,906	3.52	1,673
101	4,431	2,124	1.91	2,318	4,431	2,736	2.46	1,799	4,431	3,222	2.90	1,528
102	10,327	3,735	3.36	3,072	10,327	5,445	4.90	2,107	10,327	7,020	6.32	1,635
103	22,892	3,231	2.91	7,872	22,892	6,012	5.41	4,231	22,892	7,470	6.72	3,405
104	10,346	1,629	1.47	7,057	10,346	2,349	2.11	4,894	10,346	2,934	2.64	3,918
105	17,149	3,996	3.60	4,768	17,149	5,589	5.03	3,409	17,149	6,237	5.61	3,055
106	25,525	10,926	9.83	2,596	25,525	15,147	13.63	1,872	25,525	17,919	16.13	1,583
107	18,509	6,066	5.46	3,390	18,509	8,550	7.70	2,405	18,509	10,116	9.10	2,033
108	20,054	6,057	5.45	3,679	20,054	8,325	7.49	2,677	20,054	9,945	8.95	2,241
109	5,869	2,916	2.62	2,236	5,869	3,924	3.53	1,662	5,869	4,239	3.82	1,538
Total	**213,465**	**66,060**	**59.45**	**3,590**	**213,465**	**95,481**	**85.93**	**2,484**	**213,465**	**115,893**	**104.30**	**2,047**

Table A-IV.49: Dasymetric Densities of Okaloosa county in the 70's

Tract ID	Real 1974				Sim 1975			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	4,121	945	0.85	4,845	4,077	954	0.86	4,748
59	1,457	279	0.25	5,802	1,441	297	0.27	5,391
60	2,734	972	0.87	3,125	2,705	1,008	0.91	2,982
61	3,462	2,052	1.85	1,875	3,425	2,088	1.88	1,823
62	3,767	2,295	2.07	1,824	3,727	2,331	2.10	1,777
63	1,976	963	0.87	2,280	1,955	999	0.90	2,174
64	2,049	1,818	1.64	1,252	2,027	1,854	1.67	1,215
65	2,895	1,512	1.36	2,127	2,864	1,521	1.37	2,092
66	1,986	864	0.78	2,554	1,965	873	0.79	2,501
67	1,384	801	0.72	1,920	1,370	846	0.76	1,799
68	2,480	1,674	1.51	1,646	2,453	1,701	1.53	1,602
69	5,245	1,494	1.34	3,901	5,189	1,530	1.38	3,768
70	6,458	2,034	1.83	3,528	6,389	2,070	1.86	3,429
71	6,455	1,116	1.00	6,427	6,386	1,125	1.01	6,307
72	5,592	2,367	2.13	2,625	5,532	2,394	2.15	2,568
73	1,879	414	0.37	5,043	1,859	423	0.38	4,883
74	2,746	837	0.75	3,645	2,717	846	0.76	3,568
75	1,667	630	0.57	2,940	1,649	630	0.57	2,908
76	1,763	1,062	0.96	1,845	1,744	1,071	0.96	1,809
77	4,210	1,701	1.53	2,750	4,166	1,710	1.54	2,707
78	6,417	2,529	2.28	2,819	6,348	2,565	2.31	2,750
79	3,179	1,341	1.21	2,634	3,145	1,377	1.24	2,538
80	1,999	1,125	1.01	1,974	1,978	1,143	1.03	1,923
81	4,136	1,683	1.51	2,731	4,092	1,755	1.58	2,591
82	4,287	2,403	2.16	1,982	4,241	2,466	2.22	1,911
83	2,394	1,341	1.21	1,984	2,368	1,359	1.22	1,936
84	3,877	1,692	1.52	2,546	3,836	1,710	1.54	2,493
85	1,384	792	0.71	1,942	1,370	792	0.71	1,922
86	3,555	1,899	1.71	2,080	3,517	1,953	1.76	2,001
87	2,820	1,539	1.39	2,036	2,789	1,602	1.44	1,934
88	1,447	531	0.48	3,028	1,432	549	0.49	2,898
89	2,326	981	0.88	2,634	2,301	999	0.90	2,559
90	1,357	981	0.88	1,537	1,343	1,062	0.96	1,405
Total	**103,504**	**44,667**	**40.20**	**2,575**	**102,400**	**45,603**	**41.04**	**2,495**

Table A-IV.50: Dasymetric Densities of Okaloosa county in the 80's

Tract ID	Sim 1980				Sim 1985				Real 1986				Sim 1986			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	4,077	1,116	1.00	4,059	5,038	1,305	1.17	4,289	5,155	1,233	1.11	4,645	5,155	1,314	1.18	4,359
59	1,441	405	0.36	3,953	1,684	504	0.45	3,713	1,704	549	0.49	3,449	1,704	522	0.47	3,627
60	2,705	1,197	1.08	2,511	4,082	1,386	1.25	3,272	4,348	1,755	1.58	2,753	4,348	1,431	1.29	3,376
61	3,425	2,331	2.10	1,633	4,474	2,592	2.33	1,918	4,629	3,024	2.72	1,701	4,629	2,646	2.38	1,944
62	3,727	2,637	2.37	1,570	4,720	3,024	2.72	1,734	4,854	3,573	3.22	1,509	4,854	3,114	2.80	1,732
63	1,955	1,143	1.03	1,900	2,569	1,233	1.11	2,315	2,661	1,674	1.51	1,766	2,661	1,269	1.14	2,330
64	2,027	2,079	1.87	1,083	3,048	2,241	2.02	1,511	3,244	2,385	2.15	1,511	3,244	2,259	2.03	1,596
65	2,864	1,620	1.46	1,964	4,503	1,719	1.55	2,911	4,835	2,511	2.26	2,139	4,835	1,737	1.56	3,093
66	1,965	954	0.86	2,289	2,794	1,026	0.92	3,026	2,940	1,530	1.38	2,135	2,940	1,071	0.96	3,050
67	1,370	936	0.84	1,626	3,432	1,062	0.96	3,591	4,047	2,349	2.11	1,914	4,047	1,071	0.96	4,199
68	2,453	1,809	1.63	1,507	3,058	1,953	1.76	1,740	3,135	2,349	2.11	1,483	3,135	1,971	1.77	1,767
69	5,189	1,746	1.57	3,302	6,470	2,016	1.81	3,566	6,632	2,124	1.91	3,469	6,632	2,070	1.86	3,560
70	6,389	2,214	1.99	3,206	6,370	2,340	2.11	3,025	6,243	3,654	3.29	1,898	6,243	2,376	2.14	2,919
71	6,386	1,269	1.14	5,591	7,550	1,341	1.21	6,256	7,657	1,737	1.56	4,898	7,657	1,350	1.22	6,302
72	5,532	2,592	2.33	2,371	6,877	2,754	2.48	2,775	7,045	3,006	2.71	2,604	7,045	2,808	2.53	2,788
73	1,859	486	0.44	4,250	2,196	567	0.51	4,303	2,227	675	0.61	3,666	2,227	594	0.53	4,166
74	2,717	909	0.82	3,321	3,087	1,035	0.93	3,314	3,106	1,116	1.00	3,092	3,106	1,035	0.93	3,334
75	1,649	693	0.62	2,644	2,792	774	0.70	4,008	3,042	1,440	1.30	2,347	3,042	783	0.70	4,317
76	1,744	1,206	1.09	1,607	2,952	1,350	1.22	2,430	3,217	2,088	1.88	1,712	3,217	1,359	1.22	2,630
77	4,166	1,854	1.67	2,497	5,173	2,025	1.82	2,838	5,298	3,015	2.71	1,952	5,298	2,079	1.87	2,831
78	6,348	2,772	2.49	2,544	7,466	3,033	2.73	2,735	7,564	2,772	2.49	3,032	7,564	3,069	2.76	2,738
79	3,145	1,440	1.30	2,427	3,526	1,566	1.41	2,502	3,538	1,494	1.34	2,631	3,538	1,575	1.42	2,496
80	1,978	1,197	1.08	1,836	2,253	1,314	1.18	1,905	2,268	1,242	1.12	2,029	2,268	1,341	1.21	1,879
81	4,092	1,935	1.74	2,350	4,497	2,079	1.87	2,403	4,494	1,836	1.65	2,720	4,494	2,124	1.91	2,351
82	4,241	2,691	2.42	1,751	4,755	2,862	2.58	1,846	4,771	2,826	2.54	1,876	4,771	2,898	2.61	1,829
83	2,368	1,602	1.44	1,642	2,882	1,701	1.53	1,883	2,939	1,638	1.47	1,994	2,939	1,728	1.56	1,890
84	3,836	1,863	1.68	2,288	4,145	2,061	1.85	2,235	4,129	2,016	1.81	2,276	4,129	2,088	1.88	2,197
85	1,370	918	0.83	1,658	1,973	963	0.87	2,276	2,082	927	0.83	2,496	2,082	972	0.87	2,380
86	3,517	2,106	1.90	1,856	4,272	2,331	2.10	2,036	4,356	2,763	2.49	1,752	4,356	2,403	2.16	2,014
87	2,789	1,791	1.61	1,730	4,173	1,980	1.78	2,342	4,437	2,016	1.81	2,445	4,437	2,016	1.81	2,445
88	1,432	648	0.58	2,455	1,864	720	0.65	2,877	1,927	477	0.43	4,489	1,927	747	0.67	2,866
89	2,301	1,188	1.07	2,152	3,738	1,323	1.19	3,139	4,040	2,385	2.15	1,882	4,040	1,359	1.22	3,303
90	1,343	1,215	1.09	1,228	2,181	1,431	1.29	1,693	2,358	2,385	2.15	1,099	2,358	1,440	1.30	1,819
Total	**102,400**	**50,562**	**45.51**	**2,250**	**130,594**	**55,611**	**50.05**	**2,609**	**134,922**	**66,564**	**59.91**	**2,252**	**134,922**	**56,619**	**50.96**	**2,648**

Table A-IV.51: Dasymetric Densities of Okaloosa county in the 90's

Tract ID	Sim 1990				Real 1992				Sim 1992				Sim 1995			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	5,210	1,602	1.44	3,614	5,423	1,377	1.24	4,376	5,423	1,683	1.51	3,580	5,907	1,890	1.70	3,473
59	1,645	594	0.53	3,077	1,655	585	0.53	3,143	1,655	648	0.58	2,838	1,715	729	0.66	2,614
60	5,172	1,620	1.46	3,547	5,647	2,214	1.99	2,834	5,647	1,728	1.56	3,631	6,606	2,043	1.84	3,593
61	4,895	2,862	2.58	1,900	4,958	3,123	2.81	1,764	4,958	2,997	2.70	1,838	5,185	3,249	2.92	1,773
62	5,005	3,357	3.02	1,657	5,037	3,816	3.43	1,467	5,037	3,600	3.24	1,555	5,216	3,843	3.46	1,508
63	2,827	1,431	1.29	2,195	3,177	1,917	1.73	1,841	3,177	1,503	1.35	2,349	3,881	1,620	1.46	2,662
64	3,847	2,466	2.22	1,733	4,377	2,844	2.56	1,710	4,377	2,574	2.32	1,889	5,446	2,754	2.48	2,197
65	5,946	1,773	1.60	3,726	5,760	2,970	2.67	2,155	5,760	1,800	1.62	3,556	5,635	1,863	1.68	3,361
66	3,331	1,206	1.09	3,069	3,509	1,683	1.51	2,317	3,509	1,215	1.09	3,209	3,891	1,278	1.15	3,383
67	7,272	1,143	1.03	7,069	7,610	2,439	2.20	3,467	7,610	1,206	1.09	7,011	8,355	1,332	1.20	6,969
68	3,191	2,106	1.90	1,684	3,177	2,484	2.24	1,421	3,177	2,223	2.00	1,588	3,238	2,313	2.08	1,555
69	6,751	2,259	2.03	3,321	6,771	2,421	2.18	3,108	6,771	2,349	2.11	3,203	6,979	2,493	2.24	3,110
70	5,296	2,511	2.26	2,343	5,612	3,978	3.58	1,568	5,612	2,646	2.38	2,357	6,279	2,691	2.42	2,593
71	7,464	1,422	1.28	5,832	7,350	1,710	1.54	4,776	7,350	1,467	1.32	5,567	7,370	1,557	1.40	5,259
72	7,154	2,952	2.66	2,693	7,217	3,060	2.75	2,621	7,217	3,078	2.77	2,605	7,502	3,204	2.88	2,602
73	2,170	675	0.61	3,572	2,076	675	0.61	3,417	2,076	711	0.64	3,244	1,994	783	0.70	2,830
74	2,932	1,107	1.00	2,943	2,840	1,143	1.03	2,761	2,840	1,125	1.01	2,805	2,778	1,197	1.08	2,579
75	3,973	828	0.75	5,331	4,161	1,521	1.37	3,040	4,161	855	0.77	5,407	4,573	909	0.82	5,590
76	4,200	1,512	1.36	3,086	4,319	2,070	1.86	2,318	4,319	1,566	1.41	3,064	4,620	1,629	1.47	3,151
77	5,376	2,205	1.98	2,709	5,487	3,114	2.80	1,958	5,487	2,277	2.05	2,677	5,803	2,376	2.14	2,714
78	7,342	3,321	2.99	2,456	7,190	2,736	2.46	2,920	7,190	3,393	3.05	2,355	7,149	3,510	3.16	2,263
79	3,303	1,656	1.49	2,216	3,247	1,458	1.31	2,474	3,247	1,692	1.52	2,132	3,247	1,728	1.56	2,088
80	2,145	1,440	1.30	1,655	2,157	1,233	1.11	1,944	2,157	1,476	1.33	1,624	2,233	1,557	1.40	1,594
81	4,127	2,223	2.00	2,063	4,063	1,872	1.68	2,412	4,063	2,295	2.07	1,967	4,071	2,421	2.18	1,868
82	4,454	3,033	2.73	1,632	4,328	2,835	2.55	1,696	4,328	3,105	2.79	1,549	4,253	3,177	2.86	1,487
83	2,933	1,800	1.62	1,810	2,887	1,683	1.51	1,906	2,887	1,827	1.64	1,756	2,894	1,890	1.70	1,701
84	3,740	2,187	1.97	1,900	3,688	2,043	1.84	2,006	3,688	2,250	2.03	1,821	3,705	2,331	2.10	1,766
85	2,385	999	0.90	2,653	2,285	927	0.83	2,739	2,285	1,017	0.92	2,496	2,199	1,044	0.94	2,340
86	4,340	2,538	2.28	1,900	4,255	3,024	2.72	1,563	4,255	2,592	2.33	1,824	4,237	2,727	2.45	1,726
87	5,239	2,232	2.01	2,608	5,555	2,232	2.01	2,765	5,555	2,313	2.08	2,668	6,220	2,439	2.20	2,834
88	2,031	855	0.77	2,639	1,965	1,305	1.17	1,673	1,965	918	0.83	2,378	1,919	972	0.87	2,194
89	5,102	1,593	1.43	3,559	5,687	2,916	2.62	2,167	5,687	1,701	1.53	3,715	6,863	1,836	1.65	4,153
90	2,978	1,539	1.39	2,150	2,986	3,087	2.78	1,075	2,986	1,647	1.48	2,014	3,075	1,764	1.59	1,937
Total	**143,776**	**61,047**	**54.94**	**2,617**	**146,456**	**72,495**	**65.25**	**2,245**	**146,456**	**63,477**	**57.13**	**2,564**	**155,038**	**67,149**	**60.43**	**2,565**

Table A-IV.52: Dasymetric Densities of Okaloosa county in the 2000's

Tract ID	Sim 2000				Real 2001				Sim 2001			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	6,742	2,214	1.99	3,384	6,841	1,890	1.70	4,022	6,841	2,259	2.03	3,365
59	1,799	873	0.79	2,290	1,817	585	0.53	3,451	1,817	918	0.83	2,199
60	8,493	2,538	2.28	3,718	8,713	2,511	2.26	3,855	8,713	2,655	2.39	3,646
61	5,529	3,672	3.30	1,673	5,608	3,663	3.30	1,701	5,608	3,798	3.42	1,641
62	5,472	4,266	3.84	1,425	5,542	3,834	3.45	1,606	5,542	4,338	3.90	1,419
63	5,364	1,890	1.70	3,153	5,490	3,024	2.72	2,017	5,490	1,908	1.72	3,197
64	7,760	3,051	2.75	2,826	7,988	3,996	3.60	2,221	7,988	3,087	2.78	2,875
65	5,376	1,908	1.72	3,131	5,468	3,888	3.50	1,563	5,468	1,926	1.73	3,154
66	4,575	1,467	1.32	3,465	4,669	1,926	1.73	2,694	4,669	1,485	1.34	3,493
67	9,663	1,584	1.43	6,778	10,061	2,907	2.62	3,846	10,061	1,629	1.47	6,862
68	3,308	2,466	2.22	1,490	3,345	2,385	2.15	1,558	3,345	2,484	2.24	1,496
69	7,261	2,736	2.46	2,949	7,348	2,376	2.14	3,436	7,348	2,781	2.50	2,936
70	7,494	2,817	2.54	2,956	7,562	4,023	3.62	2,089	7,562	2,835	2.55	2,964
71	7,325	1,674	1.51	4,862	7,388	1,719	1.55	4,775	7,388	1,701	1.53	4,826
72	7,918	3,546	3.19	2,481	8,015	3,123	2.81	2,852	8,015	3,573	3.22	2,492
73	1,844	864	0.78	2,371	1,855	720	0.65	2,863	1,855	873	0.79	2,361
74	2,649	1,251	1.13	2,353	2,665	1,368	1.23	2,165	2,665	1,251	1.13	2,367
75	5,299	981	0.88	6,002	5,439	1,557	1.40	3,881	5,439	990	0.89	6,104
76	5,115	1,692	1.52	3,359	5,242	2,115	1.90	2,754	5,242	1,710	1.54	3,406
77	6,305	2,538	2.28	2,760	6,388	3,294	2.96	2,155	6,388	2,583	2.32	2,748
78	7,006	3,618	3.26	2,152	7,062	2,574	2.32	3,048	7,062	3,672	3.30	2,137
79	3,212	1,809	1.63	1,973	3,233	1,413	1.27	2,542	3,233	1,827	1.64	1,966
80	2,339	1,656	1.49	1,569	2,360	1,206	1.09	2,174	2,360	1,665	1.50	1,575
81	4,043	2,601	2.34	1,727	4,068	1,881	1.69	2,403	4,068	2,628	2.37	1,720
82	4,088	3,321	2.99	1,368	4,111	2,682	2.41	1,703	4,111	3,321	2.99	1,375
83	2,874	1,998	1.80	1,598	2,901	1,638	1.47	1,968	2,901	2,007	1.81	1,606
84	3,694	2,502	2.25	1,640	3,715	1,962	1.77	2,104	3,715	2,520	2.27	1,638
85	2,040	1,089	0.98	2,081	2,067	891	0.80	2,578	2,067	1,107	1.00	2,075
86	4,164	2,925	2.63	1,582	4,202	3,186	2.87	1,465	4,202	2,988	2.69	1,563
87	7,434	2,673	2.41	3,090	7,605	2,628	2.37	3,215	7,605	2,709	2.44	3,119
88	1,825	1,008	0.91	2,012	1,844	1,701	1.53	1,205	1,844	1,017	0.92	2,015
89	9,292	2,070	1.86	4,988	9,574	6,138	5.52	1,733	9,574	2,088	1.88	5,095
90	3,196	1,953	1.76	1,818	3,264	3,312	2.98	1,095	3,264	1,962	1.77	1,848
Total	**170,498**	**73,251**	**65.93**	**2,586**	**173,450**	**82,116**	**73.90**	**2,347**	**173,450**	**74,295**	**66.87**	**2,594**

Table A-IV.53: Projections of Dasymetric Densities for Okaloosa county in 2005

Tract ID	Sim 2005 smart				Sim 2005 normal				Sim 2005 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	7,371	1,917	1.73	4,272	7,371	2,052	1.85	3,991	7,371	2,196	1.98	3,730
59	1,921	612	0.55	3,488	1,921	648	0.58	3,294	1,921	666	0.60	3,205
60	9,804	2,592	2.33	4,203	9,804	2,781	2.50	3,917	9,804	2,988	2.69	3,646
61	6,033	3,753	3.38	1,786	6,033	3,888	3.50	1,724	6,033	4,068	3.66	1,648
62	5,923	3,924	3.53	1,677	5,923	4,113	3.70	1,600	5,923	4,293	3.86	1,533
63	6,123	3,114	2.80	2,185	6,123	3,249	2.92	2,094	6,123	3,294	2.96	2,065
64	9,112	4,149	3.73	2,440	9,112	4,383	3.94	2,310	9,112	4,455	4.01	2,273
65	5,948	3,906	3.52	1,692	5,948	3,960	3.56	1,669	5,948	3,969	3.57	1,665
66	5,148	1,971	1.77	2,902	5,148	2,061	1.85	2,775	5,148	2,061	1.85	2,775
67	12,013	2,961	2.66	4,508	12,013	3,087	2.78	4,324	12,013	3,249	2.92	4,108
68	3,555	2,421	2.18	1,632	3,555	2,484	2.24	1,590	3,555	2,520	2.27	1,567
69	7,828	2,430	2.19	3,579	7,828	2,556	2.30	3,403	7,828	2,682	2.41	3,243
70	7,967	4,095	3.69	2,162	7,967	4,149	3.73	2,134	7,967	4,329	3.90	2,045
71	7,768	1,737	1.56	4,969	7,768	1,800	1.62	4,795	7,768	1,827	1.64	4,724
72	8,552	3,177	2.86	2,991	8,552	3,303	2.97	2,877	8,552	3,393	3.05	2,801
73	1,932	765	0.69	2,806	1,932	855	0.77	2,511	1,932	873	0.79	2,459
74	2,772	1,377	1.24	2,237	2,772	1,467	1.32	2,100	2,772	1,476	1.33	2,087
75	6,133	1,593	1.43	4,278	6,133	1,629	1.47	4,183	6,133	1,620	1.46	4,206
76	5,875	2,151	1.94	3,035	5,875	2,250	2.03	2,901	5,875	2,286	2.06	2,856
77	6,842	3,339	3.01	2,277	6,842	3,447	3.10	2,205	6,842	3,654	3.29	2,081
78	7,406	2,646	2.38	3,110	7,406	2,736	2.46	3,008	7,406	2,808	2.53	2,931
79	3,373	1,440	1.30	2,603	3,373	1,485	1.34	2,524	3,373	1,539	1.39	2,435
80	2,487	1,233	1.11	2,241	2,487	1,305	1.17	2,117	2,487	1,341	1.21	2,061
81	4,235	1,899	1.71	2,478	4,235	1,971	1.77	2,387	4,235	1,998	1.80	2,355
82	4,273	2,736	2.46	1,735	4,273	2,808	2.53	1,691	4,273	2,889	2.60	1,643
83	3,062	1,683	1.51	2,022	3,062	1,692	1.52	2,011	3,062	1,710	1.54	1,990
84	3,861	1,980	1.78	2,167	3,861	2,052	1.85	2,091	3,861	2,061	1.85	2,082
85	2,213	909	0.82	2,705	2,213	891	0.80	2,760	2,213	936	0.84	2,627
86	4,427	3,249	2.92	1,514	4,427	3,330	3.00	1,477	4,427	3,429	3.09	1,434
87	8,463	2,682	2.41	3,506	8,463	2,835	2.55	3,317	8,463	2,871	2.58	3,275
88	1,953	1,746	1.57	1,243	1,953	1,827	1.64	1,188	1,953	1,890	1.70	1,148
89	10,961	6,390	5.75	1,906	10,961	6,705	6.03	1,816	10,961	6,948	6.25	1,753
90	3,606	3,384	3.05	1,184	3,606	3,447	3.10	1,162	3,606	3,591	3.23	1,116
Total	**188,940**	**83,961**	**75.56**	**2,500**	**188,940**	**87,246**	**78.52**	**2,406**	**188,940**	**89,910**	**80.92**	**2,335**

Table A-IV.54: Projections of Dasymetric Densities for Okaloosa county in 2010

Tract ID	Sim 2010 smart				Sim 2010 normal				Sim 2010 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	7,983	1,917	1.73	4,627	7,983	2,286	2.06	3,880	7,983	2,628	2.37	3,375
59	2,032	612	0.55	3,689	2,032	729	0.66	3,097	2,032	729	0.66	3,097
60	11,212	2,619	2.36	4,757	11,212	3,078	2.77	4,047	11,212	3,591	3.23	3,469
61	6,521	3,816	3.43	1,899	6,521	4,203	3.78	1,724	6,521	4,464	4.02	1,623
62	6,352	3,978	3.58	1,774	6,352	4,464	4.02	1,581	6,352	4,815	4.33	1,466
63	6,923	3,123	2.81	2,463	6,923	3,537	3.18	2,175	6,923	3,600	3.24	2,137
64	10,600	4,194	3.77	2,808	10,600	4,752	4.28	2,478	10,600	5,130	4.62	2,296
65	6,518	3,915	3.52	1,850	6,518	4,014	3.61	1,804	6,518	4,086	3.68	1,772
66	5,740	1,989	1.79	3,207	5,740	2,223	2.00	2,869	5,740	2,286	2.06	2,790
67	14,795	2,997	2.70	5,485	14,795	3,465	3.12	4,744	14,795	3,762	3.39	4,370
68	3,786	2,430	2.19	1,731	3,786	2,610	2.35	1,612	3,786	2,745	2.47	1,532
69	8,361	2,502	2.25	3,713	8,361	2,745	2.47	3,384	8,361	2,988	2.69	3,109
70	8,392	4,095	3.69	2,277	8,392	4,320	3.89	2,158	8,392	4,563	4.11	2,043
71	8,160	1,764	1.59	5,140	8,160	1,890	1.70	4,797	8,160	1,935	1.74	4,686
72	9,152	3,222	2.90	3,156	9,152	3,555	3.20	2,860	9,152	3,708	3.34	2,742
73	2,006	792	0.71	2,814	2,006	945	0.85	2,359	2,006	1,071	0.96	2,081
74	2,873	1,377	1.24	2,318	2,873	1,530	1.38	2,086	2,873	1,584	1.43	2,015
75	7,031	1,611	1.45	4,849	7,031	1,665	1.50	4,692	7,031	1,719	1.55	4,545
76	6,685	2,169	1.95	3,425	6,685	2,412	2.17	3,080	6,685	2,466	2.22	3,012
77	7,356	3,375	3.04	2,422	7,356	3,663	3.30	2,231	7,356	4,023	3.62	2,032
78	7,755	2,682	2.41	3,213	7,755	2,880	2.59	2,992	7,755	3,060	2.75	2,816
79	3,510	1,485	1.34	2,626	3,510	1,539	1.39	2,534	3,510	1,674	1.51	2,330
80	2,619	1,251	1.13	2,326	2,619	1,386	1.25	2,100	2,619	1,476	1.33	1,972
81	4,394	1,908	1.72	2,559	4,394	2,124	1.91	2,299	4,394	2,178	1.96	2,242
82	4,425	2,781	2.50	1,768	4,425	2,916	2.62	1,686	4,425	3,078	2.77	1,597
83	3,232	1,683	1.51	2,134	3,232	1,764	1.59	2,036	3,232	1,845	1.66	1,946
84	3,998	1,980	1.78	2,244	3,998	2,169	1.95	2,048	3,998	2,151	1.94	2,065
85	2,378	918	0.83	2,878	2,378	945	0.85	2,796	2,378	954	0.86	2,770
86	4,664	3,303	2.97	1,569	4,664	3,501	3.15	1,480	4,664	3,663	3.30	1,415
87	9,544	2,745	2.47	3,863	9,544	3,087	2.78	3,435	9,544	3,240	2.92	3,273
88	2,070	1,773	1.60	1,297	2,070	2,016	1.81	1,141	2,070	2,097	1.89	1,097
89	12,810	6,489	5.84	2,193	12,810	7,335	6.60	1,940	12,810	8,055	7.25	1,767
90	4,032	3,429	3.09	1,307	4,032	3,627	3.26	1,235	4,032	3,870	3.48	1,158
Total	**207,909**	**84,924**	**76.43**	**2,720**	**207,909**	**93,375**	**84.04**	**2,474**	**207,909**	**99,234**	**89.31**	**2,328**

Table A-IV.55: Projections of Dasymetric Densities for Okaloosa county in 2015

Tract ID	Sim 2015 smart				Sim 2015 normal				Sim 2015 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	8,484	1,962	1.77	4,805	8,484	2,520	2.27	3,741	8,484	3,258	2.93	2,893
59	2,110	612	0.55	3,831	2,110	810	0.73	2,894	2,110	909	0.82	2,579
60	12,582	2,637	2.37	5,301	12,582	3,429	3.09	4,077	12,582	4,329	3.90	3,229
61	6,917	3,861	3.47	1,991	6,917	4,545	4.09	1,691	6,917	5,004	4.50	1,536
62	6,684	4,014	3.61	1,850	6,684	4,878	4.39	1,522	6,684	5,409	4.87	1,373
63	7,682	3,159	2.84	2,702	7,682	3,825	3.44	2,232	7,682	4,266	3.84	2,001
64	12,099	4,239	3.82	3,171	12,099	5,220	4.70	2,575	12,099	5,760	5.18	2,334
65	7,010	3,915	3.52	1,989	7,010	4,023	3.62	1,936	7,010	4,167	3.75	1,869
66	6,279	2,016	1.81	3,461	6,279	2,331	2.10	2,993	6,279	2,547	2.29	2,739
67	17,879	3,051	2.75	6,511	17,879	3,843	3.46	5,169	17,879	4,113	3.70	4,830
68	3,956	2,448	2.20	1,796	3,956	2,709	2.44	1,623	3,956	2,907	2.62	1,512
69	8,762	2,538	2.28	3,836	8,762	2,943	2.65	3,308	8,762	3,267	2.94	2,980
70	8,673	4,122	3.71	2,338	8,673	4,491	4.04	2,146	8,673	4,806	4.33	2,005
71	8,412	1,764	1.59	5,299	8,412	1,980	1.78	4,721	8,412	2,124	1.91	4,401
72	9,609	3,222	2.90	3,314	9,609	3,672	3.30	2,908	9,609	3,951	3.56	2,702
73	2,043	810	0.73	2,802	2,043	1,053	0.95	2,156	2,043	1,233	1.11	1,841
74	2,922	1,377	1.24	2,358	2,922	1,593	1.43	2,038	2,922	1,665	1.50	1,950
75	7,910	1,629	1.47	5,395	7,910	1,755	1.58	5,008	7,910	1,827	1.64	4,811
76	7,463	2,187	1.97	3,792	7,463	2,511	2.26	3,302	7,463	2,628	2.37	3,155
77	7,759	3,384	3.05	2,548	7,759	3,897	3.51	2,212	7,759	4,338	3.90	1,987
78	7,969	2,691	2.42	3,290	7,969	3,015	2.71	2,937	7,969	3,312	2.98	2,673
79	3,583	1,512	1.36	2,633	3,583	1,611	1.45	2,471	3,583	1,746	1.57	2,280
80	2,706	1,278	1.15	2,353	2,706	1,440	1.30	2,088	2,706	1,557	1.40	1,931
81	4,474	1,935	1.74	2,569	4,474	2,178	1.96	2,282	4,474	2,340	2.11	2,124
82	4,496	2,817	2.54	1,773	4,496	3,033	2.73	1,647	4,496	3,186	2.87	1,568
83	3,347	1,692	1.52	2,198	3,347	1,854	1.67	2,006	3,347	1,953	1.76	1,904
84	4,062	1,998	1.80	2,259	4,062	2,259	2.03	1,998	4,062	2,277	2.05	1,982
85	2,507	927	0.83	3,005	2,507	972	0.87	2,866	2,507	981	0.88	2,840
86	4,820	3,339	3.01	1,604	4,820	3,744	3.37	1,430	4,820	3,897	3.51	1,374
87	10,562	2,754	2.48	4,261	10,562	3,285	2.96	3,572	10,562	3,573	3.22	3,285
88	2,153	1,791	1.61	1,336	2,153	2,169	1.95	1,103	2,153	2,277	2.05	1,051
89	14,690	6,606	5.95	2,471	14,690	8,046	7.24	2,029	14,690	9,135	8.22	1,787
90	4,423	3,465	3.12	1,418	4,423	3,780	3.40	1,300	4,423	4,167	3.75	1,179
Total	**225,027**	**85,752**	**77.18**	**2,916**	**225,027**	**99,414**	**89.47**	**2,515**	**225,027**	**108,909**	**98.02**	**2,296**

Table A-IV.56: Projections of Dasymetric Densities for Okaloosa county in 2020

Tract ID	Sim 2020 smart				Sim 2020 normal				Sim 2020 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	8,888	1,980	1.78	4,988	8,888	2,862	2.58	3,451	8,888	3,933	3.54	2,511
59	2,159	612	0.55	3,920	2,159	882	0.79	2,720	2,159	1,134	1.02	2,115
60	13,918	2,664	2.40	5,805	13,918	3,996	3.60	3,870	13,918	5,175	4.66	2,988
61	7,232	3,933	3.54	2,043	7,232	4,950	4.46	1,623	7,232	5,499	4.95	1,461
62	6,933	4,041	3.64	1,906	6,933	5,229	4.71	1,473	6,933	5,913	5.32	1,303
63	8,402	3,213	2.89	2,906	8,402	4,221	3.80	2,212	8,402	4,869	4.38	1,917
64	13,614	4,293	3.86	3,524	13,614	5,670	5.10	2,668	13,614	6,408	5.77	2,361
65	7,432	3,915	3.52	2,109	7,432	4,059	3.65	2,034	7,432	4,275	3.85	1,932
66	6,771	2,034	1.83	3,699	6,771	2,493	2.24	3,018	6,771	2,835	2.55	2,654
67	21,299	3,105	2.79	7,622	21,299	4,095	3.69	5,779	21,299	4,644	4.18	5,096
68	4,074	2,466	2.22	1,836	4,074	2,817	2.54	1,607	4,074	3,051	2.75	1,484
69	9,052	2,538	2.28	3,963	9,052	3,213	2.89	3,130	9,052	3,645	3.28	2,759
70	8,836	4,167	3.75	2,356	8,836	4,626	4.16	2,122	8,836	5,076	4.57	1,934
71	8,548	1,764	1.59	5,384	8,548	2,070	1.86	4,588	8,548	2,241	2.02	4,238
72	9,946	3,258	2.93	3,392	9,946	3,834	3.45	2,882	9,946	4,131	3.72	2,675
73	2,052	810	0.73	2,815	2,052	1,134	1.02	2,011	2,052	1,359	1.22	1,678
74	2,929	1,377	1.24	2,363	2,929	1,656	1.49	1,965	2,929	1,827	1.64	1,781
75	8,772	1,629	1.47	5,983	8,772	1,845	1.66	5,283	8,772	1,926	1.73	5,061
76	8,214	2,196	1.98	4,156	8,214	2,673	2.41	3,414	8,214	2,799	2.52	3,261
77	8,069	3,411	3.07	2,628	8,069	4,086	3.68	2,194	8,069	4,554	4.10	1,969
78	8,071	2,727	2.45	3,289	8,071	3,141	2.83	2,855	8,071	3,456	3.11	2,595
79	3,606	1,530	1.38	2,619	3,606	1,701	1.53	2,355	3,606	1,854	1.67	2,161
80	2,757	1,278	1.15	2,397	2,757	1,494	1.34	2,050	2,757	1,647	1.48	1,860
81	4,490	1,962	1.77	2,543	4,490	2,259	2.03	2,208	4,490	2,511	2.26	1,987
82	4,503	2,844	2.56	1,759	4,503	3,114	2.80	1,607	4,503	3,276	2.95	1,527
83	3,417	1,710	1.54	2,220	3,417	1,917	1.73	1,981	3,417	2,025	1.82	1,875
84	4,068	2,016	1.81	2,242	4,068	2,376	2.14	1,902	4,068	2,412	2.17	1,874
85	2,606	927	0.83	3,124	2,606	1,017	0.92	2,847	2,606	999	0.90	2,898
86	4,911	3,375	3.04	1,617	4,911	3,888	3.50	1,403	4,911	4,176	3.76	1,307
87	11,521	2,808	2.53	4,559	11,521	3,519	3.17	3,638	11,521	3,825	3.44	3,347
88	2,208	1,818	1.64	1,349	2,208	2,268	2.04	1,082	2,208	2,439	2.20	1,006
89	16,605	6,741	6.07	2,737	16,605	8,766	7.89	2,105	16,605	10,125	9.11	1,822
90	4,782	3,483	3.13	1,526	4,782	4,005	3.60	1,327	4,782	4,392	3.95	1,210
Total	**240,685**	**86,625**	**77.96**	**3,087**	**240,685**	**105,876**	**95.29**	**2,526**	**240,685**	**118,431**	**106.59**	**2,258**

Table A-IV.57: Projections of Dasymetric Densities for Okaloosa county in 2025

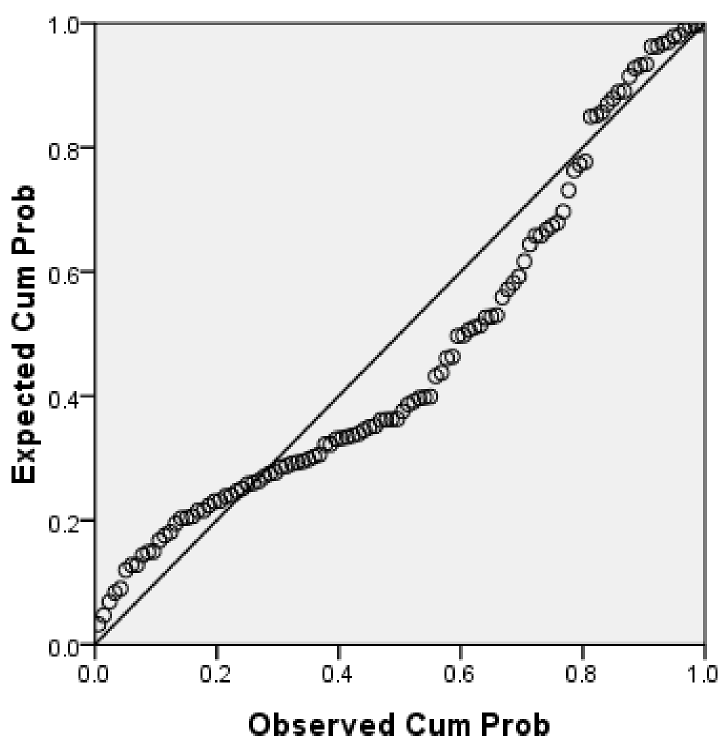
Tract ID	Sim 2025 smart				Sim 2025 normal				Sim 2025 sprawl			
	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit	Pop	Pixels	Area	Densit
58	9,186	1,998	1.80	5,108	9,186	3,222	2.90	3,168	9,186	5,004	4.50	2,040
59	2,179	612	0.55	3,956	2,179	999	0.90	2,424	2,179	1,458	1.31	1,661
60	15,189	2,700	2.43	6,251	15,189	4,527	4.07	3,728	15,189	6,300	5.67	2,679
61	7,460	3,987	3.59	2,079	7,460	5,391	4.85	1,538	7,460	6,201	5.58	1,337
62	7,095	4,068	3.66	1,938	7,095	5,715	5.14	1,379	7,095	6,381	5.74	1,235
63	9,067	3,267	2.94	3,084	9,067	4,671	4.20	2,157	9,067	5,463	4.92	1,844
64	15,113	4,356	3.92	3,855	15,113	6,174	5.56	2,720	15,113	7,047	6.34	2,383
65	7,773	3,933	3.54	2,196	7,773	4,140	3.73	2,086	7,773	4,446	4.00	1,943
66	7,203	2,079	1.87	3,850	7,203	2,754	2.48	2,906	7,203	3,096	2.79	2,585
67	25,032	3,159	2.84	8,804	25,032	4,302	3.87	6,465	25,032	5,004	4.50	5,558
68	4,140	2,466	2.22	1,865	4,140	2,934	2.64	1,568	4,140	3,195	2.88	1,440
69	9,226	2,565	2.31	3,997	9,226	3,393	3.05	3,021	9,226	3,987	3.59	2,571
70	8,881	4,176	3.76	2,363	8,881	4,734	4.26	2,084	8,881	5,274	4.75	1,871
71	8,569	1,773	1.60	5,370	8,569	2,142	1.93	4,445	8,569	2,331	2.10	4,085
72	10,156	3,294	2.96	3,426	10,156	3,969	3.57	2,843	10,156	4,356	3.92	2,591
73	2,033	828	0.75	2,728	2,033	1,278	1.15	1,768	2,033	1,494	1.34	1,512
74	2,898	1,395	1.26	2,308	2,898	1,746	1.57	1,844	2,898	1,917	1.73	1,680
75	9,598	1,656	1.49	6,440	9,598	1,926	1.73	5,537	9,598	2,016	1.81	5,290
76	8,919	2,223	2.00	4,458	8,919	2,754	2.48	3,598	8,919	2,898	2.61	3,420
77	8,278	3,447	3.10	2,668	8,278	4,266	3.84	2,156	8,278	4,743	4.27	1,939
78	8,066	2,745	2.47	3,265	8,066	3,285	2.96	2,728	8,066	3,555	3.20	2,521
79	3,581	1,566	1.41	2,541	3,581	1,836	1.65	2,167	3,581	1,917	1.73	2,076
80	2,771	1,287	1.16	2,392	2,771	1,566	1.41	1,966	2,771	1,728	1.56	1,782
81	4,446	1,998	1.80	2,472	4,446	2,358	2.12	2,095	4,446	2,592	2.33	1,906
82	4,450	2,862	2.58	1,728	4,450	3,195	2.88	1,548	4,450	3,357	3.02	1,473
83	3,442	1,710	1.54	2,237	3,442	1,980	1.78	1,932	3,442	2,052	1.85	1,864
84	4,020	2,025	1.82	2,206	4,020	2,421	2.18	1,845	4,020	2,529	2.28	1,766
85	2,672	927	0.83	3,203	2,672	1,017	0.92	2,919	2,672	1,017	0.92	2,919
86	4,937	3,411	3.07	1,608	4,937	4,068	3.66	1,348	4,937	4,428	3.99	1,239
87	12,400	2,853	2.57	4,829	12,400	3,672	3.30	3,752	12,400	4,041	3.64	3,409
88	2,234	1,854	1.67	1,339	2,234	2,322	2.09	1,069	2,234	2,538	2.28	978
89	18,519	6,804	6.12	3,024	18,519	9,423	8.48	2,184	18,519	11,151	10.04	1,845
90	5,102	3,519	3.17	1,611	5,102	4,221	3.80	1,343	5,102	4,599	4.14	1,233
Total	**254,635**	**87,543**	**78.79**	**3,232**	**254,635**	**112,401**	**101.16**	**2,517**	**254,635**	**128,115**	**115.30**	**2,208**

APPENDIX V: LINEAR REGRESSIONS, ALLOMETRIC GROWTH MODEL AND RMSE

Table A-V.1: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Classified Image 1974

R	R^2	Adjusted R^2	F test	P value
67.80	46.00	45.50	92.07	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	1,247.59	261.06	4.78	0.00
Constant *b*	1,606.65	167.44	9.60	0.00

Note: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



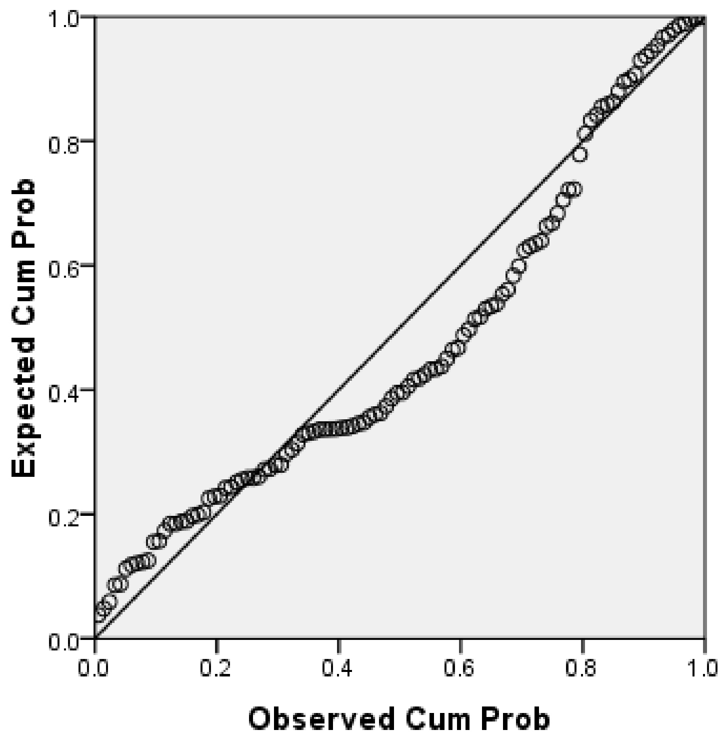
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.1: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1974

Table A-V.2: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1975

R	R^2	Adjusted R^2	F test	P value
69.40	48.10	47.60	100.15	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,216.34	251.70	4.83	0.00
Constant *b*	1,585.50	158.43	10.01	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



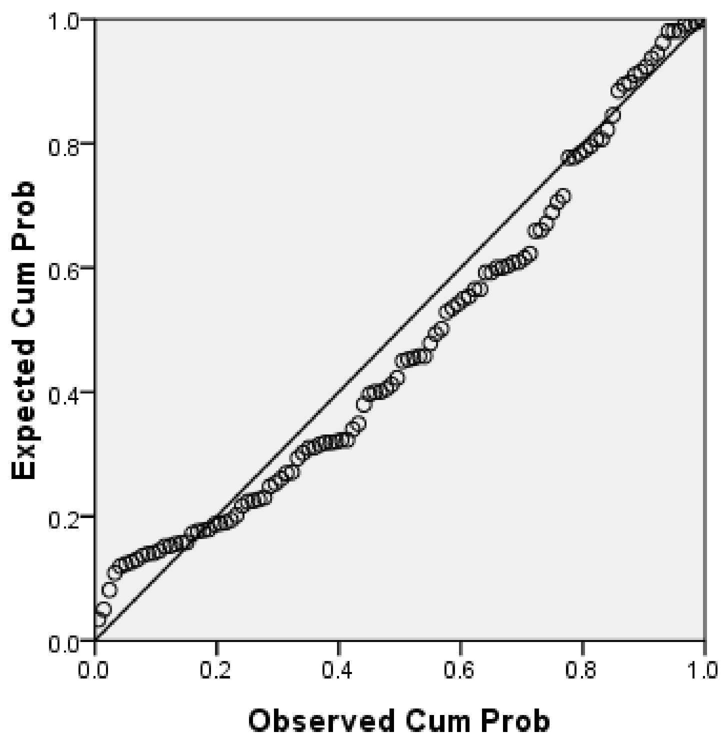
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.2: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1975

Table A-V.3: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1980

R	R^2	Adjusted R^2	F test	P value
73.50	54.00	53.50	126.55	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	1,233.10	231.23	5.33	0.00
Constant *b*	1,472.09	130.86	11.25	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



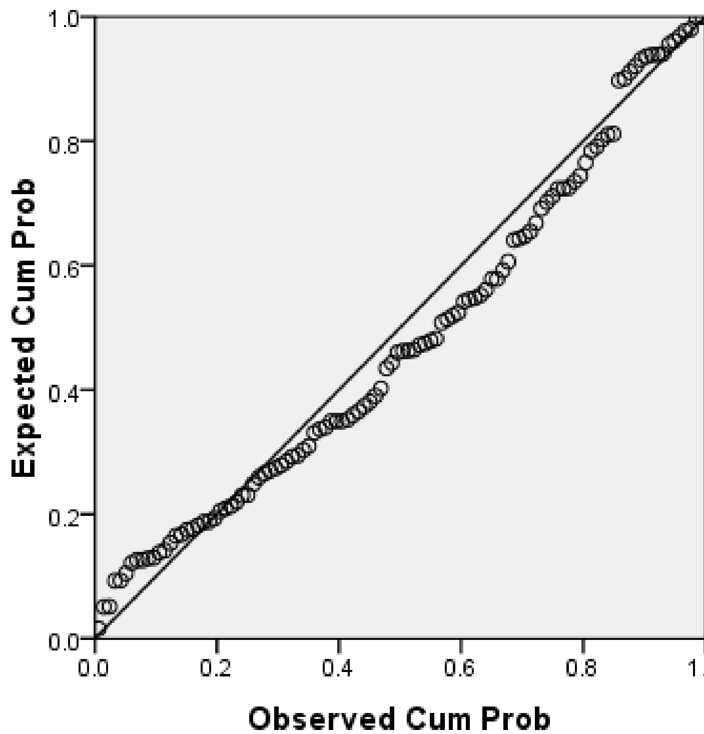
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.3: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1980

Table A-V.4: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1985

R	R^2	Adjusted R^2	F test	P value
72.50	52.60	52.10	119.78	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,674.72	246.87	6.78	0.00
Constant *b*	1,388.87	126.90	10.94	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



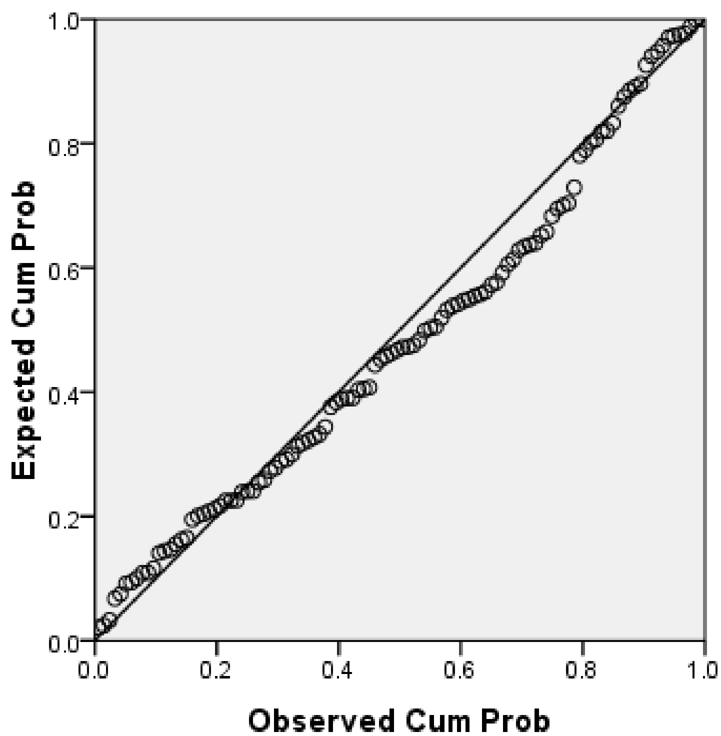
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.4: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1980

Table A-V.5: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Classified Image 1986

R	R^2	Adjusted R^2	F test	P value
71.10	50.60	50.20	110.70	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,631.83	268.74	6.07	0.00
Constant *b*	1,453.18	138.12	10.52	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



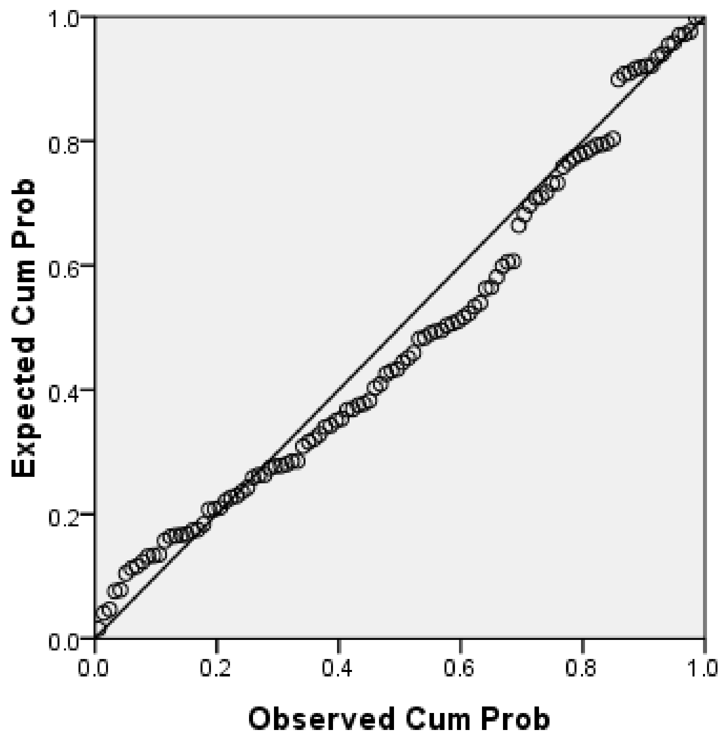
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.5: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1986

Table A-V.6: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1986

R	R^2	Adjusted R^2	F test	P value
71.5	51.2	50.7	113.17	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,765.19	254.71	6.93	0.00
Constant *b*	1,367.09	128.51	10.64	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



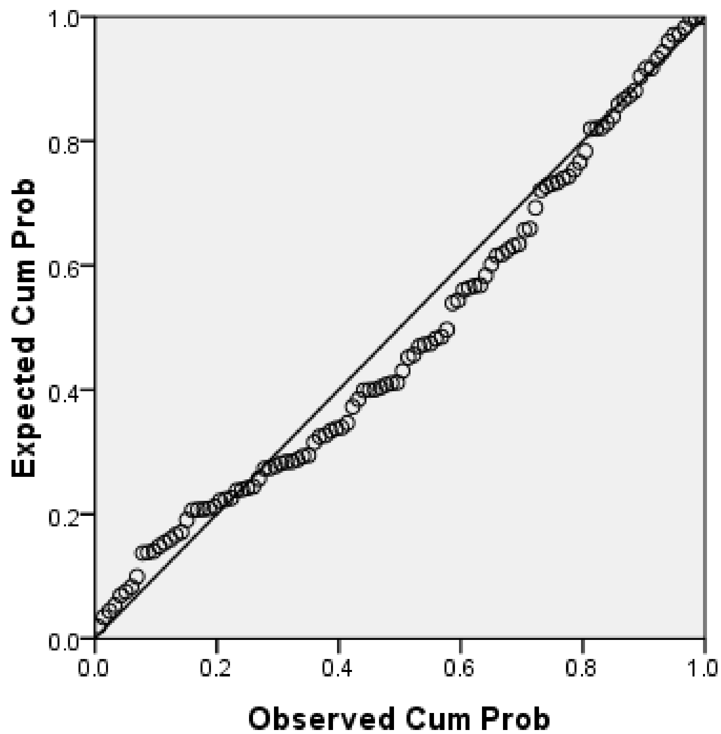
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.6: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1986

Table A-V.7: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1990

R	R^2	Adjusted R^2	F test	P value
64.4	41.5	41.0	76.70	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	2,041.22	303.81	6.72	0.00
Constant *b*	1,245.43	142.21	8.76	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



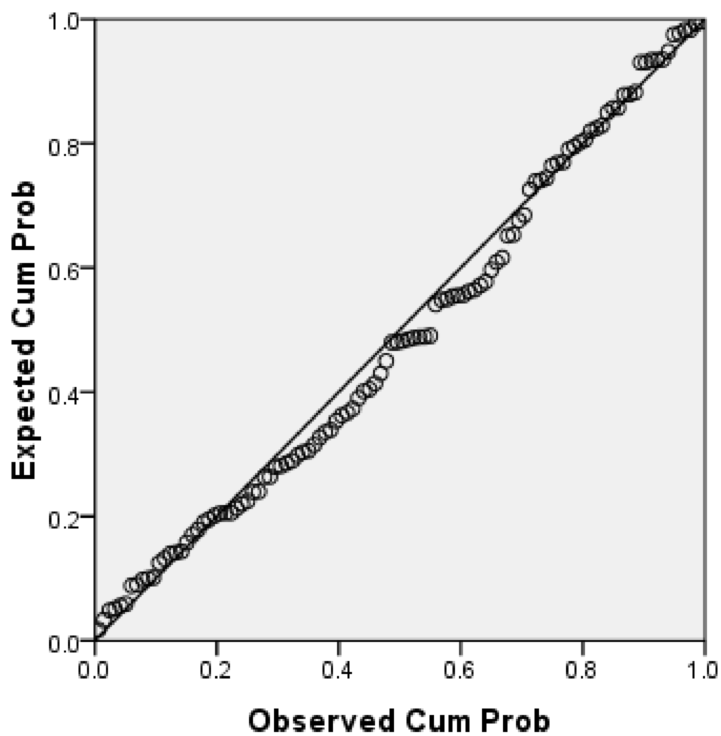
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.7: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1990

Table A-V.8: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Classified Image 1992

R	R^2	Adjusted R^2	F test	P value
72.00	51.80	51.40	116.19	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,638.06	297.16	5.51	0.00
Constant *b*	1,474.13	136.76	10.78	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



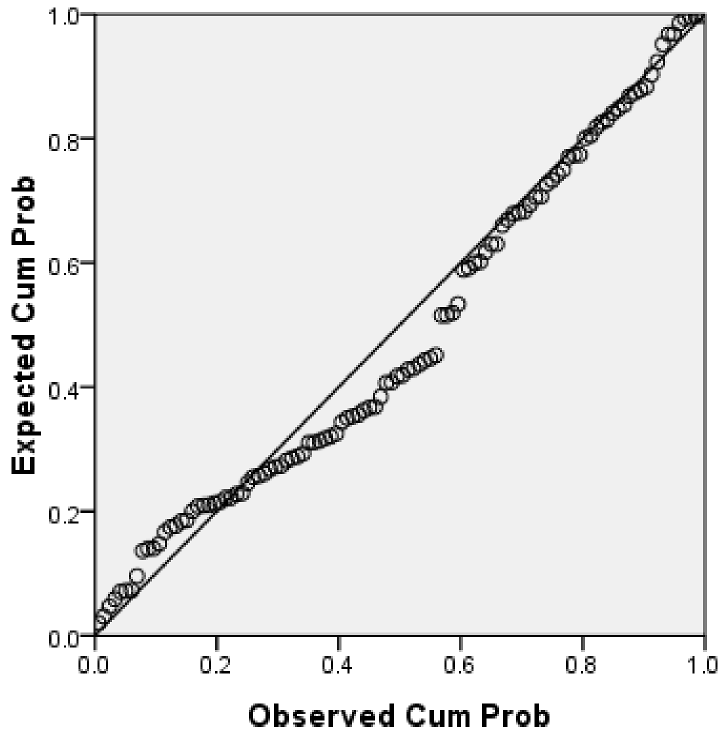
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.8: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1992

Table A-V.9: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1992

R	R^2	Adjusted R^2	F test	P value
62.50	39.00	38.40	69.08	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	2,133.33	322.40	6.62	0.00
Constant *b*	1,207.08	145.23	8.31	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



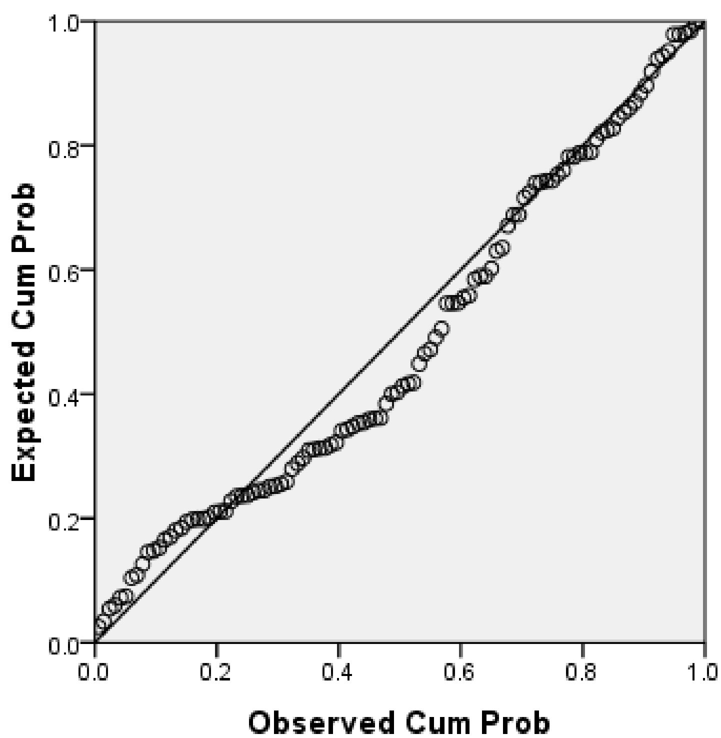
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.9: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1992

Table A-V.10: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 1995

R	R^2	Adjusted R^2	F test	P value
58.60	34.40	33.80	56.61	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	2,282.96	373.55	6.11	0.00
Constant *b*	1,196.61	159.04	7.52	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



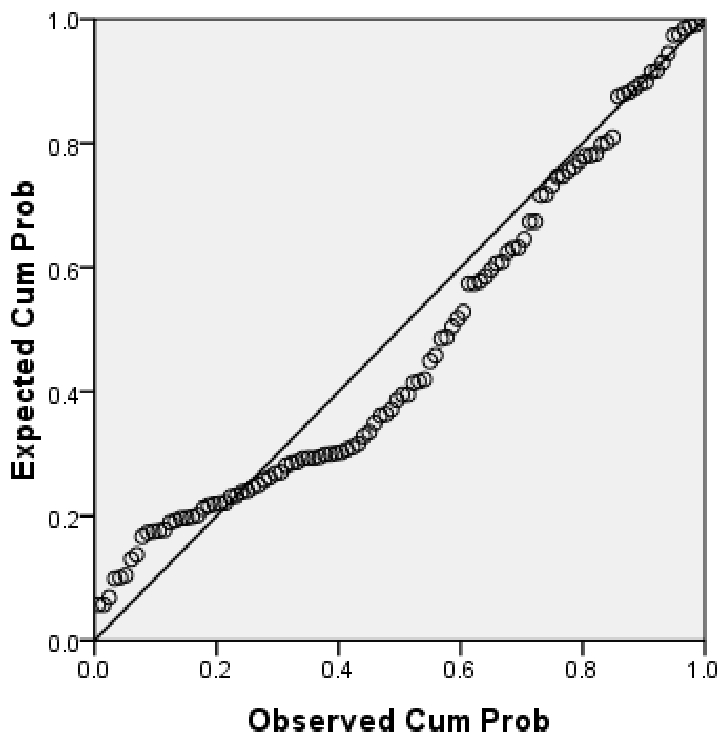
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.10: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 1995

Table A-V.11: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2000

R	R^2	Adjusted R^2	F test	P value
48.00	23.00	22.30	32.31	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	2,609.11	522.81	4.99	0.00
Constant *b*	1,156.82	203.52	5.68	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



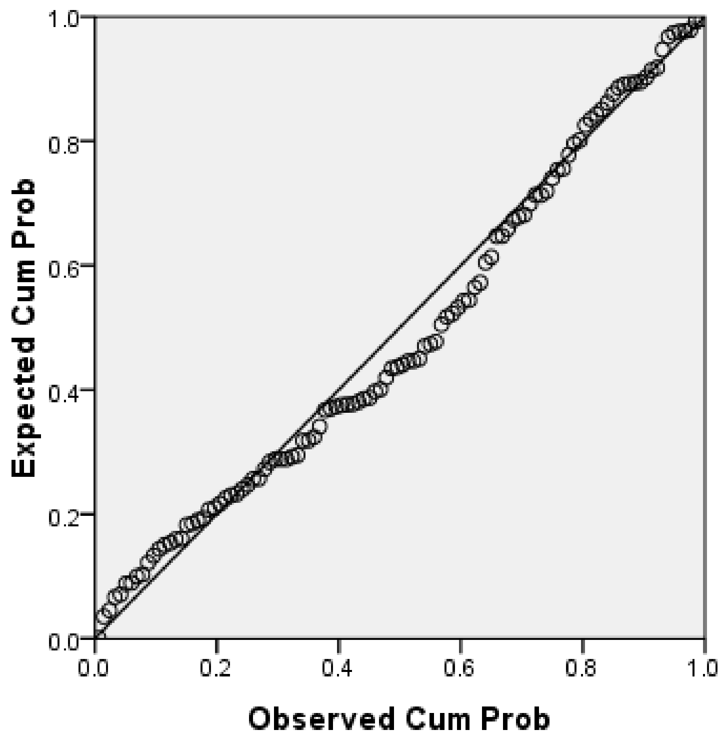
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.11: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2000

Table A-V.12: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Classified Image 2001

R	R^2	Adjusted R^2	F test	P value
77.80	60.60	60.20	165.82	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	1,829.95	321.17	5.70	0.00
Constant *b*	1,530.36	118.84	12.88	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



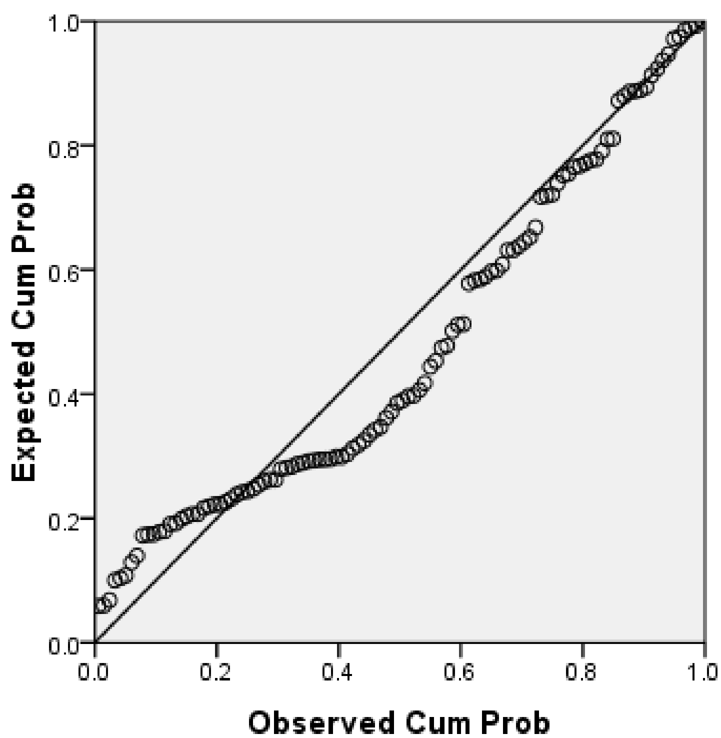
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.12: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Classified Image 2001

Table A-V.13: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2001

R	R^2	Adjusted R^2	F test	P value
47.10	22.10	21.40	30.71	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	2,650.27	544.04	4.87	0.00
Constant *b*	1,153.77	208.19	5.54	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



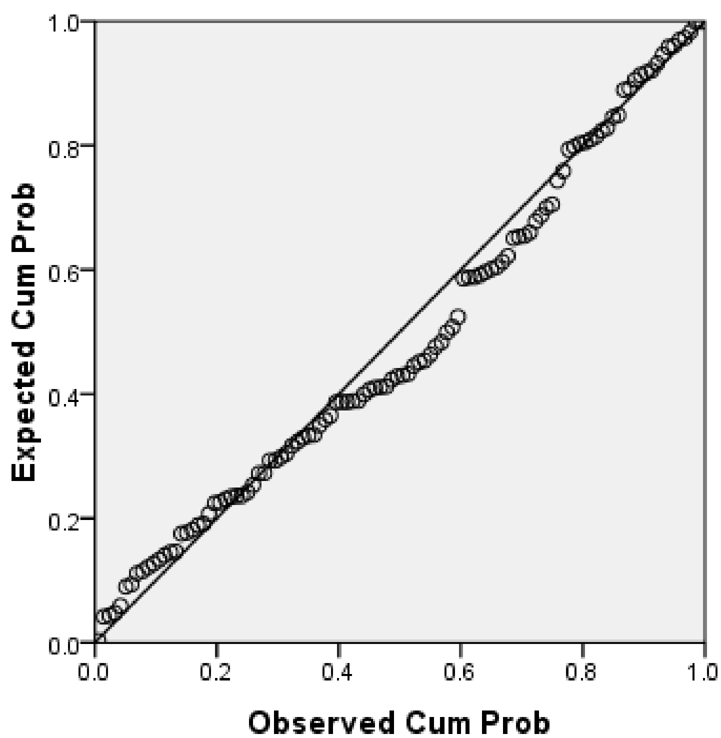
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.13: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2001

Table A-V.14: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 smart

R	R^2	Adjusted R^2	F test	P value
78.40	61.40	61.10	171.93	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,651.24	362.22	4.56	0.00
Constant *b*	1,714.81	130.78	13.11	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

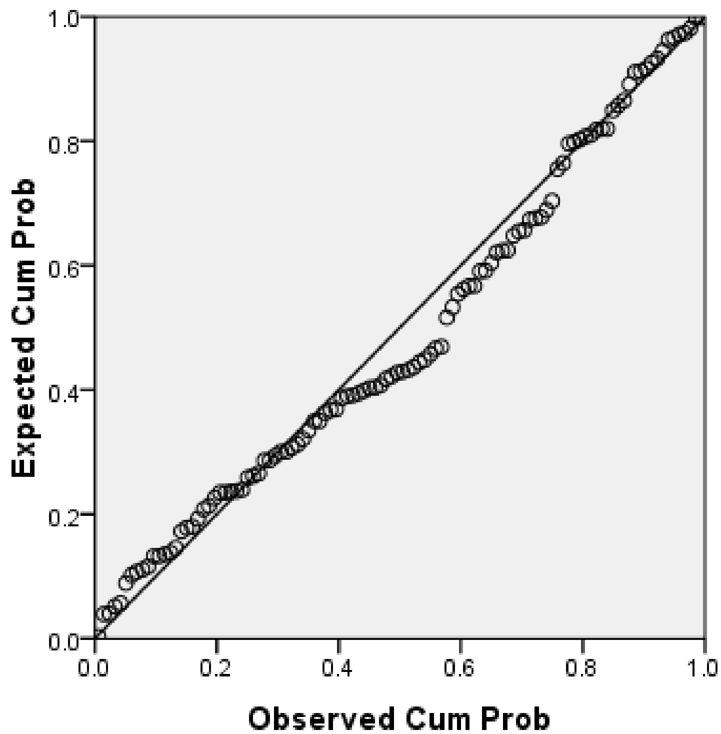
Figure A-V.14: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 smart

Table A-V.15: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 normal

R	R^2	Adjusted R^2	F test	P value
79.00	62.30	62.00	178.80	0.00

Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,638.08	356.75	4.59	0.00
Constant *b*	1,652.38	123.58	13.37	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



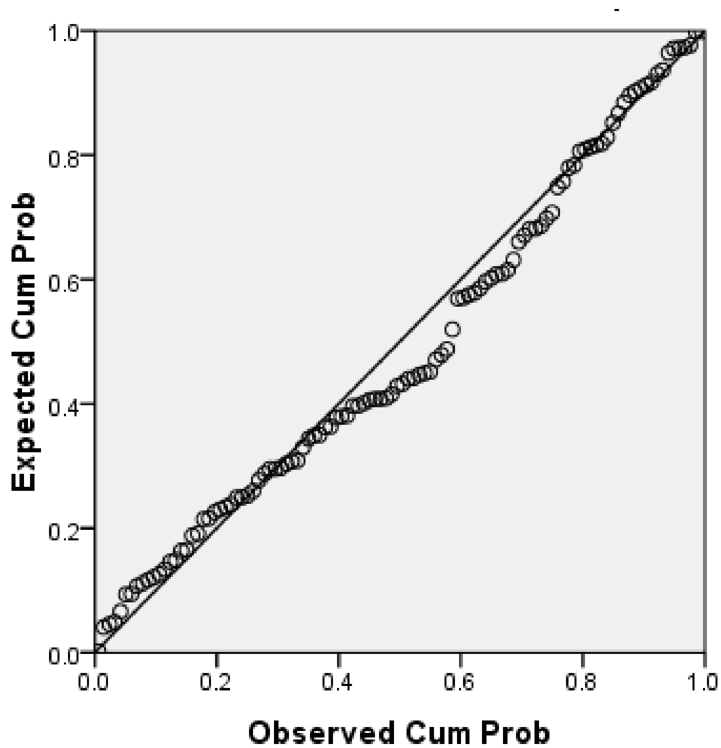
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.15: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 normal

Table A-V.16: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 sprawl

R	R^2	Adjusted R^2	F test	P value
78.90	62.30	62.00	178.60	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,645.44	356.45	4.62	0.00
Constant *b*	1,598.26	119.59	13.36	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



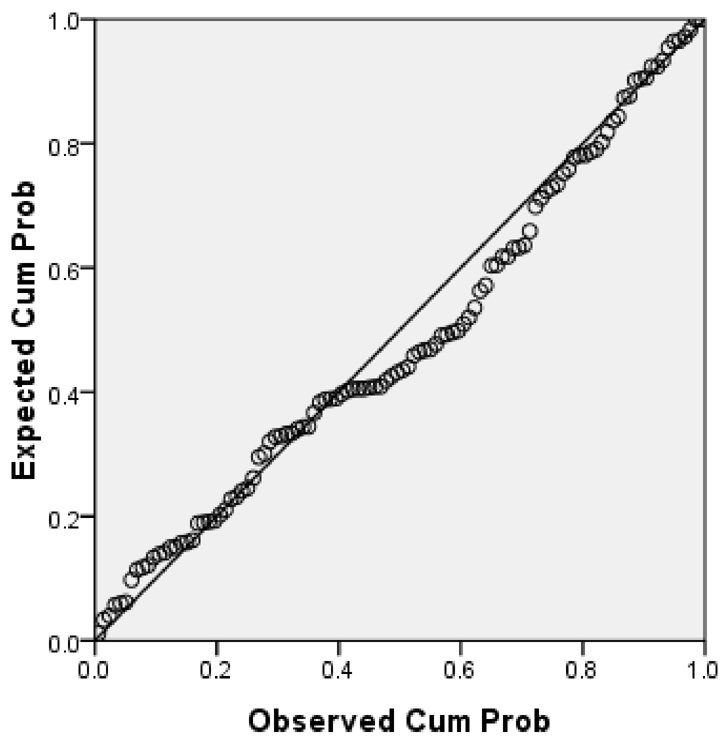
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.16: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 sprawl

Table A-V.17: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 smart

R	R^2	Adjusted R^2	F test	P value
78.70	61.90	61.50	175.17	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,342.93	435.96	3.08	0.00
Constant *b*	2,060.67	155.70	13.24	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



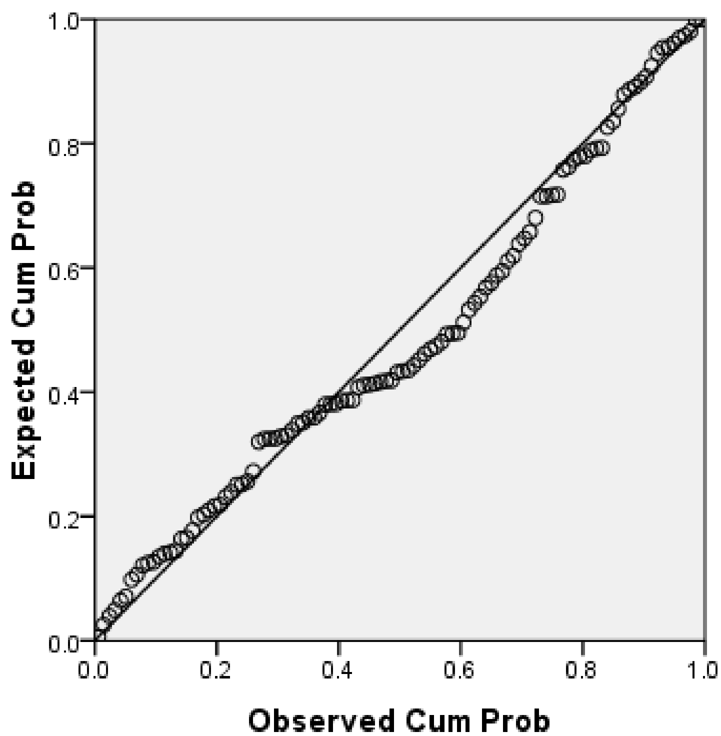
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.17: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 smart

Table A-V.18: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 normal.

R	R^2	Adjusted R^2	F test	P value
80.00	64.00	63.60	191.62	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,306.95	420.92	3.11	0.00
Constant *b*	1,868.50	134.98	13.84	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



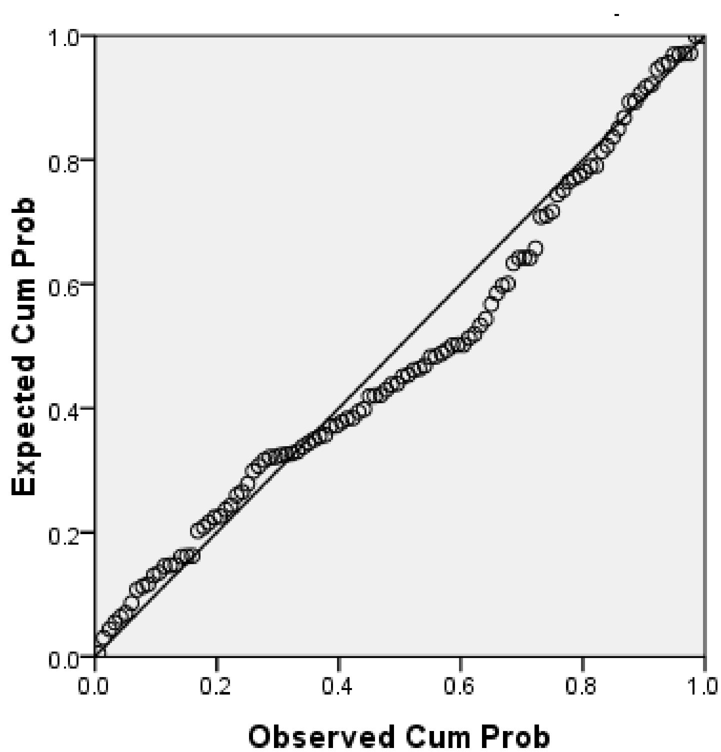
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.18: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 normal

Table A-V.19: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 sprawl

R	R^2	Adjusted R^2	F test	P value
80.50	64.80	64.50	198.62	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	1,355.69	411.22	3.30	0.00
Constant *b*	1,729.59	122.73	14.09	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



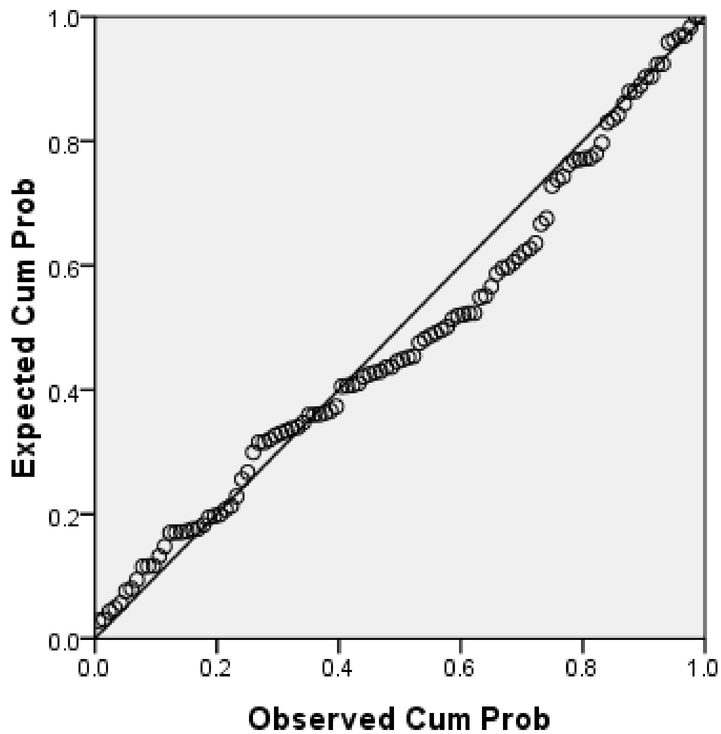
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.19: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 sprawl

Table A-V.20: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 smart

R	R^2	Adjusted R^2	F test	P value
78.40	61.40	61.10	172.14	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	961.88	516.87	1.86	0.07
Constant *b*	2,394.93	182.54	13.12	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



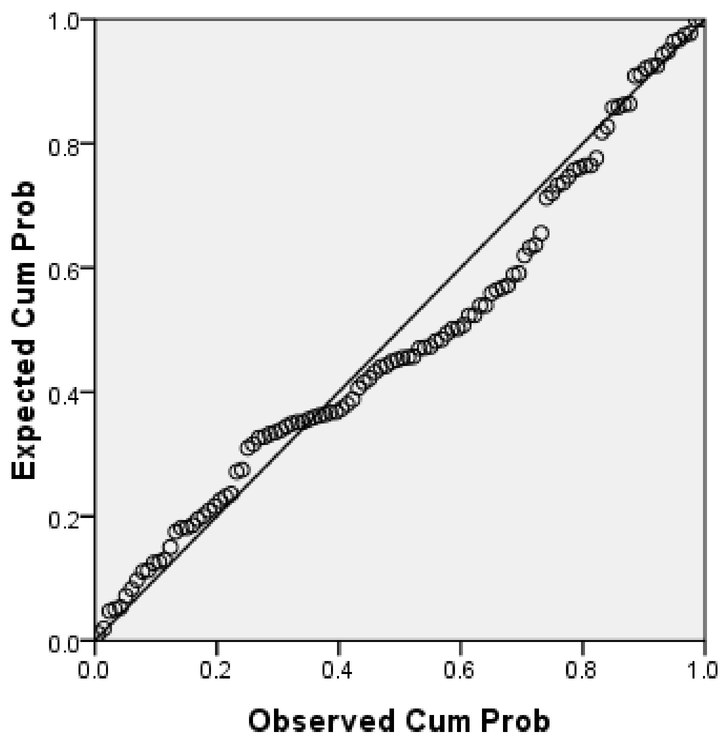
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.20: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 smart

Table A-V.21: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 normal

R	R^2	Adjusted R^2	F test	P value
80.70	65.20	64.80	201.92	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	912.63	484.02	1.89	0.06
Constant *b*	2,049.71	144.25	14.21	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



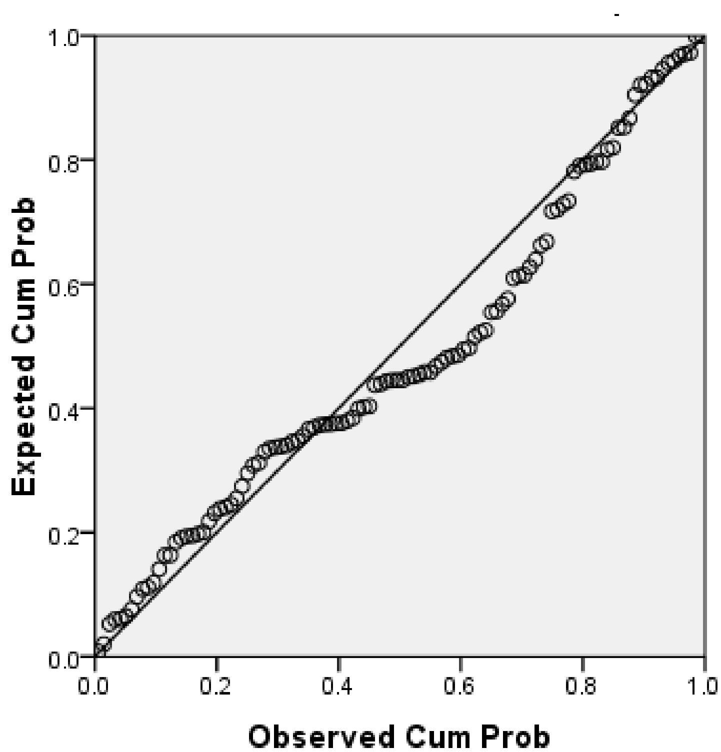
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.21: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 normal

Table A-V.22: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 sprawl

R	R^2	Adjusted R^2	F test	P value
81.30	66.10	65.80	210.98	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	990.20	469.97	2.11	0.04
Constant *b*	1,826.55	125.75	14.53	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



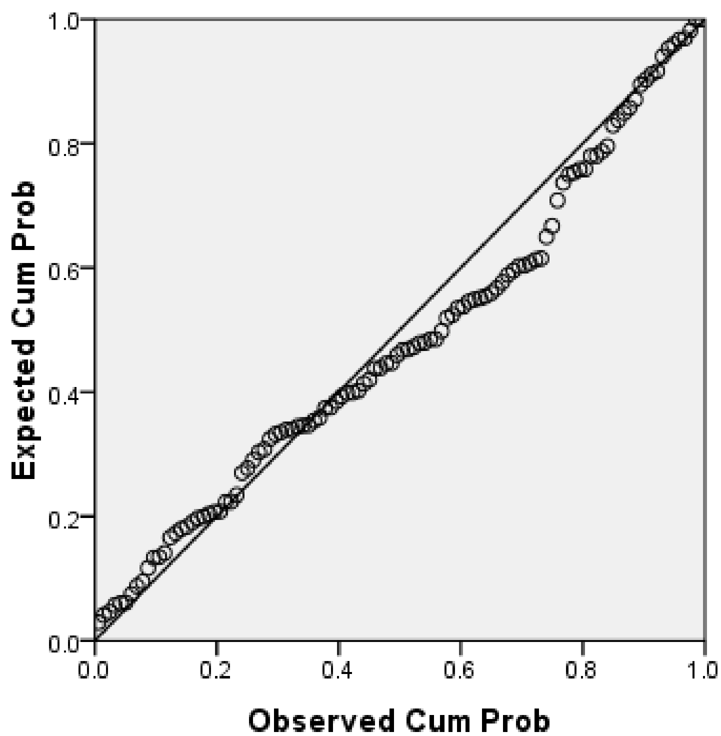
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.22: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 sprawl

Table A-V.23: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 smart

R	R^2	Adjusted R^2	F test	P value
78.20	61.10	60.70	169.47	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	494.85	603.34	0.82	0.41
Constant *b*	2,740.16	210.49	13.02	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



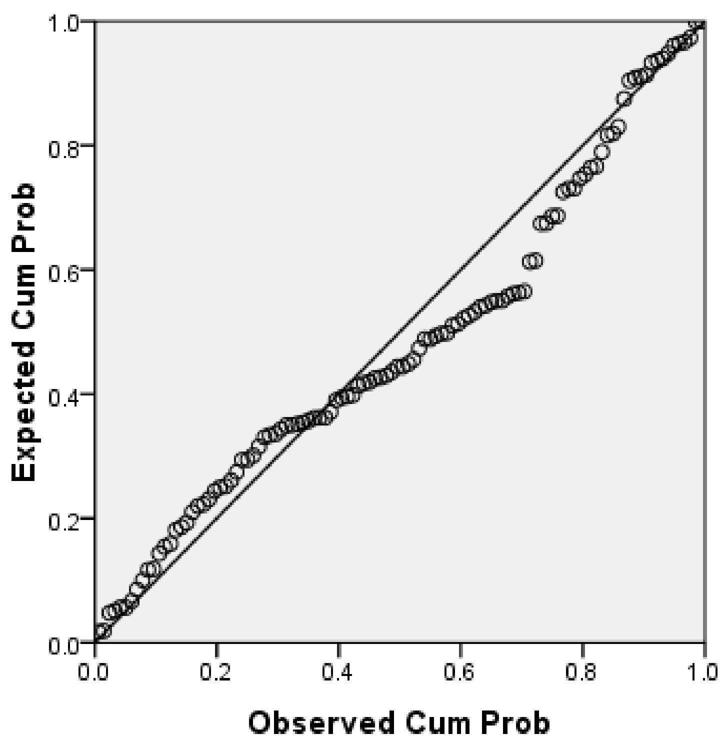
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.23: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 smart

Table A-V.24: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 normal

R	R^2	Adjusted R^2	F test	P value
81.30	66.00	65.70	210.07	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	414.29	552.51	0.75	0.46
Constant *b*	2,217.26	152.98	14.49	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



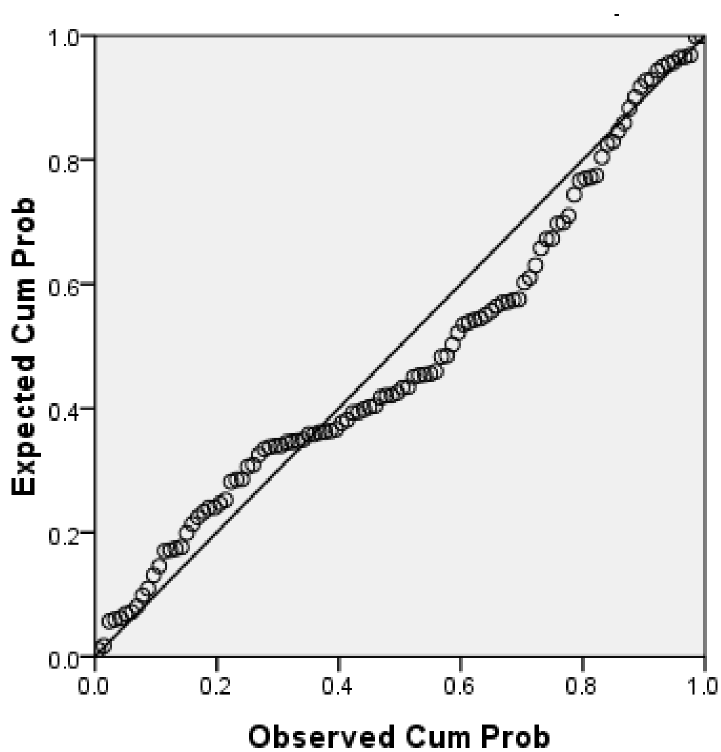
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.24: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 normal

Table A-V.25: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 sprawl

R	R^2	Adjusted R^2	F test	P value
82.20	67.60	67.30	224.99	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	491.08	531.26	0.92	0.36
Constant *b*	1,935.29	129.02	150.00	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



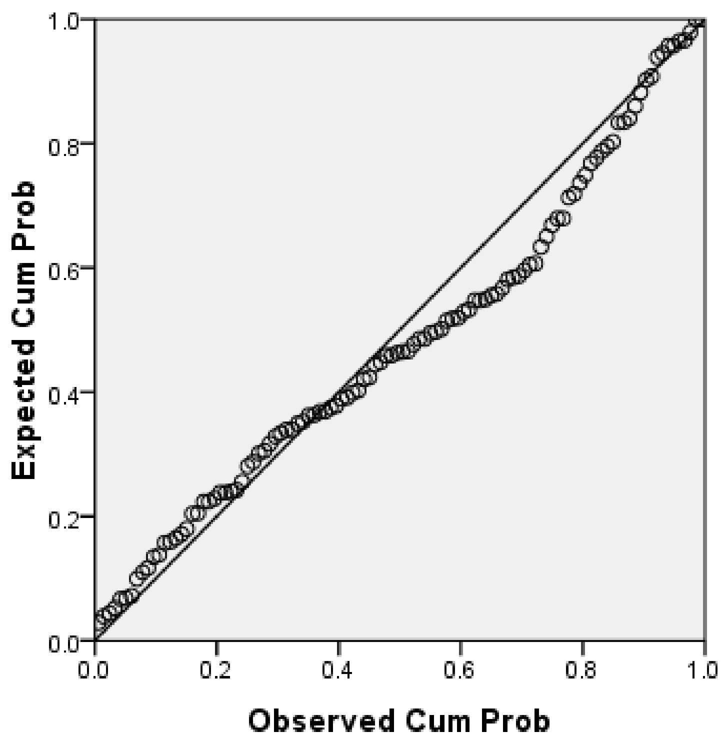
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.25: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 sprawl

Table A-V.26: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 smart

R	R^2	Adjusted R^2	F test	P value
77.80	60.50	60.10	165.23	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	-52.89	697.44	-0.08	0.94
Constant *b*	3,096.88	240.92	12.85	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



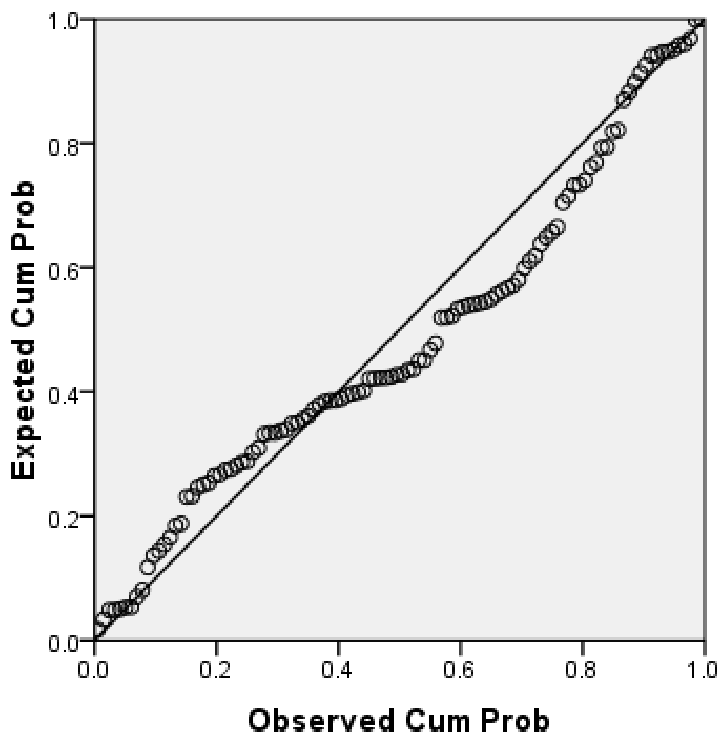
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.26: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 smart

Table A-V.27: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 normal

R	R^2	Adjusted R^2	F test	P value
81.60	66.50	66.20	214.82	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	-1,080.00	623.03	-0.17	0.86
Constant *b*	2,348.48	160.23	14.66	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



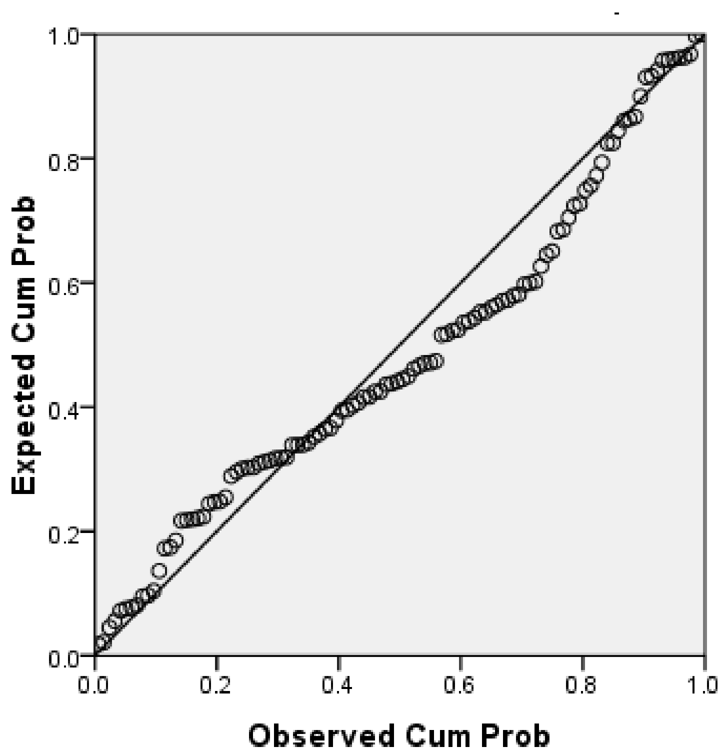
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.27: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 normal

Table A-V.28: Linear Regression for all Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 sprawl

R	R^2	Adjusted R^2	F test	P value
82.40	68.00	67.70	229.14	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	-28.06	600.65	-0.05	0.96
Constant *b*	2,013.32	133.00	15.14	0.00

Notes: Linear Regression was based on all 110 census-tracts.
Values for R, R Square, and Adjusted R Square are percentages (the original values multiplied by 100).



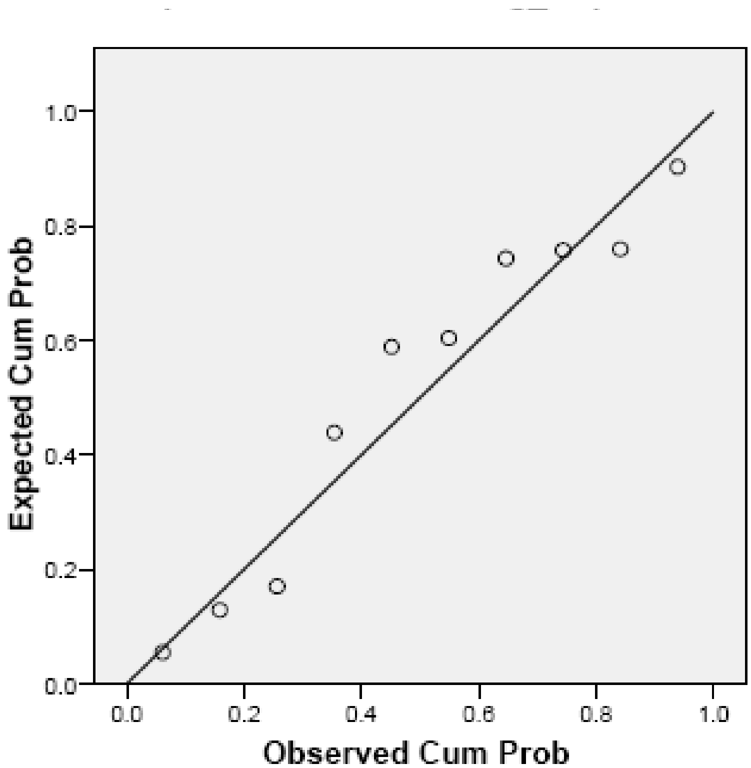
Note: The points represent the cumulative values of 110 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.28: Cumulative Plot in Percentages for all 110 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 sprawl

Table A-V.29: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1974

R	R^2	Adjusted R^2	F test	P value
85.40	72.90	69.60	21.56	0.00
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.42	0.04	78.93	0.00
Constant *b*	1.37	0.29	4.64	0.00

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results a and b coefficients are very important values that will be used after in the allometric growth model.



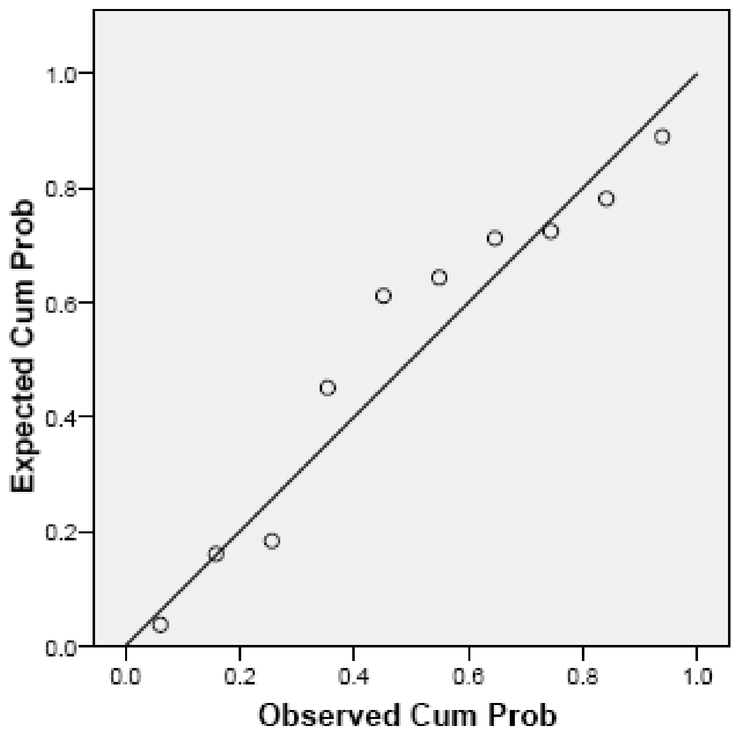
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.29: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1974

Table A-V.30: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1975

R	R^2	Adjusted R^2	F test	P value
82.30	67.80	63.70	16.82	0.00
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.41	0.05	75.38	0.00
Constant *b*	1.32	0.32	4.10	0.00

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results a and b coefficients are very important values that will be used after in the allometric growth model.



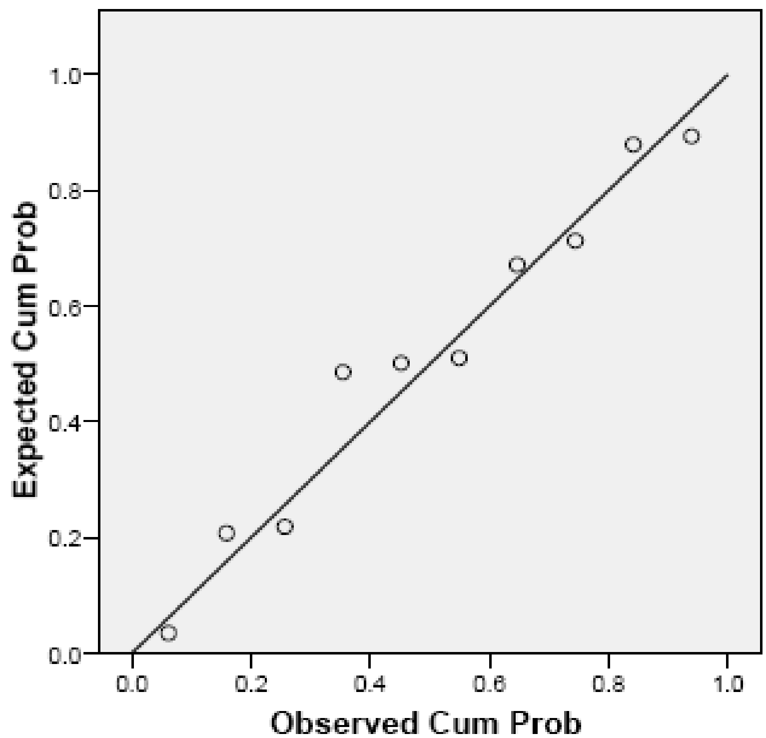
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.30: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1975

Table A-V.31: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1980

R	R^2	Adjusted R^2	F test	P value
64.40	41.40	34.10	5.66	0.05
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.41	0.06	59.18	0.00
Constant *b*	1.01	0.42	2.38	0.05

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

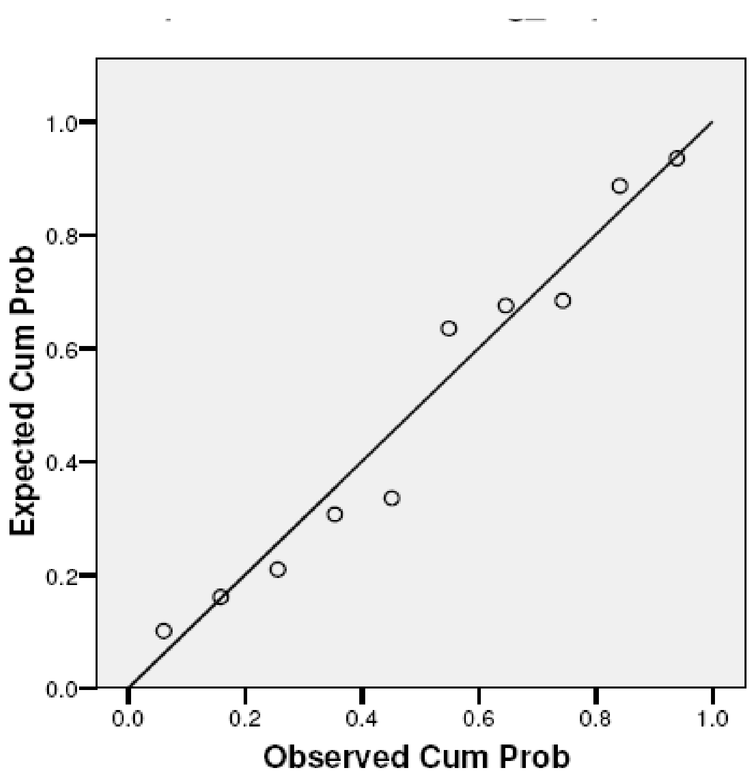
Figure A-V.31: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1980

Table A-V.32: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1985

R	R^2	Adjusted R^2	F test	P value
59.20	35.00	26.90	4.31	0.07

Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.45	0.06	55.00	0.00
Constant *b*	0.87	0.42	2.08	0.07

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



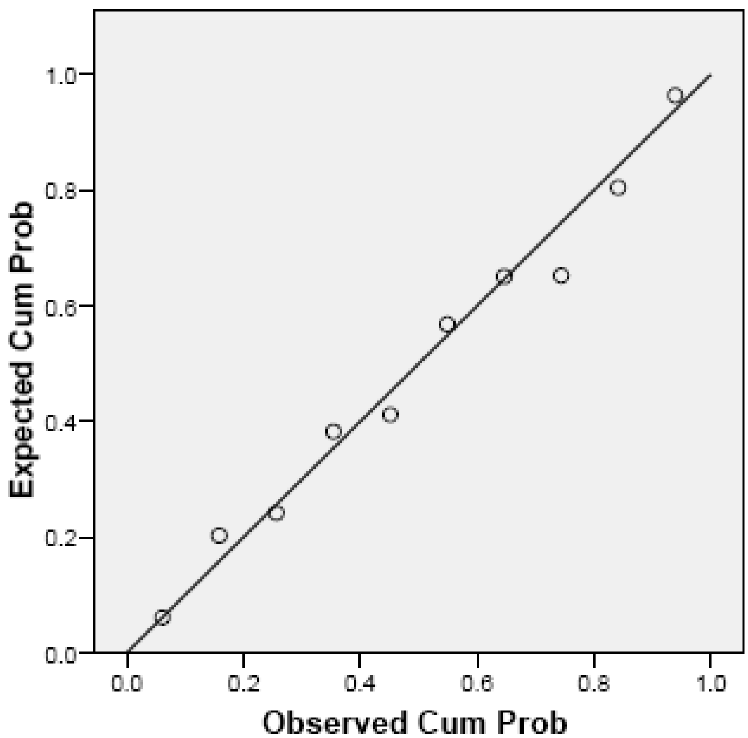
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.32: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1985

Table A-V.33: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1986

R	R^2	Adjusted R^2	F test	P value
50.90	25.90	16.70	2.80	0.13
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.47	0.07	52.75	0.00
Constant *b*	0.49	0.29	1.67	0.13

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



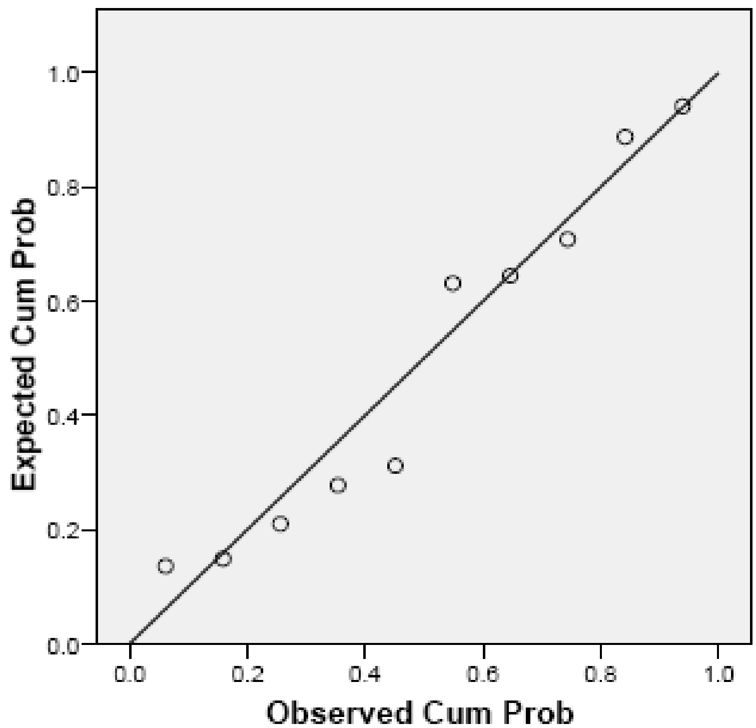
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.33: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1986

Table A-V.34: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1986

R	R^2	Adjusted R^2	F test	P value
57.60	33.20	24.80	3.97	0.08
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.46	0.07	52.72	0.00
Constant *b*	0.85	0.42	1.99	0.08

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



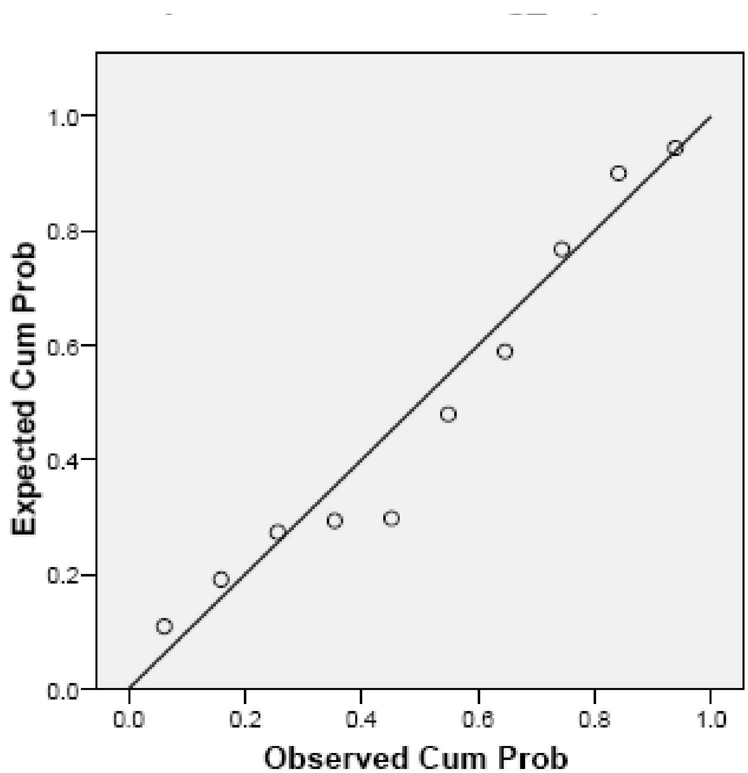
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.34: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1986

Table A-V.35: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1990

R	R^2	Adjusted R^2	F test	P value
50.80	25.80	16.50	2.78	0.13
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.46	0.08	41.92	0.00
Constant *b*	0.77	0.46	1.67	0.13

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



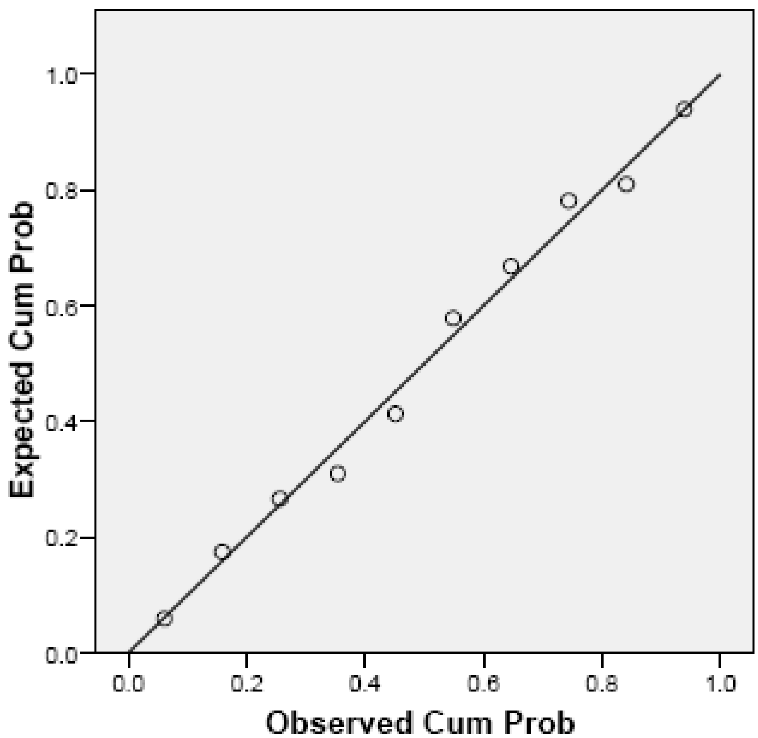
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.35: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1990

Table A-V.36: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1992

R	R^2	Adjusted R^2	F test	P value
65.30	42.60	35.50	5.95	0.04
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.45	0.07	50.41	0.00
Constant *b*	0.60	0.25	2.44	0.04

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



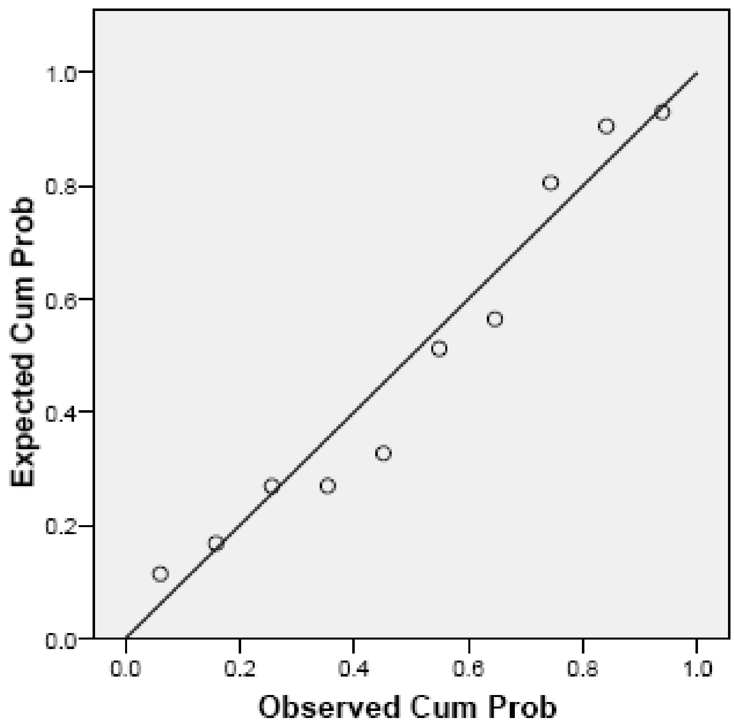
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.36: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 1992

Table A-V.37: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1992

R	R^2	Adjusted R^2	F test	P value
51.00	26.00	16.70	2.81	0.13
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.45	0.09	38.37	0.00
Constant *b*	0.78	0.46	1.68	0.13

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



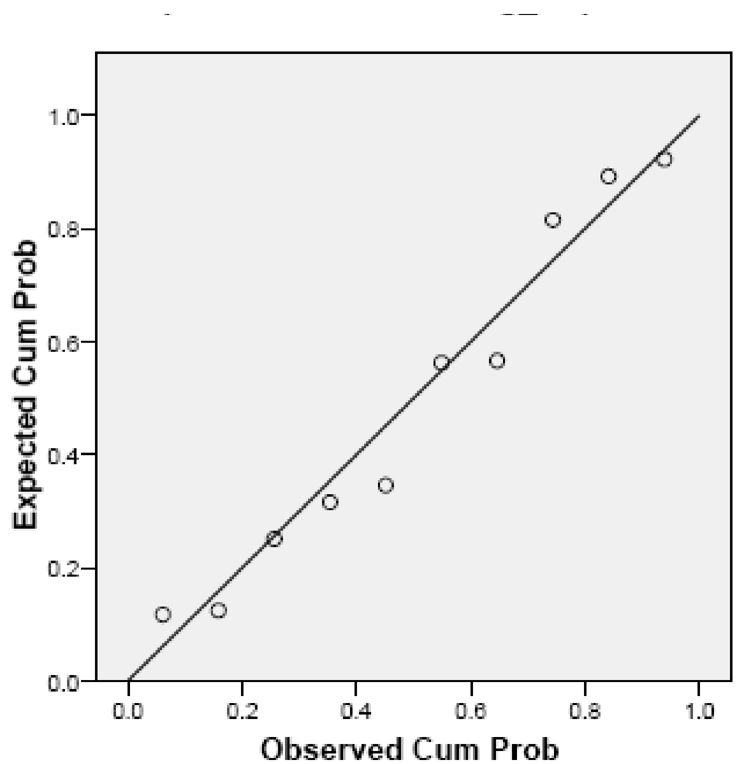
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.37: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1992

Table A-V.38: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1995

R	R^2	Adjusted R^2	F test	P value
56.50	31.90	23.40	3.75	0.09
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.43	0.10	34.35	0.00
Constant *b*	0.89	0.46	1.94	0.09

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

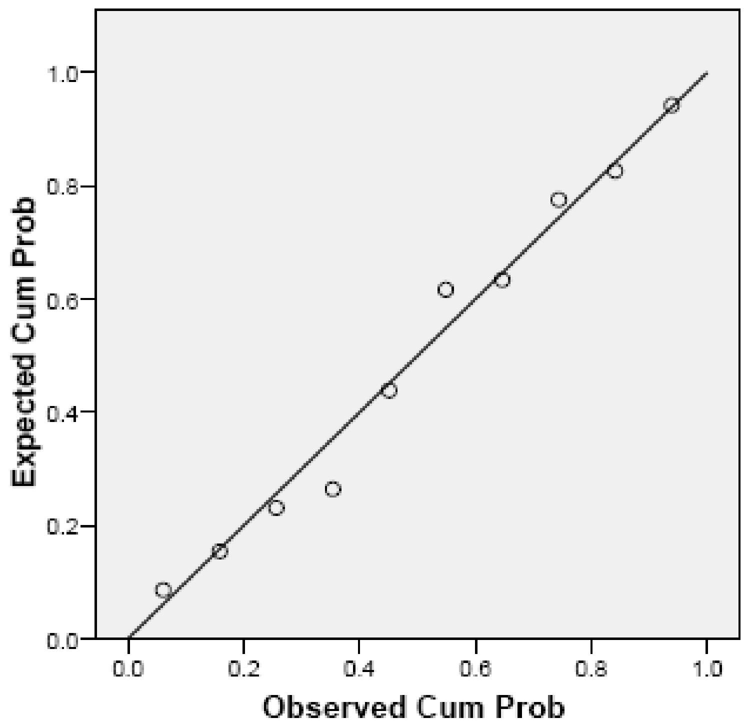
Figure A-V.38: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 1995

Table A-V.39: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2000

R	R^2	Adjusted R^2	F test	P value
68.10	46.30	39.60	6.91	0.03

Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.33	0.12	27.86	0.00
Constant *b*	1.22	0.46	2.63	0.03

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



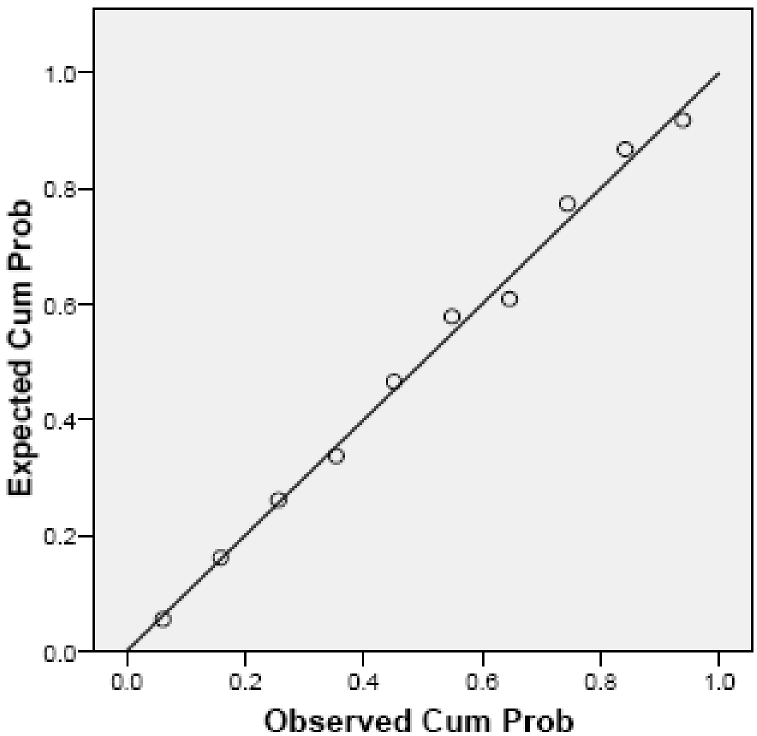
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.39: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2000

Table A-V.40: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 2001

R	R^2	Adjusted R^2	F test	P value
69.00	47.50	41.00	7.25	0.03
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.46	0.08	42.96	0.00
Constant *b*	0.69	0.26	2.69	0.03

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



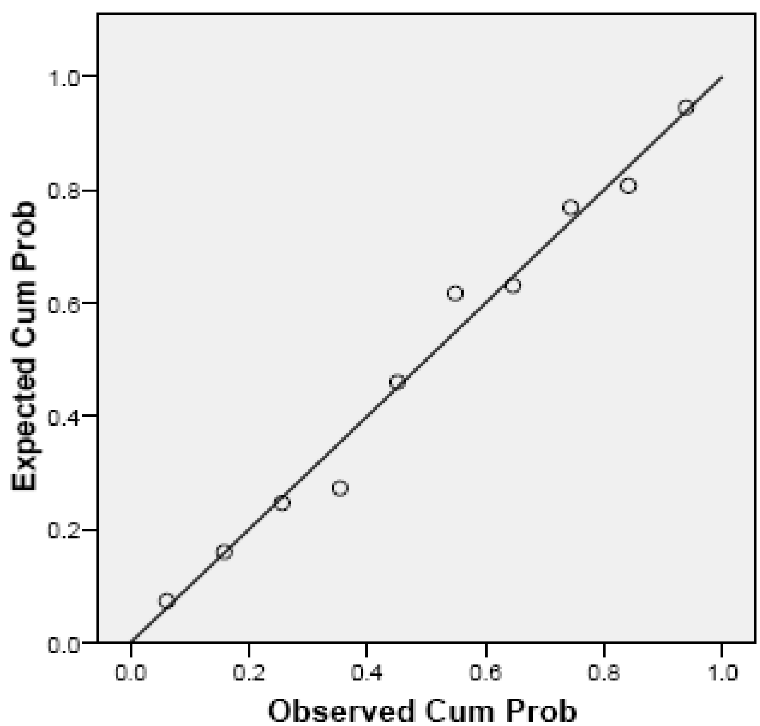
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.40: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Classified Image 2001

Table A-V.41: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2001

R	R^2	Adjusted R^2	F test	P value
69.20	47.90	41.40	7.35	0.03
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.32	0.12	27.47	0.00
Constant *b*	1.24	0.46	2.71	0.03

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



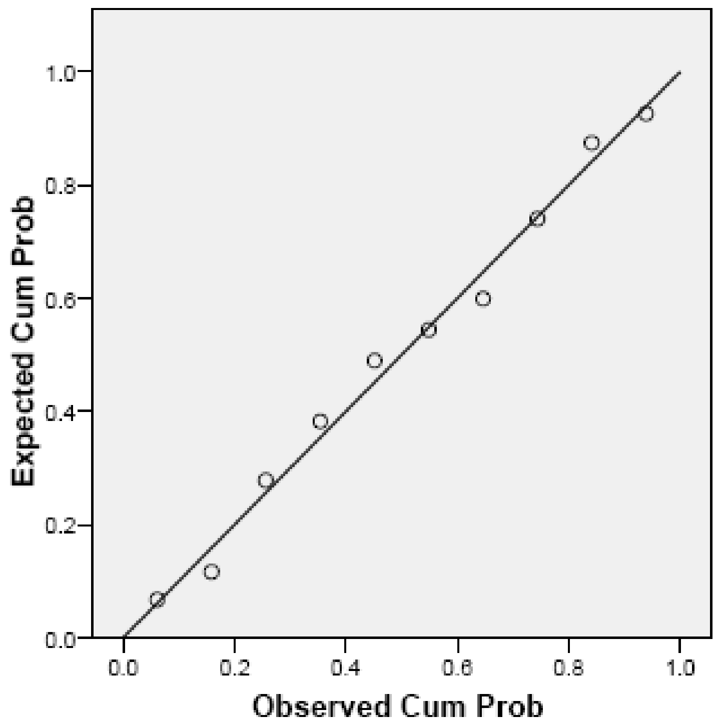
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.41: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2001

Table A-V.42: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 smart

R	R^2	Adjusted R^2	F test	P value
69.80	48.70	42.30	7.60	0.03
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.47	0.09	40.80	0.00
Constant *b*	0.73	0.27	2.76	0.03

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



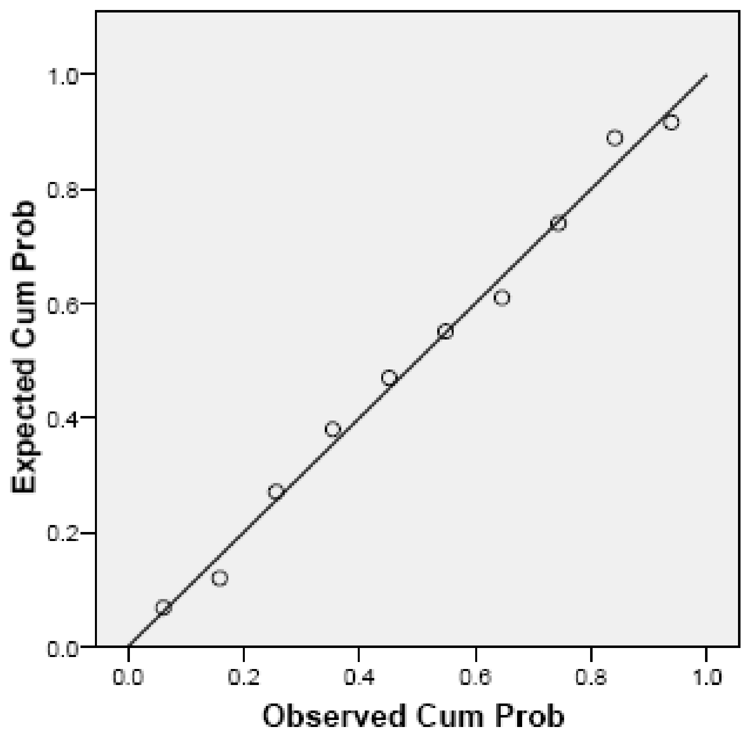
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.42: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 smart

Table A-V.43: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 normal

R	R^2	Adjusted R^2	F test	P value
70.20	49.30	43.00	7.78	0.02
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.45	0.09	39.00	0.00
Constant *b*	0.75	0.27	2.79	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



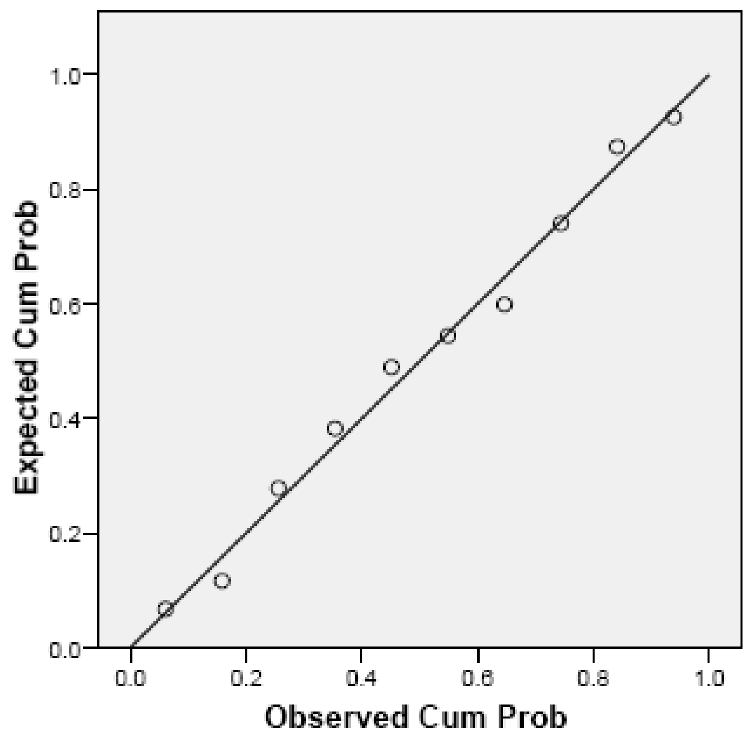
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.43: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 normal

Table A-V.44: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 sprawl

R	R^2	Adjusted R^2	F test	P value
71.10	50.60	44.40	8.19	0.02
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.44	0.09	38.01	0.00
Constant *b*	0.75	0.26	2.86	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



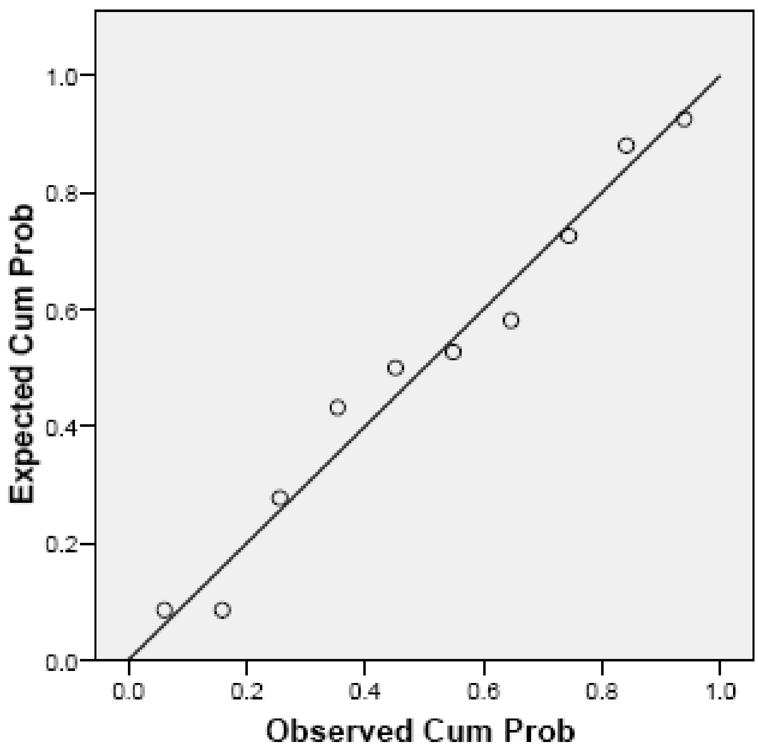
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.44: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 sprawl

Table A-V.45: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 smart

R	R^2	Adjusted R^2	F test	P value
68.30	46.70	40.00	7.00	0.03
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.49	0.09	37.54	0.00
Constant *b*	0.76	0.29	2.65	0.03

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



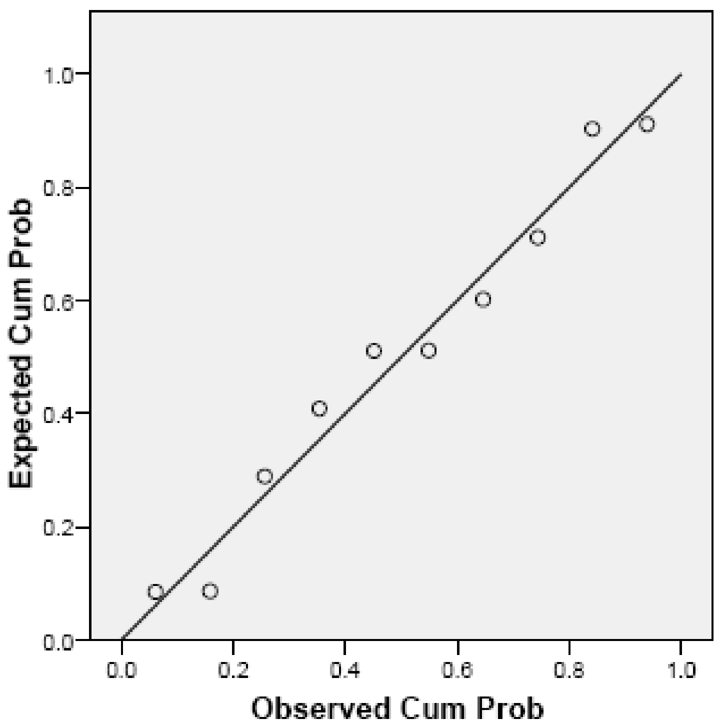
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.45: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 smart

Table A-V.46: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 normal

R	R^2	Adjusted R^2	F test	P value
70.30	49.40	43.10	7.82	0.02
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.44	0.10	33.60	0.00
Constant *b*	0.81	0.29	2.80	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



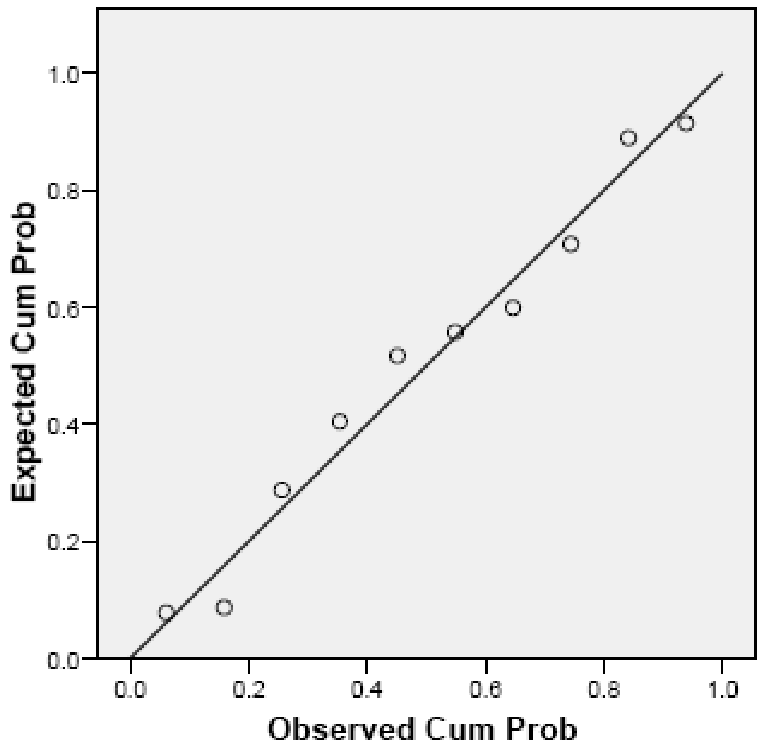
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.46: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 normal

Table A-V.47: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2010 sprawl

R	R^2	Adjusted R^2	F test	P value
72.80	53.00	47.20	9.04	0.02
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.42	0.10	33.02	0.00
Constant *b*	0.81	0.27	3.01	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results a and b coefficients are very important values that will be used after in the allometric growth model.



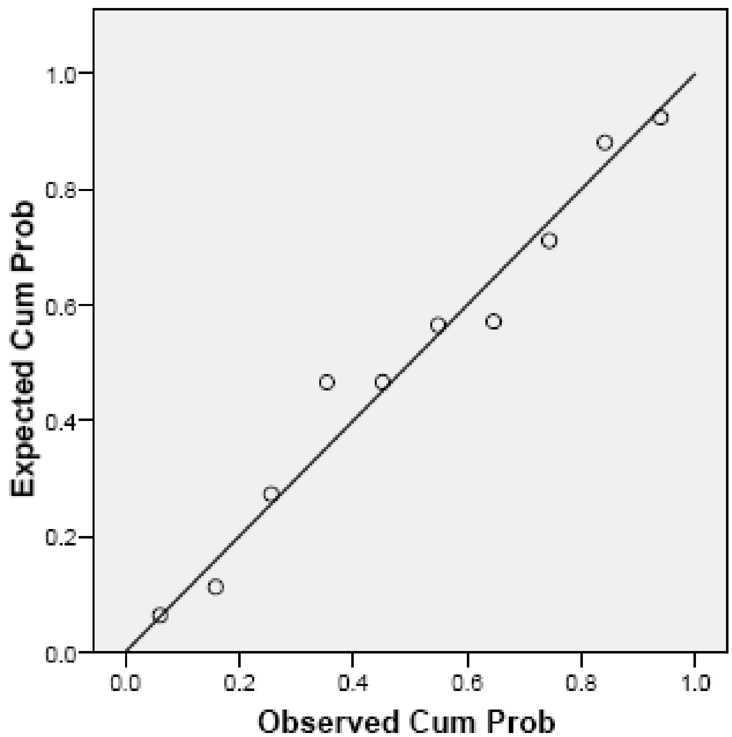
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.47: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2005 sprawl

Table A-V.48: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 smart

R	R^2	Adjusted R^2	F test	P value
66.00	43.60	36.60	6.19	0.04
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.51	0.10	34.26	0.00
Constant *b*	0.78	0.32	2.49	0.04

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



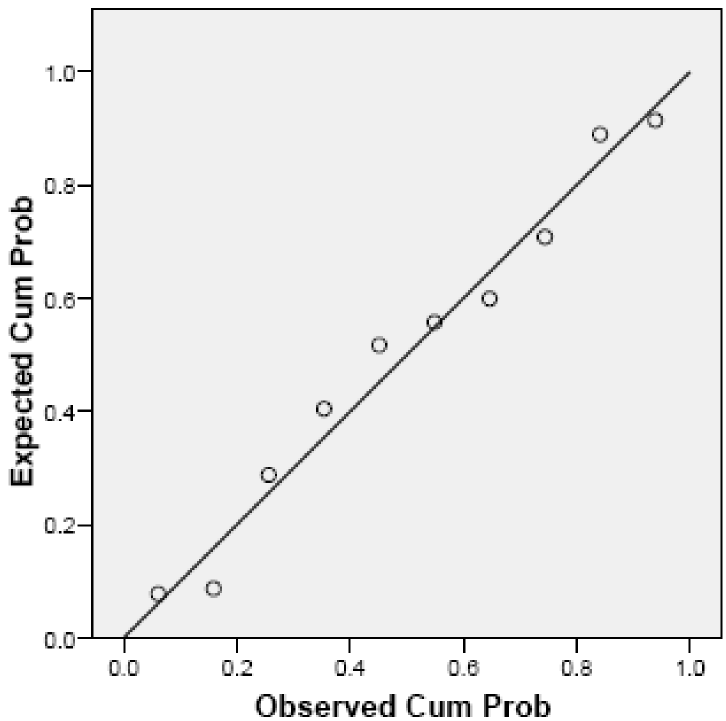
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.48: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 smart

Table A-V.49: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 normal

R	R^2	Adjusted R^2	F test	P value
70.50	49.70	43.50	7.92	0.02
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.44	0.11	30.13	0.00
Constant *b*	0.85	0.30	2.81	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



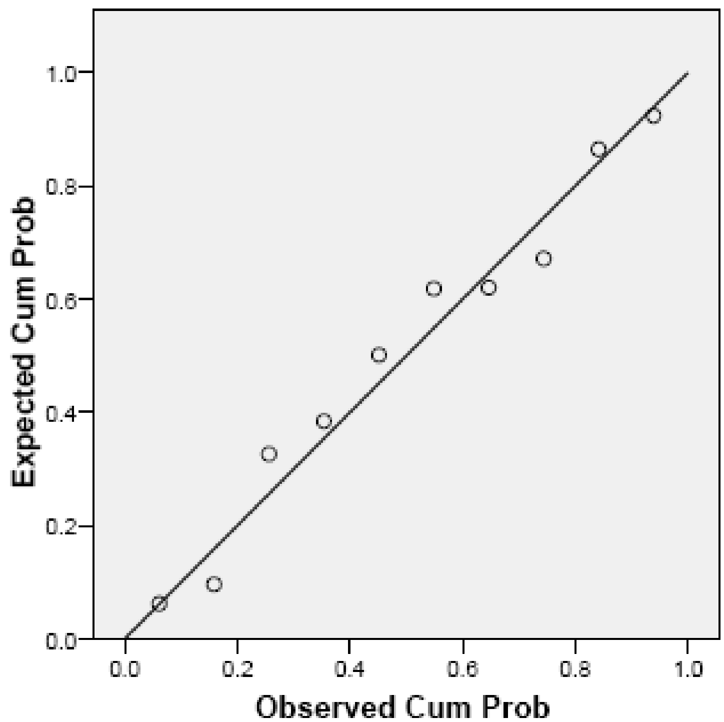
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.49: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 normal

Table A-V.50: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 sprawl

R	R^2	Adjusted R^2	F test	P value
74.70	55.80	50.30	10.10	0.01
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.39	0.12	29.36	0.00
Constant *b*	0.86	0.27	3.18	0.01

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



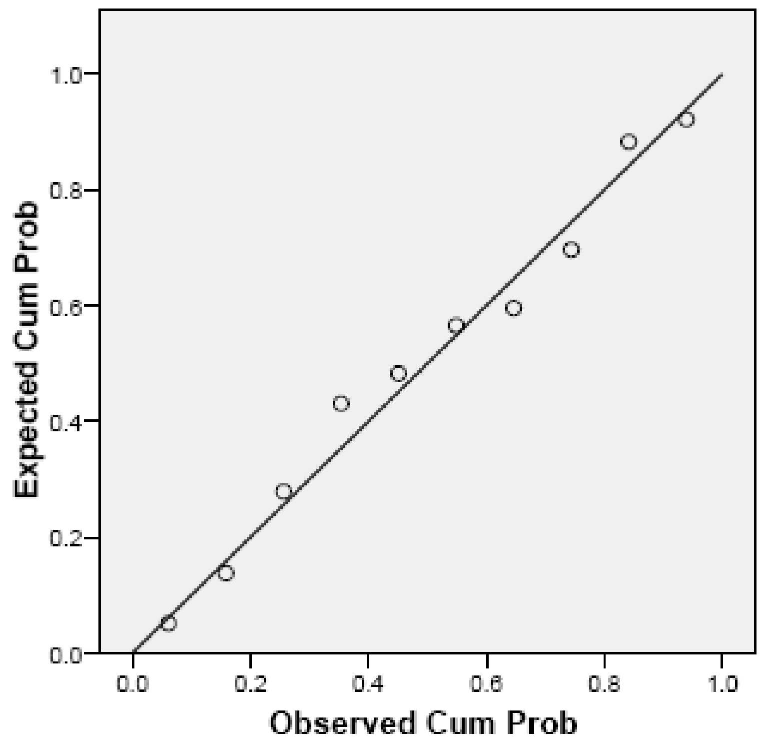
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.50: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2015 sprawl

Table A-V.51: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 smart

R	R^2	Adjusted R^2	F test	P value
64.50	41.50	34.20	5.69	0.04
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.52	0.11	31.70	0.00
Constant *b*	0.81	0.34	2.38	0.04

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



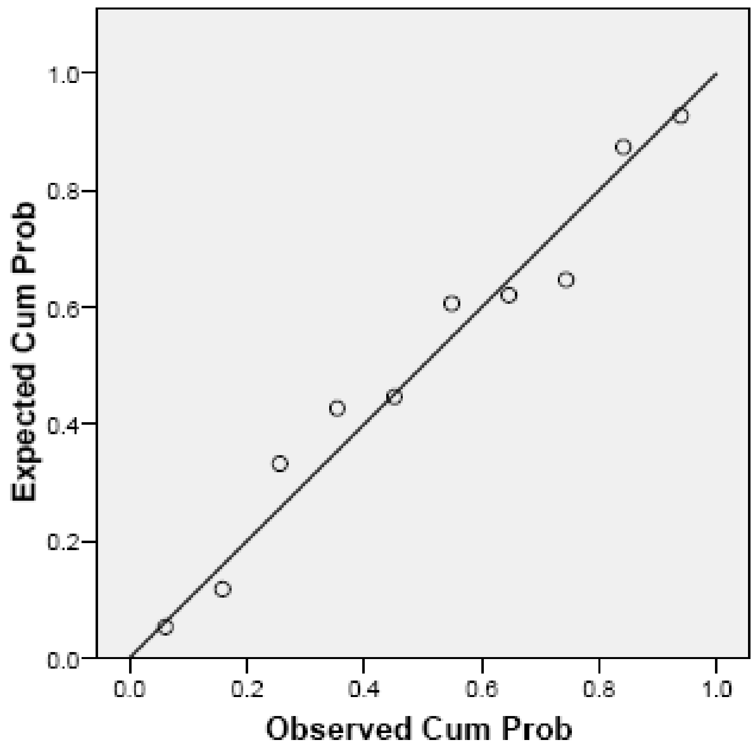
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.51: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 smart

Table A-V.52: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 normal

R	R^2	Adjusted R^2	F test	P value
72.90	53.20	47.30	9.08	0.02
Model	Coefficients			
	Constants	Std. Error	t test	P value
Constant *a*	3.41	0.12	27.81	0.00
Constant *b*	0.91	0.30	3.01	0.02

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



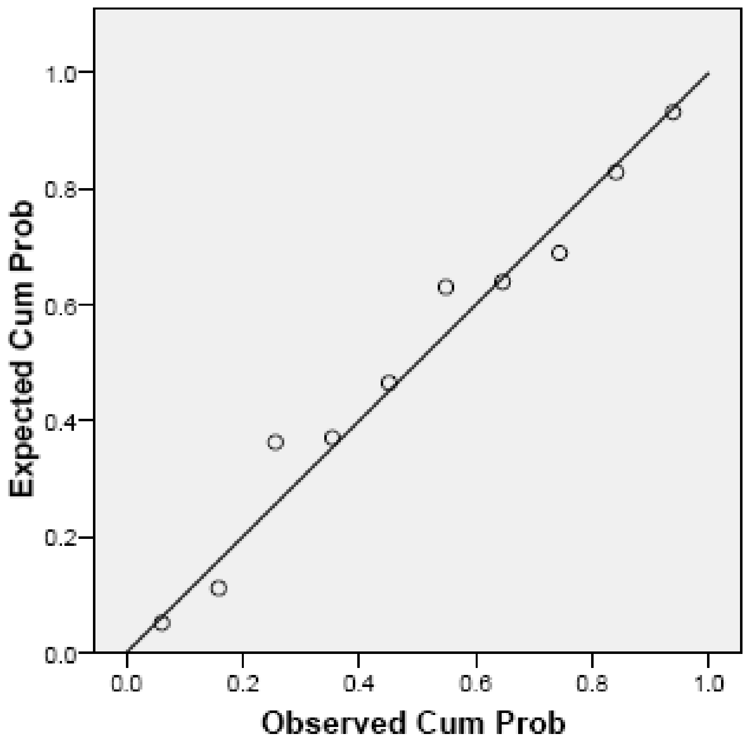
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.52: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 normal

Table A-V.53: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 sprawl

R	R^2	Adjusted R^2	F test	P value
77.80	60.50	55.60	12.27	0.01
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.34	0.13	26.77	0.00
Constant *b*	0.94	0.27	3.50	0.01

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



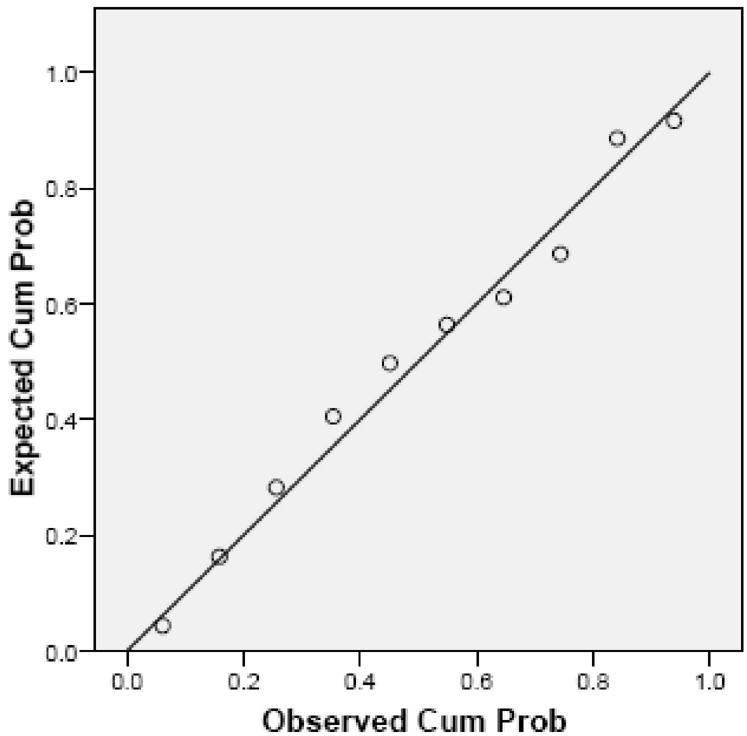
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.53: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2020 sprawl

Table A-V.54: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 smart

R	R^2	Adjusted R^2	F test	P value
62.50	39.00	31.40	5.12	0.05
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.53	0.12	29.02	0.00
Constant *b*	0.83	0.37	2.26	0.05

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



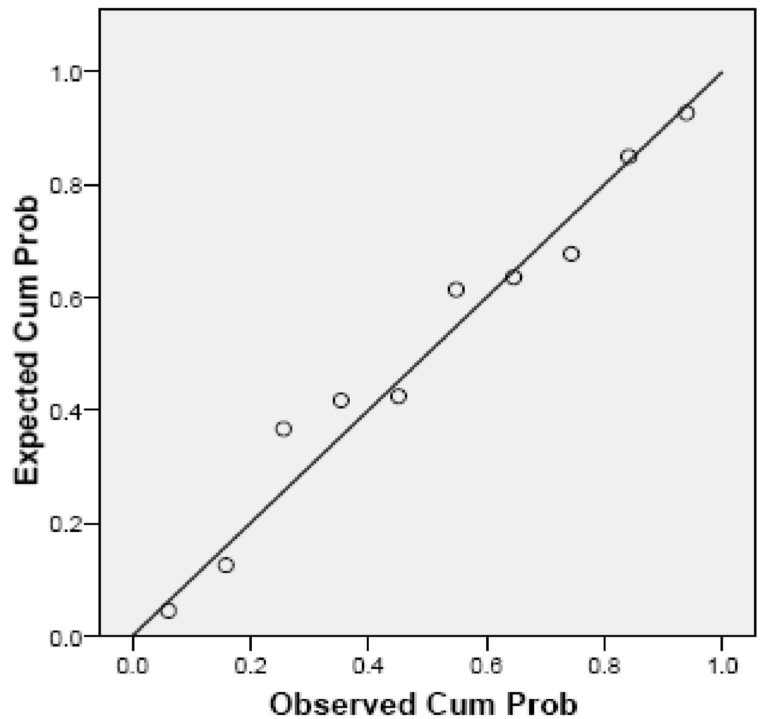
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.54: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 normal

Table A-V.55: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 normal

R	R^2	Adjusted R^2	F test	P value
75.20	56.60	51.20	10.44	0.01
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.36	0.13	25.11	0.00
Constant *b*	1.00	0.31	3.23	0.01

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



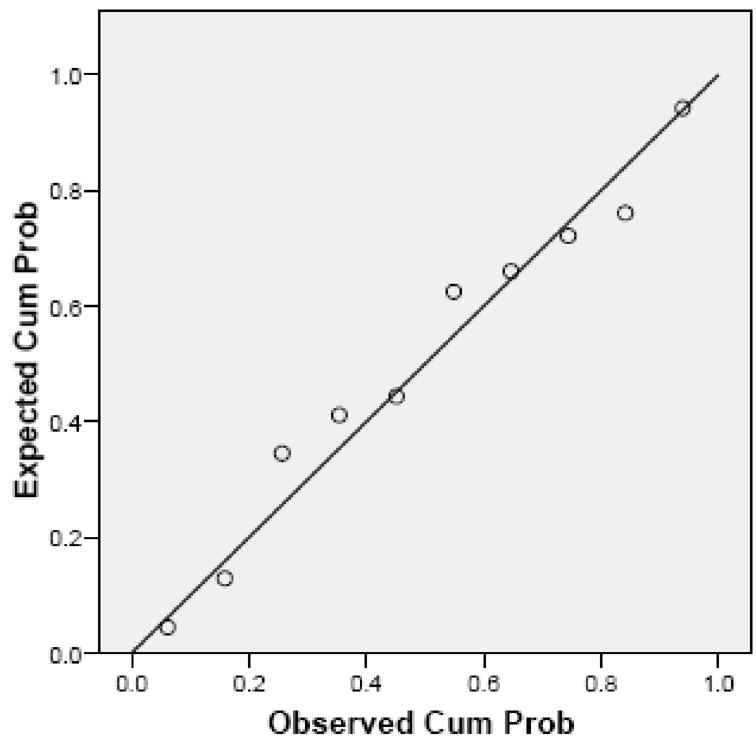
Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.55: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 normal

Table A-V.56: Linear Regression for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 sprawl

R	R^2	Adjusted R^2	F test	P value
80.70	65.10	60.70	14.89	0.01
	Coefficients			
Model	Constants	Std. Error	t test	P value
Constant *a*	3.29	0.13	25.14	0.00
Constant *b*	1.01	0.26	3.86	0.01

Notes: Linear regression was based on just 10 selected census-tracts.
Therefore, R, R Square, Adjusted R Square (in percentages) and the Std. Error of the Estimate are just partial results.
a and b coefficients are very important values that will be used after in the allometric growth model.



Note: The points represent the cumulative values of 10 different census-tracts with their respective Urban Areas (independent variable X) and Population Estimations (dependent variable Y).

Figure A-V.56: Cumulative Plot in Percentages for 10 Census-tracts: Population Estimations based on Urban Areas of Simulation 2025 sprawl

Table A-V.57: Allometric Growth Model and RMSE for Real 1974 in Escambia county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	3,743	3.42	1.37	1.68	0.23	3.73	5,376	1,633	2,666,923
1	4,607	3.42	1.37	2.66	0.42	4.00	10,016	5,409	29,252,264
2	5,517	3.42	1.37	1.30	0.11	3.57	3,757	-1,760	3,098,293
3	2,253	3.42	1.37	0.70	-0.16	3.21	1,609	-644	414,930
4	4,180	3.42	1.37	1.35	0.13	3.60	3,983	-197	38,770
5	8,569	3.42	1.37	3.19	0.50	4.11	12,866	4,297	18,462,892
6	3,391	3.42	1.37	0.94	-0.03	3.38	2,421	-970	940,409
7	5,218	3.42	1.37	2.24	0.35	3.90	7,951	2,733	7,468,903
8	2,662	3.42	1.37	1.10	0.04	3.48	3,009	347	120,325
9	3,595	3.42	1.37	1.98	0.30	3.83	6,686	3,091	9,554,154
10	2,089	3.42	1.37	0.79	-0.10	3.28	1,923		
11	4,538	3.42	1.37	2.48	0.39	3.96	9,109	4,571	20,896,975
12	4,567	3.42	1.37	2.59	0.41	3.99	9,683	5,116	26,176,986
13	3,527	3.42	1.37	1.96	0.29	3.82	6,611	3,084	9,512,480
14	5,829	3.42	1.37	1.73	0.24	3.75	5,589	-240	57,590
15	3,373	3.42	1.37	2.12	0.33	3.87	7,369	3,996	15,965,513
16	5,077	3.42	1.37	2.82	0.45	4.04	10,859	5,782	33,430,931
17	3,305	3.42	1.37	1.14	0.06	3.50	3,161	-144	20,737
18	3,424	3.42	1.37	1.36	0.13	3.60	4,016	592	350,128
19	4,824	3.42	1.37	2.49	0.40	3.96	9,191	4,367	19,068,480
20	4,587	3.42	1.37	1.28	0.11	3.57	3,693		
21	2,967	3.42	1.37	1.01	0.01	3.43	2,681	-286	81,539
22	3,623	3.42	1.37	1.32	0.12	3.59	3,853	230	53,063
23	6,708	3.42	1.37	2.35	0.37	3.93	8,465	1,757	3,086,997
24	6,511	3.42	1.37	1.48	0.17	3.65	4,513	-1,998	3,990,618
25	7,125	3.42	1.37	1.59	0.20	3.70	4,957	-2,168	4,700,550
26	4,692	3.42	1.37	2.22	0.35	3.89	7,834	3,142	9,869,244
27	1,196	3.42	1.37	0.36	-0.44	2.82	664	-532	282,844
28	3,552	3.42	1.37	2.02	0.30	3.84	6,874	3,322	11,034,561
29	869	3.42	1.37	0.22	-0.66	2.52	331	-538	289,931
30	4,099	3.42	1.37	1.19	0.08	3.52	3,346		
31	2,265	3.42	1.37	0.61	-0.22	3.13	1,335	-930	865,798
32	3,369	3.42	1.37	0.96	-0.02	3.40	2,507	-862	742,712
33	2,282	3.42	1.37	0.63	-0.20	3.15	1,408	-874	763,938
34	2,874	3.42	1.37	0.68	-0.17	3.19	1,558	-1,316	1,731,964
35	5,699	3.42	1.37	1.34	0.13	3.59	3,918	-1,781	3,171,666
36	7,232	3.42	1.37	1.68	0.23	3.73	5,376	-1,856	3,444,470
37	5,522	3.42	1.37	1.09	0.04	3.47	2,949	-2,573	6,622,394
38	3,766	3.42	1.37	1.51	0.18	3.67	4,649	883	779,058
39	4,917	3.42	1.37	2.58	0.41	3.98	9,601	4,684	21,937,684
40	1,228	3.42	1.37	0.59	-0.23	3.11	1,286		
41	4,428	3.42	1.37	2.31	0.36	3.92	8,266	3,838	14,732,175
42	1,084	3.42	1.37	0.36	-0.45	2.81	644	-440	193,520
43	3,682	3.42	1.37	1.84	0.26	3.78	6,058	2,376	5,644,885
44	1,409	3.42	1.37	0.66	-0.18	3.18	1,508	99	9,704
45	4,851	3.42	1.37	2.49	0.40	3.96	9,150	4,299	18,481,485
46	4,822	3.42	1.37	2.94	0.47	4.06	11,503	6,681	44,639,961
47	3,397	3.42	1.37	2.40	0.38	3.94	8,705	5,308	28,176,191
48	4,924	3.42	1.37	2.71	0.43	4.01	10,267	5,343	28,543,771
49	3,511	3.42	1.37	1.74	0.24	3.75	5,625	2,114	4,467,843
50	1,852	3.42	1.37	0.58	-0.24	3.09	1,238		
51	2,556	3.42	1.37	2.23	0.35	3.90	7,873	5,317	28,266,392
52	2,476	3.42	1.37	2.05	0.31	3.85	7,025	4,549	20,694,408
53	3,174	3.42	1.37	1.62	0.21	3.71	5,096	1,922	3,692,645
54	3,938	3.42	1.37	1.13	0.05	3.49	3,100	-838	702,399
55	3,129	3.42	1.37	0.86	-0.07	3.33	2,141	-988	976,712
56	4,279	3.42	1.37	1.09	0.04	3.47	2,979	-1,300	1,690,785
57	4,525	3.42	1.37	1.22	0.09	3.54	3,471	-1,054	1,110,605
Total	227,408			91.56			301,629	**RMSE**	**2,510.77**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.58: Allometric Growth Model and RMSE for Real 1974 in Santa Rosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,947	3.42	1.37	0.71	-0.15	3.22	1,660	-1,287	1,655,919
92	4,338	3.42	1.37	1.06	0.03	3.46	2,859	-1,479	2,188,045
93	1,609	3.42	1.37	0.42	-0.38	2.91	809	-800	639,694
94	4,313	3.42	1.37	0.75	-0.12	3.25	1,790	-2,523	6,363,757
95	3,512	3.42	1.37	1.80	0.25	3.77	5,876	2,364	5,590,218
96	2,343	3.42	1.37	0.88	-0.05	3.35	2,224	-119	14,185
97	7,842	3.42	1.37	3.21	0.51	4.11	12,955	5,113	26,144,216
98	2,178	3.42	1.37	0.87	-0.06	3.34	2,196	18	327
99	2,692	3.42	1.37	1.39	0.14	3.61	4,114	1,422	2,022,055
100	1,491	3.42	1.37	0.85	-0.07	3.32	2,113		
101	1,734	3.42	1.37	1.17	0.07	3.52	3,284	1,550	2,402,877
102	2,923	3.42	1.37	1.94	0.29	3.82	6,537	3,614	13,058,886
103	2,299	3.42	1.37	1.45	0.16	3.64	4,379	2,080	4,326,938
104	498	3.42	1.37	0.14	-0.86	2.24	176	-322	103,874
105	2,166	3.42	1.37	1.23	0.09	3.54	3,503	1,337	1,786,464
106	1,209	3.42	1.37	1.00	0.00	3.42	2,652	1,443	2,082,796
107	1,085	3.42	1.37	0.77	-0.11	3.27	1,843	758	574,793
108	1,578	3.42	1.37	0.56	-0.25	3.08	1,191	-387	149,882
109	5,645	3.42	1.37	1.18	0.07	3.52	3,315	-2,330	5,428,437
Total	52,402			21.40			63,477	**RMSE**	**2,510.77**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.59: Allometric Growth Model and RMSE for Real 1974 in Okaloosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	4,121	3.42	1.37	0.85	-0.07	3.32	2,113	-2,008	4,031,368
59	1,457	3.42	1.37	0.25	-0.60	2.60	399	-1,058	1,118,941
60	2,734	3.42	1.37	0.87	-0.06	3.34	2,196		
61	3,462	3.42	1.37	1.85	0.27	3.78	6,094	2,632	6,929,425
62	3,767	3.42	1.37	2.07	0.32	3.85	7,101	3,334	11,116,091
63	1,976	3.42	1.37	0.87	-0.06	3.34	2,168	192	36,997
64	2,049	3.42	1.37	1.64	0.21	3.71	5,165	3,116	9,711,693
65	2,895	3.42	1.37	1.36	0.13	3.60	4,016	1,121	1,256,005
66	1,986	3.42	1.37	0.78	-0.11	3.27	1,870	-116	13,525
67	1,384	3.42	1.37	0.72	-0.14	3.23	1,686	302	91,203
68	2,480	3.42	1.37	1.51	0.18	3.66	4,615	2,135	4,557,023
69	5,245	3.42	1.37	1.34	0.13	3.60	3,951	-1,294	1,675,586
70	6,458	3.42	1.37	1.83	0.26	3.78	6,021		
71	6,455	3.42	1.37	1.00	0.00	3.42	2,652	-3,803	14,461,367
72	5,592	3.42	1.37	2.13	0.33	3.87	7,407	1,815	3,294,704
73	1,879	3.42	1.37	0.37	-0.43	2.84	684	-1,195	1,427,040
74	2,746	3.42	1.37	0.75	-0.12	3.25	1,790	-956	913,265
75	1,667	3.42	1.37	0.57	-0.25	3.08	1,214	-453	204,764
76	1,763	3.42	1.37	0.96	-0.02	3.39	2,478	715	511,878
77	4,210	3.42	1.37	1.53	0.18	3.67	4,717	507	256,735
78	6,417	3.42	1.37	2.28	0.36	3.91	8,108	1,691	2,860,089
79	3,179	3.42	1.37	1.21	0.08	3.53	3,408	229	52,669
80	1,999	3.42	1.37	1.01	0.01	3.43	2,681		
81	4,136	3.42	1.37	1.51	0.18	3.67	4,649	513	262,803
82	4,287	3.42	1.37	2.16	0.33	3.88	7,561	3,274	10,722,004
83	2,394	3.42	1.37	1.21	0.08	3.53	3,408	1,014	1,029,205
84	3,877	3.42	1.37	1.52	0.18	3.67	4,683	806	649,045
85	1,384	3.42	1.37	0.71	-0.15	3.22	1,660	276	76,273
86	3,555	3.42	1.37	1.71	0.23	3.74	5,482	1,927	3,714,367
87	2,820	3.42	1.37	1.39	0.14	3.61	4,114	1,294	1,674,410
88	1,447	3.42	1.37	0.48	-0.32	2.98	962	-485	235,656
89	2,326	3.42	1.37	0.88	-0.05	3.35	2,224	-102	10,425
90	1,357	3.42	1.37	0.88	-0.05	3.35	2,224		
Total	103,504			40.20			119,505	**RMSE**	**2,510.77**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL REAL 74	Pop 383,314			Area 153.16			AntilogPop 484,610	**RMSE**	**2,510.77**

Table A-V.60: Allometric Growth Model and RMSE for Simulation 1975 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	3,548	3.41	1.32	1.71	0.23	3.72	5,191	1,643	2,699,529
1	4,454	3.41	1.32	2.70	0.43	3.98	9,480	5,026	25,264,686
2	5,260	3.41	1.32	1.30	0.12	3.56	3,633	-1,627	2,648,627
3	2,186	3.41	1.32	0.70	-0.15	3.21	1,612	-574	329,473
4	3,855	3.41	1.32	1.35	0.13	3.58	3,812	-43	1,824
5	8,246	3.41	1.32	3.26	0.51	4.08	12,156	3,910	15,285,457
6	3,292	3.41	1.32	0.96	-0.02	3.38	2,410	-882	777,264
7	5,216	3.41	1.32	2.28	0.36	3.88	7,577	2,361	5,573,932
8	2,652	3.41	1.32	1.10	0.04	3.46	2,907	255	65,116
9	3,690	3.41	1.32	2.01	0.30	3.81	6,425	2,735	7,480,493
10	2,187	3.41	1.32	0.81	-0.09	3.29	1,937		
11	4,750	3.41	1.32	2.52	0.40	3.94	8,663	3,913	15,307,764
12	4,557	3.41	1.32	2.62	0.42	3.96	9,144	4,587	21,037,367
13	3,527	3.41	1.32	2.01	0.30	3.81	6,425	2,898	8,398,688
14	5,772	3.41	1.32	1.78	0.25	3.74	5,485	-287	82,213
15	3,437	3.41	1.32	2.15	0.33	3.85	7,013	3,576	12,785,575
16	5,267	3.41	1.32	2.87	0.46	4.01	10,277	5,010	25,104,410
17	3,154	3.41	1.32	1.16	0.06	3.49	3,106	-48	2,275
18	3,303	3.41	1.32	1.38	0.14	3.59	3,903	600	359,938
19	4,690	3.41	1.32	2.51	0.40	3.94	8,626	3,936	15,490,252
20	4,419	3.41	1.32	1.30	0.12	3.56	3,633		
21	2,852	3.41	1.32	1.04	0.02	3.43	2,684	-168	28,359
22	3,519	3.41	1.32	1.35	0.13	3.58	3,812	293	86,019
23	6,582	3.41	1.32	2.41	0.38	3.91	8,152	1,570	2,463,401
24	6,271	3.41	1.32	1.49	0.17	3.64	4,333	-1,938	3,756,963
25	6,954	3.41	1.32	1.59	0.20	3.67	4,710	-2,244	5,037,613
26	4,519	3.41	1.32	2.24	0.35	3.87	7,399	2,880	8,297,068
27	1,256	3.41	1.32	0.41	-0.39	2.89	776	-480	230,436
28	3,754	3.41	1.32	2.03	0.31	3.81	6,528	2,774	7,694,191
29	814	3.41	1.32	0.23	-0.64	2.56	361	-453	205,253
30	4,346	3.41	1.32	1.23	0.09	3.53	3,367		
31	2,317	3.41	1.32	0.62	-0.21	3.14	1,372	-945	892,942
32	3,447	3.41	1.32	0.97	-0.01	3.39	2,464	-983	965,411
33	2,319	3.41	1.32	0.64	-0.19	3.15	1,419	-900	809,497
34	2,941	3.41	1.32	0.69	-0.16	3.19	1,563	-1,378	1,898,148
35	5,534	3.41	1.32	1.37	0.14	3.59	3,873	-1,661	2,760,012
36	7,178	3.41	1.32	1.73	0.24	3.72	5,256	-1,922	3,693,807
37	5,531	3.41	1.32	1.09	0.04	3.46	2,879	-2,652	7,033,134
38	3,917	3.41	1.32	1.55	0.19	3.66	4,552	635	402,720
39	4,880	3.41	1.32	2.62	0.42	3.96	9,144	4,264	18,178,719
40	1,319	3.41	1.32	0.62	-0.21	3.14	1,372		
41	4,771	3.41	1.32	2.31	0.36	3.89	7,720	2,949	8,694,309
42	1,170	3.41	1.32	0.36	-0.44	2.83	675	-495	244,814
43	3,973	3.41	1.32	1.85	0.27	3.76	5,783	1,810	3,277,540
44	1,521	3.41	1.32	0.67	-0.17	3.18	1,515	-6	37
45	4,823	3.41	1.32	2.54	0.40	3.94	8,736	3,913	15,312,533
46	4,963	3.41	1.32	2.99	0.48	4.04	10,856	5,893	34,728,979
47	3,517	3.41	1.32	2.46	0.39	3.92	8,406	4,889	23,903,072
48	5,098	3.41	1.32	2.72	0.43	3.98	9,593	4,495	20,207,731
49	3,831	3.41	1.32	1.79	0.25	3.74	5,518	1,687	2,846,669
50	1,981	3.41	1.32	0.61	-0.22	3.12	1,325		
51	2,727	3.41	1.32	2.27	0.36	3.88	7,541	4,814	23,177,921
52	2,642	3.41	1.32	2.13	0.33	3.84	6,943	4,301	18,497,865
53	3,386	3.41	1.32	1.68	0.22	3.70	5,062	1,676	2,807,372
54	3,733	3.41	1.32	1.15	0.06	3.49	3,078	-655	429,469
55	3,099	3.41	1.32	0.93	-0.03	3.37	2,330	-769	591,646
56	4,296	3.41	1.32	1.13	0.05	3.48	3,021	-1,275	1,626,716
57	4,451	3.41	1.32	1.26	0.10	3.54	3,455	-996	992,174
Total	227,694			93.24			290,987	**RMSE**	**2,277.78**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.61: Allometric Growth Model and RMSE for Simulation 1975 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,855	3.41	1.32	0.77	-0.11	3.26	1,810	-1,045	1,091,008
92	4,200	3.41	1.32	1.09	0.04	3.45	2,851	-1,349	1,820,131
93	1,616	3.41	1.32	0.43	-0.37	2.92	838	-778	605,283
94	3,828	3.41	1.32	0.78	-0.11	3.26	1,836	-1,992	3,969,317
95	3,628	3.41	1.32	1.82	0.26	3.75	5,650	2,022	4,090,205
96	2,420	3.41	1.32	0.92	-0.04	3.36	2,276	-144	20,598
97	7,442	3.41	1.32	3.27	0.51	4.09	12,236	4,794	22,978,157
98	2,209	3.41	1.32	0.89	-0.05	3.34	2,197	-12	143
99	2,748	3.41	1.32	1.44	0.16	3.62	4,147	1,399	1,957,751
100	1,551	3.41	1.32	0.87	-0.06	3.33	2,144		
101	1,768	3.41	1.32	1.20	0.08	3.51	3,250	1,482	2,197,707
102	2,948	3.41	1.32	1.99	0.30	3.80	6,357	3,409	11,619,520
103	2,500	3.41	1.32	1.51	0.18	3.64	4,395	1,895	3,590,965
104	538	3.41	1.32	0.44	-0.36	2.93	859	321	102,999
105	2,198	3.41	1.32	1.27	0.10	3.55	3,514	1,316	1,731,558
106	1,228	3.41	1.32	1.01	0.01	3.42	2,601	1,373	1,884,818
107	1,101	3.41	1.32	0.79	-0.10	3.27	1,861	760	577,551
108	1,601	3.41	1.32	0.57	-0.25	3.08	1,210	-391	153,002
109	5,520	3.41	1.32	1.21	0.08	3.52	3,279	-2,241	5,019,892
Total	51,899			22.26			63,312	**RMSE**	**2,277.78**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.62: Allometric Growth Model and RMSE for Simulation 1975 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	4,077	3.41	1.32	0.86	-0.07	3.32	2,092	-1,985	3,939,416
59	1,441	3.41	1.32	0.27	-0.57	2.65	448	-993	985,310
60	2,705	3.41	1.32	0.91	-0.04	3.35	2,250		
61	3,425	3.41	1.32	1.88	0.27	3.77	5,884	2,459	6,044,796
62	3,727	3.41	1.32	2.10	0.32	3.83	6,804	3,077	9,467,120
63	1,955	3.41	1.32	0.90	-0.05	3.35	2,223	268	72,063
64	2,027	3.41	1.32	1.67	0.22	3.70	5,029	3,002	9,013,625
65	2,864	3.41	1.32	1.37	0.14	3.59	3,873	1,009	1,017,418
66	1,965	3.41	1.32	0.79	-0.10	3.27	1,861	-104	10,823
67	1,370	3.41	1.32	0.76	-0.12	3.25	1,785	415	172,535
68	2,453	3.41	1.32	1.53	0.18	3.65	4,489	2,036	4,144,463
69	5,189	3.41	1.32	1.38	0.14	3.59	3,903	-1,286	1,653,929
70	6,389	3.41	1.32	1.86	0.27	3.76	5,817		
71	6,386	3.41	1.32	1.01	0.01	3.42	2,601	-3,785	14,327,082
72	5,532	3.41	1.32	2.15	0.33	3.85	7,048	1,516	2,297,178
73	1,859	3.41	1.32	0.38	-0.42	2.85	715	-1,144	1,308,497
74	2,717	3.41	1.32	0.76	-0.12	3.25	1,785	-932	867,929
75	1,649	3.41	1.32	0.57	-0.25	3.08	1,210	-439	192,857
76	1,744	3.41	1.32	0.96	-0.02	3.39	2,437	693	480,768
77	4,166	3.41	1.32	1.54	0.19	3.66	4,520	354	125,438
78	6,348	3.41	1.32	2.31	0.36	3.89	7,720	1,372	1,881,318
79	3,145	3.41	1.32	1.24	0.09	3.53	3,396	251	63,100
80	1,978	3.41	1.32	1.03	0.01	3.42	2,656		
81	4,092	3.41	1.32	1.58	0.20	3.67	4,678	586	343,215
82	4,241	3.41	1.32	2.22	0.35	3.87	7,329	3,088	9,534,311
83	2,368	3.41	1.32	1.22	0.09	3.52	3,338	970	940,355
84	3,836	3.41	1.32	1.54	0.19	3.66	4,520	684	468,092
85	1,370	3.41	1.32	0.71	-0.15	3.21	1,637	267	71,025
86	3,517	3.41	1.32	1.76	0.24	3.73	5,387	1,870	3,495,977
87	2,789	3.41	1.32	1.44	0.16	3.62	4,147	1,358	1,844,698
88	1,432	3.41	1.32	0.49	-0.31	3.00	1,009	-423	179,038
89	2,301	3.41	1.32	0.90	-0.05	3.35	2,223	-78	6,015
90	1,343	3.41	1.32	0.96	-0.02	3.38	2,410		
Total	102,400			41.04			117,224	**RMSE**	**2,277.78**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 75	Pop 381,993		Area 156.54		AntilogPop 471,523	**RMSE**	**2,277.78**

Table A-V.63: Allometric Growth Model and RMSE for Simulation 1980 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	2,707	3.41	1.01	1.79	0.25	3.66	4,578	1,871	3,499,523
1	3,748	3.41	1.01	2.91	0.46	3.87	7,461	3,713	13,789,876
2	4,131	3.41	1.01	1.34	0.13	3.53	3,411	-720	518,750
3	1,872	3.41	1.01	0.77	-0.11	3.29	1,956	84	7,089
4	2,564	3.41	1.01	1.40	0.15	3.55	3,577	1,013	1,026,802
5	6,778	3.41	1.01	3.60	0.56	3.97	9,242	2,464	6,070,572
6	2,830	3.41	1.01	1.02	0.01	3.41	2,600	-230	53,054
7	5,180	3.41	1.01	2.48	0.39	3.80	6,353	1,173	1,375,484
8	2,593	3.41	1.01	1.21	0.08	3.49	3,078	485	235,049
9	4,181	3.41	1.01	2.18	0.34	3.75	5,580	1,399	1,956,150
10	2,733	3.41	1.01	0.90	-0.05	3.36	2,288		
11	5,933	3.41	1.01	2.78	0.44	3.85	7,127	1,194	1,424,807
12	4,487	3.41	1.01	2.90	0.46	3.87	7,441	2,954	8,723,415
13	3,513	3.41	1.01	2.18	0.34	3.75	5,580	2,067	4,270,936
14	5,473	3.41	1.01	1.97	0.29	3.70	5,037	-436	190,319
15	3,760	3.41	1.01	2.37	0.37	3.78	6,060	2,300	5,290,791
16	6,299	3.41	1.01	3.26	0.51	3.92	8,362	2,063	4,255,166
17	2,488	3.41	1.01	1.22	0.08	3.49	3,099	611	372,857
18	2,748	3.41	1.01	1.47	0.17	3.58	3,765	1,017	1,033,783
19	4,056	3.41	1.01	2.74	0.44	3.85	7,022	2,966	8,797,416
20	3,655	3.41	1.01	1.42	0.15	3.56	3,619		
21	2,331	3.41	1.01	1.14	0.06	3.46	2,911	580	336,912
22	3,029	3.41	1.01	1.56	0.19	3.60	3,973	944	891,312
23	5,962	3.41	1.01	2.66	0.42	3.83	6,813	851	723,960
24	5,175	3.41	1.01	1.64	0.21	3.62	4,182	-993	987,020
25	6,136	3.41	1.01	1.82	0.26	3.67	4,661	-1,475	2,175,210
26	3,730	3.41	1.01	2.34	0.37	3.78	5,997	2,267	5,141,449
27	1,595	3.41	1.01	0.44	-0.36	3.04	1,108	-487	237,604
28	4,921	3.41	1.01	2.20	0.34	3.75	5,642	721	520,257
29	584	3.41	1.01	0.23	-0.63	2.77	592	8	67
30	5,794	3.41	1.01	1.38	0.14	3.55	3,515		
31	2,586	3.41	1.01	0.70	-0.15	3.25	1,790	-796	633,043
32	3,846	3.41	1.01	1.10	0.04	3.45	2,807	-1,039	1,078,505
33	2,507	3.41	1.01	0.75	-0.13	3.28	1,894	-613	375,776
34	3,282	3.41	1.01	0.76	-0.12	3.29	1,935	-1,347	1,813,170
35	4,762	3.41	1.01	1.52	0.18	3.59	3,890	-872	760,825
36	6,884	3.41	1.01	1.97	0.29	3.70	5,037	-1,847	3,412,352
37	5,553	3.41	1.01	1.22	0.08	3.49	3,099	-2,454	6,023,981
38	4,745	3.41	1.01	1.78	0.25	3.66	4,557	-188	35,403
39	4,678	3.41	1.01	2.98	0.47	3.88	7,650	2,972	8,831,918
40	1,875	3.41	1.01	0.74	-0.13	3.27	1,873		
41	6,896	3.41	1.01	2.55	0.41	3.82	6,541	-355	126,036
42	1,703	3.41	1.01	0.40	-0.40	3.00	1,004	-699	488,155
43	5,785	3.41	1.01	2.09	0.32	3.73	5,350	-435	189,314
44	2,214	3.41	1.01	0.75	-0.12	3.28	1,915	-299	89,565
45	4,666	3.41	1.01	2.88	0.46	3.87	7,399	2,733	7,467,570
46	5,706	3.41	1.01	3.52	0.55	3.96	9,053	3,347	11,203,885
47	4,165	3.41	1.01	2.78	0.44	3.85	7,127	2,962	8,771,387
48	6,038	3.41	1.01	2.96	0.47	3.88	7,608	1,570	2,464,865
49	5,896	3.41	1.01	2.00	0.30	3.71	5,120	-776	601,805
50	2,765	3.41	1.01	0.68	-0.17	3.24	1,728		
51	3,746	3.41	1.01	2.55	0.41	3.82	6,541	2,795	7,811,940
52	3,629	3.41	1.01	2.46	0.39	3.80	6,311	2,682	7,193,119
53	4,652	3.41	1.01	1.93	0.29	3.69	4,932	280	78,619
54	2,845	3.41	1.01	1.28	0.11	3.51	3,265	420	176,456
55	2,943	3.41	1.01	1.09	0.04	3.44	2,766	-177	31,359
56	4,364	3.41	1.01	1.39	0.14	3.55	3,536	-828	686,134
57	4,080	3.41	1.01	1.38	0.14	3.55	3,515	-565	319,397
Total	233,797			103.49			264,871	**RMSE**	**1,486.91**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.64: Allometric Growth Model and RMSE for Simulation 1980 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,702	3.41	1.01	0.90	-0.05	3.36	2,288	-414	171,271
92	3,969	3.41	1.01	1.29	0.11	3.52	3,286	-683	466,657
93	1,813	3.41	1.01	0.49	-0.31	3.09	1,232	-581	338,115
94	2,427	3.41	1.01	0.85	-0.07	3.34	2,164	-263	69,366
95	4,617	3.41	1.01	2.11	0.33	3.73	5,413	796	632,890
96	3,081	3.41	1.01	1.09	0.04	3.44	2,766	-315	99,278
97	6,413	3.41	1.01	3.66	0.56	3.97	9,410	2,997	8,979,307
98	2,590	3.41	1.01	1.00	0.00	3.41	2,558	-32	1,017
99	3,319	3.41	1.01	1.58	0.20	3.61	4,036	717	513,531
100	2,039	3.41	1.01	1.09	0.04	3.45	2,787		
101	2,118	3.41	1.01	1.35	0.13	3.54	3,452	1,334	1,780,598
102	3,362	3.41	1.01	2.22	0.35	3.75	5,684	2,322	5,391,998
103	4,041	3.41	1.01	1.85	0.27	3.68	4,745	704	495,040
104	838	3.41	1.01	0.46	-0.34	3.07	1,170	332	109,910
105	2,582	3.41	1.01	1.39	0.14	3.55	3,536	954	909,483
106	1,446	3.41	1.01	1.04	0.02	3.43	2,662	1,216	1,478,659
107	1,293	3.41	1.01	0.90	-0.05	3.36	2,288	995	990,325
108	1,880	3.41	1.01	0.62	-0.21	3.20	1,583	-297	88,080
109	5,458	3.41	1.01	1.37	0.14	3.54	3,494	-1,964	3,857,188
Total	55,988			25.27			64,551	**RMSE**	**1,486.91**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.65: Allometric Growth Model and RMSE for Simulation 1980 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	4,077	3.41	1.01	1.00	0.00	3.41	2,558	-1,519	2,307,012
59	1,441	3.41	1.01	0.36	-0.44	2.96	922	-519	269,585
60	2,705	3.41	1.01	1.08	0.03	3.44	2,745		
61	3,425	3.41	1.01	2.10	0.32	3.73	5,371	1,946	3,786,056
62	3,727	3.41	1.01	2.37	0.38	3.78	6,081	2,354	5,541,652
63	1,955	3.41	1.01	1.03	0.01	3.42	2,620	665	442,815
64	2,027	3.41	1.01	1.87	0.27	3.68	4,786	2,759	7,613,844
65	2,864	3.41	1.01	1.46	0.16	3.57	3,723	859	738,040
66	1,965	3.41	1.01	0.86	-0.07	3.34	2,184	219	48,126
67	1,370	3.41	1.01	0.84	-0.07	3.33	2,143	773	597,337
68	2,453	3.41	1.01	1.63	0.21	3.62	4,161	1,708	2,916,123
69	5,189	3.41	1.01	1.57	0.20	3.60	4,015	-1,174	1,378,814
70	6,389	3.41	1.01	1.99	0.30	3.71	5,099		
71	6,386	3.41	1.01	1.14	0.06	3.46	2,911	-3,475	12,072,557
72	5,532	3.41	1.01	2.33	0.37	3.78	5,977	445	197,650
73	1,859	3.41	1.01	0.44	-0.36	3.04	1,108	-751	564,671
74	2,717	3.41	1.01	0.82	-0.09	3.32	2,081	-636	404,960
75	1,649	3.41	1.01	0.62	-0.21	3.20	1,583	-66	4,327
76	1,744	3.41	1.01	1.09	0.04	3.44	2,766	1,022	1,044,312
77	4,166	3.41	1.01	1.67	0.22	3.63	4,265	99	9,781
78	6,348	3.41	1.01	2.49	0.40	3.81	6,395	47	2,174
79	3,145	3.41	1.01	1.30	0.11	3.52	3,307	162	26,143
80	1,978	3.41	1.01	1.08	0.03	3.44	2,745		
81	4,092	3.41	1.01	1.74	0.24	3.65	4,453	361	130,005
82	4,241	3.41	1.01	2.42	0.38	3.79	6,206	1,965	3,863,108
83	2,368	3.41	1.01	1.44	0.16	3.57	3,681	1,313	1,725,116
84	3,836	3.41	1.01	1.68	0.22	3.63	4,286	450	202,273
85	1,370	3.41	1.01	0.83	-0.08	3.32	2,101	731	534,918
86	3,517	3.41	1.01	1.90	0.28	3.69	4,849	1,332	1,774,004
87	2,789	3.41	1.01	1.61	0.21	3.61	4,119	1,330	1,768,841
88	1,432	3.41	1.01	0.58	-0.23	3.17	1,480	48	2,277
89	2,301	3.41	1.01	1.07	0.03	3.44	2,724	423	179,222
90	1,343	3.41	1.01	1.09	0.04	3.45	2,787		
Total	102,400			45.51			116,232	**RMSE**	**1,486.91**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 80	Pop 392,185			Area 174.27			AntilogPop 445,654	**RMSE**	**1,486.91**

Table A-V.66: Allometric Growth Model and RMSE for Simulation 1985 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	2457	3.45	0.87	1.90	0.28	3.69	4,925	2,468	6,089,127
1	3599	3.45	0.87	3.14	0.50	3.88	7,606	4,007	16,058,477
2	3994	3.45	0.87	1.45	0.16	3.59	3,889	-105	10,946
3	1812	3.45	0.87	0.84	-0.07	3.39	2,429	617	380,668
4	2398	3.45	0.87	1.46	0.16	3.59	3,908	1,510	2,280,731
5	6387	3.45	0.87	3.82	0.58	3.95	8,998	2,611	6,819,447
6	2848	3.45	0.87	1.09	0.04	3.48	3,045	197	38,999
7	6001	3.45	0.87	2.68	0.43	3.82	6,627	626	392,457
8	3051	3.45	0.87	1.26	0.10	3.54	3,433	382	145,926
9	5023	3.45	0.87	2.45	0.39	3.79	6,139	1,116	1,244,498
10	3060	3.45	0.87	0.95	-0.02	3.43	2,690		
11	6646	3.45	0.87	3.09	0.49	3.88	7,504	858	736,538
12	4887	3.45	0.87	3.11	0.49	3.88	7,538	2,651	7,029,232
13	3918	3.45	0.87	2.41	0.38	3.78	6,033	2,115	4,473,403
14	5313	3.45	0.87	2.11	0.32	3.73	5,376	63	3,937
15	4269	3.45	0.87	2.54	0.41	3.80	6,331	2,062	4,253,179
16	6544	3.45	0.87	3.59	0.55	3.93	8,533	1,989	3,955,089
17	2147	3.45	0.87	1.30	0.11	3.55	3,529	1,382	1,909,405
18	2364	3.45	0.87	1.58	0.20	3.62	4,189	1,825	3,330,842
19	3892	3.45	0.87	2.93	0.47	3.86	7,162	3,270	10,695,330
20	3316	3.45	0.87	1.50	0.18	3.60	4,002		
21	2378	3.45	0.87	1.23	0.09	3.53	3,375	997	994,646
22	2818	3.45	0.87	1.75	0.24	3.66	4,577	1,759	3,095,824
23	5714	3.45	0.87	2.81	0.45	3.84	6,904	1,190	1,416,909
24	5210	3.45	0.87	1.82	0.26	3.68	4,742	-468	218,644
25	6098	3.45	0.87	2.03	0.31	3.72	5,214	-884	781,401
26	3874	3.45	0.87	2.46	0.39	3.79	6,156	2,282	5,208,125
27	2045	3.45	0.87	0.47	-0.33	3.17	1,464	-581	337,532
28	6465	3.45	0.87	2.40	0.38	3.78	6,015	-450	202,116
29	733	3.45	0.87	0.26	-0.59	2.94	874	141	19,944
30	7276	3.45	0.87	1.56	0.19	3.62	4,133		
31	2909	3.45	0.87	0.85	-0.07	3.39	2,449	-460	211,398
32	4328	3.45	0.87	1.19	0.08	3.52	3,279	-1,049	1,100,730
33	2772	3.45	0.87	0.84	-0.07	3.39	2,429	-343	117,661
34	3692	3.45	0.87	0.81	-0.09	3.37	2,348	-1,344	1,806,940
35	4648	3.45	0.87	1.68	0.23	3.65	4,430	-218	47,463
36	6953	3.45	0.87	2.12	0.33	3.73	5,412	-1,541	2,375,989
37	5398	3.45	0.87	1.42	0.15	3.58	3,814	-1,584	2,509,339
38	4769	3.45	0.87	1.93	0.29	3.70	4,979	210	44,132
39	5895	3.45	0.87	3.38	0.53	3.91	8,097	2,202	4,848,010
40	2073	3.45	0.87	0.84	-0.07	3.39	2,429		
41	7612	3.45	0.87	2.88	0.46	3.85	7,059	-553	305,441
42	1881	3.45	0.87	0.43	-0.37	3.13	1,354	-527	277,778
43	6389	3.45	0.87	2.29	0.36	3.76	5,786	-603	363,980
44	2446	3.45	0.87	0.87	-0.06	3.40	2,490	44	1,902
45	4774	3.45	0.87	3.31	0.52	3.90	7,962	3,188	10,163,162
46	6797	3.45	0.87	4.03	0.61	3.98	9,444	2,647	7,006,422
47	4895	3.45	0.87	3.05	0.48	3.87	7,402	2,507	6,284,647
48	7096	3.45	0.87	3.24	0.51	3.89	7,810	714	509,577
49	6943	3.45	0.87	2.27	0.36	3.76	5,732	-1,211	1,465,359
50	3589	3.45	0.87	0.79	-0.10	3.36	2,287		
51	4934	3.45	0.87	2.83	0.45	3.84	6,939	2,005	4,019,338
52	4781	3.45	0.87	2.73	0.44	3.83	6,731	1,950	3,804,437
53	6129	3.45	0.87	2.17	0.34	3.74	5,519	-610	372,271
54	2924	3.45	0.87	1.40	0.15	3.58	3,776	852	726,060
55	3446	3.45	0.87	1.25	0.10	3.53	3,414	-32	1,037
56	4604	3.45	0.87	1.57	0.20	3.62	4,170	-434	187,985
57	4081	3.45	0.87	1.57	0.20	3.62	4,170	89	7,997
Total	**253,295**			**113.73**			289,055	**RMSE**	**1,414.76**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.67: Allometric Growth Model and RMSE for Simulation 1985 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,675	3.45	0.88	1.04	0.02	3.46	2,910	235	55,117
92	3,998	3.45	0.88	1.58	0.20	3.63	4,220	222	49,199
93	2,490	3.45	0.88	0.62	-0.21	3.27	1,858	-632	399,868
94	2,369	3.45	0.88	0.91	-0.04	3.41	2,586	217	47,149
95	5,505	3.45	0.88	2.35	0.37	3.78	5,991	486	236,067
96	3,672	3.45	0.88	1.25	0.10	3.53	3,426	-246	60,571
97	6,527	3.45	0.88	3.94	0.60	3.98	9,451	2,924	8,551,600
98	3,215	3.45	0.88	1.17	0.07	3.51	3,229	14	187
99	4,104	3.45	0.88	1.82	0.26	3.68	4,788	684	468,087
100	2,540	3.45	0.88	1.26	0.10	3.54	3,446		
101	2,640	3.45	0.88	1.53	0.18	3.61	4,105	1,465	2,146,083
102	4,190	3.45	0.88	2.52	0.40	3.80	6,372	2,182	4,762,656
103	4,886	3.45	0.88	2.19	0.34	3.75	5,625	739	545,431
104	1,079	3.45	0.88	0.46	-0.34	3.15	1,424	345	119,296
105	4,295	3.45	0.88	1.53	0.18	3.61	4,105	-190	36,118
106	2,323	3.45	0.88	1.07	0.03	3.48	2,990	667	444,778
107	2,152	3.45	0.88	0.95	-0.02	3.43	2,688	536	287,104
108	3,128	3.45	0.88	0.72	-0.14	3.32	2,111	-1,017	1,034,137
109	5,546	3.45	0.88	1.57	0.20	3.62	4,201	-1,345	1,809,844
Total	67,334			28.46			75,525	**RMSE**	**1,414.76**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.68: Allometric Growth Model and RMSE for Simulation 1985 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,038	3.45	0.88	1.17	0.07	3.51	3,248	-1,790	3,202,381
59	1,684	3.45	0.88	0.45	-0.34	3.15	1,402	-282	79,352
60	4,082	3.45	0.88	1.25	0.10	3.53	3,426		
61	4,474	3.45	0.88	2.33	0.37	3.77	5,954	1,480	2,191,496
62	4,720	3.45	0.88	2.72	0.43	3.83	6,823	2,103	4,420,923
63	2,569	3.45	0.88	1.11	0.05	3.49	3,090	521	271,130
64	3,048	3.45	0.88	2.02	0.30	3.72	5,236	2,188	4,789,278
65	4,503	3.45	0.88	1.55	0.19	3.62	4,143	-360	129,395
66	2,794	3.45	0.88	0.92	-0.03	3.42	2,627	-167	27,931
67	3,432	3.45	0.88	0.96	-0.02	3.43	2,708	-724	524,037
68	3,058	3.45	0.88	1.76	0.24	3.67	4,638	1,580	2,494,898
69	6,470	3.45	0.88	1.81	0.26	3.68	4,769	-1,701	2,892,133
70	6,370	3.45	0.88	2.11	0.32	3.74	5,440		
71	7,550	3.45	0.88	1.21	0.08	3.52	3,327	-4,223	17,829,656
72	6,877	3.45	0.88	2.48	0.39	3.80	6,282	-595	354,260
73	2,196	3.45	0.88	0.51	-0.29	3.19	1,556	-640	409,598
74	3,087	3.45	0.88	0.93	-0.03	3.42	2,647	-440	193,415
75	2,792	3.45	0.88	0.70	-0.16	3.31	2,048	-744	553,364
76	2,952	3.45	0.88	1.22	0.08	3.52	3,347	395	156,178
77	5,173	3.45	0.88	1.82	0.26	3.68	4,788	-385	148,095
78	7,466	3.45	0.88	2.73	0.44	3.84	6,841	-625	391,218
79	3,526	3.45	0.88	1.41	0.15	3.58	3,816	290	84,043
80	2,253	3.45	0.88	1.18	0.07	3.51	3,268		
81	4,497	3.45	0.88	1.87	0.27	3.69	4,901	404	163,006
82	4,755	3.45	0.88	2.58	0.41	3.81	6,499	1,744	3,040,956
83	2,882	3.45	0.88	1.53	0.18	3.61	4,105	1,223	1,495,611
84	4,145	3.45	0.88	1.85	0.27	3.69	4,863	718	515,890
85	1,973	3.45	0.88	0.87	-0.06	3.40	2,484	511	261,042
86	4,272	3.45	0.88	2.10	0.32	3.73	5,422	1,150	1,321,824
87	4,173	3.45	0.88	1.78	0.25	3.67	4,694	521	271,536
88	1,864	3.45	0.88	0.65	-0.19	3.28	1,921	57	3,296
89	3,738	3.45	0.88	1.19	0.08	3.52	3,288	-450	202,489
90	2,181	3.45	0.88	1.29	0.11	3.55	3,524		
Total	130,594			50.05			133,127	**RMSE**	**1,414.76**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 85	Pop 451,223			Area 192.25			AntilogPop 497,707	**RMSE**	**1,414.76**

Table A-V.69: Allometric Growth Model and RMSE for Real 1986 in Escambia county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	2402	3.47	0.49	1.74	0.24	3.59	3,911	1,509	2,277,234
1	3558	3.47	0.49	2.82	0.45	3.69	4,954	1,396	1,949,630
2	3954	3.47	0.49	1.32	0.12	3.53	3,414	-540	291,713
3	1794	3.47	0.49	0.76	-0.12	3.42	2,605	811	658,346
4	2359	3.47	0.49	1.36	0.13	3.54	3,465	1,106	1,223,055
5	6292	3.47	0.49	3.26	0.51	3.73	5,318	-974	948,848
6	2843	3.47	0.49	1.03	0.01	3.48	3,020	177	31,395
7	6160	3.47	0.49	2.37	0.38	3.66	4,553	-1,607	2,582,432
8	3142	3.47	0.49	1.13	0.05	3.50	3,157	15	228
9	5195	3.47	0.49	2.19	0.34	3.64	4,374	-821	674,256
10	3120	3.47	0.49	0.92	-0.03	3.46	2,864		
11	6777	3.47	0.49	2.66	0.43	3.68	4,820	-1,957	3,831,487
12	4956	3.47	0.49	2.90	0.46	3.70	5,024	68	4,582
13	3992	3.47	0.49	2.20	0.34	3.64	4,382	390	151,956
14	5264	3.47	0.49	1.85	0.27	3.60	4,025	-1,239	1,534,059
15	4365	3.47	0.49	2.28	0.36	3.65	4,460	95	9,115
16	6573	3.47	0.49	3.30	0.52	3.73	5,357	-1,216	1,479,297
17	2077	3.47	0.49	1.16	0.06	3.51	3,201	1,124	1,264,212
18	2287	3.47	0.49	1.45	0.16	3.55	3,575	1,288	1,657,692
19	3847	3.47	0.49	2.59	0.41	3.68	4,754	907	823,356
20	3241	3.47	0.49	1.34	0.13	3.54	3,434		
21	2380	3.47	0.49	1.15	0.06	3.50	3,190	810	656,684
22	2769	3.47	0.49	1.39	0.14	3.54	3,505	736	541,964
23	5647	3.47	0.49	2.48	0.39	3.67	4,651	-996	991,823
24	5200	3.47	0.49	1.52	0.18	3.56	3,662	-1,538	2,366,499
25	6071	3.47	0.49	1.49	0.17	3.56	3,623	-2,448	5,991,750
26	3891	3.47	0.49	2.72	0.43	3.69	4,870	979	957,777
27	2142	3.47	0.49	0.61	-0.22	3.37	2,332	190	36,085
28	6807	3.47	0.49	3.23	0.51	3.72	5,298	-1,509	2,275,907
29	765	3.47	0.49	0.28	-0.56	3.20	1,581	816	666,393
30	7592	3.47	0.49	1.63	0.21	3.58	3,784		
31	2969	3.47	0.49	0.92	-0.03	3.46	2,864	-105	10,979
32	4417	3.47	0.49	1.49	0.17	3.56	3,623	-794	630,127
33	2819	3.47	0.49	0.78	-0.11	3.42	2,632	-187	34,798
34	3768	3.47	0.49	0.77	-0.11	3.42	2,619	-1,149	1,320,299
35	4610	3.47	0.49	1.56	0.19	3.57	3,700	-910	828,638
36	6945	3.47	0.49	1.83	0.26	3.60	4,008	-2,937	8,625,661
37	5350	3.47	0.49	1.30	0.11	3.53	3,383	-1,967	3,869,486
38	4759	3.47	0.49	1.77	0.25	3.60	3,938	-821	674,449
39	6155	3.47	0.49	2.96	0.47	3.71	5,072	-1,083	1,173,580
40	2108	3.47	0.49	0.75	-0.12	3.41	2,592		
41	7740	3.47	0.49	3.03	0.48	3.71	5,133	-2,607	6,798,000
42	1912	3.47	0.49	0.57	-0.25	3.35	2,254	342	117,161
43	6497	3.47	0.49	2.35	0.37	3.66	4,530	-1,967	3,868,869
44	2487	3.47	0.49	0.66	-0.18	3.39	2,436	-51	2,560
45	4781	3.47	0.49	2.99	0.48	3.71	5,099	318	101,057
46	7018	3.47	0.49	3.60	0.56	3.75	5,584	-1,434	2,056,881
47	5040	3.47	0.49	2.70	0.43	3.69	4,848	-192	36,763
48	7306	3.47	0.49	2.93	0.47	3.70	5,051	-2,255	5,084,255
49	7152	3.47	0.49	2.18	0.34	3.64	4,366	-2,786	7,762,312
50	3770	3.47	0.49	0.79	-0.10	3.42	2,646		
51	5198	3.47	0.49	2.51	0.40	3.67	4,681	-517	267,444
52	5036	3.47	0.49	2.57	0.41	3.68	4,732	-304	92,141
53	6457	3.47	0.49	1.93	0.29	3.61	4,111	-2,346	5,502,919
54	2931	3.47	0.49	1.47	0.17	3.56	3,594	663	439,660
55	3546	3.47	0.49	0.88	-0.05	3.45	2,802	-744	553,782
56	4638	3.47	0.49	1.29	0.11	3.53	3,373	-1,265	1,601,487
57	4068	3.47	0.49	1.44	0.16	3.55	3,565	-503	253,316
Total	**256939**			**105.11**			224,401	**RMSE**	**1,211.23**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.70: Allometric Growth Model and RMSE for Real 1986 in Santa Rosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,671	3.47	0.49	0.63	-0.20	3.38	2,377	-294	86,258
92	4,006	3.47	0.49	1.42	0.15	3.55	3,535	-471	221,777
93	2,659	3.47	0.49	0.56	-0.25	3.35	2,238	-421	176,890
94	2,359	3.47	0.49	0.57	-0.25	3.35	2,254	-105	10,965
95	5,710	3.47	0.49	2.18	0.34	3.64	4,366	-1,344	1,806,585
96	3,809	3.47	0.49	1.09	0.04	3.49	3,101	-708	501,539
97	6,554	3.47	0.49	3.75	0.57	3.76	5,700	-854	729,505
98	3,362	3.47	0.49	1.13	0.05	3.50	3,157	-205	41,990
99	4,289	3.47	0.49	1.82	0.26	3.60	3,999	-290	83,906
100	2,659	3.47	0.49	0.95	-0.02	3.46	2,901		
101	2,763	3.47	0.49	1.45	0.16	3.55	3,575	812	658,555
102	4,385	3.47	0.49	2.43	0.39	3.66	4,606	221	48,882
103	5,083	3.47	0.49	2.19	0.34	3.64	4,374	-709	502,867
104	1,137	3.47	0.49	0.36	-0.45	3.25	1,795	658	432,621
105	4,770	3.47	0.49	2.08	0.32	3.63	4,269	-501	250,832
106	2,562	3.47	0.49	2.24	0.35	3.65	4,421	1,859	3,457,092
107	2,390	3.47	0.49	1.49	0.17	3.56	3,623	1,233	1,520,770
108	3,474	3.47	0.49	1.14	0.06	3.50	3,179	-295	86,843
109	5,567	3.47	0.49	1.97	0.29	3.62	4,153	-1,414	1,998,398
Total	70,209			29.43			67,625	**RMSE**	**1,211.23**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.71: Allometric Growth Model and RMSE for Real 1986 for Okaloosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,155	3.47	0.49	1.11	0.05	3.50	3,135	-2,020	4,081,613
59	1,704	3.47	0.49	0.49	-0.31	3.32	2,107	403	162,403
60	4,348	3.47	0.49	1.58	0.20	3.57	3,728		
61	4,629	3.47	0.49	2.72	0.43	3.69	4,870	241	57,918
62	4,854	3.47	0.49	3.22	0.51	3.72	5,285	431	186,047
63	2,661	3.47	0.49	1.51	0.18	3.56	3,642	981	963,300
64	3,244	3.47	0.49	2.15	0.33	3.64	4,334	1,090	1,187,903
65	4,835	3.47	0.49	2.26	0.35	3.65	4,445	-390	152,211
66	2,940	3.47	0.49	1.38	0.14	3.54	3,485	545	297,146
67	4,047	3.47	0.49	2.11	0.33	3.63	4,302	255	64,855
68	3,135	3.47	0.49	2.11	0.33	3.63	4,302	1,167	1,361,108
69	6,632	3.47	0.49	1.91	0.28	3.61	4,094	-2,538	6,440,578
70	6,243	3.47	0.49	3.29	0.52	3.73	5,344		
71	7,657	3.47	0.49	1.56	0.19	3.57	3,709	-3,948	15,585,494
72	7,045	3.47	0.49	2.71	0.43	3.69	4,855	-2,190	4,794,317
73	2,227	3.47	0.49	0.61	-0.22	3.37	2,332	105	11,017
74	3,106	3.47	0.49	1.00	0.00	3.47	2,985	-121	14,655
75	3,042	3.47	0.49	1.30	0.11	3.53	3,383	341	116,212
76	3,217	3.47	0.49	1.88	0.27	3.61	4,060	843	710,566
77	5,298	3.47	0.49	2.71	0.43	3.69	4,863	-435	189,626
78	7,564	3.47	0.49	2.49	0.40	3.67	4,666	-2,898	8,398,416
79	3,538	3.47	0.49	1.34	0.13	3.54	3,445	-93	8,723
80	2,268	3.47	0.49	1.12	0.05	3.50	3,146		
81	4,494	3.47	0.49	1.65	0.22	3.58	3,811	-683	465,823
82	4,771	3.47	0.49	2.54	0.41	3.67	4,710	-61	3,671
83	2,939	3.47	0.49	1.47	0.17	3.56	3,604	665	441,965
84	4,129	3.47	0.49	1.81	0.26	3.60	3,991	-138	19,155
85	2,082	3.47	0.49	0.83	-0.08	3.44	2,725	643	413,471
86	4,356	3.47	0.49	2.49	0.40	3.67	4,659	303	91,539
87	4,437	3.47	0.49	1.81	0.26	3.60	3,991	-446	199,275
88	1,927	3.47	0.49	0.43	-0.37	3.29	1,966	39	1,557
89	4,040	3.47	0.49	2.15	0.33	3.64	4,334	294	86,383
90	2,358	3.47	0.49	2.15	0.33	3.64	4,334		
Total	134,922			59.91			128,640	**RMSE**	**1,211.23**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL REAL 86	Pop 462,070			Area 194.45			AntilogPop 420,666	**RMSE**	**1,211.23**

Table A-V.72: Allometric Growth Model and RMSE for Simulation 1986 in Escambia

	Log Pop = a + b * Log Area								
Tract ID	Pop	a	b	Area	Log Area	Log Pop	AntilogPop	Pop Est-PopAct	(PopEst-PopAct)^2
0	2402	3.46	0.85	1.90	0.28	3.69	4,923	2,521	6,355,004
1	3558	3.46	0.85	3.16	0.50	3.88	7,553	3,995	15,960,018
2	3954	3.46	0.85	1.47	0.17	3.60	3,948	-6	33
3	1794	3.46	0.85	0.85	-0.07	3.40	2,492	698	487,418
4	2359	3.46	0.85	1.46	0.16	3.59	3,930	1,571	2,467,545
5	6292	3.46	0.85	3.86	0.59	3.95	8,938	2,646	7,002,118
6	2843	3.46	0.85	1.12	0.05	3.50	3,140	297	87,943
7	6160	3.46	0.85	2.72	0.43	3.82	6,659	499	249,269
8	3142	3.46	0.85	1.30	0.11	3.55	3,558	416	172,683
9	5195	3.46	0.85	2.49	0.40	3.79	6,187	992	984,490
10	3120	3.46	0.85	0.96	-0.02	3.44	2,750		
11	6777	3.46	0.85	3.13	0.50	3.88	7,504	727	528,348
12	4956	3.46	0.85	3.13	0.50	3.88	7,504	2,548	6,491,668
13	3992	3.46	0.85	2.45	0.39	3.79	6,102	2,110	4,453,088
14	5264	3.46	0.85	2.15	0.33	3.74	5,466	202	40,932
15	4365	3.46	0.85	2.59	0.41	3.81	6,390	2,025	4,101,859
16	6573	3.46	0.85	3.66	0.56	3.93	8,556	1,983	3,931,589
17	2077	3.46	0.85	1.30	0.12	3.55	3,576	1,499	2,247,993
18	2287	3.46	0.85	1.60	0.20	3.63	4,241	1,954	3,819,090
19	3847	3.46	0.85	3.01	0.48	3.86	7,257	3,410	11,630,551
20	3241	3.46	0.85	1.51	0.18	3.61	4,040		
21	2380	3.46	0.85	1.26	0.10	3.54	3,463	1,083	1,173,712
22	2769	3.46	0.85	1.77	0.25	3.67	4,638	1,869	3,493,735
23	5647	3.46	0.85	2.86	0.46	3.84	6,943	1,296	1,679,297
24	5200	3.46	0.85	1.85	0.27	3.68	4,799	-401	161,031
25	6071	3.46	0.85	2.06	0.31	3.72	5,257	-814	662,274
26	3891	3.46	0.85	2.51	0.40	3.79	6,221	2,330	5,429,586
27	2142	3.46	0.85	0.49	-0.31	3.19	1,553	-589	346,769
28	6807	3.46	0.85	2.48	0.39	3.79	6,153	-654	427,391
29	765	3.46	0.85	0.26	-0.59	2.96	913	148	21,936
30	7592	3.46	0.85	1.59	0.20	3.63	4,223		
31	2969	3.46	0.85	0.86	-0.07	3.40	2,512	-457	208,671
32	4417	3.46	0.85	1.24	0.09	3.53	3,426	-991	982,914
33	2819	3.46	0.85	0.86	-0.07	3.40	2,512	-307	94,129
34	3768	3.46	0.85	0.84	-0.07	3.39	2,472	-1,296	1,679,401
35	4610	3.46	0.85	1.72	0.23	3.65	4,513	-97	9,493
36	6945	3.46	0.85	2.17	0.34	3.74	5,501	-1,444	2,085,059
37	5350	3.46	0.85	1.44	0.16	3.59	3,893	-1,457	2,123,101
38	4759	3.46	0.85	1.98	0.30	3.71	5,082	323	104,175
39	6155	3.46	0.85	3.47	0.54	3.91	8,170	2,015	4,061,572
40	2108	3.46	0.85	0.87	-0.06	3.40	2,532		
41	7740	3.46	0.85	2.92	0.47	3.85	7,076	-664	441,424
42	1912	3.46	0.85	0.43	-0.37	3.15	1,399	-513	263,615
43	6497	3.46	0.85	2.32	0.36	3.76	5,812	-685	469,710
44	2487	3.46	0.85	0.87	-0.06	3.41	2,552	65	4,250
45	4781	3.46	0.85	3.43	0.54	3.91	8,106	3,325	11,054,060
46	7018	3.46	0.85	4.11	0.61	3.98	9,443	2,425	5,882,174
47	5040	3.46	0.85	3.09	0.49	3.87	7,422	2,382	5,673,308
48	7306	3.46	0.85	3.32	0.52	3.90	7,879	573	328,352
49	7152	3.46	0.85	2.31	0.36	3.76	5,794	-1,358	1,842,887
50	3770	3.46	0.85	0.81	-0.09	3.38	2,391		
51	5198	3.46	0.85	2.89	0.46	3.85	7,009	1,811	3,280,798
52	5036	3.46	0.85	2.75	0.44	3.83	6,709	1,673	2,800,521
53	6457	3.46	0.85	2.23	0.35	3.75	5,622	-835	696,898
54	2931	3.46	0.85	1.45	0.16	3.59	3,911	980	961,156
55	3546	3.46	0.85	1.31	0.12	3.56	3,595	49	2,410
56	4638	3.46	0.85	1.63	0.21	3.63	4,314	-324	105,038
57	4068	3.46	0.85	1.61	0.21	3.63	4,278	210	43,934
Total	**256939**			**115.88**			292,806	**RMSE**	**1,405.18**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.73: Allometric Growth Model and RMSE for Simulation 1986 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,671	3.46	0.85	1.06	0.03	3.48	3,004	333	111,185
92	4,006	3.46	0.85	1.65	0.22	3.64	4,368	362	131,224
93	2,659	3.46	0.85	0.69	-0.16	3.32	2,085	-574	329,902
94	2,359	3.46	0.85	0.94	-0.03	3.43	2,711	352	123,936
95	5,710	3.46	0.85	2.41	0.38	3.78	6,017	307	94,271
96	3,809	3.46	0.85	1.26	0.10	3.54	3,482	-327	106,765
97	6,554	3.46	0.85	4.00	0.60	3.96	9,223	2,669	7,123,210
98	3,362	3.46	0.85	1.21	0.08	3.53	3,350	-12	150
99	4,289	3.46	0.85	1.84	0.26	3.68	4,781	492	241,988
100	2,659	3.46	0.85	1.31	0.12	3.56	3,595		
101	2,763	3.46	0.85	1.56	0.19	3.62	4,168	1,405	1,975,051
102	4,385	3.46	0.85	2.55	0.41	3.80	6,306	1,921	3,689,588
103	5,083	3.46	0.85	2.25	0.35	3.75	5,674	591	349,256
104	1,137	3.46	0.85	0.49	-0.31	3.19	1,553	416	173,164
105	4,770	3.46	0.85	1.56	0.19	3.62	4,150	-620	384,266
106	2,562	3.46	0.85	1.07	0.03	3.48	3,024	462	213,270
107	2,390	3.46	0.85	0.96	-0.02	3.44	2,770	380	144,532
108	3,474	3.46	0.85	0.72	-0.14	3.34	2,167	-1,307	1,707,656
109	5,567	3.46	0.85	1.59	0.20	3.63	4,223	-1,344	1,806,202
Total	70,209			29.13			76,652	**RMSE**	**1,405.18**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.74: Allometric Growth Model and RMSE for Simulation 1986 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,155	3.46	0.85	1.18	0.07	3.52	3,293	-1,862	3,468,279
59	1,704	3.46	0.85	0.47	-0.33	3.18	1,509	-195	37,920
60	4,348	3.46	0.85	1.29	0.11	3.55	3,539		
61	4,629	3.46	0.85	2.38	0.38	3.77	5,949	1,320	1,741,654
62	4,854	3.46	0.85	2.80	0.45	3.83	6,826	1,972	3,890,201
63	2,661	3.46	0.85	1.14	0.06	3.50	3,197	536	287,433
64	3,244	3.46	0.85	2.03	0.31	3.72	5,205	1,961	3,844,271
65	4,835	3.46	0.85	1.56	0.19	3.62	4,168	-667	444,402
66	2,940	3.46	0.85	0.96	-0.02	3.44	2,770	-170	28,841
67	4,047	3.46	0.85	0.96	-0.02	3.44	2,770	-1,277	1,630,285
68	3,135	3.46	0.85	1.77	0.25	3.67	4,638	1,503	2,259,470
69	6,632	3.46	0.85	1.86	0.27	3.68	4,834	-1,798	3,231,875
70	6,243	3.46	0.85	2.14	0.33	3.73	5,432		
71	7,657	3.46	0.85	1.22	0.08	3.53	3,369	-4,288	18,389,210
72	7,045	3.46	0.85	2.53	0.40	3.80	6,255	-790	624,028
73	2,227	3.46	0.85	0.53	-0.27	3.23	1,683	-544	295,513
74	3,106	3.46	0.85	0.93	-0.03	3.43	2,691	-415	171,989
75	3,042	3.46	0.85	0.70	-0.15	3.33	2,126	-916	839,053
76	3,217	3.46	0.85	1.22	0.09	3.53	3,388	171	29,140
77	5,298	3.46	0.85	1.87	0.27	3.69	4,852	-446	198,904
78	7,564	3.46	0.85	2.76	0.44	3.83	6,743	-821	674,191
79	3,538	3.46	0.85	1.42	0.15	3.58	3,837	299	89,640
80	2,268	3.46	0.85	1.21	0.08	3.53	3,350		
81	4,494	3.46	0.85	1.91	0.28	3.69	4,941	447	199,460
82	4,771	3.46	0.85	2.61	0.42	3.81	6,424	1,653	2,732,532
83	2,939	3.46	0.85	1.56	0.19	3.62	4,150	1,211	1,466,782
84	4,129	3.46	0.85	1.88	0.27	3.69	4,870	741	548,719
85	2,082	3.46	0.85	0.87	-0.06	3.41	2,552	470	221,078
86	4,356	3.46	0.85	2.16	0.33	3.74	5,484	1,128	1,271,655
87	4,437	3.46	0.85	1.81	0.26	3.67	4,727	290	84,377
88	1,927	3.46	0.85	0.67	-0.17	3.31	2,043	116	13,481
89	4,040	3.46	0.85	1.22	0.09	3.53	3,388	-652	425,491
90	2,358	3.46	0.85	1.30	0.11	3.55	3,558		
Total	134,922			50.96			134,561	**RMSE**	**1,405.18**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 86	Pop 462,070			Area 195.96			AntilogPop 504,019	**RMSE**	**1,405.18**

Table A-V.75: Allometric Growth Model and RMSE for Simulation 1990 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	2,107	3.46	0.77	1.94	0.29	3.68	4,807	2,700	7,289,964
1	3,266	3.46	0.77	3.29	0.52	3.86	7,213	3,947	15,580,986
2	3,649	3.46	0.77	1.54	0.19	3.60	4,014	365	133,028
3	1,657	3.46	0.77	0.90	-0.05	3.42	2,651	994	987,187
4	2,120	3.46	0.77	1.49	0.17	3.59	3,916	1,796	3,223,903
5	5,687	3.46	0.77	4.03	0.61	3.93	8,445	2,758	7,607,833
6	2,710	3.46	0.77	1.21	0.08	3.52	3,327	617	380,665
7	6,581	3.46	0.77	2.97	0.47	3.82	6,672	91	8,327
8	3,399	3.46	0.77	1.36	0.13	3.56	3,650	251	62,986
9	5,716	3.46	0.77	2.62	0.42	3.78	6,060	344	118,514
10	3,243	3.46	0.77	1.04	0.02	3.47	2,959		
11	7,046	3.46	0.77	3.30	0.52	3.86	7,241	195	37,905
12	5,037	3.46	0.77	3.30	0.52	3.86	7,241	2,204	4,856,259
13	4,136	3.46	0.77	2.59	0.41	3.78	6,002	1,866	3,483,515
14	4,874	3.46	0.77	2.28	0.36	3.74	5,444	570	325,252
15	4,589	3.46	0.77	2.71	0.43	3.79	6,218	1,629	2,655,242
16	6,430	3.46	0.77	3.99	0.60	3.92	8,367	1,937	3,750,307
17	1,748	3.46	0.77	1.36	0.13	3.56	3,650	1,902	3,617,487
18	1,920	3.46	0.77	1.69	0.23	3.64	4,320	2,400	5,760,937
19	3,529	3.46	0.77	3.22	0.51	3.85	7,090	3,561	12,677,288
20	2,840	3.46	0.77	1.55	0.19	3.61	4,030		
21	2,295	3.46	0.77	1.34	0.13	3.56	3,600	1,305	1,701,847
22	2,477	3.46	0.77	1.89	0.28	3.67	4,698	2,221	4,934,580
23	5,174	3.46	0.77	2.98	0.47	3.83	6,686	1,512	2,287,009
24	4,958	3.46	0.77	2.01	0.30	3.69	4,930	-28	771
25	5,729	3.46	0.77	2.24	0.35	3.73	5,355	-374	140,127
26	3,806	3.46	0.77	2.58	0.41	3.78	5,973	2,167	4,697,776
27	2,485	3.46	0.77	0.55	-0.26	3.26	1,816	-669	447,944
28	8,052	3.46	0.77	2.71	0.43	3.79	6,204	-1,848	3,414,528
29	872	3.46	0.77	0.26	-0.59	3.01	1,015	143	20,356
30	8,658	3.46	0.77	1.81	0.26	3.66	4,558		
31	3,098	3.46	0.77	0.92	-0.03	3.43	2,706	-392	153,893
32	4,609	3.46	0.77	1.38	0.14	3.57	3,683	-926	856,608
33	2,899	3.46	0.77	0.95	-0.02	3.44	2,761	-138	19,178
34	3,932	3.46	0.77	0.87	-0.06	3.41	2,577	-1,355	1,837,307
35	4,287	3.46	0.77	1.89	0.28	3.67	4,698	411	169,243
36	6,640	3.46	0.77	2.38	0.38	3.75	5,622	-1,018	1,035,699
37	4,959	3.46	0.77	1.58	0.20	3.61	4,095	-864	746,443
38	4,532	3.46	0.77	2.12	0.33	3.71	5,144	612	374,226
39	7,038	3.46	0.77	3.73	0.57	3.90	7,943	905	819,519
40	2,169	3.46	0.77	0.95	-0.02	3.44	2,761		
41	7,952	3.46	0.77	3.21	0.51	3.85	7,076	-876	767,853
42	1,965	3.46	0.77	0.44	-0.36	3.18	1,520	-445	198,290
43	6,677	3.46	0.77	2.53	0.40	3.77	5,886	-791	625,305
44	2,556	3.46	0.77	0.95	-0.02	3.44	2,761	205	41,826
45	4,620	3.46	0.77	3.72	0.57	3.90	7,930	3,310	10,955,694
46	7,669	3.46	0.77	4.56	0.66	3.97	9,284	1,615	2,608,762
47	5,448	3.46	0.77	3.37	0.53	3.87	7,350	1,902	3,617,807
48	7,896	3.46	0.77	3.47	0.54	3.88	7,513	-383	146,535
49	7,743	3.46	0.77	2.48	0.39	3.76	5,799	-1,944	3,780,472
50	4,416	3.46	0.77	0.89	-0.05	3.42	2,632		
51	6,162	3.46	0.77	3.12	0.49	3.84	6,924	762	579,892
52	5,970	3.46	0.77	3.05	0.48	3.83	6,798	828	685,954
53	7,654	3.46	0.77	2.56	0.41	3.77	5,944	-1,710	2,922,693
54	2,842	3.46	0.77	1.72	0.23	3.64	4,368	1,526	2,328,648
55	3,822	3.46	0.77	1.56	0.19	3.61	4,063	241	57,873
56	4,594	3.46	0.77	1.87	0.27	3.67	4,667	73	5,362
57	3,859	3.46	0.77	1.74	0.24	3.64	4,416	557	309,840
Total	262,798			124.73			295,071	**RMSE**	**1,488.86**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.76: Allometric Growth Model and RMSE for Simulation 1990 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,589	3.46	0.77	1.33	0.12	3.55	3,583	994	987,431
92	3,938	3.46	0.77	1.77	0.25	3.65	4,479	541	292,594
93	3,352	3.46	0.77	0.82	-0.09	3.39	2,464	-888	788,082
94	2,260	3.46	0.77	1.01	0.01	3.46	2,905	645	416,187
95	6,424	3.46	0.77	2.65	0.42	3.79	6,104	-320	102,699
96	4,285	3.46	0.77	1.35	0.13	3.56	3,633	-652	424,862
97	6,495	3.46	0.77	4.30	0.63	3.95	8,874	2,379	5,660,028
98	3,908	3.46	0.77	1.31	0.12	3.55	3,549	-359	128,940
99	4,969	3.46	0.77	1.90	0.28	3.67	4,714	-255	65,050
100	3,100	3.46	0.77	1.45	0.16	3.58	3,833		
101	3,221	3.46	0.77	1.73	0.24	3.64	4,400	1,179	1,389,496
102	5,113	3.46	0.77	2.83	0.45	3.81	6,418	1,305	1,703,486
103	5,784	3.46	0.77	2.62	0.42	3.78	6,060	276	76,319
104	1,362	3.46	0.77	0.51	-0.29	3.23	1,712	350	122,328
105	7,014	3.46	0.77	1.67	0.22	3.63	4,272	-2,742	7,517,232
106	3,664	3.46	0.77	1.13	0.05	3.50	3,171	-493	243,301
107	3,514	3.46	0.77	1.06	0.03	3.48	3,012	-502	251,803
108	5,108	3.46	0.77	0.80	-0.10	3.38	2,427	-2,681	7,190,427
109	5,509	3.46	0.77	1.77	0.25	3.65	4,463	-1,046	1,093,859
Total	81,609			32.02			80,073	**RMSE**	**1,488.86**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.77: Allometric Growth Model and RMSE for Simulation 1990 for Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,210	3.46	0.77	1.44	0.16	3.58	3,817	-1,393	1,941,612
59	1,645	3.46	0.77	0.53	-0.27	3.25	1,774	129	16,730
60	5,172	3.46	0.77	1.46	0.16	3.59	3,850		
61	4,895	3.46	0.77	2.58	0.41	3.78	5,973	1,078	1,163,023
62	5,005	3.46	0.77	3.02	0.48	3.83	6,756	1,751	3,067,091
63	2,827	3.46	0.77	1.29	0.11	3.54	3,498	671	450,341
64	3,847	3.46	0.77	2.22	0.35	3.73	5,325	1,478	2,183,551
65	5,946	3.46	0.77	1.60	0.20	3.62	4,127	-1,819	3,307,244
66	3,331	3.46	0.77	1.09	0.04	3.49	3,065	-266	70,588
67	7,272	3.46	0.77	1.03	0.01	3.47	2,941	-4,331	18,758,037
68	3,191	3.46	0.77	1.90	0.28	3.67	4,714	1,523	2,319,380
69	6,751	3.46	0.77	2.03	0.31	3.70	4,976	-1,775	3,149,886
70	5,296	3.46	0.77	2.26	0.35	3.73	5,400		
71	7,464	3.46	0.77	1.28	0.11	3.54	3,481	-3,983	15,863,671
72	7,154	3.46	0.77	2.66	0.42	3.79	6,118	-1,036	1,073,425
73	2,170	3.46	0.77	0.61	-0.22	3.29	1,958	-212	44,782
74	2,932	3.46	0.77	1.00	0.00	3.46	2,869	-63	3,947
75	3,973	3.46	0.77	0.75	-0.13	3.36	2,293	-1,680	2,822,567
76	4,200	3.46	0.77	1.36	0.13	3.56	3,650	-550	302,534
77	5,376	3.46	0.77	1.98	0.30	3.69	4,884	-492	241,942
78	7,342	3.46	0.77	2.99	0.48	3.83	6,700	-642	411,768
79	3,303	3.46	0.77	1.49	0.17	3.59	3,916	613	375,185
80	2,145	3.46	0.77	1.30	0.11	3.55	3,515		
81	4,127	3.46	0.77	2.00	0.30	3.69	4,915	788	620,747
82	4,454	3.46	0.77	2.73	0.44	3.80	6,247	1,793	3,215,324
83	2,933	3.46	0.77	1.62	0.21	3.62	4,176	1,243	1,544,693
84	3,740	3.46	0.77	1.97	0.29	3.69	4,853	1,113	1,239,470
85	2,385	3.46	0.77	0.90	-0.05	3.42	2,651	266	70,529
86	4,340	3.46	0.77	2.28	0.36	3.74	5,444	1,104	1,219,498
87	5,239	3.46	0.77	2.01	0.30	3.69	4,930	-309	95,339
88	2,031	3.46	0.77	0.77	-0.11	3.37	2,350	319	102,055
89	5,102	3.46	0.77	1.43	0.16	3.58	3,800	-1,302	1,695,154
90	2,978	3.46	0.77	1.39	0.14	3.57	3,700		
Total	143,776			54.94			138,668	**RMSE**	**1,488.86**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 90	Pop 488,183			Area 211.69			AntilogPop 513,811	**RMSE**	**1,488.86**

Table A-V.78: Allometric Growth Model and RMSE for Real 1992 in Escambia county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	2,071	3.45	0.60	1.69	0.23	3.59	3,877	1,806	3,261,542
1	3,192	3.45	0.60	2.67	0.43	3.71	5,092	1,900	3,611,336
2	3,567	3.45	0.60	1.34	0.13	3.53	3,367	-200	40,123
3	1,634	3.45	0.60	0.81	-0.09	3.40	2,497	863	744,243
4	2,061	3.45	0.60	1.27	0.10	3.51	3,268	1,207	1,457,496
5	5,512	3.45	0.60	3.40	0.53	3.77	5,881	369	136,103
6	2,666	3.45	0.60	1.03	0.01	3.46	2,880	214	45,637
7	6,470	3.45	0.60	2.47	0.39	3.69	4,858	-1,612	2,597,280
8	3,284	3.45	0.60	1.15	0.06	3.49	3,078	-206	42,398
9	5,747	3.45	0.60	2.22	0.35	3.66	4,557	-1,190	1,415,510
10	3,157	3.45	0.60	0.92	-0.03	3.43	2,700		
11	6,900	3.45	0.60	2.66	0.42	3.71	5,074	-1,826	3,334,627
12	5,022	3.45	0.60	3.02	0.48	3.74	5,479	457	208,554
13	4,044	3.45	0.60	2.12	0.33	3.65	4,437	393	154,465
14	4,780	3.45	0.60	1.87	0.27	3.61	4,116	-664	441,317
15	4,728	3.45	0.60	2.38	0.38	3.68	4,753	25	626
16	6,304	3.45	0.60	3.79	0.58	3.80	6,273	-31	937
17	1,643	3.45	0.60	1.13	0.05	3.48	3,039	1,396	1,949,103
18	2,055	3.45	0.60	1.47	0.17	3.55	3,558	1,503	2,258,854
19	3,411	3.45	0.60	2.64	0.42	3.70	5,055	1,644	2,704,087
20	2,725	3.45	0.60	1.36	0.13	3.53	3,403		
21	2,256	3.45	0.60	1.16	0.06	3.49	3,091	835	697,251
22	2,413	3.45	0.60	1.54	0.19	3.56	3,663	1,250	1,561,331
23	5,136	3.45	0.60	2.67	0.43	3.71	5,092	-44	1,905
24	4,722	3.45	0.60	1.67	0.22	3.58	3,844	-878	771,492
25	5,607	3.45	0.60	1.75	0.24	3.60	3,954	-1,653	2,732,476
26	4,618	3.45	0.60	3.16	0.50	3.75	5,626	1,008	1,016,884
27	2,512	3.45	0.60	1.53	0.18	3.56	3,651	1,139	1,297,348
28	9,328	3.45	0.60	4.46	0.65	3.84	6,908	-2,420	5,855,649
29	1,069	3.45	0.60	0.34	-0.47	3.17	1,487	418	175,109
30	8,451	3.45	0.60	2.46	0.39	3.69	4,849		
31	2,998	3.45	0.60	1.43	0.16	3.55	3,511	513	262,960
32	4,834	3.45	0.60	1.77	0.25	3.60	3,976	-858	736,514
33	2,849	3.45	0.60	0.84	-0.07	3.41	2,556	-293	85,940
34	3,694	3.45	0.60	1.15	0.06	3.49	3,078	-616	379,342
35	4,224	3.45	0.60	1.80	0.25	3.60	4,019	-205	41,948
36	6,665	3.45	0.60	2.38	0.38	3.68	4,753	-1,912	3,655,698
37	4,902	3.45	0.60	1.38	0.14	3.53	3,427	-1,475	2,174,939
38	4,555	3.45	0.60	2.09	0.32	3.64	4,396	-159	25,137
39	7,175	3.45	0.60	3.64	0.56	3.79	6,120	-1,055	1,112,870
40	2,262	3.45	0.60	0.92	-0.03	3.43	2,700		
41	8,090	3.45	0.60	3.74	0.57	3.79	6,225	-1,865	3,477,292
42	2,039	3.45	0.60	0.70	-0.16	3.36	2,282	243	58,910
43	6,649	3.45	0.60	3.18	0.50	3.75	5,652	-997	993,600
44	2,472	3.45	0.60	0.93	-0.03	3.43	2,714	242	58,541
45	4,585	3.45	0.60	3.38	0.53	3.77	5,856	1,271	1,614,951
46	7,952	3.45	0.60	3.94	0.60	3.81	6,416	-1,536	2,358,250
47	5,532	3.45	0.60	3.20	0.51	3.75	5,669	137	18,868
48	7,998	3.45	0.60	2.98	0.47	3.74	5,435	-2,563	6,570,435
49	7,916	3.45	0.60	2.40	0.38	3.68	4,772	-3,144	9,882,921
50	4,460	3.45	0.60	1.26	0.10	3.51	3,256		
51	6,578	3.45	0.60	2.79	0.45	3.72	5,220	-1,358	1,843,497
52	6,343	3.45	0.60	3.05	0.48	3.74	5,514	-829	687,776
53	7,884	3.45	0.60	2.48	0.39	3.69	4,868	-3,016	9,096,886
54	2,907	3.45	0.60	1.70	0.23	3.59	3,888	981	962,435
55	3,913	3.45	0.60	0.96	-0.02	3.44	2,770	-1,143	1,306,634
56	4,651	3.45	0.60	1.22	0.09	3.50	3,193	-1,458	2,125,424
57	4,040	3.45	0.60	1.54	0.19	3.56	3,663	-377	142,482
Total	265,252			119.01			245,337	**RMSE**	**1,324.93**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.79: Allometric Growth Model and RMSE for Real 1992 in Santa Rosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,816	3.45	0.60	0.66	-0.18	3.34	2,202	-614	377,533
92	4,046	3.45	0.60	1.47	0.17	3.55	3,570	-476	226,889
93	3,908	3.45	0.60	0.79	-0.10	3.39	2,467	-1,441	2,077,162
94	2,293	3.45	0.60	0.47	-0.33	3.26	1,804	-489	239,546
95	6,844	3.45	0.60	2.20	0.34	3.66	4,537	-2,307	5,320,590
96	4,674	3.45	0.60	1.12	0.05	3.48	3,026	-1,648	2,715,802
97	6,526	3.45	0.60	3.78	0.58	3.80	6,265	-261	67,920
98	4,161	3.45	0.60	1.18	0.07	3.50	3,130	-1,031	1,063,855
99	5,581	3.45	0.60	2.50	0.40	3.69	4,896	-685	468,772
100	3,250	3.45	0.60	1.12	0.05	3.48	3,026		
101	3,262	3.45	0.60	1.56	0.19	3.57	3,685	423	179,352
102	5,501	3.45	0.60	2.51	0.40	3.69	4,906	-595	354,281
103	6,583	3.45	0.60	2.31	0.36	3.67	4,666	-1,917	3,676,405
104	1,694	3.45	0.60	0.41	-0.38	3.22	1,670	-24	563
105	7,459	3.45	0.60	2.22	0.35	3.66	4,557	-2,902	8,420,166
106	4,535	3.45	0.60	3.43	0.53	3.77	5,906	1,371	1,879,541
107	4,166	3.45	0.60	1.87	0.27	3.61	4,116	-50	2,532
108	5,810	3.45	0.60	1.40	0.15	3.54	3,463	-2,347	5,507,414
109	5,637	3.45	0.60	2.00	0.30	3.63	4,284	-1,353	1,831,779
Total	88,746			33.01			72,175	**RMSE**	**1,324.93**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.80: Allometric Growth Model and RMSE for Real 1992 in Okaloosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,423	3.45	0.60	1.24	0.09	3.51	3,218	-2,205	4,860,708
59	1,655	3.45	0.60	0.53	-0.28	3.29	1,931	276	75,913
60	5,647	3.45	0.60	1.99	0.30	3.63	4,273		
61	4,958	3.45	0.60	2.81	0.45	3.72	5,247	289	83,739
62	5,037	3.45	0.60	3.43	0.54	3.77	5,914	877	769,646
63	3,177	3.45	0.60	1.73	0.24	3.59	3,921	744	553,688
64	4,377	3.45	0.60	2.56	0.41	3.70	4,962	585	342,519
65	5,760	3.45	0.60	2.67	0.43	3.71	5,092	-668	445,754
66	3,509	3.45	0.60	1.51	0.18	3.56	3,628	119	14,137
67	7,610	3.45	0.60	2.20	0.34	3.66	4,527	-3,083	9,502,464
68	3,177	3.45	0.60	2.24	0.35	3.66	4,577	1,400	1,960,217
69	6,771	3.45	0.60	2.18	0.34	3.65	4,507	-2,264	5,123,811
70	5,612	3.45	0.60	3.58	0.55	3.78	6,063		
71	7,350	3.45	0.60	1.54	0.19	3.56	3,663	-3,687	13,597,418
72	7,217	3.45	0.60	2.75	0.44	3.71	5,184	-2,033	4,133,406
73	2,076	3.45	0.60	0.61	-0.22	3.32	2,103	27	713
74	2,840	3.45	0.60	1.03	0.01	3.46	2,880	40	1,570
75	4,161	3.45	0.60	1.37	0.14	3.53	3,415	-746	556,244
76	4,319	3.45	0.60	1.86	0.27	3.61	4,105	-214	45,780
77	5,487	3.45	0.60	2.80	0.45	3.72	5,238	-249	61,830
78	7,190	3.45	0.60	2.46	0.39	3.69	4,849	-2,341	5,480,861
79	3,247	3.45	0.60	1.31	0.12	3.52	3,330	83	6,891
80	2,157	3.45	0.60	1.11	0.05	3.48	3,013		
81	4,063	3.45	0.60	1.68	0.23	3.59	3,866	-197	38,853
82	4,328	3.45	0.60	2.55	0.41	3.69	4,953	625	390,463
83	2,887	3.45	0.60	1.51	0.18	3.56	3,628	741	548,929
84	3,688	3.45	0.60	1.84	0.26	3.61	4,073	385	148,215
85	2,285	3.45	0.60	0.83	-0.08	3.41	2,541	256	65,610
86	4,255	3.45	0.60	2.72	0.43	3.71	5,147	892	796,424
87	5,555	3.45	0.60	2.01	0.30	3.63	4,294	-1,261	1,590,341
88	1,965	3.45	0.60	1.17	0.07	3.49	3,117	1,152	1,326,533
89	5,687	3.45	0.60	2.62	0.42	3.70	5,037	-650	422,666
90	2,986	3.45	0.60	2.78	0.44	3.72	5,211		
Total	146,456			65.25			137,508	**RMSE**	**1,324.93**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL REAL 92	Pop 500,454			Area 217.26			AntilogPop 455,020	**RMSE**	**1,324.93**

Table A-V.81: Allometric Growth Model and RMSE for Simulation 1992 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	2,071	3.45	0.78	1.98	0.30	3.68	4,799	2,728	7,444,389
1	3,192	3.45	0.78	3.35	0.53	3.86	7,241	4,049	16,398,325
2	3,567	3.45	0.78	1.60	0.20	3.61	4,063	496	246,473
3	1,634	3.45	0.78	0.92	-0.04	3.42	2,637	1,003	1,005,841
4	2,061	3.45	0.78	1.52	0.18	3.59	3,918	1,857	3,449,512
5	5,512	3.45	0.78	4.11	0.61	3.93	8,478	2,966	8,797,634
6	2,666	3.45	0.78	1.24	0.09	3.52	3,338	672	451,635
7	6,470	3.45	0.78	3.03	0.48	3.83	6,691	221	48,871
8	3,284	3.45	0.78	1.40	0.15	3.57	3,673	389	151,191
9	5,747	3.45	0.78	2.71	0.43	3.79	6,142	395	155,761
10	3,157	3.45	0.78	1.06	0.03	3.47	2,958		
11	6,900	3.45	0.78	3.42	0.53	3.87	7,350	450	202,608
12	5,022	3.45	0.78	3.38	0.53	3.86	7,282	2,260	5,108,852
13	4,044	3.45	0.78	2.66	0.43	3.78	6,056	2,012	4,047,801
14	4,780	3.45	0.78	2.36	0.37	3.74	5,504	724	524,757
15	4,728	3.45	0.78	2.83	0.45	3.80	6,340	1,612	2,599,969
16	6,304	3.45	0.78	4.16	0.62	3.93	8,556	2,252	5,071,671
17	1,643	3.45	0.78	1.36	0.13	3.56	3,590	1,947	3,790,729
18	2,055	3.45	0.78	1.72	0.23	3.63	4,302	2,247	5,049,910
19	3,411	3.45	0.78	3.32	0.52	3.86	7,187	3,776	14,258,119
20	2,725	3.45	0.78	1.58	0.20	3.61	4,031		
21	2,256	3.45	0.78	1.37	0.14	3.56	3,607	1,351	1,824,103
22	2,413	3.45	0.78	1.99	0.30	3.68	4,830	2,417	5,841,982
23	5,136	3.45	0.78	3.09	0.49	3.83	6,788	1,652	2,730,093
24	4,722	3.45	0.78	2.10	0.32	3.70	5,027	305	93,305
25	5,607	3.45	0.78	2.31	0.36	3.73	5,416	-191	36,519
26	4,618	3.45	0.78	2.61	0.42	3.77	5,955	1,337	1,788,722
27	2,512	3.45	0.78	0.57	-0.25	3.26	1,817	-695	483,416
28	9,328	3.45	0.78	2.82	0.45	3.80	6,326	-3,002	9,010,184
29	1,069	3.45	0.78	0.29	-0.54	3.03	1,083	14	194
30	8,451	3.45	0.78	1.90	0.28	3.67	4,646		
31	2,998	3.45	0.78	0.96	-0.02	3.44	2,745	-253	63,899
32	4,834	3.45	0.78	1.45	0.16	3.58	3,772	-1,062	1,128,779
33	2,849	3.45	0.78	1.00	0.00	3.45	2,835	-14	209
34	3,694	3.45	0.78	0.89	-0.05	3.41	2,582	-1,112	1,235,901
35	4,224	3.45	0.78	2.02	0.30	3.69	4,876	652	424,822
36	6,665	3.45	0.78	2.51	0.40	3.76	5,782	-883	779,627
37	4,902	3.45	0.78	1.64	0.21	3.62	4,143	-759	575,360
38	4,555	3.45	0.78	2.15	0.33	3.71	5,133	578	333,920
39	7,175	3.45	0.78	3.87	0.59	3.91	8,098	923	852,565
40	2,262	3.45	0.78	1.04	0.02	3.46	2,905		
41	8,090	3.45	0.78	3.36	0.53	3.86	7,255	-835	697,076
42	2,039	3.45	0.78	0.49	-0.31	3.21	1,611	-428	182,843
43	6,649	3.45	0.78	2.64	0.42	3.78	6,013	-636	404,612
44	2,472	3.45	0.78	1.01	0.01	3.46	2,852	380	144,639
45	4,585	3.45	0.78	3.93	0.59	3.91	8,190	3,605	12,999,359
46	7,952	3.45	0.78	4.76	0.68	3.98	9,514	1,562	2,440,786
47	5,532	3.45	0.78	3.47	0.54	3.87	7,445	1,913	3,658,809
48	7,998	3.45	0.78	3.58	0.55	3.88	7,620	-378	143,084
49	7,916	3.45	0.78	2.54	0.41	3.77	5,840	-2,076	4,309,789
50	4,460	3.45	0.78	0.91	-0.04	3.42	2,619		
51	6,578	3.45	0.78	3.32	0.52	3.86	7,187	609	370,872
52	6,343	3.45	0.78	3.22	0.51	3.85	7,009	666	443,648
53	7,884	3.45	0.78	2.75	0.44	3.79	6,213	-1,671	2,792,691
54	2,907	3.45	0.78	1.77	0.25	3.64	4,397	1,490	2,219,015
55	3,913	3.45	0.78	1.67	0.22	3.62	4,207	294	86,536
56	4,651	3.45	0.78	1.98	0.30	3.68	4,815	164	26,810
57	4,040	3.45	0.78	1.80	0.25	3.65	4,459	419	175,789
Total	265,252			129.47			299,753	**RMSE**	**1,578.56**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.82: Allometric Growth Model and RMSE for Simulation 1992 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	2,816	3.45	0.78	1.52	0.18	3.59	3,918	1,102	1,215,035
92	4,046	3.45	0.78	1.87	0.27	3.66	4,599	553	306,138
93	3,908	3.45	0.78	0.86	-0.07	3.40	2,509	-1,399	1,957,385
94	2,293	3.45	0.78	1.06	0.03	3.47	2,958	665	442,590
95	6,844	3.45	0.78	2.75	0.44	3.79	6,199	-645	416,484
96	4,674	3.45	0.78	1.45	0.16	3.58	3,772	-902	814,398
97	6,526	3.45	0.78	4.39	0.64	3.95	8,930	2,404	5,779,348
98	4,161	3.45	0.78	1.37	0.14	3.56	3,607	-554	307,367
99	5,581	3.45	0.78	1.96	0.29	3.68	4,769	-812	659,658
100	3,250	3.45	0.78	1.51	0.18	3.59	3,902		
101	3,262	3.45	0.78	1.84	0.26	3.66	4,537	1,275	1,626,176
102	5,501	3.45	0.78	2.96	0.47	3.82	6,579	1,078	1,163,056
103	6,583	3.45	0.78	2.78	0.44	3.80	6,255	-328	107,274
104	1,694	3.45	0.78	0.53	-0.27	3.24	1,735	41	1,716
105	7,459	3.45	0.78	1.77	0.25	3.64	4,412	-3,047	9,282,267
106	4,535	3.45	0.78	1.17	0.07	3.51	3,201	-1,334	1,778,377
107	4,166	3.45	0.78	1.11	0.05	3.49	3,063	-1,103	1,216,252
108	5,810	3.45	0.78	0.81	-0.09	3.38	2,398	-3,412	11,643,546
109	5,637	3.45	0.78	1.86	0.27	3.66	4,584	-1,053	1,109,232
Total	88,746			33.59			81,929	**RMSE**	**1,578.56**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.83: Allometric Growth Model and RMSE for Simulation 1992 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,423	3.45	0.78	1.51	0.18	3.59	3,902	-1,521	2,313,254
59	1,655	3.45	0.78	0.58	-0.23	3.27	1,857	202	40,794
60	5,647	3.45	0.78	1.56	0.19	3.60	3,983		
61	4,958	3.45	0.78	2.70	0.43	3.79	6,113	1,155	1,334,303
62	5,037	3.45	0.78	3.24	0.51	3.85	7,050	2,013	4,053,143
63	3,177	3.45	0.78	1.35	0.13	3.55	3,573	396	157,088
64	4,377	3.45	0.78	2.32	0.36	3.73	5,431	1,054	1,110,239
65	5,760	3.45	0.78	1.62	0.21	3.61	4,112	-1,648	2,717,478
66	3,509	3.45	0.78	1.09	0.04	3.48	3,028	-481	231,058
67	7,610	3.45	0.78	1.09	0.04	3.48	3,011	-4,599	21,152,196
68	3,177	3.45	0.78	2.00	0.30	3.69	4,845	1,668	2,783,184
69	6,771	3.45	0.78	2.11	0.33	3.70	5,058	-1,713	2,935,613
70	5,612	3.45	0.78	2.38	0.38	3.74	5,548		
71	7,350	3.45	0.78	1.32	0.12	3.54	3,507	-3,843	14,771,905
72	7,217	3.45	0.78	2.77	0.44	3.80	6,241	-976	952,030
73	2,076	3.45	0.78	0.64	-0.19	3.30	1,996	-80	6,404
74	2,840	3.45	0.78	1.01	0.01	3.46	2,852	12	152
75	4,161	3.45	0.78	0.77	-0.11	3.36	2,304	-1,857	3,448,689
76	4,319	3.45	0.78	1.41	0.15	3.57	3,689	-630	396,472
77	5,487	3.45	0.78	2.05	0.31	3.69	4,937	-550	302,926
78	7,190	3.45	0.78	3.05	0.48	3.83	6,733	-457	209,043
79	3,247	3.45	0.78	1.52	0.18	3.59	3,918	671	450,625
80	2,157	3.45	0.78	1.33	0.12	3.55	3,523		
81	4,063	3.45	0.78	2.07	0.32	3.70	4,967	904	817,122
82	4,328	3.45	0.78	2.79	0.45	3.80	6,284	1,956	3,825,281
83	2,887	3.45	0.78	1.64	0.22	3.62	4,159	1,272	1,619,065
84	3,688	3.45	0.78	2.03	0.31	3.69	4,891	1,203	1,447,236
85	2,285	3.45	0.78	0.92	-0.04	3.42	2,637	352	123,845
86	4,255	3.45	0.78	2.33	0.37	3.74	5,460	1,205	1,452,512
87	5,555	3.45	0.78	2.08	0.32	3.70	4,997	-558	311,108
88	1,965	3.45	0.78	0.83	-0.08	3.39	2,435	470	220,865
89	5,687	3.45	0.78	1.53	0.18	3.59	3,934	-1,753	3,071,286
90	2,986	3.45	0.78	1.48	0.17	3.58	3,837		
Total	146,456			57.13			140,814	**RMSE**	**1,578.56**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 92	Pop 500,454		Area 220.19		AntilogPop 522,495	**RMSE** **1,578.56**

Table A-V.84: Allometric Growth Model and RMSE for Simulation 1995 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	2,068	3.43	0.89	2.01	0.30	3.70	4,969	2,901	8,418,572
1	3,160	3.43	0.89	3.47	0.54	3.91	8,089	4,929	24,295,570
2	3,532	3.43	0.89	1.61	0.21	3.61	4,086	554	307,179
3	1,639	3.43	0.89	0.93	-0.03	3.40	2,510	871	757,935
4	2,024	3.43	0.89	1.56	0.19	3.60	3,958	1,934	3,741,138
5	5,388	3.43	0.89	4.20	0.62	3.98	9,581	4,193	17,584,232
6	2,664	3.43	0.89	1.30	0.12	3.53	3,385	721	519,310
7	6,459	3.43	0.89	3.13	0.50	3.87	7,364	905	819,194
8	3,195	3.43	0.89	1.45	0.16	3.57	3,719	524	274,606
9	5,932	3.43	0.89	2.84	0.45	3.83	6,767	835	697,877
10	3,106	3.43	0.89	1.10	0.04	3.46	2,913		
11	6,848	3.43	0.89	3.52	0.55	3.91	8,173	1,325	1,755,129
12	5,120	3.43	0.89	3.51	0.54	3.91	8,156	3,036	9,217,718
13	4,004	3.43	0.89	2.78	0.44	3.82	6,630	2,626	6,896,367
14	4,754	3.43	0.89	2.42	0.38	3.77	5,868	1,114	1,241,742
15	5,063	3.43	0.89	2.97	0.47	3.85	7,041	1,978	3,912,290
16	6,268	3.43	0.89	4.38	0.64	4.00	9,942	3,674	13,495,213
17	1,533	3.43	0.89	1.40	0.15	3.56	3,608	2,075	4,305,613
18	2,327	3.43	0.89	1.77	0.25	3.65	4,449	2,122	4,504,432
19	3,321	3.43	0.89	3.43	0.54	3.90	8,005	4,684	21,941,599
20	2,623	3.43	0.89	1.65	0.22	3.62	4,177		
21	2,253	3.43	0.89	1.46	0.16	3.57	3,737	1,484	2,203,721
22	2,377	3.43	0.89	2.13	0.33	3.72	5,236	2,859	8,172,792
23	5,202	3.43	0.89	3.22	0.51	3.88	7,567	2,365	5,594,502
24	4,497	3.43	0.89	2.15	0.33	3.72	5,271	774	599,372
25	5,560	3.43	0.89	2.58	0.41	3.79	6,199	639	407,943
26	6,306	3.43	0.89	2.67	0.43	3.81	6,406	100	10,045
27	2,615	3.43	0.89	0.62	-0.21	3.24	1,757	-858	736,430
28	11,888	3.43	0.89	2.98	0.47	3.85	7,058	-4,830	23,328,863
29	1,481	3.43	0.89	0.30	-0.52	2.96	916	-565	319,513
30	8,349	3.43	0.89	2.05	0.31	3.70	5,058		
31	2,924	3.43	0.89	1.06	0.03	3.45	2,818	-106	11,296
32	5,314	3.43	0.89	1.57	0.20	3.60	3,995	-1,319	1,740,195
33	2,842	3.43	0.89	1.04	0.02	3.44	2,779	-63	3,914
34	3,447	3.43	0.89	0.96	-0.02	3.41	2,568	-879	773,148
35	4,231	3.43	0.89	2.13	0.33	3.72	5,236	1,005	1,009,642
36	6,864	3.43	0.89	2.70	0.43	3.81	6,458	-406	164,859
37	4,935	3.43	0.89	1.75	0.24	3.64	4,395	-540	291,450
38	4,698	3.43	0.89	2.31	0.36	3.75	5,623	925	856,396
39	7,560	3.43	0.89	4.09	0.61	3.97	9,351	1,791	3,208,542
40	2,466	3.43	0.89	1.09	0.04	3.46	2,894		
41	8,499	3.43	0.89	3.61	0.56	3.92	8,373	-126	15,775
42	2,205	3.43	0.89	0.49	-0.31	3.15	1,407	-798	636,155
43	6,766	3.43	0.89	2.83	0.45	3.83	6,733	-33	1,082
44	2,409	3.43	0.89	1.08	0.03	3.46	2,856	447	199,745
45	4,642	3.43	0.89	4.23	0.63	3.98	9,631	4,989	24,885,890
46	8,593	3.43	0.89	5.11	0.71	4.06	11,399	2,806	7,874,008
47	5,796	3.43	0.89	3.64	0.56	3.93	8,423	2,627	6,903,512
48	8,348	3.43	0.89	3.76	0.58	3.94	8,673	325	105,733
49	8,377	3.43	0.89	2.76	0.44	3.82	6,596	-1,781	3,172,979
50	4,635	3.43	0.89	0.97	-0.01	3.42	2,606		
51	7,423	3.43	0.89	3.60	0.56	3.92	8,357	934	871,811
52	7,107	3.43	0.89	3.41	0.53	3.90	7,955	848	718,787
53	8,436	3.43	0.89	2.91	0.46	3.84	6,904	-1,532	2,345,983
54	3,077	3.43	0.89	1.93	0.29	3.68	4,791	1,714	2,937,566
55	4,150	3.43	0.89	1.87	0.27	3.67	4,665	515	265,696
56	4,851	3.43	0.89	2.18	0.34	3.73	5,342	491	240,949
57	4,431	3.43	0.89	1.98	0.30	3.69	4,898	467	218,236
Total	276,582			136.66			328,326	**RMSE**	**1,992.46**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.85: Allometric Growth Model and RMSE for Simulation 1995 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,113	3.43	0.89	1.71	0.23	3.63	4,305	1,192	1,419,851
92	4,108	3.43	0.89	2.03	0.31	3.70	5,023	915	837,012
93	4,791	3.43	0.89	0.97	-0.01	3.42	2,606	-2,185	4,772,628
94	2,285	3.43	0.89	1.19	0.08	3.49	3,122	837	700,032
95	7,334	3.43	0.89	2.99	0.48	3.85	7,075	-259	67,054
96	5,186	3.43	0.89	1.59	0.20	3.61	4,031	-1,155	1,333,038
97	6,408	3.43	0.89	4.64	0.67	4.02	10,463	4,055	16,440,371
98	4,457	3.43	0.89	1.50	0.18	3.58	3,830	-627	393,571
99	6,472	3.43	0.89	2.07	0.32	3.71	5,112	-1,360	1,850,315
100	3,400	3.43	0.89	1.63	0.21	3.62	4,123		
101	3,241	3.43	0.89	1.93	0.29	3.68	4,791	1,550	2,402,292
102	5,982	3.43	0.89	3.19	0.50	3.88	7,500	1,518	2,303,174
103	7,787	3.43	0.89	3.08	0.49	3.86	7,262	-525	275,370
104	2,288	3.43	0.89	0.53	-0.27	3.19	1,532	-756	571,755
105	7,971	3.43	0.89	1.90	0.28	3.68	4,737	-3,234	10,457,407
106	6,077	3.43	0.89	1.21	0.08	3.50	3,159	-2,918	8,512,340
107	5,235	3.43	0.89	1.17	0.07	3.49	3,084	-2,151	4,627,260
108	6,864	3.43	0.89	0.93	-0.03	3.40	2,510	-4,354	18,960,847
109	5,690	3.43	0.89	1.94	0.29	3.68	4,827	-863	745,274
Total	98,689			36.22			89,090	**RMSE**	**1,992.46**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.86: Allometric Growth Model and RMSE for Simulation 1995 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	5,907	3.43	0.89	1.70	0.23	3.63	4,286	-1,621	2,626,234
59	1,715	3.43	0.89	0.66	-0.18	3.26	1,838	123	15,067
60	6,606	3.43	0.89	1.84	0.26	3.66	4,594		
61	5,185	3.43	0.89	2.92	0.47	3.84	6,939	1,754	3,074,846
62	5,216	3.43	0.89	3.46	0.54	3.91	8,056	2,840	8,062,872
63	3,881	3.43	0.89	1.46	0.16	3.57	3,737	-144	20,594
64	5,446	3.43	0.89	2.48	0.39	3.78	5,990	544	296,277
65	5,635	3.43	0.89	1.68	0.22	3.63	4,232	-1,403	1,968,541
66	3,891	3.43	0.89	1.15	0.06	3.48	3,027	-864	746,314
67	8,355	3.43	0.89	1.20	0.08	3.50	3,141	-5,214	27,190,479
68	3,238	3.43	0.89	2.08	0.32	3.71	5,129	1,891	3,577,714
69	6,979	3.43	0.89	2.24	0.35	3.74	5,483	-1,496	2,238,415
70	6,279	3.43	0.89	2.42	0.38	3.77	5,868		
71	7,370	3.43	0.89	1.40	0.15	3.56	3,608	-3,762	14,152,667
72	7,502	3.43	0.89	2.88	0.46	3.84	6,853	-649	421,170
73	1,994	3.43	0.89	0.70	-0.15	3.29	1,958	-36	1,276
74	2,778	3.43	0.89	1.08	0.03	3.46	2,856	78	6,073
75	4,573	3.43	0.89	0.82	-0.09	3.35	2,236	-2,337	5,461,254
76	4,620	3.43	0.89	1.47	0.17	3.57	3,756	-864	746,588
77	5,803	3.43	0.89	2.14	0.33	3.72	5,254	-549	301,946
78	7,149	3.43	0.89	3.16	0.50	3.87	7,432	283	80,030
79	3,247	3.43	0.89	1.56	0.19	3.60	3,958	711	505,809
80	2,233	3.43	0.89	1.40	0.15	3.56	3,608		
81	4,071	3.43	0.89	2.18	0.34	3.73	5,342	1,271	1,615,099
82	4,253	3.43	0.89	2.86	0.46	3.83	6,802	2,549	6,495,666
83	2,894	3.43	0.89	1.70	0.23	3.63	4,286	1,392	1,938,872
84	3,705	3.43	0.89	2.10	0.32	3.71	5,165	1,460	2,131,473
85	2,199	3.43	0.89	0.94	-0.03	3.40	2,529	330	108,890
86	4,237	3.43	0.89	2.45	0.39	3.77	5,938	1,701	2,893,656
87	6,220	3.43	0.89	2.20	0.34	3.73	5,377	-843	710,381
88	1,919	3.43	0.89	0.87	-0.06	3.38	2,373	454	206,410
89	6,863	3.43	0.89	1.65	0.22	3.62	4,177	-2,686	7,212,533
90	3,075	3.43	0.89	1.59	0.20	3.61	4,031		
Total	155,038			60.43			149,860	**RMSE**	**1,992.46**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 95	Pop 530,309			Area 233.31			AntilogPop 567,276	**RMSE**	**1,992.46**

Table A-V.87: Allometric Growth Model and RMSE for Simulation 2000 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	2,021	3.33	1.22	2.07	0.32	3.72	5,225	3,204	10,265,729
1	3,044	3.33	1.22	3.56	0.55	4.00	10,111	7,067	49,948,393
2	3,402	3.33	1.22	1.68	0.23	3.61	4,057	655	428,504
3	1,613	3.33	1.22	1.03	0.01	3.35	2,223	610	372,353
4	1,923	3.33	1.22	1.61	0.21	3.58	3,844	1,921	3,688,941
5	5,080	3.33	1.22	4.41	0.64	4.12	13,096	8,016	64,256,077
6	2,607	3.33	1.22	1.39	0.14	3.50	3,195	588	345,698
7	6,310	3.33	1.22	3.41	0.53	3.98	9,582	3,272	10,704,099
8	2,990	3.33	1.22	1.50	0.18	3.55	3,517	527	277,330
9	6,127	3.33	1.22	3.10	0.49	3.93	8,538	2,411	5,813,527
10	2,960	3.33	1.22	1.17	0.07	3.41	2,591		
11	6,623	3.33	1.22	3.73	0.57	4.03	10,674	4,051	16,414,153
12	5,179	3.33	1.22	3.77	0.58	4.04	10,844	5,665	32,096,797
13	3,858	3.33	1.22	2.98	0.47	3.91	8,132	4,274	18,269,374
14	4,616	3.33	1.22	2.63	0.42	3.84	6,989	2,373	5,632,199
15	5,559	3.33	1.22	3.09	0.49	3.93	8,484	2,925	8,554,496
16	6,081	3.33	1.22	4.78	0.68	4.16	14,458	8,377	70,176,148
17	1,339	3.33	1.22	1.44	0.16	3.53	3,355	2,016	4,064,651
18	2,805	3.33	1.22	1.90	0.28	3.67	4,683	1,878	3,526,609
19	3,110	3.33	1.22	3.62	0.56	4.01	10,308	7,198	51,809,051
20	2,411	3.33	1.22	1.71	0.23	3.62	4,128		
21	2,201	3.33	1.22	1.51	0.18	3.55	3,563	1,362	1,855,096
22	2,270	3.33	1.22	2.31	0.36	3.77	5,955	3,685	13,580,979
23	5,205	3.33	1.22	3.48	0.54	3.99	9,832	4,627	21,409,007
24	4,061	3.33	1.22	2.31	0.36	3.77	5,955	1,894	3,588,138
25	5,371	3.33	1.22	2.83	0.45	3.88	7,623	2,252	5,073,205
26	10,389	3.33	1.22	2.76	0.44	3.87	7,411	-2,978	8,869,093
27	2,738	3.33	1.22	0.70	-0.16	3.14	1,382	-1,356	1,837,970
28	17,455	3.33	1.22	3.22	0.51	3.95	8,947	-8,508	72,377,908
29	2,501	3.33	1.22	0.33	-0.48	2.75	560	-1,941	3,766,286
30	8,012	3.33	1.22	2.31	0.36	3.77	5,955		
31	2,748	3.33	1.22	1.18	0.07	3.42	2,635	-113	12,757
32	6,096	3.33	1.22	1.77	0.25	3.63	4,296	-1,800	3,241,516
33	2,773	3.33	1.22	1.21	0.08	3.43	2,701	-72	5,155
34	3,008	3.33	1.22	1.05	0.02	3.36	2,287	-721	519,279
35	4,155	3.33	1.22	2.38	0.38	3.79	6,185	2,030	4,121,995
36	7,061	3.33	1.22	2.94	0.47	3.90	7,998	937	877,555
37	4,887	3.33	1.22	1.88	0.27	3.67	4,634	-253	63,917
38	4,846	3.33	1.22	2.47	0.39	3.81	6,469	1,623	2,632,562
39	8,079	3.33	1.22	4.58	0.66	4.14	13,744	5,665	32,097,002
40	2,791	3.33	1.22	1.30	0.12	3.47	2,969		
41	9,040	3.33	1.22	4.06	0.61	4.07	11,845	2,805	7,869,610
42	2,462	3.33	1.22	0.53	-0.27	3.00	1,001	-1,461	2,134,297
43	6,824	3.33	1.22	3.09	0.49	3.93	8,484	1,660	2,754,959
44	2,259	3.33	1.22	1.13	0.05	3.39	2,482	223	49,669
45	4,642	3.33	1.22	4.76	0.68	4.16	14,398	9,756	95,187,318
46	9,580	3.33	1.22	5.59	0.75	4.24	17,498	7,918	62,702,296
47	6,136	3.33	1.22	4.02	0.60	4.07	11,701	5,565	30,972,950
48	8,781	3.33	1.22	3.99	0.60	4.07	11,615	2,834	8,032,226
49	9,018	3.33	1.22	3.07	0.49	3.93	8,430	-588	346,272
50	4,841	3.33	1.22	1.17	0.07	3.42	2,613		
51	8,896	3.33	1.22	3.88	0.59	4.05	11,214	2,318	5,374,522
52	8,416	3.33	1.22	3.86	0.59	4.05	11,157	2,741	7,514,448
53	9,251	3.33	1.22	3.21	0.51	3.95	8,893	-358	128,378
54	3,315	3.33	1.22	2.17	0.34	3.74	5,525	2,210	4,884,509
55	4,485	3.33	1.22	2.34	0.37	3.78	6,057	1,572	2,472,067
56	5,097	3.33	1.22	2.56	0.41	3.83	6,754	1,657	2,745,687
57	5,062	3.33	1.22	2.20	0.34	3.75	5,601	539	290,066
Total	294,410			148.74			404,407	**RMSE**	**3,494.65**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.88: Allometric Growth Model and RMSE for Simulation 2000 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,612	3.33	1.22	1.97	0.29	3.69	4,903	1,291	1,667,713
92	4,132	3.33	1.22	2.45	0.39	3.81	6,417	2,285	5,220,534
93	6,611	3.33	1.22	1.13	0.05	3.40	2,504	-4,107	16,870,338
94	2,227	3.33	1.22	1.43	0.15	3.52	3,309	1,082	1,171,160
95	8,075	3.33	1.22	3.38	0.53	3.98	9,471	1,396	1,948,405
96	6,056	3.33	1.22	1.81	0.26	3.65	4,440	-1,616	2,611,040
97	6,093	3.33	1.22	4.97	0.70	4.18	15,148	9,055	81,994,453
98	4,902	3.33	1.22	1.60	0.21	3.58	3,820	-1,082	1,170,443
99	8,136	3.33	1.22	2.38	0.38	3.79	6,185	-1,951	3,805,349
100	3,595	3.33	1.22	1.87	0.27	3.66	4,610		
101	3,142	3.33	1.22	2.15	0.33	3.74	5,475	2,333	5,442,291
102	6,750	3.33	1.22	3.56	0.55	4.00	10,083	3,333	11,111,632
103	10,120	3.33	1.22	3.72	0.57	4.03	10,646	526	276,842
104	3,714	3.33	1.22	0.56	-0.25	3.02	1,057	-2,657	7,060,615
105	8,738	3.33	1.22	2.08	0.32	3.72	5,250	-3,488	12,166,784
106	9,740	3.33	1.22	1.34	0.13	3.49	3,059	-6,681	44,637,955
107	7,532	3.33	1.22	1.28	0.11	3.46	2,901	-4,631	21,442,542
108	8,903	3.33	1.22	1.08	0.03	3.37	2,352	-6,551	42,916,944
109	5,665	3.33	1.22	2.15	0.33	3.74	5,450	-215	46,314
Total	117,743			40.91			107,080	**RMSE**	**3,494.65**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.89: Allometric Growth Model and RMSE for Simulation 2000 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	6,742	3.33	1.22	1.99	0.30	3.70	4,977	-1,765	3,114,194
59	1,799	3.33	1.22	0.79	-0.10	3.20	1,601	-198	39,311
60	8,493	3.33	1.22	2.28	0.36	3.77	5,879		
61	5,529	3.33	1.22	3.30	0.52	3.96	9,222	3,693	13,640,266
62	5,472	3.33	1.22	3.84	0.58	4.04	11,072	5,600	31,357,419
63	5,364	3.33	1.22	1.70	0.23	3.61	4,104	-1,260	1,587,095
64	7,760	3.33	1.22	2.75	0.44	3.87	7,358	-402	161,646
65	5,376	3.33	1.22	1.72	0.23	3.62	4,152	-1,224	1,498,426
66	4,575	3.33	1.22	1.32	0.12	3.48	3,014	-1,561	2,437,660
67	9,663	3.33	1.22	1.43	0.15	3.52	3,309	-6,354	40,370,759
68	3,308	3.33	1.22	2.22	0.35	3.75	5,676	2,368	5,608,587
69	7,261	3.33	1.22	2.46	0.39	3.81	6,443	-818	669,658
70	7,494	3.33	1.22	2.54	0.40	3.82	6,676		
71	7,325	3.33	1.22	1.51	0.18	3.55	3,540	-3,785	14,327,690
72	7,918	3.33	1.22	3.19	0.50	3.95	8,838	920	846,368
73	1,844	3.33	1.22	0.78	-0.11	3.20	1,581	-263	69,361
74	2,649	3.33	1.22	1.13	0.05	3.39	2,482	-167	27,934
75	5,299	3.33	1.22	0.88	-0.05	3.27	1,845	-3,454	11,928,068
76	5,115	3.33	1.22	1.52	0.18	3.55	3,586	-1,529	2,337,049
77	6,305	3.33	1.22	2.28	0.36	3.77	5,879	-426	181,552
78	7,006	3.33	1.22	3.26	0.51	3.96	9,057	2,051	4,207,493
79	3,212	3.33	1.22	1.63	0.21	3.59	3,891	679	460,773
80	2,339	3.33	1.22	1.49	0.17	3.54	3,493		
81	4,043	3.33	1.22	2.34	0.37	3.78	6,057	2,014	4,057,327
82	4,088	3.33	1.22	2.99	0.48	3.91	8,159	4,071	16,574,792
83	2,874	3.33	1.22	1.80	0.25	3.64	4,392	1,518	2,303,869
84	3,694	3.33	1.22	2.25	0.35	3.76	5,777	2,083	4,340,634
85	2,040	3.33	1.22	0.98	-0.01	3.32	2,096	56	3,118
86	4,164	3.33	1.22	2.63	0.42	3.84	6,989	2,825	7,981,899
87	7,434	3.33	1.22	2.41	0.38	3.80	6,262	-1,172	1,372,898
88	1,825	3.33	1.22	0.91	-0.04	3.28	1,907	82	6,788
89	9,292	3.33	1.22	1.86	0.27	3.66	4,586	-4,706	22,150,867
90	3,196	3.33	1.22	1.76	0.24	3.63	4,272		
Total	170,498			65.93			168,173	**RMSE**	**3,494.65**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 2000	Pop 582,651		Area 255.57		AntilogPop 679,660	**RMSE**	**3,494.65**

Table A-V.90: Allometric Growth Model and RMSE for Real 2001 in Escambia county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,992	3.46	0.69	1.64	0.21	3.61	4,031	2,039	4,157,129
1	3,015	3.46	0.69	2.69	0.43	3.76	5,691	2,676	7,158,862
2	3,362	3.46	0.69	1.30	0.11	3.54	3,429	67	4,468
3	1,600	3.46	0.69	0.76	-0.12	3.37	2,370	770	593,665
4	1,888	3.46	0.69	1.30	0.11	3.54	3,429	1,541	2,374,204
5	5,020	3.46	0.69	3.26	0.51	3.81	6,499	1,479	2,186,332
6	2,589	3.46	0.69	1.01	0.01	3.46	2,889	300	89,986
7	6,326	3.46	0.69	2.43	0.39	3.72	5,304	-1,022	1,044,303
8	2,993	3.46	0.69	1.09	0.04	3.48	3,032	39	1,505
9	6,188	3.46	0.69	2.21	0.34	3.70	4,968	-1,220	1,488,291
10	2,984	3.46	0.69	0.91	-0.04	3.43	2,677		
11	6,681	3.46	0.69	2.65	0.42	3.75	5,631	-1,050	1,102,521
12	5,185	3.46	0.69	2.81	0.45	3.77	5,868	683	466,252
13	3,861	3.46	0.69	2.07	0.32	3.68	4,738	877	769,750
14	4,592	3.46	0.69	1.74	0.24	3.62	4,209	-383	146,526
15	5,608	3.46	0.69	2.28	0.36	3.71	5,081	-527	277,577
16	6,110	3.46	0.69	3.79	0.58	3.86	7,222	1,112	1,235,869
17	1,314	3.46	0.69	1.09	0.04	3.48	3,047	1,733	3,004,938
18	2,788	3.46	0.69	1.43	0.15	3.56	3,663	875	766,178
19	3,080	3.46	0.69	2.48	0.39	3.73	5,377	2,297	5,278,441
20	2,378	3.46	0.69	1.34	0.13	3.54	3,503		
21	2,183	3.46	0.69	1.12	0.05	3.49	3,094	911	830,497
22	2,247	3.46	0.69	1.47	0.17	3.57	3,750	1,503	2,257,630
23	5,173	3.46	0.69	2.54	0.41	3.74	5,475	302	91,004
24	4,017	3.46	0.69	1.57	0.20	3.59	3,919	-98	9,520
25	5,334	3.46	0.69	1.70	0.23	3.62	4,141	-1,193	1,423,168
26	10,502	3.46	0.69	3.37	0.53	3.82	6,655	-3,847	14,800,433
27	2,783	3.46	0.69	2.07	0.32	3.68	4,751	1,968	3,873,976
28	17,983	3.46	0.69	9.15	0.96	4.12	13,315	-4,668	21,794,840
29	2,536	3.46	0.69	0.82	-0.09	3.40	2,492	-44	1,967
30	8,130	3.46	0.69	2.94	0.47	3.78	6,054		
31	2,759	3.46	0.69	1.24	0.09	3.52	3,324	565	319,255
32	6,162	3.46	0.69	1.69	0.23	3.62	4,127	-2,035	4,139,846
33	2,783	3.46	0.69	0.81	-0.09	3.39	2,475	-308	95,168
34	3,013	3.46	0.69	1.12	0.05	3.49	3,094	81	6,612
35	4,123	3.46	0.69	1.65	0.22	3.61	4,059	-64	4,153
36	7,050	3.46	0.69	2.11	0.32	3.68	4,803	-2,247	5,050,623
37	4,874	3.46	0.69	1.35	0.13	3.55	3,532	-1,342	1,800,241
38	4,876	3.46	0.69	2.17	0.34	3.69	4,905	29	825
39	8,137	3.46	0.69	4.50	0.65	3.91	8,139	2	4
40	2,841	3.46	0.69	1.04	0.02	3.47	2,937		
41	9,190	3.46	0.69	4.03	0.61	3.88	7,540	-1,650	2,722,820
42	2,507	3.46	0.69	0.81	-0.09	3.39	2,475	-32	1,056
43	6,927	3.46	0.69	2.87	0.46	3.77	5,950	-977	955,067
44	2,288	3.46	0.69	0.93	-0.03	3.44	2,727	439	192,323
45	4,634	3.46	0.69	3.53	0.55	3.84	6,875	2,241	5,023,466
46	9,702	3.46	0.69	3.75	0.57	3.86	7,168	-2,534	6,420,837
47	6,207	3.46	0.69	2.92	0.47	3.78	6,031	-176	30,931
48	8,880	3.46	0.69	2.78	0.44	3.76	5,821	-3,059	9,358,701
49	9,211	3.46	0.69	2.57	0.41	3.74	5,511	-3,700	13,690,627
50	4,939	3.46	0.69	1.17	0.07	3.50	3,187		
51	9,117	3.46	0.69	4.03	0.61	3.88	7,540	-1,577	2,487,234
52	8,622	3.46	0.69	3.38	0.53	3.82	6,666	-1,956	3,826,073
53	9,453	3.46	0.69	2.79	0.45	3.77	5,833	-3,620	13,107,494
54	3,292	3.46	0.69	2.08	0.32	3.68	4,764	1,472	2,167,121
55	4,506	3.46	0.69	1.22	0.08	3.52	3,279	-1,227	1,506,372
56	5,110	3.46	0.69	1.36	0.13	3.55	3,547	-1,563	2,443,172
57	5,063	3.46	0.69	1.68	0.23	3.61	4,114	-949	901,315
Total	296,708			126.60			276,724	**RMSE**	**1,721.66**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.91: Allometric Growth Model and RMSE for Real 2001 in Santa Rosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,658	3.46	0.69	0.99	-0.01	3.45	2,841	-817	668,012
92	4,167	3.46	0.69	1.61	0.21	3.60	3,989	-178	31,591
93	6,846	3.46	0.69	1.73	0.24	3.62	4,196	-2,650	7,024,534
94	2,213	3.46	0.69	0.53	-0.27	3.27	1,855	-358	128,445
95	8,296	3.46	0.69	3.29	0.52	3.82	6,543	-1,753	3,071,491
96	6,234	3.46	0.69	1.51	0.18	3.58	3,821	-2,413	5,823,858
97	6,118	3.46	0.69	3.64	0.56	3.85	7,017	899	808,087
98	5,029	3.46	0.69	2.26	0.35	3.70	5,044	15	212
99	8,390	3.46	0.69	3.63	0.56	3.85	7,006	-1,384	1,915,214
100	3,698	3.46	0.69	1.83	0.26	3.64	4,358		
101	3,213	3.46	0.69	1.76	0.24	3.63	4,236	1,023	1,047,242
102	6,925	3.46	0.69	3.03	0.48	3.79	6,181	-744	553,478
103	10,546	3.46	0.69	2.70	0.43	3.76	5,702	-4,844	23,459,542
104	3,903	3.46	0.69	1.26	0.10	3.53	3,369	-534	285,023
105	9,054	3.46	0.69	3.30	0.52	3.82	6,566	-2,488	6,191,206
106	10,209	3.46	0.69	9.01	0.95	4.12	13,167	2,958	8,749,493
107	7,875	3.46	0.69	4.97	0.70	3.94	8,709	834	696,154
108	9,276	3.46	0.69	4.94	0.69	3.94	8,680	-596	355,507
109	5,722	3.46	0.69	2.49	0.40	3.73	5,402	-320	102,494
Total	121,372			54.49			108,681	**RMSE**	**1,721.66**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.92: Allometric Growth Model and RMSE for Real 2001 for Okaloosa county

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	6,841	3.46	0.69	1.70	0.23	3.62	4,141	-2,700	7,289,817
59	1,817	3.46	0.69	0.53	-0.28	3.26	1,835	18	326
60	8,713	3.46	0.69	2.26	0.35	3.70	5,044		
61	5,608	3.46	0.69	3.30	0.52	3.82	6,555	947	896,078
62	5,542	3.46	0.69	3.45	0.54	3.83	6,765	1,223	1,496,913
63	5,490	3.46	0.69	2.72	0.43	3.76	5,738	248	61,553
64	7,988	3.46	0.69	3.60	0.56	3.84	6,963	-1,025	1,051,414
65	5,468	3.46	0.69	3.50	0.54	3.83	6,831	1,363	1,859,057
66	4,669	3.46	0.69	1.73	0.24	3.62	4,196	-473	224,092
67	10,061	3.46	0.69	2.62	0.42	3.75	5,583	-4,478	20,051,618
68	3,345	3.46	0.69	2.15	0.33	3.69	4,867	1,522	2,315,116
69	7,348	3.46	0.69	2.14	0.33	3.69	4,854	-2,494	6,221,042
70	7,562	3.46	0.69	3.62	0.56	3.84	6,995		
71	7,388	3.46	0.69	1.55	0.19	3.59	3,877	-3,511	12,325,243
72	8,015	3.46	0.69	2.81	0.45	3.77	5,868	-2,147	4,610,354
73	1,855	3.46	0.69	0.65	-0.19	3.33	2,119	264	69,959
74	2,665	3.46	0.69	1.23	0.09	3.52	3,309	644	414,650
75	5,439	3.46	0.69	1.40	0.15	3.56	3,620	-1,819	3,309,245
76	5,242	3.46	0.69	1.90	0.28	3.65	4,477	-765	584,869
77	6,388	3.46	0.69	2.96	0.47	3.78	6,089	-299	89,414
78	7,062	3.46	0.69	2.32	0.36	3.71	5,131	-1,931	3,728,550
79	3,233	3.46	0.69	1.27	0.10	3.53	3,384	151	22,831
80	2,360	3.46	0.69	1.09	0.04	3.48	3,032		
81	4,068	3.46	0.69	1.69	0.23	3.62	4,127	59	3,521
82	4,111	3.46	0.69	2.41	0.38	3.72	5,280	1,169	1,365,446
83	2,901	3.46	0.69	1.47	0.17	3.57	3,750	849	720,022
84	3,715	3.46	0.69	1.77	0.25	3.63	4,250	535	286,104
85	2,067	3.46	0.69	0.80	-0.10	3.39	2,457	390	152,340
86	4,202	3.46	0.69	2.87	0.46	3.77	5,950	1,748	3,054,541
87	7,605	3.46	0.69	2.37	0.37	3.72	5,206	-2,399	5,757,494
88	1,844	3.46	0.69	1.53	0.18	3.59	3,849	2,005	4,020,209
89	9,574	3.46	0.69	5.52	0.74	3.97	9,379	-195	38,207
90	3,264	3.46	0.69	2.98	0.47	3.79	6,112		
Total	173,450			73.90			161,631	**RMSE**	**1,721.66**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL REAL 2001	Pop 591,530			Area 255.00			AntilogPop 547,037	**RMSE**	**1,721.66**

Table A-V.93: Allometric Growth Model and RMSE for Simulation 2001 in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,992	3.32	1.24	2.09	0.32	3.72	5,255	3,263	10,650,094
1	3,015	3.32	1.24	3.60	0.56	4.01	10,326	7,311	53,450,329
2	3,362	3.32	1.24	1.70	0.23	3.61	4,072	710	504,564
3	1,600	3.32	1.24	1.04	0.02	3.34	2,205	605	366,255
4	1,888	3.32	1.24	1.62	0.21	3.58	3,833	1,945	3,784,752
5	5,020	3.32	1.24	4.44	0.65	4.13	13,365	8,345	69,635,475
6	2,589	3.32	1.24	1.39	0.14	3.50	3,157	568	322,794
7	6,326	3.32	1.24	3.43	0.54	3.99	9,726	3,400	11,557,711
8	2,993	3.32	1.24	1.51	0.18	3.54	3,504	511	260,918
9	6,188	3.32	1.24	3.18	0.50	3.95	8,852	2,664	7,099,492
10	2,984	3.32	1.24	1.19	0.08	3.42	2,618		
11	6,681	3.32	1.24	3.79	0.58	4.04	10,991	4,310	18,578,356
12	5,185	3.32	1.24	3.81	0.58	4.04	11,049	5,864	34,392,228
13	3,861	3.32	1.24	3.03	0.48	3.92	8,325	4,464	19,930,139
14	4,592	3.32	1.24	2.64	0.42	3.85	7,022	2,430	5,907,157
15	5,608	3.32	1.24	3.12	0.49	3.94	8,630	3,022	9,131,041
16	6,110	3.32	1.24	4.84	0.69	4.17	14,892	8,782	77,119,114
17	1,314	3.32	1.24	1.45	0.16	3.52	3,341	2,027	4,109,395
18	2,788	3.32	1.24	1.90	0.28	3.67	4,681	1,893	3,584,566
19	3,080	3.32	1.24	3.67	0.56	4.02	10,556	7,476	55,897,565
20	2,378	3.32	1.24	1.74	0.24	3.62	4,193		
21	2,183	3.32	1.24	1.53	0.18	3.55	3,574	1,391	1,934,757
22	2,247	3.32	1.24	2.35	0.37	3.78	6,075	3,828	14,651,204
23	5,173	3.32	1.24	3.55	0.55	4.01	10,125	4,952	24,523,304
24	4,017	3.32	1.24	2.36	0.37	3.79	6,101	2,084	4,341,611
25	5,334	3.32	1.24	2.88	0.46	3.89	7,805	2,471	6,103,440
26	10,502	3.32	1.24	2.79	0.45	3.88	7,506	-2,996	8,975,986
27	2,783	3.32	1.24	0.70	-0.15	3.14	1,367	-1,416	2,005,869
28	17,983	3.32	1.24	3.31	0.52	3.97	9,301	-8,682	75,373,973
29	2,536	3.32	1.24	0.34	-0.47	2.74	554	-1,982	3,926,761
30	8,130	3.32	1.24	2.36	0.37	3.79	6,101		
31	2,759	3.32	1.24	1.21	0.08	3.43	2,662	-97	9,430
32	6,162	3.32	1.24	1.83	0.26	3.65	4,460	-1,702	2,896,160
33	2,783	3.32	1.24	1.25	0.10	3.44	2,773	-10	100
34	3,013	3.32	1.24	1.06	0.03	3.36	2,269	-744	552,933
35	4,123	3.32	1.24	2.43	0.39	3.80	6,335	2,212	4,894,206
36	7,050	3.32	1.24	2.99	0.48	3.91	8,188	1,138	1,294,219
37	4,874	3.32	1.24	1.92	0.28	3.67	4,731	-143	20,533
38	4,876	3.32	1.24	2.54	0.41	3.83	6,704	1,828	3,340,160
39	8,137	3.32	1.24	4.69	0.67	4.16	14,308	6,171	38,078,292
40	2,841	3.32	1.24	1.31	0.12	3.47	2,953		
41	9,190	3.32	1.24	4.13	0.62	4.09	12,226	3,036	9,218,663
42	2,507	3.32	1.24	0.57	-0.25	3.02	1,044	-1,463	2,140,447
43	6,927	3.32	1.24	3.13	0.50	3.94	8,658	1,731	2,994,776
44	2,288	3.32	1.24	1.15	0.06	3.40	2,508	220	48,325
45	4,634	3.32	1.24	4.86	0.69	4.17	14,953	10,319	106,491,71
46	9,702	3.32	1.24	5.66	0.75	4.26	18,068	8,366	69,996,971
47	6,207	3.32	1.24	4.11	0.61	4.09	12,167	5,960	35,519,787
48	8,880	3.32	1.24	4.05	0.61	4.08	11,930	3,050	9,301,885
49	9,211	3.32	1.24	3.13	0.50	3.94	8,685	-526	276,318
50	4,939	3.32	1.24	1.20	0.08	3.42	2,640		
51	9,117	3.32	1.24	3.99	0.60	4.07	11,723	2,606	6,792,855
52	8,622	3.32	1.24	3.95	0.60	4.06	11,576	2,954	8,727,152
53	9,453	3.32	1.24	3.26	0.51	3.96	9,132	-321	102,771
54	3,292	3.32	1.24	2.21	0.34	3.75	5,637	2,345	5,497,225
55	4,506	3.32	1.24	2.44	0.39	3.80	6,361	1,855	3,442,733
56	5,110	3.32	1.24	2.63	0.42	3.84	6,996	1,886	3,556,183
57	5,063	3.32	1.24	2.23	0.35	3.75	5,688	625	390,405
Total	296,708			151.29			414,479	**RMSE**	**3,664.09**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.94: Allometric Growth Model and RMSE for Simulation 2001 in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,658	3.32	1.24	2.06	0.31	3.71	5,155	1,497	2,240,058
92	4,167	3.32	1.24	2.54	0.40	3.82	6,677	2,510	6,300,949
93	6,846	3.32	1.24	1.17	0.07	3.41	2,552	-4,294	18,441,292
94	2,213	3.32	1.24	1.46	0.16	3.53	3,364	1,151	1,325,507
95	8,296	3.32	1.24	3.44	0.54	3.99	9,754	1,458	2,126,031
96	6,234	3.32	1.24	1.87	0.27	3.66	4,583	-1,651	2,726,556
97	6,118	3.32	1.24	5.00	0.70	4.19	15,480	9,362	87,650,581
98	5,029	3.32	1.24	1.62	0.21	3.58	3,833	-1,196	1,429,355
99	8,390	3.32	1.24	2.43	0.39	3.80	6,335	-2,055	4,221,853
100	3,698	3.32	1.24	1.90	0.28	3.67	4,681		
101	3,213	3.32	1.24	2.21	0.34	3.75	5,637	2,424	5,873,915
102	6,925	3.32	1.24	3.65	0.56	4.02	10,470	3,545	12,566,437
103	10,546	3.32	1.24	3.83	0.58	4.05	11,137	591	349,210
104	3,903	3.32	1.24	0.56	-0.25	3.01	1,026	-2,877	8,279,853
105	9,054	3.32	1.24	2.15	0.33	3.74	5,433	-3,621	13,113,918
106	10,209	3.32	1.24	1.36	0.13	3.49	3,089	-7,120	50,699,137
107	7,875	3.32	1.24	1.30	0.12	3.47	2,930	-4,945	24,452,853
108	9,276	3.32	1.24	1.13	0.05	3.39	2,464	-6,812	46,401,422
109	5,722	3.32	1.24	2.19	0.34	3.75	5,560	-162	26,253
Total	121,372			41.86			110,159	**RMSE**	**3,664.09**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.95: Allometric Growth Model and RMSE for Simulation 2001 in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	6,841	3.32	1.24	2.03	0.31	3.71	5,079	-1,762	3,103,388
59	1,817	3.32	1.24	0.83	-0.08	3.22	1,664	-153	23,274
60	8,713	3.32	1.24	2.39	0.38	3.79	6,205		
61	5,608	3.32	1.24	3.42	0.53	3.99	9,669	4,061	16,490,547
62	5,542	3.32	1.24	3.90	0.59	4.06	11,400	5,858	34,317,200
63	5,490	3.32	1.24	1.72	0.23	3.61	4,120	-1,370	1,875,708
64	7,988	3.32	1.24	2.78	0.44	3.87	7,479	-509	259,102
65	5,468	3.32	1.24	1.73	0.24	3.62	4,169	-1,299	1,688,306
66	4,669	3.32	1.24	1.34	0.13	3.48	3,020	-1,649	2,717,628
67	10,061	3.32	1.24	1.47	0.17	3.53	3,387	-6,674	44,535,874
68	3,345	3.32	1.24	2.24	0.35	3.76	5,713	2,368	5,609,609
69	7,348	3.32	1.24	2.50	0.40	3.82	6,572	-776	602,788
70	7,562	3.32	1.24	2.55	0.41	3.83	6,730		
71	7,388	3.32	1.24	1.53	0.18	3.55	3,574	-3,814	14,546,937
72	8,015	3.32	1.24	3.22	0.51	3.95	8,964	949	901,092
73	1,855	3.32	1.24	0.79	-0.10	3.19	1,564	-291	84,710
74	2,665	3.32	1.24	1.13	0.05	3.39	2,442	-223	49,572
75	5,439	3.32	1.24	0.89	-0.05	3.26	1,828	-3,611	13,041,683
76	5,242	3.32	1.24	1.54	0.19	3.56	3,597	-1,645	2,704,711
77	6,388	3.32	1.24	2.32	0.37	3.78	5,997	-391	152,940
78	7,062	3.32	1.24	3.30	0.52	3.97	9,273	2,211	4,888,580
79	3,233	3.32	1.24	1.64	0.22	3.59	3,905	672	451,336
80	2,360	3.32	1.24	1.50	0.18	3.54	3,480		
81	4,068	3.32	1.24	2.37	0.37	3.79	6,127	2,059	4,237,995
82	4,111	3.32	1.24	2.99	0.48	3.91	8,188	4,077	16,618,973
83	2,901	3.32	1.24	1.81	0.26	3.64	4,387	1,486	2,208,047
84	3,715	3.32	1.24	2.27	0.36	3.76	5,816	2,101	4,415,177
85	2,067	3.32	1.24	1.00	0.00	3.32	2,099	32	1,022
86	4,202	3.32	1.24	2.69	0.43	3.86	7,183	2,981	8,886,081
87	7,605	3.32	1.24	2.44	0.39	3.80	6,361	-1,244	1,546,391
88	1,844	3.32	1.24	0.92	-0.04	3.28	1,890	46	2,082
89	9,574	3.32	1.24	1.88	0.27	3.66	4,607	-4,967	24,667,470
90	3,264	3.32	1.24	1.77	0.25	3.63	4,265		
Total	173,450			66.87			170,757	**RMSE**	**3,664.09**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM 2001	Pop 591,530			Area 260.02			AntilogPop 695,395	**RMSE**	**3,664.09**

Table A-V.96: Allometric Growth Model and RMSE for Sim 2005 Smart in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,864	3.45	0.73	1.66	0.22	3.61	4,097	2,233	4,984,989
1	2,872	3.45	0.73	2.70	0.43	3.77	5,846	2,974	8,845,663
2	3,178	3.45	0.73	1.30	0.12	3.54	3,432	254	64,418
3	1,534	3.45	0.73	0.79	-0.10	3.38	2,385	851	724,200
4	1,737	3.45	0.73	1.32	0.12	3.54	3,463	1,726	2,979,091
5	4,744	3.45	0.73	3.31	0.52	3.83	6,797	2,053	4,214,516
6	2,494	3.45	0.73	1.04	0.02	3.46	2,901	407	165,414
7	6,328	3.45	0.73	2.48	0.39	3.74	5,495	-833	694,192
8	2,977	3.45	0.73	1.10	0.04	3.48	3,033	56	3,082
9	6,378	3.45	0.73	2.28	0.36	3.71	5,175	-1,203	1,446,012
10	3,055	3.45	0.73	0.92	-0.03	3.43	2,665		
11	6,853	3.45	0.73	2.71	0.43	3.77	5,859	-994	987,978
12	5,162	3.45	0.73	2.88	0.46	3.79	6,127	965	930,926
13	3,837	3.45	0.73	2.10	0.32	3.69	4,863	1,026	1,051,848
14	4,455	3.45	0.73	1.77	0.25	3.63	4,300	-155	24,035
15	5,756	3.45	0.73	2.32	0.37	3.72	5,243	-513	263,577
16	6,170	3.45	0.73	3.84	0.58	3.88	7,573	1,403	1,968,266
17	1,209	3.45	0.73	1.12	0.05	3.49	3,065	1,856	3,445,271
18	2,695	3.45	0.73	1.45	0.16	3.57	3,709	1,014	1,028,265
19	2,934	3.45	0.73	2.54	0.40	3.75	5,587	2,653	7,036,692
20	2,230	3.45	0.73	1.34	0.13	3.54	3,494		
21	2,093	3.45	0.73	1.13	0.05	3.49	3,081	988	976,953
22	2,136	3.45	0.73	1.49	0.17	3.58	3,785	1,649	2,718,198
23	5,001	3.45	0.73	2.56	0.41	3.75	5,626	625	390,470
24	3,809	3.45	0.73	1.59	0.20	3.60	3,964	155	24,052
25	5,139	3.45	0.73	1.74	0.24	3.63	4,242	-897	804,149
26	10,865	3.45	0.73	3.39	0.53	3.84	6,918	-3,947	15,576,063
27	2,945	3.45	0.73	2.09	0.32	3.69	4,849	1,904	3,624,560
28	20,066	3.45	0.73	9.34	0.97	4.16	14,529	-5,537	30,656,636
29	2,654	3.45	0.73	0.84	-0.07	3.40	2,491	-163	26,511
30	8,536	3.45	0.73	3.01	0.48	3.80	6,341		
31	2,778	3.45	0.73	1.28	0.11	3.53	3,385	607	368,227
32	6,370	3.45	0.73	1.73	0.24	3.62	4,213	-2,157	4,651,381
33	2,797	3.45	0.73	0.83	-0.08	3.39	2,456	-341	116,300
34	3,005	3.45	0.73	1.12	0.05	3.49	3,065	60	3,617
35	3,958	3.45	0.73	1.67	0.22	3.61	4,111	153	23,515
36	6,939	3.45	0.73	2.13	0.33	3.69	4,918	-2,021	4,086,338
37	4,778	3.45	0.73	1.37	0.14	3.55	3,556	-1,222	1,493,310
38	4,951	3.45	0.73	2.20	0.34	3.70	5,027	76	5,736
39	8,293	3.45	0.73	4.67	0.67	3.94	8,747	454	206,157
40	3,024	3.45	0.73	1.06	0.03	3.47	2,950		
41	9,720	3.45	0.73	4.15	0.62	3.90	8,013	-1,707	2,912,636
42	2,672	3.45	0.73	0.82	-0.09	3.39	2,438	-234	54,616
43	7,284	3.45	0.73	3.01	0.48	3.80	6,328	-956	913,821
44	2,383	3.45	0.73	0.93	-0.03	3.43	2,682	299	89,225
45	4,557	3.45	0.73	3.65	0.56	3.86	7,302	2,745	7,534,018
46	10,109	3.45	0.73	3.85	0.59	3.88	7,585	-2,524	6,372,309
47	6,437	3.45	0.73	3.00	0.48	3.80	6,316	-121	14,749
48	9,202	3.45	0.73	2.82	0.45	3.78	6,038	-3,164	10,010,544
49	9,930	3.45	0.73	2.62	0.42	3.76	5,730	-4,200	17,640,622
50	5,300	3.45	0.73	1.19	0.08	3.51	3,210		
51	9,963	3.45	0.73	4.10	0.61	3.90	7,944	-2,019	4,074,691
52	9,406	3.45	0.73	3.46	0.54	3.85	7,015	-2,391	5,717,230
53	10,209	3.45	0.73	2.84	0.45	3.78	6,076	-4,133	17,080,316
54	3,173	3.45	0.73	2.12	0.33	3.69	4,904	1,731	2,995,732
55	4,548	3.45	0.73	1.25	0.10	3.52	3,322	-1,226	1,503,590
56	5,111	3.45	0.73	1.42	0.15	3.56	3,648	-1,463	2,140,084
57	5,018	3.45	0.73	1.71	0.23	3.62	4,184	-834	695,124
Total	303,621			129.13			286,097	**RMSE**	**2,006.31**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.97: Allometric Growth Model and RMSE for Sim 2005 Smart in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,826	3.45	0.73	1.01	0.01	3.45	2,851	-975	951,171
92	4,286	3.45	0.73	1.67	0.22	3.61	4,111	-175	30,503
93	7,827	3.45	0.73	1.77	0.25	3.63	4,286	-3,541	12,541,759
94	2,146	3.45	0.73	0.54	-0.27	3.26	1,805	-341	116,408
95	9,185	3.45	0.73	3.41	0.53	3.84	6,943	-2,242	5,028,634
96	6,955	3.45	0.73	1.59	0.20	3.60	3,964	-2,991	8,945,558
97	6,179	3.45	0.73	3.70	0.57	3.87	7,373	1,194	1,425,387
98	5,535	3.45	0.73	2.33	0.37	3.72	5,256	-279	77,849
99	9,432	3.45	0.73	3.73	0.57	3.87	7,420	-2,012	4,047,567
100	4,115	3.45	0.73	1.88	0.27	3.65	4,486		
101	3,491	3.45	0.73	1.83	0.26	3.64	4,400	909	826,803
102	7,623	3.45	0.73	3.13	0.50	3.81	6,515	-1,108	1,228,542
103	12,359	3.45	0.73	2.76	0.44	3.77	5,949	-6,410	41,090,820
104	4,729	3.45	0.73	1.34	0.13	3.55	3,510	-1,219	1,486,914
105	10,372	3.45	0.73	3.38	0.53	3.84	6,894	-3,478	12,095,604
106	12,250	3.45	0.73	9.32	0.97	4.16	14,511	2,261	5,110,669
107	9,352	3.45	0.73	5.18	0.71	3.97	9,437	85	7,282
108	10,864	3.45	0.73	5.07	0.71	3.97	9,286	-1,578	2,491,446
109	5,918	3.45	0.73	2.54	0.40	3.75	5,587	-331	109,775
Total	136,444			56.19			114,581	**RMSE**	**2,006.31**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.98: Allometric Growth Model and RMSE for Sim 2005 Smart in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,371	3.45	0.73	1.73	0.24	3.62	4,213	-3,158	9,971,107
59	1,921	3.45	0.73	0.55	-0.26	3.26	1,825	-96	9,308
60	9,804	3.45	0.73	2.33	0.37	3.72	5,256		
61	6,033	3.45	0.73	3.38	0.53	3.84	6,894	861	741,539
62	5,923	3.45	0.73	3.53	0.55	3.85	7,123	1,200	1,440,007
63	6,123	3.45	0.73	2.80	0.45	3.78	6,013	-110	12,188
64	9,112	3.45	0.73	3.73	0.57	3.87	7,420	-1,692	2,862,379
65	5,948	3.45	0.73	3.52	0.55	3.85	7,099	1,151	1,324,888
66	5,148	3.45	0.73	1.77	0.25	3.63	4,300	-848	719,161
67	12,013	3.45	0.73	2.66	0.43	3.76	5,795	-6,218	38,668,391
68	3,555	3.45	0.73	2.18	0.34	3.70	5,000	1,445	2,086,626
69	7,828	3.45	0.73	2.19	0.34	3.70	5,013	-2,815	7,923,481
70	7,967	3.45	0.73	3.69	0.57	3.87	7,349		
71	7,768	3.45	0.73	1.56	0.19	3.59	3,920	-3,848	14,810,788
72	8,552	3.45	0.73	2.86	0.46	3.79	6,102	-2,450	6,004,829
73	1,932	3.45	0.73	0.69	-0.16	3.33	2,149	217	46,976
74	2,772	3.45	0.73	1.24	0.09	3.52	3,306	534	285,119
75	6,133	3.45	0.73	1.43	0.16	3.57	3,679	-2,454	6,024,023
76	5,875	3.45	0.73	1.94	0.29	3.66	4,584	-1,291	1,665,575
77	6,842	3.45	0.73	3.01	0.48	3.80	6,328	-514	264,134
78	7,406	3.45	0.73	2.38	0.38	3.73	5,336	-2,070	4,284,783
79	3,373	3.45	0.73	1.30	0.11	3.53	3,416	43	1,864
80	2,487	3.45	0.73	1.11	0.05	3.48	3,049		
81	4,235	3.45	0.73	1.71	0.23	3.62	4,184	-51	2,575
82	4,273	3.45	0.73	2.46	0.39	3.74	5,468	1,195	1,429,149
83	3,062	3.45	0.73	1.51	0.18	3.58	3,830	768	589,562
84	3,861	3.45	0.73	1.78	0.25	3.63	4,314	453	205,526
85	2,213	3.45	0.73	0.82	-0.09	3.39	2,438	225	50,760
86	4,427	3.45	0.73	2.92	0.47	3.79	6,203	1,776	3,152,680
87	8,463	3.45	0.73	2.41	0.38	3.73	5,389	-3,074	9,448,571
88	1,953	3.45	0.73	1.57	0.20	3.59	3,934	1,981	3,925,934
89	10,961	3.45	0.73	5.75	0.76	4.01	10,183	-778	604,695
90	3,606	3.45	0.73	3.05	0.48	3.81	6,390		
Total	188,940			75.56			167,502	**RMSE**	**2,006.31**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM05sma	Pop 629,005		Area 260.88		AntilogPop 568,180	**RMSE**	**2,006.31**

Table A-V.99: Allometric Growth Model and RMSE for Sim 2005 Normal in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,864	3.47	0.75	1.72	0.23	3.64	4,382	2,518	6,338,985
1	2,872	3.47	0.75	2.81	0.45	3.80	6,335	3,463	11,988,997
2	3,178	3.47	0.75	1.33	0.12	3.56	3,616	438	192,001
3	1,534	3.47	0.75	0.79	-0.10	3.39	2,441	907	823,509
4	1,737	3.47	0.75	1.34	0.13	3.56	3,633	1,896	3,593,528
5	4,744	3.47	0.75	3.37	0.53	3.86	7,255	2,511	6,304,382
6	2,494	3.47	0.75	1.09	0.04	3.50	3,126	632	399,856
7	6,328	3.47	0.75	2.64	0.42	3.78	6,046	-282	79,796
8	2,977	3.47	0.75	1.13	0.05	3.51	3,213	236	55,486
9	6,378	3.47	0.75	2.34	0.37	3.74	5,525	-853	728,345
10	3,055	3.47	0.75	0.96	-0.02	3.45	2,827		
11	6,853	3.47	0.75	2.79	0.45	3.80	6,294	-559	313,036
12	5,162	3.47	0.75	2.96	0.47	3.82	6,592	1,430	2,045,484
13	3,837	3.47	0.75	2.18	0.34	3.72	5,236	1,399	1,957,264
14	4,455	3.47	0.75	1.83	0.26	3.66	4,596	141	20,000
15	5,756	3.47	0.75	2.33	0.37	3.74	5,510	-246	60,386
16	6,170	3.47	0.75	4.05	0.61	3.92	8,325	2,155	4,643,374
17	1,209	3.47	0.75	1.17	0.07	3.52	3,298	2,089	4,363,902
18	2,695	3.47	0.75	1.48	0.17	3.59	3,925	1,230	1,513,357
19	2,934	3.47	0.75	2.64	0.42	3.78	6,046	3,112	9,681,548
20	2,230	3.47	0.75	1.38	0.14	3.57	3,715		
21	2,093	3.47	0.75	1.16	0.06	3.51	3,264	1,171	1,371,030
22	2,136	3.47	0.75	1.54	0.19	3.61	4,037	1,901	3,613,650
23	5,001	3.47	0.75	2.65	0.42	3.78	6,059	1,058	1,120,178
24	3,809	3.47	0.75	1.65	0.22	3.63	4,257	448	201,113
25	5,139	3.47	0.75	1.76	0.24	3.65	4,459	-680	462,663
26	10,865	3.47	0.75	3.44	0.54	3.87	7,372	-3,493	12,201,477
27	2,945	3.47	0.75	2.20	0.34	3.72	5,265	2,320	5,382,931
28	20,066	3.47	0.75	9.86	0.99	4.21	16,194	-3,872	14,995,268
29	2,654	3.47	0.75	0.86	-0.07	3.42	2,609	-45	2,024
30	8,536	3.47	0.75	3.10	0.49	3.83	6,820		
31	2,778	3.47	0.75	1.30	0.12	3.55	3,567	789	621,866
32	6,370	3.47	0.75	1.80	0.25	3.66	4,535	-1,835	3,365,634
33	2,797	3.47	0.75	0.87	-0.06	3.42	2,627	-170	28,765
34	3,005	3.47	0.75	1.14	0.06	3.51	3,230	225	50,492
35	3,958	3.47	0.75	1.69	0.23	3.64	4,335	377	142,333
36	6,939	3.47	0.75	2.21	0.34	3.72	5,294	-1,645	2,705,523
37	4,778	3.47	0.75	1.43	0.16	3.58	3,829	-949	901,514
38	4,951	3.47	0.75	2.33	0.37	3.74	5,510	559	312,776
39	8,293	3.47	0.75	4.79	0.68	3.97	9,434	1,141	1,301,800
40	3,024	3.47	0.75	1.14	0.06	3.51	3,230		
41	9,720	3.47	0.75	4.36	0.64	3.94	8,794	-926	858,021
42	2,672	3.47	0.75	0.86	-0.07	3.42	2,609	-63	3,968
43	7,284	3.47	0.75	3.05	0.48	3.83	6,726	-558	310,838
44	2,383	3.47	0.75	1.00	0.00	3.46	2,916	533	284,148
45	4,557	3.47	0.75	3.82	0.58	3.90	7,974	3,417	11,673,276
46	10,109	3.47	0.75	4.15	0.62	3.93	8,474	-1,635	2,673,719
47	6,437	3.47	0.75	3.12	0.49	3.84	6,847	410	167,726
48	9,202	3.47	0.75	2.88	0.46	3.81	6,457	-2,745	7,534,976
49	9,930	3.47	0.75	2.75	0.44	3.79	6,225	-3,705	13,727,364
50	5,300	3.47	0.75	1.20	0.08	3.52	3,349		
51	9,963	3.47	0.75	4.23	0.63	3.93	8,597	-1,366	1,865,015
52	9,406	3.47	0.75	3.63	0.56	3.88	7,668	-1,738	3,019,377
53	10,209	3.47	0.75	2.96	0.47	3.82	6,579	-3,630	13,178,883
54	3,173	3.47	0.75	2.22	0.35	3.72	5,309	2,136	4,561,007
55	4,548	3.47	0.75	1.29	0.11	3.55	3,533	-1,015	1,029,429
56	5,111	3.47	0.75	1.47	0.17	3.59	3,909	-1,202	1,444,490
57	5,018	3.47	0.75	1.77	0.25	3.65	4,490	-528	279,301
Total	303,621			134.00			308,316	**RMSE**	**1,884.30**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.100: Allometric Growth Model and RMSE for Sim 2005 Normal in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,826	3.47	0.75	1.14	0.06	3.51	3,230	-596	355,569
92	4,286	3.47	0.75	1.79	0.25	3.66	4,520	234	54,823
93	7,827	3.47	0.75	1.87	0.27	3.67	4,672	-3,155	9,952,279
94	2,146	3.47	0.75	0.58	-0.23	3.29	1,954	-192	37,025
95	9,185	3.47	0.75	3.60	0.56	3.88	7,617	-1,568	2,458,332
96	6,955	3.47	0.75	1.63	0.21	3.62	4,211	-2,744	7,532,079
97	6,179	3.47	0.75	3.83	0.58	3.90	7,986	1,807	3,266,154
98	5,535	3.47	0.75	2.51	0.40	3.77	5,822	287	82,470
99	9,432	3.47	0.75	3.87	0.59	3.91	8,049	-1,383	1,911,821
100	4,115	3.47	0.75	1.95	0.29	3.68	4,823		
101	3,491	3.47	0.75	1.87	0.27	3.67	4,672	1,181	1,395,415
102	7,623	3.47	0.75	3.31	0.52	3.86	7,163	-460	211,283
103	12,359	3.47	0.75	3.05	0.48	3.83	6,740	-5,619	31,574,865
104	4,729	3.47	0.75	1.43	0.15	3.58	3,812	-917	840,287
105	10,372	3.47	0.75	3.53	0.55	3.88	7,514	-2,858	8,167,027
106	12,250	3.47	0.75	9.66	0.98	4.20	15,944	3,694	13,646,761
107	9,352	3.47	0.75	5.40	0.73	4.01	10,327	975	951,494
108	10,864	3.47	0.75	5.39	0.73	4.01	10,304	-560	313,294
109	5,918	3.47	0.75	2.68	0.43	3.79	6,115	197	38,707
Total	136,444			59.10			125,476	**RMSE**	**1,884.30**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.101: Allometric Growth Model and RMSE for Sim 2005 Normal in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,371	3.47	0.75	1.85	0.27	3.67	4,627	-2,744	7,530,556
59	1,921	3.47	0.75	0.58	-0.23	3.29	1,954	33	1,062
60	9,804	3.47	0.75	2.50	0.40	3.76	5,808		
61	6,033	3.47	0.75	3.50	0.54	3.87	7,463	1,430	2,043,681
62	5,923	3.47	0.75	3.70	0.57	3.89	7,783	1,860	3,460,739
63	6,123	3.47	0.75	2.92	0.47	3.81	6,525	402	161,383
64	9,112	3.47	0.75	3.94	0.60	3.91	8,162	-950	901,719
65	5,948	3.47	0.75	3.56	0.55	3.88	7,566	1,618	2,616,969
66	5,148	3.47	0.75	1.85	0.27	3.67	4,642	-506	256,051
67	12,013	3.47	0.75	2.78	0.44	3.80	6,280	-5,733	32,869,419
68	3,555	3.47	0.75	2.24	0.35	3.73	5,338	1,783	3,177,696
69	7,828	3.47	0.75	2.30	0.36	3.74	5,453	-2,375	5,641,018
70	7,967	3.47	0.75	3.73	0.57	3.89	7,834		
71	7,768	3.47	0.75	1.62	0.21	3.62	4,195	-3,573	12,767,346
72	8,552	3.47	0.75	2.97	0.47	3.82	6,606	-1,946	3,788,192
73	1,932	3.47	0.75	0.77	-0.11	3.38	2,404	472	222,521
74	2,772	3.47	0.75	1.32	0.12	3.56	3,600	828	685,044
75	6,133	3.47	0.75	1.47	0.17	3.59	3,893	-2,240	5,017,360
76	5,875	3.47	0.75	2.03	0.31	3.70	4,957	-918	842,996
77	6,842	3.47	0.75	3.10	0.49	3.83	6,820	-22	487
78	7,406	3.47	0.75	2.46	0.39	3.76	5,738	-1,668	2,783,296
79	3,373	3.47	0.75	1.34	0.13	3.56	3,633	260	67,423
80	2,487	3.47	0.75	1.17	0.07	3.52	3,298		
81	4,235	3.47	0.75	1.77	0.25	3.65	4,490	255	64,776
82	4,273	3.47	0.75	2.53	0.40	3.77	5,850	1,577	2,487,718
83	3,062	3.47	0.75	1.52	0.18	3.60	4,005	943	889,499
84	3,861	3.47	0.75	1.85	0.27	3.67	4,627	766	586,471
85	2,213	3.47	0.75	0.80	-0.10	3.39	2,479	266	70,772
86	4,427	3.47	0.75	3.00	0.48	3.82	6,646	2,219	4,924,052
87	8,463	3.47	0.75	2.55	0.41	3.77	5,892	-2,571	6,608,621
88	1,953	3.47	0.75	1.64	0.22	3.63	4,242	2,289	5,238,768
89	10,961	3.47	0.75	6.03	0.78	4.05	11,218	257	66,105
90	3,606	3.47	0.75	3.10	0.49	3.83	6,820		
Total	188,940			78.52			180,845	**RMSE**	**1,884.30**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM05norm	Pop			Area			AntilogPop		
	629,005			271.62			614,638	**RMSE**	**1,884.30**

Table A-V.102: Allometric Growth Model and RMSE for Sim 2005 Sprawl in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,864	3.44	0.75	1.73	0.24	3.62	4,137	2,273	5,165,073
1	2,872	3.44	0.75	2.88	0.46	3.78	6,066	3,194	10,198,846
2	3,178	3.44	0.75	1.34	0.13	3.53	3,402	224	50,156
3	1,534	3.44	0.75	0.83	-0.08	3.37	2,369	835	697,981
4	1,737	3.44	0.75	1.34	0.13	3.53	3,402	1,665	2,772,078
5	4,744	3.44	0.75	3.54	0.55	3.85	7,077	2,333	5,440,880
6	2,494	3.44	0.75	1.14	0.06	3.48	3,023	529	279,512
7	6,328	3.44	0.75	2.66	0.43	3.76	5,716	-612	374,225
8	2,977	3.44	0.75	1.15	0.06	3.48	3,039	62	3,819
9	6,378	3.44	0.75	2.39	0.38	3.72	5,266	-1,112	1,236,381
10	3,055	3.44	0.75	1.03	0.01	3.45	2,794		
11	6,853	3.44	0.75	2.92	0.47	3.79	6,130	-723	523,430
12	5,162	3.44	0.75	3.02	0.48	3.80	6,282	1,120	1,254,654
13	3,837	3.44	0.75	2.24	0.35	3.70	5,009	1,172	1,373,404
14	4,455	3.44	0.75	1.85	0.27	3.64	4,339	-116	13,553
15	5,756	3.44	0.75	2.36	0.37	3.72	5,212	-544	295,625
16	6,170	3.44	0.75	4.22	0.63	3.91	8,077	1,907	3,636,125
17	1,209	3.44	0.75	1.17	0.07	3.49	3,087	1,878	3,526,693
18	2,695	3.44	0.75	1.47	0.17	3.56	3,647	952	906,612
19	2,934	3.44	0.75	2.63	0.42	3.75	5,664	2,730	7,452,457
20	2,230	3.44	0.75	1.43	0.15	3.55	3,571		
21	2,093	3.44	0.75	1.24	0.09	3.51	3,214	1,121	1,257,020
22	2,136	3.44	0.75	1.57	0.20	3.58	3,842	1,706	2,911,954
23	5,001	3.44	0.75	2.75	0.44	3.77	5,846	845	714,755
24	3,809	3.44	0.75	1.73	0.24	3.62	4,122	313	98,053
25	5,139	3.44	0.75	1.83	0.26	3.63	4,310	-829	687,356
26	10,865	3.44	0.75	3.47	0.54	3.84	6,967	-3,898	15,196,826
27	2,945	3.44	0.75	2.29	0.36	3.71	5,104	2,159	4,661,964
28	20,066	3.44	0.75	10.00	1.00	4.19	15,447	-4,619	21,333,325
29	2,654	3.44	0.75	0.89	-0.05	3.40	2,508	-146	21,349
30	8,536	3.44	0.75	3.21	0.51	3.82	6,571		
31	2,778	3.44	0.75	1.36	0.13	3.54	3,448	670	449,390
32	6,370	3.44	0.75	1.81	0.26	3.63	4,267	-2,103	4,423,297
33	2,797	3.44	0.75	0.87	-0.06	3.39	2,474	-323	104,639
34	3,005	3.44	0.75	1.13	0.05	3.48	3,007	2	2
35	3,958	3.44	0.75	1.81	0.26	3.63	4,281	323	104,469
36	6,939	3.44	0.75	2.25	0.35	3.70	5,036	-1,903	3,620,672
37	4,778	3.44	0.75	1.46	0.16	3.56	3,632	-1,146	1,313,319
38	4,951	3.44	0.75	2.36	0.37	3.72	5,212	261	68,271
39	8,293	3.44	0.75	4.98	0.70	3.96	9,150	857	734,222
40	3,024	3.44	0.75	1.14	0.06	3.48	3,023		
41	9,720	3.44	0.75	4.42	0.65	3.92	8,367	-1,353	1,831,661
42	2,672	3.44	0.75	0.85	-0.07	3.38	2,422	-250	62,665
43	7,284	3.44	0.75	3.23	0.51	3.82	6,609	-675	456,106
44	2,383	3.44	0.75	1.00	0.00	3.44	2,728	345	118,787
45	4,557	3.44	0.75	3.87	0.59	3.88	7,570	3,013	9,079,706
46	10,109	3.44	0.75	4.20	0.62	3.91	8,054	-2,055	4,224,934
47	6,437	3.44	0.75	3.22	0.51	3.82	6,584	147	21,526
48	9,202	3.44	0.75	3.09	0.49	3.81	6,383	-2,819	7,945,810
49	9,930	3.44	0.75	2.84	0.45	3.78	6,001	-3,929	15,433,994
50	5,300	3.44	0.75	1.24	0.09	3.51	3,214		
51	9,963	3.44	0.75	4.39	0.64	3.92	8,320	-1,643	2,697,883
52	9,406	3.44	0.75	3.90	0.59	3.88	7,618	-1,788	3,197,500
53	10,209	3.44	0.75	3.04	0.48	3.80	6,307	-3,902	15,222,270
54	3,173	3.44	0.75	2.37	0.38	3.72	5,239	2,066	4,269,193
55	4,548	3.44	0.75	1.41	0.15	3.55	3,541	-1,007	1,014,906
56	5,111	3.44	0.75	1.60	0.20	3.59	3,887	-1,224	1,498,071
57	5,018	3.44	0.75	1.87	0.27	3.64	4,381	-637	405,208
Total	303,621			138.02			295,994	**RMSE**	**1,918.16**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.103: Allometric Growth Model and RMSE for Sim 2005 Sprawl in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	3,826	3.44	0.75	1.13	0.05	3.48	3,007	-819	671,492
92	4,286	3.44	0.75	1.94	0.29	3.65	4,495	209	43,708
93	7,827	3.44	0.75	2.02	0.30	3.67	4,636	-3,191	10,183,897
94	2,146	3.44	0.75	0.63	-0.20	3.29	1,937	-209	43,856
95	9,185	3.44	0.75	3.78	0.58	3.87	7,439	-1,746	3,048,966
96	6,955	3.44	0.75	1.75	0.24	3.62	4,166	-2,789	7,780,089
97	6,179	3.44	0.75	4.02	0.60	3.89	7,784	1,605	2,574,882
98	5,535	3.44	0.75	2.62	0.42	3.75	5,638	103	10,545
99	9,432	3.44	0.75	4.03	0.60	3.89	7,795	-1,637	2,678,322
100	4,115	3.44	0.75	2.02	0.30	3.67	4,636		
101	3,491	3.44	0.75	1.94	0.29	3.65	4,495	1,004	1,008,146
102	7,623	3.44	0.75	3.43	0.53	3.84	6,905	-718	514,953
103	12,359	3.44	0.75	3.07	0.49	3.80	6,358	-6,001	36,012,546
104	4,729	3.44	0.75	1.39	0.14	3.55	3,510	-1,219	1,486,138
105	10,372	3.44	0.75	3.66	0.56	3.86	7,258	-3,114	9,694,095
106	12,250	3.44	0.75	10.12	1.01	4.19	15,588	3,338	11,143,512
107	9,352	3.44	0.75	5.54	0.74	4.00	9,912	560	313,131
108	10,864	3.44	0.75	5.56	0.74	4.00	9,933	-931	866,078
109	5,918	3.44	0.75	2.74	0.44	3.77	5,833	-85	7,147
Total	136,444			61.3656			121,325	**RMSE**	**1,918.16**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.104: Allometric Growth Model and RMSE for Sim 2005 Sprawl in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,371	3.44	0.75	1.98	0.30	3.66	4,566	-2,805	7,870,268
59	1,921	3.44	0.75	0.60	-0.22	3.27	1,861	-60	3,550
60	9,804	3.44	0.75	2.69	0.43	3.76	5,755		
61	6,033	3.44	0.75	3.66	0.56	3.86	7,258	1,225	1,501,767
62	5,923	3.44	0.75	3.86	0.59	3.88	7,558	1,635	2,674,344
63	6,123	3.44	0.75	2.96	0.47	3.79	6,193	70	4,935
64	9,112	3.44	0.75	4.01	0.60	3.89	7,772	-1,340	1,796,029
65	5,948	3.44	0.75	3.57	0.55	3.85	7,125	1,177	1,385,858
66	5,148	3.44	0.75	1.85	0.27	3.64	4,353	-795	632,211
67	12,013	3.44	0.75	2.92	0.47	3.79	6,130	-5,883	34,615,389
68	3,555	3.44	0.75	2.27	0.36	3.70	5,063	1,508	2,275,318
69	7,828	3.44	0.75	2.41	0.38	3.72	5,306	-2,522	6,358,998
70	7,967	3.44	0.75	3.90	0.59	3.88	7,606		
71	7,768	3.44	0.75	1.64	0.22	3.60	3,976	-3,792	14,381,251
72	8,552	3.44	0.75	3.05	0.48	3.80	6,333	-2,219	4,925,259
73	1,932	3.44	0.75	0.79	-0.10	3.36	2,282	350	122,197
74	2,772	3.44	0.75	1.33	0.12	3.53	3,386	614	377,536
75	6,133	3.44	0.75	1.46	0.16	3.56	3,632	-2,501	6,255,009
76	5,875	3.44	0.75	2.06	0.31	3.67	4,706	-1,169	1,367,479
77	6,842	3.44	0.75	3.29	0.52	3.83	6,696	-146	21,420
78	7,406	3.44	0.75	2.53	0.40	3.74	5,493	-1,913	3,660,760
79	3,373	3.44	0.75	1.39	0.14	3.54	3,495	122	14,779
80	2,487	3.44	0.75	1.21	0.08	3.50	3,151		
81	4,235	3.44	0.75	1.80	0.25	3.63	4,252	17	304
82	4,273	3.44	0.75	2.60	0.41	3.75	5,611	1,338	1,791,359
83	3,062	3.44	0.75	1.54	0.19	3.58	3,783	721	519,428
84	3,861	3.44	0.75	1.85	0.27	3.64	4,353	492	241,949
85	2,213	3.44	0.75	0.84	-0.07	3.38	2,404	191	36,598
86	4,427	3.44	0.75	3.09	0.49	3.81	6,383	1,956	3,826,596
87	8,463	3.44	0.75	2.58	0.41	3.75	5,585	-2,878	8,282,281
88	1,953	3.44	0.75	1.70	0.23	3.61	4,078	2,125	4,517,318
89	10,961	3.44	0.75	6.25	0.80	4.04	10,856	-105	11,030
90	3,606	3.44	0.75	3.23	0.51	3.82	6,609		
Total	188,940			80.92			173,610	**RMSE**	**1,918.16**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM05spraw	Pop 629,005			Area 280.31			AntilogPop 590,929	**RMSE**	**1,918.16**

Table A-V.105: Allometric Growth Model and RMSE for Sim 2010 Smart in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,772	3.49	0.76	1.69	0.23	3.67	4,631	2,859	8,173,853
1	2,793	3.49	0.76	2.71	0.43	3.82	6,641	3,848	14,805,140
2	3,060	3.49	0.76	1.30	0.12	3.58	3,794	734	538,759
3	1,503	3.49	0.76	0.81	-0.09	3.42	2,637	1,134	1,285,576
4	1,616	3.49	0.76	1.32	0.12	3.58	3,830	2,214	4,901,605
5	4,565	3.49	0.76	3.33	0.52	3.89	7,764	3,199	10,230,419
6	2,459	3.49	0.76	1.05	0.02	3.51	3,222	763	582,279
7	6,539	3.49	0.76	2.49	0.40	3.79	6,228	-311	96,840
8	3,055	3.49	0.76	1.10	0.04	3.52	3,335	280	78,445
9	6,841	3.49	0.76	2.32	0.37	3.77	5,901	-940	884,144
10	3,250	3.49	0.76	0.95	-0.02	3.47	2,973		
11	7,306	3.49	0.76	2.71	0.43	3.82	6,641	-665	442,565
12	5,302	3.49	0.76	2.92	0.46	3.85	7,016	1,714	2,938,244
13	3,933	3.49	0.76	2.11	0.33	3.74	5,488	1,555	2,417,310
14	4,431	3.49	0.76	1.80	0.25	3.69	4,849	418	175,135
15	6,141	3.49	0.76	2.34	0.37	3.77	5,932	-209	43,639
16	6,452	3.49	0.76	3.86	0.59	3.94	8,699	2,247	5,049,123
17	1,125	3.49	0.76	1.13	0.05	3.53	3,391	2,266	5,135,396
18	2,669	3.49	0.76	1.45	0.16	3.61	4,114	1,445	2,087,970
19	2,852	3.49	0.76	2.54	0.41	3.80	6,320	3,468	12,029,015
20	2,126	3.49	0.76	1.34	0.13	3.59	3,866		
21	2,051	3.49	0.76	1.13	0.05	3.53	3,410	1,359	1,846,241
22	2,071	3.49	0.76	1.51	0.18	3.63	4,236	2,165	4,688,682
23	4,950	3.49	0.76	2.59	0.41	3.81	6,412	1,462	2,138,464
24	3,682	3.49	0.76	1.60	0.20	3.65	4,426	744	554,193
25	5,066	3.49	0.76	1.75	0.24	3.68	4,749	-317	100,468
26	11,710	3.49	0.76	3.39	0.53	3.90	7,879	-3,831	14,678,929
27	3,263	3.49	0.76	2.12	0.33	3.74	5,504	2,241	5,021,304
28	23,769	3.49	0.76	9.40	0.97	4.23	17,164	-6,605	43,628,184
29	2,901	3.49	0.76	0.85	-0.07	3.44	2,737	-164	26,903
30	9,371	3.49	0.76	3.02	0.48	3.86	7,209		
31	2,894	3.49	0.76	1.29	0.11	3.57	3,758	864	746,394
32	6,859	3.49	0.76	1.75	0.24	3.68	4,749	-2,110	4,451,959
33	2,908	3.49	0.76	0.83	-0.08	3.43	2,677	-231	53,348
34	3,093	3.49	0.76	1.13	0.05	3.53	3,391	298	88,888
35	3,886	3.49	0.76	1.69	0.23	3.67	4,631	745	555,018
36	7,027	3.49	0.76	2.16	0.33	3.75	5,584	-1,443	2,082,555
37	4,814	3.49	0.76	1.39	0.14	3.60	3,973	-841	707,696
38	5,212	3.49	0.76	2.22	0.35	3.76	5,695	483	233,672
39	8,773	3.49	0.76	4.74	0.68	4.01	10,167	1,394	1,943,028
40	3,376	3.49	0.76	1.08	0.03	3.52	3,279		
41	10,770	3.49	0.76	4.19	0.62	3.97	9,251	-1,519	2,307,319
42	2,989	3.49	0.76	0.83	-0.08	3.43	2,677	-312	97,326
43	8,011	3.49	0.76	3.03	0.48	3.86	7,224	-787	619,926
44	2,590	3.49	0.76	0.93	-0.03	3.47	2,934	344	118,316
45	4,609	3.49	0.76	3.69	0.57	3.92	8,391	3,782	14,301,995
46	10,993	3.49	0.76	3.90	0.59	3.94	8,769	-2,224	4,947,934
47	6,959	3.49	0.76	3.05	0.48	3.86	7,253	294	86,518
48	9,937	3.49	0.76	2.84	0.45	3.84	6,882	-3,055	9,334,717
49	11,268	3.49	0.76	2.63	0.42	3.81	6,489	-4,779	22,841,173
50	5,980	3.49	0.76	1.21	0.08	3.55	3,576		
51	11,497	3.49	0.76	4.12	0.62	3.96	9,141	-2,356	5,548,630
52	10,834	3.49	0.76	3.48	0.54	3.91	8,036	-2,798	7,827,507
53	11,609	3.49	0.76	2.92	0.46	3.85	7,016	-4,593	21,094,449
54	3,129	3.49	0.76	2.14	0.33	3.74	5,536	2,407	5,793,150
55	4,753	3.49	0.76	1.26	0.10	3.57	3,685	-1,068	1,139,564
56	5,282	3.49	0.76	1.44	0.16	3.61	4,096	-1,186	1,405,623
57	5,125	3.49	0.76	1.73	0.24	3.67	4,715	-410	167,771
Total	323,801			130.31			324,573	**RMSE**	**2,394.14**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.106: Allometric Growth Model and RMSE for Sim 2010 Smart in Santa Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,069	3.49	0.76	1.02	0.01	3.50	3,146	-923	851,836
92	4,463	3.49	0.76	1.68	0.23	3.66	4,614	151	22,818
93	9,305	3.49	0.76	1.78	0.25	3.68	4,816	-4,489	20,150,424
94	2,076	3.49	0.76	0.54	-0.27	3.29	1,942	-134	18,011
95	10,490	3.49	0.76	3.47	0.54	3.90	8,008	-2,482	6,162,015
96	8,020	3.49	0.76	1.60	0.21	3.65	4,444	-3,576	12,790,651
97	6,292	3.49	0.76	3.74	0.57	3.93	8,489	2,197	4,827,882
98	6,275	3.49	0.76	2.40	0.38	3.78	6,042	-233	54,492
99	10,979	3.49	0.76	3.77	0.58	3.93	8,531	-2,448	5,991,101
100	4,730	3.49	0.76	1.92	0.28	3.71	5,098		
101	3,895	3.49	0.76	1.85	0.27	3.70	4,966	1,071	1,146,800
102	8,645	3.49	0.76	3.16	0.50	3.87	7,459	-1,186	1,407,602
103	15,155	3.49	0.76	2.80	0.45	3.83	6,807	-8,348	69,694,091
104	6,045	3.49	0.76	1.39	0.14	3.60	3,990	-2,055	4,221,009
105	12,363	3.49	0.76	3.42	0.53	3.90	7,922	-4,441	19,724,680
106	15,471	3.49	0.76	9.46	0.98	4.24	17,243	1,772	3,139,429
107	11,660	3.49	0.76	5.27	0.72	4.04	11,032	-628	394,251
108	13,310	3.49	0.76	5.13	0.71	4.03	10,798	-2,512	6,308,687
109	6,208	3.49	0.76	2.56	0.41	3.80	6,351	143	20,455
Total	159,451			56.98			131,697	**RMSE**	**2,394.14**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.107: Allometric Growth Model and RMSE for Sim 2010 Smart in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,983	3.49	0.76	1.73	0.24	3.67	4,699	-3,284	10,787,561
59	2,032	3.49	0.76	0.55	-0.26	3.29	1,964	-68	4,638
60	11,212	3.49	0.76	2.36	0.37	3.78	5,963		
61	6,521	3.49	0.76	3.43	0.54	3.90	7,950	1,429	2,043,241
62	6,352	3.49	0.76	3.58	0.55	3.91	8,207	1,855	3,441,077
63	6,923	3.49	0.76	2.81	0.45	3.83	6,822	-101	10,256
64	10,600	3.49	0.76	3.77	0.58	3.93	8,545	-2,055	4,221,624
65	6,518	3.49	0.76	3.52	0.55	3.91	8,108	1,590	2,526,593
66	5,740	3.49	0.76	1.79	0.25	3.68	4,833	-907	823,023
67	14,795	3.49	0.76	2.70	0.43	3.82	6,610	-8,185	66,987,127
68	3,786	3.49	0.76	2.19	0.34	3.75	5,632	1,846	3,406,846
69	8,361	3.49	0.76	2.25	0.35	3.76	5,759	-2,602	6,771,391
70	8,392	3.49	0.76	3.69	0.57	3.92	8,391		
71	8,160	3.49	0.76	1.59	0.20	3.64	4,409	-3,751	14,068,014
72	9,152	3.49	0.76	2.90	0.46	3.84	6,986	-2,166	4,690,120
73	2,006	3.49	0.76	0.71	-0.15	3.38	2,391	385	148,597
74	2,873	3.49	0.76	1.24	0.09	3.56	3,649	776	602,345
75	7,031	3.49	0.76	1.45	0.16	3.61	4,114	-2,917	8,509,000
76	6,685	3.49	0.76	1.95	0.29	3.71	5,163	-1,522	2,314,984
77	7,356	3.49	0.76	3.04	0.48	3.86	7,238	-118	13,830
78	7,755	3.49	0.76	2.41	0.38	3.78	6,073	-1,682	2,830,041
79	3,510	3.49	0.76	1.34	0.13	3.59	3,866	356	126,599
80	2,619	3.49	0.76	1.13	0.05	3.53	3,391		
81	4,394	3.49	0.76	1.72	0.23	3.67	4,682	288	82,769
82	4,425	3.49	0.76	2.50	0.40	3.80	6,243	1,818	3,306,039
83	3,232	3.49	0.76	1.51	0.18	3.63	4,254	1,022	1,043,925
84	3,998	3.49	0.76	1.78	0.25	3.68	4,816	818	669,251
85	2,378	3.49	0.76	0.83	-0.08	3.43	2,677	299	89,418
86	4,664	3.49	0.76	2.97	0.47	3.85	7,120	2,456	6,032,535
87	9,544	3.49	0.76	2.47	0.39	3.79	6,181	-3,363	11,307,004
88	2,070	3.49	0.76	1.60	0.20	3.65	4,426	2,356	5,552,818
89	12,810	3.49	0.76	5.84	0.77	4.08	11,927	-883	779,016
90	4,032	3.49	0.76	3.09	0.49	3.86	7,327		
Total	207,909			76.43			190,418	**RMSE**	**2,394.14**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM10smart	Pop 691,161			Area 263.72			AntilogPop 646,688	**RMSE**	**2,394.14**

Table A-V.108: Allometric Growth Model and RMSE for Sim 2010 Normal in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log Pop	AntilogPop		
0	1,772	3.44	0.81	1.78	0.25	3.65	4,418	2,646	7,001,633
1	2,793	3.44	0.81	2.96	0.47	3.82	6,644	3,851	14,832,245
2	3,060	3.44	0.81	1.39	0.14	3.56	3,606	546	298,189
3	1,503	3.44	0.81	0.85	-0.07	3.39	2,434	931	866,729
4	1,616	3.44	0.81	1.37	0.14	3.55	3,572	1,956	3,826,070
5	4,565	3.44	0.81	3.61	0.56	3.89	7,809	3,244	10,524,399
6	2,459	3.44	0.81	1.17	0.07	3.50	3,157	698	487,478
7	6,539	3.44	0.81	2.82	0.45	3.81	6,394	-145	21,114
8	3,055	3.44	0.81	1.19	0.08	3.50	3,192	137	18,837
9	6,841	3.44	0.81	2.46	0.39	3.76	5,734	-1,107	1,226,111
10	3,250	3.44	0.81	1.06	0.03	3.46	2,909		
11	7,306	3.44	0.81	2.92	0.46	3.82	6,571	-735	540,508
12	5,302	3.44	0.81	3.10	0.49	3.84	6,907	1,605	2,576,417
13	3,933	3.44	0.81	2.31	0.36	3.74	5,443	1,510	2,280,310
14	4,431	3.44	0.81	1.96	0.29	3.68	4,771	340	115,486
15	6,141	3.44	0.81	2.45	0.39	3.76	5,718	-423	178,511
16	6,452	3.44	0.81	4.34	0.64	3.96	9,056	2,604	6,781,829
17	1,125	3.44	0.81	1.23	0.09	3.52	3,279	2,154	4,641,780
18	2,669	3.44	0.81	1.56	0.19	3.60	3,959	1,290	1,663,964
19	2,852	3.44	0.81	2.86	0.46	3.81	6,468	3,616	13,072,799
20	2,126	3.44	0.81	1.48	0.17	3.58	3,809		
21	2,051	3.44	0.81	1.27	0.10	3.53	3,366	1,315	1,729,631
22	2,071	3.44	0.81	1.60	0.21	3.61	4,058	1,987	3,949,618
23	4,950	3.44	0.81	2.75	0.44	3.80	6,275	1,325	1,755,518
24	3,682	3.44	0.81	1.74	0.24	3.64	4,337	655	428,958
25	5,066	3.44	0.81	1.85	0.27	3.66	4,547	-519	269,258
26	11,710	3.44	0.81	3.49	0.54	3.88	7,597	-4,113	16,918,859
27	3,263	3.44	0.81	2.35	0.37	3.74	5,520	2,257	5,093,626
28	23,769	3.44	0.81	10.59	1.02	4.27	18,576	-5,193	26,965,096
29	2,901	3.44	0.81	0.97	-0.01	3.43	2,711	-190	36,267
30	9,371	3.44	0.81	3.37	0.53	3.87	7,383		
31	2,894	3.44	0.81	1.41	0.15	3.56	3,657	763	582,126
32	6,859	3.44	0.81	1.97	0.29	3.68	4,787	-2,072	4,294,365
33	2,908	3.44	0.81	0.94	-0.03	3.42	2,637	-271	73,172
34	3,093	3.44	0.81	1.16	0.06	3.49	3,122	29	844
35	3,886	3.44	0.81	1.80	0.25	3.65	4,450	564	318,552
36	7,027	3.44	0.81	2.36	0.37	3.74	5,535	-1,492	2,225,340
37	4,814	3.44	0.81	1.53	0.18	3.59	3,909	-905	819,001
38	5,212	3.44	0.81	2.46	0.39	3.76	5,734	522	272,172
39	8,773	3.44	0.81	5.14	0.71	4.02	10,369	1,596	2,546,149
40	3,376	3.44	0.81	1.26	0.10	3.52	3,332		
41	10,770	3.44	0.81	4.60	0.66	3.98	9,490	-1,280	1,639,660
42	2,989	3.44	0.81	0.92	-0.04	3.41	2,582	-407	165,340
43	8,011	3.44	0.81	3.35	0.53	3.87	7,354	-657	431,258
44	2,590	3.44	0.81	1.06	0.03	3.46	2,909	319	101,829
45	4,609	3.44	0.81	4.16	0.62	3.94	8,755	4,146	17,192,500
46	10,993	3.44	0.81	4.49	0.65	3.97	9,301	-1,692	2,864,448
47	6,959	3.44	0.81	3.38	0.53	3.87	7,397	438	192,038
48	9,937	3.44	0.81	3.13	0.50	3.84	6,965	-2,972	8,831,560
49	11,268	3.44	0.81	2.96	0.47	3.82	6,644	-4,624	21,378,921
50	5,980	3.44	0.81	1.30	0.12	3.54	3,435		
51	11,497	3.44	0.81	4.58	0.66	3.98	9,449	-2,048	4,193,936
52	10,834	3.44	0.81	3.94	0.60	3.92	8,383	-2,451	6,008,555
53	11,609	3.44	0.81	3.21	0.51	3.85	7,095	-4,514	20,371,942
54	3,129	3.44	0.81	2.41	0.38	3.75	5,642	2,513	6,316,746
55	4,753	3.44	0.81	1.57	0.20	3.60	3,992	-761	578,889
56	5,282	3.44	0.81	1.69	0.23	3.63	4,239	-1,043	1,087,576
57	5,125	3.44	0.81	1.94	0.29	3.68	4,739	-386	148,975
Total	323,801			143.58			326,125	**RMSE**	**2,287.02**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.109: Allometric Growth Model and RMSE for Sim 2010 Normal in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,069	3.44	0.81	1.44	0.16	3.57	3,725	-344	118,624
92	4,463	3.44	0.81	2.07	0.32	3.70	4,976	513	263,521
93	9,305	3.44	0.81	2.11	0.33	3.71	5,071	-4,234	17,930,952
94	2,076	3.44	0.81	0.66	-0.18	3.30	1,994	-82	6,688
95	10,490	3.44	0.81	3.93	0.59	3.92	8,355	-2,135	4,558,199
96	8,020	3.44	0.81	1.83	0.26	3.65	4,515	-3,505	12,285,566
97	6,292	3.44	0.81	4.08	0.61	3.94	8,618	2,326	5,409,487
98	6,275	3.44	0.81	2.93	0.47	3.82	6,600	325	105,764
99	10,979	3.44	0.81	4.23	0.63	3.95	8,865	-2,114	4,468,771
100	4,730	3.44	0.81	2.19	0.34	3.72	5,211		
101	3,895	3.44	0.81	1.96	0.29	3.68	4,771	876	767,081
102	8,645	3.44	0.81	3.72	0.57	3.90	7,992	-653	426,301
103	15,155	3.44	0.81	3.50	0.54	3.88	7,611	-7,544	56,912,702
104	6,045	3.44	0.81	1.61	0.21	3.61	4,075	-1,970	3,881,385
105	12,363	3.44	0.81	3.85	0.59	3.91	8,216	-4,147	17,198,622
106	15,471	3.44	0.81	10.65	1.03	4.27	18,668	3,197	10,219,514
107	11,660	3.44	0.81	5.90	0.77	4.06	11,591	-69	4,776
108	13,310	3.44	0.81	5.85	0.77	4.06	11,514	-1,796	3,226,218
109	6,208	3.44	0.81	2.84	0.45	3.81	6,423	215	46,351
Total	159,451			65.34			138,790	**RMSE**	**2,287.02**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.110: Allometric Growth Model and RMSE for Sim 2010 Normal in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,983	3.44	0.81	2.06	0.31	3.70	4,961	-3,022	9,134,854
59	2,032	3.44	0.81	0.66	-0.18	3.30	1,975	-57	3,295
60	11,212	3.44	0.81	2.77	0.44	3.80	6,305		
61	6,521	3.44	0.81	3.78	0.58	3.91	8,104	1,583	2,506,415
62	6,352	3.44	0.81	4.02	0.60	3.93	8,507	2,155	4,645,775
63	6,923	3.44	0.81	3.18	0.50	3.85	7,052	129	16,670
64	10,600	3.44	0.81	4.28	0.63	3.95	8,947	-1,653	2,732,107
65	6,518	3.44	0.81	3.61	0.56	3.89	7,809	1,291	1,667,025
66	5,740	3.44	0.81	2.00	0.30	3.69	4,850	-890	791,883
67	14,795	3.44	0.81	3.12	0.49	3.84	6,936	-7,859	61,761,072
68	3,786	3.44	0.81	2.35	0.37	3.74	5,520	1,734	3,006,431
69	8,361	3.44	0.81	2.47	0.39	3.76	5,749	-2,612	6,823,077
70	8,392	3.44	0.81	3.89	0.59	3.92	8,286		
71	8,160	3.44	0.81	1.70	0.23	3.63	4,255	-3,905	15,245,344
72	9,152	3.44	0.81	3.20	0.51	3.85	7,081	-2,071	4,288,934
73	2,006	3.44	0.81	0.85	-0.07	3.39	2,434	428	183,169
74	2,873	3.44	0.81	1.38	0.14	3.55	3,589	716	512,742
75	7,031	3.44	0.81	1.50	0.18	3.58	3,842	-3,189	10,168,481
76	6,685	3.44	0.81	2.17	0.34	3.71	5,180	-1,505	2,265,534
77	7,356	3.44	0.81	3.30	0.52	3.86	7,254	-102	10,423
78	7,755	3.44	0.81	2.59	0.41	3.78	5,976	-1,779	3,165,858
79	3,510	3.44	0.81	1.39	0.14	3.56	3,606	96	9,229
80	2,619	3.44	0.81	1.25	0.10	3.52	3,314		
81	4,394	3.44	0.81	1.91	0.28	3.67	4,675	281	79,109
82	4,425	3.44	0.81	2.62	0.42	3.78	6,036	1,611	2,594,827
83	3,232	3.44	0.81	1.59	0.20	3.60	4,025	793	629,311
84	3,998	3.44	0.81	1.95	0.29	3.68	4,755	757	572,952
85	2,378	3.44	0.81	0.85	-0.07	3.39	2,434	56	3,134
86	4,664	3.44	0.81	3.15	0.50	3.84	6,994	2,330	5,429,851
87	9,544	3.44	0.81	2.78	0.44	3.80	6,320	-3,224	10,397,094
88	2,070	3.44	0.81	1.81	0.26	3.65	4,483	2,413	5,821,079
89	12,810	3.44	0.81	6.60	0.82	4.10	12,695	-115	13,230
90	4,032	3.44	0.81	3.26	0.51	3.86	7,196		
Total	207,909			84.04			191,145	**RMSE**	**2,287.02**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM10norm	Pop		Area		AntilogPop		
	691,161		292.96		656,060	**RMSE**	**2,287.02**

Table A-V.111: Allometric Growth Model and RMSE for Sim 2010 Sprawl in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,772	3.42	0.81	1.81	0.26	3.63	4,234	2,462	6,062,372
1	2,793	3.42	0.81	3.07	0.49	3.81	6,517	3,724	13,866,419
2	3,060	3.42	0.81	1.42	0.15	3.54	3,477	417	173,779
3	1,503	3.42	0.81	0.91	-0.04	3.38	2,419	916	838,818
4	1,616	3.42	0.81	1.45	0.16	3.55	3,541	1,925	3,706,941
5	4,565	3.42	0.81	3.86	0.59	3.89	7,843	3,278	10,746,534
6	2,459	3.42	0.81	1.25	0.10	3.50	3,134	675	455,174
7	6,539	3.42	0.81	2.99	0.48	3.80	6,377	-162	26,366
8	3,055	3.42	0.81	1.22	0.08	3.49	3,067	12	152
9	6,841	3.42	0.81	2.64	0.42	3.76	5,766	-1,075	1,156,493
10	3,250	3.42	0.81	1.15	0.06	3.47	2,934		
11	7,306	3.42	0.81	3.16	0.50	3.82	6,670	-636	404,339
12	5,302	3.42	0.81	3.22	0.51	3.83	6,781	1,479	2,187,880
13	3,933	3.42	0.81	2.48	0.39	3.74	5,476	1,543	2,381,876
14	4,431	3.42	0.81	2.13	0.33	3.69	4,842	411	168,899
15	6,141	3.42	0.81	2.54	0.41	3.75	5,592	-549	300,907
16	6,452	3.42	0.81	4.74	0.68	3.97	9,275	2,823	7,967,173
17	1,125	3.42	0.81	1.24	0.09	3.49	3,117	1,992	3,968,512
18	2,669	3.42	0.81	1.53	0.18	3.57	3,701	1,032	1,065,775
19	2,852	3.42	0.81	2.96	0.47	3.80	6,334	3,482	12,127,410
20	2,126	3.42	0.81	1.54	0.19	3.57	3,717		
21	2,051	3.42	0.81	1.31	0.12	3.51	3,265	1,214	1,474,724
22	2,071	3.42	0.81	1.71	0.23	3.61	4,048	1,977	3,908,509
23	4,950	3.42	0.81	2.92	0.47	3.80	6,264	1,314	1,726,593
24	3,682	3.42	0.81	1.87	0.27	3.64	4,357	675	455,995
25	5,066	3.42	0.81	2.08	0.32	3.68	4,752	-314	98,613
26	11,710	3.42	0.81	3.52	0.55	3.86	7,289	-4,421	19,541,956
27	3,263	3.42	0.81	2.48	0.39	3.74	5,476	2,213	4,898,843
28	23,769	3.42	0.81	11.32	1.05	4.27	18,832	-4,937	24,374,309
29	2,901	3.42	0.81	1.02	0.01	3.43	2,662	-239	57,146
30	9,371	3.42	0.81	3.65	0.56	3.87	7,493		
31	2,894	3.42	0.81	1.50	0.18	3.56	3,638	744	552,866
32	6,859	3.42	0.81	1.97	0.29	3.66	4,540	-2,319	5,375,804
33	2,908	3.42	0.81	0.96	-0.02	3.40	2,524	-384	147,684
34	3,093	3.42	0.81	1.17	0.07	3.47	2,967	-126	15,825
35	3,886	3.42	0.81	1.95	0.29	3.65	4,510	624	389,397
36	7,027	3.42	0.81	2.56	0.41	3.75	5,621	-1,406	1,975,732
37	4,814	3.42	0.81	1.52	0.18	3.57	3,685	-1,129	1,273,661
38	5,212	3.42	0.81	2.57	0.41	3.75	5,636	424	179,650
39	8,773	3.42	0.81	5.58	0.75	4.03	10,594	1,821	3,316,981
40	3,376	3.42	0.81	1.27	0.10	3.50	3,183		
41	10,770	3.42	0.81	4.97	0.70	3.98	9,634	-1,136	1,290,645
42	2,989	3.42	0.81	0.94	-0.03	3.40	2,489	-500	250,127
43	8,011	3.42	0.81	3.52	0.55	3.86	7,289	-722	520,748
44	2,590	3.42	0.81	1.10	0.04	3.45	2,832	242	58,792
45	4,609	3.42	0.81	4.34	0.64	3.94	8,638	4,029	16,232,215
46	10,993	3.42	0.81	4.82	0.68	3.97	9,403	-1,590	2,527,124
47	6,959	3.42	0.81	3.67	0.56	3.88	7,534	575	330,237
48	9,937	3.42	0.81	3.33	0.52	3.84	6,961	-2,976	8,858,476
49	11,268	3.42	0.81	3.23	0.51	3.83	6,795	-4,473	20,007,754
50	5,980	3.42	0.81	1.39	0.14	3.53	3,412		
51	11,497	3.42	0.81	4.97	0.70	3.98	9,647	-1,850	3,423,574
52	10,834	3.42	0.81	4.42	0.65	3.94	8,769	-2,065	4,265,403
53	11,609	3.42	0.81	3.43	0.54	3.85	7,139	-4,470	19,979,522
54	3,129	3.42	0.81	2.62	0.42	3.76	5,722	2,593	6,725,844
55	4,753	3.42	0.81	1.85	0.27	3.64	4,327	-426	181,835
56	5,282	3.42	0.81	1.94	0.29	3.65	4,480	-802	643,902
57	5,125	3.42	0.81	2.17	0.34	3.69	4,917	-208	43,397
Total	323,801			152.94			326,140	**RMSE**	**2,257.32**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.112: Allometric Growth Model and RMSE for Sim 2010 Sprawl in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,069	3.42	0.81	1.43	0.15	3.54	3,493	-576	331,762
92	4,463	3.42	0.81	2.39	0.38	3.73	5,316	853	727,163
93	9,305	3.42	0.81	2.36	0.37	3.72	5,257	-4,048	16,385,780
94	2,076	3.42	0.81	0.92	-0.03	3.39	2,454	378	142,830
95	10,490	3.42	0.81	4.31	0.63	3.93	8,585	-1,905	3,627,204
96	8,020	3.42	0.81	2.00	0.30	3.66	4,601	-3,419	11,688,930
97	6,292	3.42	0.81	4.48	0.65	3.95	8,860	2,568	6,594,638
98	6,275	3.42	0.81	2.96	0.47	3.80	6,334	59	3,533
99	10,979	3.42	0.81	4.50	0.65	3.95	8,899	-2,080	4,326,151
100	4,730	3.42	0.81	2.34	0.37	3.72	5,228		
101	3,895	3.42	0.81	2.13	0.33	3.69	4,842	947	896,757
102	8,645	3.42	0.81	4.17	0.62	3.92	8,362	-283	80,226
103	15,155	3.42	0.81	3.75	0.57	3.88	7,669	-7,486	56,046,296
104	6,045	3.42	0.81	1.69	0.23	3.60	4,017	-2,028	4,113,706
105	12,363	3.42	0.81	4.26	0.63	3.93	8,507	-3,856	14,871,259
106	15,471	3.42	0.81	11.53	1.06	4.28	19,105	3,634	13,208,150
107	11,660	3.42	0.81	6.44	0.81	4.08	11,901	241	58,257
108	13,310	3.42	0.81	6.46	0.81	4.08	11,938	-1,372	1,882,754
109	6,208	3.42	0.81	3.01	0.48	3.81	6,405	197	38,694
Total	159,451			71.13			141,773	**RMSE**	**2,257.32**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.113: Allometric Growth Model and RMSE for Sim 2010 Sprawl in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	7,983	3.42	0.81	2.37	0.37	3.72	5,272	-2,711	7,350,892
59	2,032	3.42	0.81	0.66	-0.18	3.27	1,859	-173	30,052
60	11,212	3.42	0.81	3.23	0.51	3.83	6,795		
61	6,521	3.42	0.81	4.02	0.60	3.91	8,110	1,589	2,525,162
62	6,352	3.42	0.81	4.33	0.64	3.94	8,625	2,273	5,165,702
63	6,923	3.42	0.81	3.24	0.51	3.83	6,809	-114	13,033
64	10,600	3.42	0.81	4.62	0.66	3.96	9,081	-1,519	2,307,939
65	6,518	3.42	0.81	3.68	0.57	3.88	7,547	1,029	1,059,212
66	5,740	3.42	0.81	2.06	0.31	3.67	4,707	-1,033	1,067,449
67	14,795	3.42	0.81	3.39	0.53	3.85	7,057	-7,738	59,878,022
68	3,786	3.42	0.81	2.47	0.39	3.74	5,462	1,676	2,808,234
69	8,361	3.42	0.81	2.69	0.43	3.77	5,852	-2,509	6,296,483
70	8,392	3.42	0.81	4.11	0.61	3.92	8,256		
71	8,160	3.42	0.81	1.74	0.24	3.61	4,110	-4,050	16,400,280
72	9,152	3.42	0.81	3.34	0.52	3.84	6,974	-2,178	4,741,739
73	2,006	3.42	0.81	0.96	-0.02	3.41	2,541	535	286,308
74	2,873	3.42	0.81	1.43	0.15	3.54	3,493	620	384,415
75	7,031	3.42	0.81	1.55	0.19	3.57	3,733	-3,298	10,875,644
76	6,685	3.42	0.81	2.22	0.35	3.70	5,006	-1,679	2,819,092
77	7,356	3.42	0.81	3.62	0.56	3.87	7,452	96	9,300
78	7,755	3.42	0.81	2.75	0.44	3.78	5,966	-1,789	3,200,156
79	3,510	3.42	0.81	1.51	0.18	3.56	3,654	144	20,600
80	2,619	3.42	0.81	1.33	0.12	3.52	3,298		
81	4,394	3.42	0.81	1.96	0.29	3.66	4,525	131	17,220
82	4,425	3.42	0.81	2.77	0.44	3.78	5,995	1,570	2,463,702
83	3,232	3.42	0.81	1.66	0.22	3.60	3,954	722	521,515
84	3,998	3.42	0.81	1.94	0.29	3.65	4,480	482	231,905
85	2,378	3.42	0.81	0.86	-0.07	3.36	2,313	-65	4,228
86	4,664	3.42	0.81	3.30	0.52	3.84	6,906	2,242	5,024,568
87	9,544	3.42	0.81	2.92	0.46	3.80	6,250	-3,294	10,851,172
88	2,070	3.42	0.81	1.89	0.28	3.64	4,388	2,318	5,372,752
89	12,810	3.42	0.81	7.25	0.86	4.12	13,105	295	86,908
90	4,032	3.42	0.81	3.48	0.54	3.86	7,221		
Total	207,909			89.31			190,794	**RMSE**	**2,257.32**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM10spraw	Pop 691,161		Area 313.39		AntilogPop 658,707	**RMSE**	**2,257.32**

Table A-V.114: Allometric Growth Model and RMSE for Sim 2015 Smart in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,655	3.51	0.78	1.69	0.23	3.69	4,878	3,223	10,388,102
1	2,667	3.51	0.78	2.72	0.43	3.85	7,078	4,411	19,455,726
2	2,894	3.51	0.78	1.32	0.12	3.60	4,014	1,120	1,255,021
3	1,447	3.51	0.78	0.82	-0.09	3.44	2,758	1,311	1,719,486
4	1,477	3.51	0.78	1.33	0.12	3.61	4,034	2,557	6,536,061
5	4,315	3.51	0.78	3.34	0.52	3.92	8,305	3,990	15,918,885
6	2,381	3.51	0.78	1.08	0.03	3.53	3,423	1,042	1,084,862
7	6,637	3.51	0.78	2.51	0.40	3.82	6,645	8	60
8	3,079	3.51	0.78	1.12	0.05	3.55	3,523	444	197,171
9	7,208	3.51	0.78	2.32	0.37	3.80	6,255	-953	908,090
10	3,396	3.51	0.78	0.96	-0.02	3.49	3,116		
11	7,652	3.51	0.78	2.74	0.44	3.85	7,111	-541	292,818
12	5,349	3.51	0.78	2.92	0.47	3.87	7,488	2,139	4,573,261
13	3,959	3.51	0.78	2.12	0.33	3.77	5,824	1,865	3,477,180
14	4,329	3.51	0.78	1.81	0.26	3.71	5,132	803	645,504
15	6,437	3.51	0.78	2.34	0.37	3.80	6,289	-148	21,842
16	6,627	3.51	0.78	3.90	0.59	3.97	9,392	2,765	7,645,590
17	1,028	3.51	0.78	1.13	0.05	3.55	3,563	2,535	6,426,259
18	2,596	3.51	0.78	1.45	0.16	3.64	4,320	1,724	2,972,357
19	2,723	3.51	0.78	2.59	0.41	3.83	6,812	4,089	16,721,871
20	1,990	3.51	0.78	1.36	0.13	3.61	4,111		
21	1,974	3.51	0.78	1.15	0.06	3.56	3,603	1,629	2,653,156
22	1,972	3.51	0.78	1.54	0.19	3.66	4,527	2,555	6,527,204
23	4,814	3.51	0.78	2.62	0.42	3.84	6,862	2,048	4,195,360
24	3,496	3.51	0.78	1.62	0.21	3.67	4,713	1,217	1,480,094
25	4,907	3.51	0.78	1.78	0.25	3.71	5,078	171	29,317
26	12,396	3.51	0.78	3.40	0.53	3.93	8,431	-3,965	15,721,131
27	3,552	3.51	0.78	2.17	0.34	3.77	5,928	2,376	5,645,489
28	27,658	3.51	0.78	9.48	0.98	4.27	18,824	-8,834	78,041,045
29	3,116	3.51	0.78	0.86	-0.07	3.46	2,865	-251	63,109
30	10,106	3.51	0.78	3.05	0.48	3.89	7,746		
31	2,962	3.51	0.78	1.30	0.11	3.60	3,956	994	988,508
32	7,255	3.51	0.78	1.77	0.25	3.70	5,042	-2,213	4,897,405
33	2,969	3.51	0.78	0.83	-0.08	3.45	2,801	-168	28,216
34	3,128	3.51	0.78	1.13	0.05	3.55	3,543	415	172,257
35	3,747	3.51	0.78	1.71	0.23	3.69	4,915	1,168	1,363,330
36	6,990	3.51	0.78	2.18	0.34	3.77	5,945	-1,045	1,091,276
37	4,765	3.51	0.78	1.39	0.14	3.62	4,187	-578	334,044
38	5,390	3.51	0.78	2.26	0.35	3.79	6,118	728	529,912
39	9,116	3.51	0.78	4.80	0.68	4.04	11,049	1,933	3,736,898
40	3,703	3.51	0.78	1.08	0.03	3.53	3,423		
41	11,721	3.51	0.78	4.24	0.63	4.00	10,013	-1,708	2,917,787
42	3,283	3.51	0.78	0.83	-0.08	3.44	2,780	-503	253,331
43	8,655	3.51	0.78	3.06	0.49	3.89	7,763	-892	796,422
44	2,766	3.51	0.78	0.94	-0.03	3.49	3,075	309	95,228
45	4,580	3.51	0.78	3.70	0.57	3.95	9,008	4,428	19,606,849
46	11,742	3.51	0.78	3.97	0.60	3.98	9,514	-2,228	4,963,707
47	7,389	3.51	0.78	3.10	0.49	3.89	7,843	454	206,081
48	10,541	3.51	0.78	2.88	0.46	3.87	7,406	-3,135	9,827,653
49	12,559	3.51	0.78	2.66	0.42	3.84	6,945	-5,614	31,512,490
50	6,628	3.51	0.78	1.22	0.09	3.58	3,781		
51	13,033	3.51	0.78	4.16	0.62	3.99	9,878	-3,155	9,957,137
52	12,256	3.51	0.78	3.54	0.55	3.94	8,697	-3,559	12,663,597
53	12,967	3.51	0.78	2.93	0.47	3.88	7,504	-5,463	29,846,833
54	3,032	3.51	0.78	2.17	0.34	3.77	5,928	2,896	8,386,953
55	4,878	3.51	0.78	1.27	0.10	3.59	3,898	-980	960,475
56	5,362	3.51	0.78	1.46	0.16	3.64	4,339	-1,023	1,046,606
57	5,142	3.51	0.78	1.76	0.24	3.70	5,024	-118	13,959
Total	340,396			131.58			347,020	**RMSE**	**2,905.01**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.115: Allometric Growth Model and RMSE for Sim 2015 Smart in Santa Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,135	3.51	0.78	1.04	0.02	3.52	3,321	-814	662,148
92	4,441	3.51	0.78	1.73	0.24	3.70	4,969	528	279,118
93	10,570	3.51	0.78	1.82	0.26	3.71	5,168	-5,402	29,176,353
94	1,919	3.51	0.78	0.55	-0.26	3.31	2,023	104	10,761
95	11,448	3.51	0.78	3.47	0.54	3.93	8,572	-2,876	8,269,490
96	8,837	3.51	0.78	1.61	0.21	3.67	4,694	-4,143	17,163,555
97	6,122	3.51	0.78	3.80	0.58	3.96	9,193	3,071	9,430,326
98	6,797	3.51	0.78	2.46	0.39	3.82	6,544	-253	64,147
99	12,212	3.51	0.78	3.83	0.58	3.97	9,254	-2,958	8,748,013
100	5,194	3.51	0.78	1.93	0.29	3.73	5,401		
101	4,152	3.51	0.78	1.90	0.28	3.73	5,330	1,178	1,387,403
102	9,368	3.51	0.78	3.20	0.51	3.90	8,035	-1,333	1,776,963
103	17,758	3.51	0.78	2.84	0.45	3.86	7,308	-10,450	109,201,42
104	7,385	3.51	0.78	1.42	0.15	3.63	4,244	-3,141	9,864,732
105	14,081	3.51	0.78	3.44	0.54	3.93	8,510	-5,571	31,040,491
106	18,669	3.51	0.78	9.62	0.98	4.28	19,051	382	145,608
107	13,890	3.51	0.78	5.33	0.73	4.08	11,988	-1,902	3,618,169
108	15,583	3.51	0.78	5.23	0.72	4.07	11,816	-3,767	14,189,455
109	6,222	3.51	0.78	2.58	0.41	3.83	6,779	557	310,066
Total	178,783			57.80			142,200	**RMSE**	**2,905.01**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.116: Allometric Growth Model and RMSE for Sim 2015 Smart in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,484	3.51	0.78	1.77	0.25	3.70	5,042	-3,442	11,847,420
59	2,110	3.51	0.78	0.55	-0.26	3.31	2,023	-87	7,615
60	12,582	3.51	0.78	2.37	0.38	3.80	6,357		
61	6,917	3.51	0.78	3.47	0.54	3.93	8,572	1,655	2,740,110
62	6,684	3.51	0.78	3.61	0.56	3.95	8,838	2,154	4,637,681
63	7,682	3.51	0.78	2.84	0.45	3.86	7,324	-358	127,866
64	12,099	3.51	0.78	3.82	0.58	3.96	9,224	-2,875	8,267,903
65	7,010	3.51	0.78	3.52	0.55	3.94	8,666	1,656	2,742,941
66	6,279	3.51	0.78	1.81	0.26	3.71	5,150	-1,129	1,273,584
67	17,879	3.51	0.78	2.75	0.44	3.85	7,127	-10,752	115,597,71
68	3,956	3.51	0.78	2.20	0.34	3.78	5,997	2,041	4,166,821
69	8,762	3.51	0.78	2.28	0.36	3.79	6,169	-2,593	6,721,234
70	8,673	3.51	0.78	3.71	0.57	3.96	9,023		
71	8,412	3.51	0.78	1.59	0.20	3.67	4,639	-3,773	14,239,024
72	9,609	3.51	0.78	2.90	0.46	3.87	7,439	-2,170	4,710,239
73	2,043	3.51	0.78	0.73	-0.14	3.40	2,520	477	227,406
74	2,922	3.51	0.78	1.24	0.09	3.58	3,820	898	806,198
75	7,910	3.51	0.78	1.47	0.17	3.64	4,358	-3,552	12,617,771
76	7,463	3.51	0.78	1.97	0.29	3.74	5,490	-1,973	3,892,967
77	7,759	3.51	0.78	3.05	0.48	3.89	7,730	-29	820
78	7,969	3.51	0.78	2.42	0.38	3.81	6,459	-1,510	2,279,508
79	3,583	3.51	0.78	1.36	0.13	3.61	4,111	528	278,257
80	2,706	3.51	0.78	1.15	0.06	3.56	3,603		
81	4,474	3.51	0.78	1.74	0.24	3.70	4,988	514	263,695
82	4,496	3.51	0.78	2.54	0.40	3.83	6,695	2,199	4,836,173
83	3,347	3.51	0.78	1.52	0.18	3.65	4,489	1,142	1,305,165
84	4,062	3.51	0.78	1.80	0.25	3.71	5,114	1,052	1,107,504
85	2,507	3.51	0.78	0.83	-0.08	3.45	2,801	294	86,449
86	4,820	3.51	0.78	3.01	0.48	3.88	7,650	2,830	8,006,903
87	10,562	3.51	0.78	2.48	0.39	3.82	6,577	-3,985	15,876,603
88	2,153	3.51	0.78	1.61	0.21	3.67	4,694	2,541	6,457,229
89	14,690	3.51	0.78	5.95	0.77	4.12	13,060	-1,630	2,655,450
90	4,423	3.51	0.78	3.12	0.49	3.90	7,875		
Total	225,027			77.18			203,626	**RMSE**	**2,905.01**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM15smart	Pop		Area		AntilogPop		
	744,206		266.56		692,847	**RMSE**	**2,905.01**

Table A-V.117: Allometric Growth Model and RMSE for Sim 2015 Normal in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,655	3.44	0.85	1.85	0.27	3.66	4,583	2,928	8,571,635
1	2,667	3.44	0.85	3.03	0.48	3.84	6,962	4,295	18,448,722
2	2,894	3.44	0.85	1.43	0.15	3.57	3,682	788	621,536
3	1,447	3.44	0.85	0.88	-0.05	3.39	2,456	1,009	1,018,844
4	1,477	3.44	0.85	1.39	0.14	3.56	3,612	2,135	4,556,224
5	4,315	3.44	0.85	3.76	0.58	3.92	8,354	4,039	16,310,889
6	2,381	3.44	0.85	1.28	0.11	3.53	3,362	981	961,410
7	6,637	3.44	0.85	2.99	0.48	3.84	6,883	246	60,745
8	3,079	3.44	0.85	1.22	0.08	3.51	3,217	138	19,077
9	7,208	3.44	0.85	2.63	0.42	3.79	6,183	-1,025	1,050,274
10	3,396	3.44	0.85	1.13	0.05	3.48	3,035		
11	7,652	3.44	0.85	3.08	0.49	3.85	7,056	-596	354,666
12	5,349	3.44	0.85	3.26	0.51	3.87	7,400	2,051	4,207,240
13	3,959	3.44	0.85	2.42	0.38	3.76	5,763	1,804	3,252,663
14	4,329	3.44	0.85	2.11	0.32	3.71	5,121	792	626,658
15	6,437	3.44	0.85	2.57	0.41	3.78	6,054	-383	146,449
16	6,627	3.44	0.85	4.69	0.67	4.00	10,072	3,445	11,870,823
17	1,028	3.44	0.85	1.27	0.10	3.52	3,344	2,316	5,361,673
18	2,596	3.44	0.85	1.61	0.21	3.61	4,085	1,489	2,217,363
19	2,723	3.44	0.85	3.01	0.48	3.84	6,931	4,208	17,704,944
20	1,990	3.44	0.85	1.55	0.19	3.60	3,946		
21	1,974	3.44	0.85	1.30	0.11	3.53	3,397	1,423	2,026,169
22	1,972	3.44	0.85	1.70	0.23	3.63	4,275	2,303	5,304,218
23	4,814	3.44	0.85	2.96	0.47	3.83	6,820	2,006	4,025,481
24	3,496	3.44	0.85	1.85	0.27	3.66	4,583	1,087	1,180,994
25	4,907	3.44	0.85	1.97	0.29	3.68	4,836	-71	5,008
26	12,396	3.44	0.85	3.56	0.55	3.90	7,972	-4,424	19,574,201
27	3,552	3.44	0.85	2.47	0.39	3.77	5,860	2,308	5,327,212
28	27,658	3.44	0.85	11.32	1.05	4.33	21,201	-6,457	41,690,039
29	3,116	3.44	0.85	1.07	0.03	3.46	2,888	-228	52,113
30	10,106	3.44	0.85	3.68	0.57	3.91	8,201		
31	2,962	3.44	0.85	1.58	0.20	3.60	4,016	1,054	1,110,047
32	7,255	3.44	0.85	2.11	0.32	3.71	5,121	-2,134	4,555,589
33	2,969	3.44	0.85	1.00	0.00	3.43	2,720	-249	61,780
34	3,128	3.44	0.85	1.17	0.07	3.50	3,126	-2	3
35	3,747	3.44	0.85	1.89	0.28	3.67	4,668	921	847,345
36	6,990	3.44	0.85	2.57	0.41	3.78	6,054	-936	875,509
37	4,765	3.44	0.85	1.58	0.20	3.60	4,016	-749	561,619
38	5,390	3.44	0.85	2.62	0.42	3.79	6,167	777	603,871
39	9,116	3.44	0.85	5.50	0.74	4.06	11,524	2,408	5,798,023
40	3,703	3.44	0.85	1.34	0.13	3.54	3,487		
41	11,721	3.44	0.85	4.98	0.70	4.03	10,599	-1,122	1,258,642
42	3,283	3.44	0.85	0.96	-0.02	3.42	2,645	-638	406,412
43	8,655	3.44	0.85	3.56	0.55	3.90	7,972	-683	466,863
44	2,766	3.44	0.85	1.09	0.04	3.47	2,943	177	31,357
45	4,580	3.44	0.85	4.49	0.65	3.99	9,704	5,124	26,251,897
46	11,742	3.44	0.85	4.83	0.68	4.01	10,322	-1,420	2,017,137
47	7,389	3.44	0.85	3.63	0.56	3.91	8,110	721	519,273
48	10,541	3.44	0.85	3.30	0.52	3.87	7,493	-3,048	9,287,996
49	12,559	3.44	0.85	3.14	0.50	3.86	7,182	-5,377	28,914,397
50	6,628	3.44	0.85	1.37	0.14	3.55	3,558		
51	13,033	3.44	0.85	5.01	0.70	4.03	10,643	-2,390	5,713,150
52	12,256	3.44	0.85	4.31	0.63	3.97	9,377	-2,879	8,288,485
53	12,967	3.44	0.85	3.54	0.55	3.90	7,941	-5,026	25,260,408
54	3,032	3.44	0.85	2.62	0.42	3.79	6,167	3,135	9,828,797
55	4,878	3.44	0.85	1.81	0.26	3.65	4,498	-380	144,652
56	5,362	3.44	0.85	1.94	0.29	3.68	4,769	-593	351,796
57	5,142	3.44	0.85	2.11	0.33	3.71	5,137	-5	23
Total	340,396			153.05			352,092	**RMSE**	**2,680.47**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.118: Allometric Growth Model and RMSE for Sim 2015 Normal in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,135	3.44	0.85	1.66	0.22	3.62	4,189	54	2,907
92	4,441	3.44	0.85	2.28	0.36	3.74	5,468	1,027	1,054,682
93	10,570	3.44	0.85	2.32	0.36	3.74	5,550	-5,020	25,199,610
94	1,919	3.44	0.85	0.77	-0.11	3.34	2,187	268	71,817
95	11,448	3.44	0.85	4.28	0.63	3.97	9,317	-2,131	4,539,386
96	8,837	3.44	0.85	2.00	0.30	3.69	4,903	-3,934	15,473,081
97	6,122	3.44	0.85	4.34	0.64	3.97	9,437	3,315	10,986,363
98	6,797	3.44	0.85	3.24	0.51	3.87	7,369	572	327,222
99	12,212	3.44	0.85	4.59	0.66	4.00	9,896	-2,316	5,365,140
100	5,194	3.44	0.85	2.40	0.38	3.76	5,714		
101	4,152	3.44	0.85	2.12	0.33	3.71	5,154	1,002	1,003,767
102	9,368	3.44	0.85	4.05	0.61	3.95	8,898	-470	220,763
103	17,758	3.44	0.85	4.03	0.61	3.95	8,868	-8,890	79,031,029
104	7,385	3.44	0.85	1.76	0.24	3.64	4,395	-2,990	8,938,924
105	14,081	3.44	0.85	4.30	0.63	3.97	9,362	-4,719	22,267,725
106	18,669	3.44	0.85	11.63	1.07	4.34	21,700	3,031	9,188,660
107	13,890	3.44	0.85	6.39	0.81	4.12	13,083	-807	651,610
108	15,583	3.44	0.85	6.33	0.80	4.11	12,985	-2,598	6,751,532
109	6,222	3.44	0.85	3.09	0.49	3.85	7,072	850	722,755
Total	178,783			71.58			155,547	**RMSE**	**2,680.47**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.119: Allometric Growth Model and RMSE for Sim 2015 Normal in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,484	3.44	0.85	2.27	0.36	3.74	5,452	-3,032	9,195,877
59	2,110	3.44	0.85	0.73	-0.14	3.32	2,089	-21	428
60	12,582	3.44	0.85	3.09	0.49	3.85	7,072		
61	6,917	3.44	0.85	4.09	0.61	3.95	8,973	2,056	4,228,273
62	6,684	3.44	0.85	4.39	0.64	3.98	9,526	2,842	8,075,550
63	7,682	3.44	0.85	3.44	0.54	3.89	7,756	74	5,531
64	12,099	3.44	0.85	4.70	0.67	4.00	10,087	-2,012	4,047,726
65	7,010	3.44	0.85	3.62	0.56	3.91	8,094	1,084	1,175,723
66	6,279	3.44	0.85	2.10	0.32	3.71	5,104	-1,175	1,380,695
67	17,879	3.44	0.85	3.46	0.54	3.89	7,787	-10,092	101,844,40
68	3,956	3.44	0.85	2.44	0.39	3.76	5,795	1,839	3,382,171
69	8,762	3.44	0.85	2.65	0.42	3.79	6,215	-2,547	6,485,637
70	8,673	3.44	0.85	4.04	0.61	3.95	8,883		
71	8,412	3.44	0.85	1.78	0.25	3.65	4,446	-3,966	15,725,295
72	9,609	3.44	0.85	3.30	0.52	3.87	7,493	-2,116	4,475,854
73	2,043	3.44	0.85	0.95	-0.02	3.42	2,608	565	319,085
74	2,922	3.44	0.85	1.43	0.16	3.57	3,700	778	605,357
75	7,910	3.44	0.85	1.58	0.20	3.60	4,016	-3,894	15,166,449
76	7,463	3.44	0.85	2.26	0.35	3.74	5,435	-2,028	4,112,487
77	7,759	3.44	0.85	3.51	0.54	3.90	7,880	121	14,535
78	7,969	3.44	0.85	2.71	0.43	3.80	6,344	-1,625	2,642,072
79	3,583	3.44	0.85	1.45	0.16	3.57	3,735	152	23,209
80	2,706	3.44	0.85	1.30	0.11	3.53	3,397		
81	4,474	3.44	0.85	1.96	0.29	3.68	4,819	345	119,308
82	4,496	3.44	0.85	2.73	0.44	3.80	6,376	1,880	3,532,678
83	3,347	3.44	0.85	1.67	0.22	3.62	4,206	859	738,187
84	4,062	3.44	0.85	2.03	0.31	3.70	4,970	908	825,249
85	2,507	3.44	0.85	0.87	-0.06	3.39	2,437	-70	4,855
86	4,820	3.44	0.85	3.37	0.53	3.88	7,617	2,797	7,825,147
87	10,562	3.44	0.85	2.96	0.47	3.83	6,820	-3,742	13,999,868
88	2,153	3.44	0.85	1.95	0.29	3.68	4,803	2,650	7,020,253
89	14,690	3.44	0.85	7.24	0.86	4.16	14,540	-150	22,644
90	4,423	3.44	0.85	3.40	0.53	3.89	7,679		
Total	225,027			89.47			206,157	**RMSE**	**2,680.47**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM15norm	Pop 744,206		Area 314.10		AntilogPop 713,796	**RMSE**	**2,680.47**

Table A-V.120: Allometric Growth Model and RMSE for Sim 2015 Sprawl in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,655	3.39	0.86	1.91	0.28	3.63	4,277	2,622	6,874,253
1	2,667	3.39	0.86	3.25	0.51	3.83	6,762	4,095	16,765,535
2	2,894	3.39	0.86	1.50	0.18	3.54	3,466	572	326,626
3	1,447	3.39	0.86	0.96	-0.02	3.37	2,350	903	815,109
4	1,477	3.39	0.86	1.49	0.17	3.54	3,449	1,972	3,890,051
5	4,315	3.39	0.86	4.06	0.61	3.91	8,196	3,881	15,060,535
6	2,381	3.39	0.86	1.36	0.13	3.50	3,189	808	652,197
7	6,637	3.39	0.86	3.31	0.52	3.84	6,878	241	58,064
8	3,079	3.39	0.86	1.30	0.11	3.49	3,057	-22	485
9	7,208	3.39	0.86	2.89	0.46	3.79	6,116	-1,092	1,193,420
10	3,396	3.39	0.86	1.26	0.10	3.48	2,991		
11	7,652	3.39	0.86	3.45	0.54	3.85	7,124	-528	278,489
12	5,349	3.39	0.86	3.60	0.56	3.87	7,384	2,035	4,139,720
13	3,959	3.39	0.86	2.64	0.42	3.75	5,654	1,695	2,872,816
14	4,329	3.39	0.86	2.31	0.36	3.70	5,034	705	497,087
15	6,437	3.39	0.86	2.74	0.44	3.77	5,833	-604	364,441
16	6,627	3.39	0.86	5.27	0.72	4.01	10,263	3,636	13,222,879
17	1,028	3.39	0.86	1.26	0.10	3.48	2,991	1,963	3,852,674
18	2,596	3.39	0.86	1.65	0.22	3.58	3,771	1,175	1,380,523
19	2,723	3.39	0.86	3.18	0.50	3.82	6,630	3,907	15,266,640
20	1,990	3.39	0.86	1.67	0.22	3.58	3,803		
21	1,974	3.39	0.86	1.40	0.15	3.51	3,270	1,296	1,680,692
22	1,972	3.39	0.86	1.83	0.26	3.61	4,120	2,148	4,613,233
23	4,814	3.39	0.86	3.15	0.50	3.82	6,586	1,772	3,141,370
24	3,496	3.39	0.86	1.98	0.30	3.65	4,417	921	849,050
25	4,907	3.39	0.86	2.20	0.34	3.68	4,835	-72	5,181
26	12,396	3.39	0.86	3.60	0.56	3.87	7,384	-5,012	25,123,850
27	3,552	3.39	0.86	2.64	0.42	3.75	5,654	2,102	4,418,145
28	27,658	3.39	0.86	12.56	1.10	4.34	21,758	-5,900	34,809,600
29	3,116	3.39	0.86	1.17	0.07	3.45	2,808	-308	95,040
30	10,106	3.39	0.86	4.16	0.62	3.92	8,379		
31	2,962	3.39	0.86	1.68	0.23	3.58	3,835	873	761,704
32	7,255	3.39	0.86	2.13	0.33	3.67	4,696	-2,559	6,546,005
33	2,969	3.39	0.86	1.00	0.00	3.39	2,453	-516	266,548
34	3,128	3.39	0.86	1.19	0.08	3.45	2,841	-287	82,286
35	3,747	3.39	0.86	2.07	0.32	3.66	4,588	841	707,760
36	6,990	3.39	0.86	2.82	0.45	3.78	5,982	-1,008	1,015,811
37	4,765	3.39	0.86	1.65	0.22	3.58	3,771	-994	988,123
38	5,390	3.39	0.86	2.90	0.46	3.79	6,130	740	548,133
39	9,116	3.39	0.86	6.15	0.79	4.07	11,734	2,618	6,855,886
40	3,703	3.39	0.86	1.39	0.14	3.51	3,254		
41	11,721	3.39	0.86	5.48	0.74	4.03	10,617	-1,104	1,218,644
42	3,283	3.39	0.86	1.05	0.02	3.41	2,555	-728	530,094
43	8,655	3.39	0.86	3.92	0.59	3.90	7,955	-700	490,070
44	2,766	3.39	0.86	1.20	0.08	3.46	2,858	92	8,434
45	4,580	3.39	0.86	4.92	0.69	3.99	9,688	5,108	26,089,298
46	11,742	3.39	0.86	5.47	0.74	4.03	10,604	-1,138	1,296,167
47	7,389	3.39	0.86	4.07	0.61	3.92	8,224	835	697,310
48	10,541	3.39	0.86	3.63	0.56	3.87	7,441	-3,100	9,609,580
49	12,559	3.39	0.86	3.57	0.55	3.87	7,341	-5,218	27,232,680
50	6,628	3.39	0.86	1.58	0.20	3.56	3,627		
51	13,033	3.39	0.86	5.48	0.74	4.03	10,617	-2,416	5,836,680
52	12,256	3.39	0.86	4.97	0.70	3.99	9,770	-2,486	6,178,634
53	12,967	3.39	0.86	3.85	0.59	3.89	7,827	-5,140	26,419,785
54	3,032	3.39	0.86	2.89	0.46	3.79	6,116	3,084	9,508,356
55	4,878	3.39	0.86	2.31	0.36	3.70	5,034	156	24,350
56	5,362	3.39	0.86	2.49	0.40	3.73	5,368	6	37
57	5,142	3.39	0.86	2.44	0.39	3.72	5,277	135	18,308
Total	340,396			168.07			348,631	**RMSE**	**2,641.50**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.121: Allometric Growth Model and RMSE for Sim 2015 Sprawl in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,135	3.39	0.86	1.79	0.25	3.61	4,041	-94	8,841
92	4,441	3.39	0.86	2.92	0.46	3.79	6,160	1,719	2,954,752
93	10,570	3.39	0.86	2.75	0.44	3.77	5,848	-4,722	22,295,220
94	1,919	3.39	0.86	1.14	0.06	3.44	2,741	822	675,138
95	11,448	3.39	0.86	4.85	0.69	3.98	9,564	-1,884	3,550,430
96	8,837	3.39	0.86	2.41	0.38	3.72	5,232	-3,605	12,997,226
97	6,122	3.39	0.86	4.87	0.69	3.98	9,591	3,469	12,036,215
98	6,797	3.39	0.86	3.53	0.55	3.86	7,269	472	222,353
99	12,212	3.39	0.86	4.95	0.69	3.99	9,729	-2,483	6,165,015
100	5,194	3.39	0.86	2.76	0.44	3.77	5,878		
101	4,152	3.39	0.86	2.32	0.37	3.70	5,065	913	832,751
102	9,368	3.39	0.86	4.79	0.68	3.98	9,453	85	7,273
103	17,758	3.39	0.86	4.58	0.66	3.96	9,107	-8,651	74,843,750
104	7,385	3.39	0.86	2.00	0.30	3.65	4,449	-2,936	8,622,573
105	14,081	3.39	0.86	4.86	0.69	3.98	9,578	-4,503	20,281,199
106	18,669	3.39	0.86	13.12	1.12	4.35	22,592	3,923	15,388,847
107	13,890	3.39	0.86	7.42	0.87	4.14	13,804	-86	7,375
108	15,583	3.39	0.86	7.36	0.87	4.14	13,713	-1,870	3,497,163
109	6,222	3.39	0.86	3.29	0.52	3.83	6,834	612	374,979
Total	178,783			81.72			160,646	**RMSE**	**2,641.50**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.122: Allometric Growth Model and RMSE for Sim 2015 Sprawl in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,484	3.39	0.86	2.93	0.47	3.79	6,189	-2,295	5,264,750
59	2,110	3.39	0.86	0.82	-0.09	3.31	2,054	-56	3,102
60	12,582	3.39	0.86	3.90	0.59	3.90	7,912		
61	6,917	3.39	0.86	4.50	0.65	3.95	8,968	2,051	4,204,914
62	6,684	3.39	0.86	4.87	0.69	3.98	9,591	2,907	8,452,538
63	7,682	3.39	0.86	3.84	0.58	3.89	7,813	131	17,094
64	12,099	3.39	0.86	5.18	0.71	4.01	10,127	-1,972	3,889,727
65	7,010	3.39	0.86	3.75	0.57	3.88	7,656	646	417,113
66	6,279	3.39	0.86	2.29	0.36	3.70	5,004	-1,275	1,626,882
67	17,879	3.39	0.86	3.70	0.57	3.88	7,570	-10,309	106,274,48
68	3,956	3.39	0.86	2.62	0.42	3.75	5,609	1,653	2,732,264
69	8,762	3.39	0.86	2.94	0.47	3.79	6,204	-2,558	6,542,005
70	8,673	3.39	0.86	4.33	0.64	3.94	8,660		
71	8,412	3.39	0.86	1.91	0.28	3.63	4,277	-4,135	17,099,221
72	9,609	3.39	0.86	3.56	0.55	3.86	7,312	-2,297	5,277,430
73	2,043	3.39	0.86	1.11	0.05	3.43	2,673	630	397,355
74	2,922	3.39	0.86	1.50	0.18	3.54	3,466	544	295,405
75	7,910	3.39	0.86	1.64	0.22	3.57	3,755	-4,155	17,264,191
76	7,463	3.39	0.86	2.37	0.37	3.71	5,141	-2,322	5,393,100
77	7,759	3.39	0.86	3.90	0.59	3.90	7,927	168	28,070
78	7,969	3.39	0.86	2.98	0.47	3.80	6,278	-1,691	2,859,370
79	3,583	3.39	0.86	1.57	0.20	3.56	3,611	28	767
80	2,706	3.39	0.86	1.40	0.15	3.51	3,270		
81	4,474	3.39	0.86	2.11	0.32	3.67	4,650	176	31,033
82	4,496	3.39	0.86	2.87	0.46	3.78	6,071	1,575	2,481,050
83	3,347	3.39	0.86	1.76	0.24	3.60	3,978	631	397,785
84	4,062	3.39	0.86	2.05	0.31	3.66	4,542	480	230,200
85	2,507	3.39	0.86	0.88	-0.05	3.34	2,194	-313	97,871
86	4,820	3.39	0.86	3.51	0.54	3.86	7,225	2,405	5,785,525
87	10,562	3.39	0.86	3.22	0.51	3.83	6,703	-3,859	14,889,876
88	2,153	3.39	0.86	2.05	0.31	3.66	4,542	2,389	5,706,325
89	14,690	3.39	0.86	8.22	0.91	4.18	15,084	394	155,269
90	4,423	3.39	0.86	3.75	0.57	3.88	7,656		
Total	225,027			98.02			203,711	**RMSE**	**2,641.50**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM15spraw	Pop 744,206			Area 347.81			AntilogPop 712,989	**RMSE**	**2,641.50**

Table A-V.123: Allometric Growth Model and RMSE for Sim 2020 Smart in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,531	3.52	0.81	1.70	0.23	3.71	5,107	3,576	12,788,829
1	2,523	3.52	0.81	2.75	0.44	3.88	7,534	5,011	25,114,517
2	2,710	3.52	0.81	1.33	0.12	3.62	4,183	1,473	2,170,823
3	1,379	3.52	0.81	0.82	-0.09	3.45	2,829	1,450	2,102,534
4	1,338	3.52	0.81	1.33	0.12	3.62	4,183	2,845	8,096,137
5	4,040	3.52	0.81	3.38	0.53	3.95	8,884	4,844	23,462,088
6	2,284	3.52	0.81	1.10	0.04	3.56	3,597	1,313	1,723,379
7	6,673	3.52	0.81	2.55	0.41	3.85	7,084	411	168,994
8	3,074	3.52	0.81	1.13	0.05	3.56	3,661	587	344,179
9	7,522	3.52	0.81	2.33	0.37	3.82	6,590	-932	868,858
10	3,514	3.52	0.81	0.96	-0.02	3.51	3,229		
11	7,938	3.52	0.81	2.76	0.44	3.88	7,552	-386	148,752
12	5,346	3.52	0.81	2.93	0.47	3.90	7,925	2,579	6,653,684
13	3,948	3.52	0.81	2.17	0.34	3.79	6,218	2,270	5,152,996
14	4,189	3.52	0.81	1.82	0.26	3.73	5,400	1,211	1,465,465
15	6,682	3.52	0.81	2.34	0.37	3.82	6,608	-74	5,427
16	6,742	3.52	0.81	4.00	0.60	4.01	10,186	3,444	11,858,129
17	930	3.52	0.81	1.13	0.05	3.57	3,682	2,752	7,572,988
18	2,501	3.52	0.81	1.47	0.17	3.66	4,530	2,029	4,116,664
19	2,575	3.52	0.81	2.62	0.42	3.86	7,229	4,654	21,659,038
20	1,846	3.52	0.81	1.36	0.13	3.63	4,266		
21	1,882	3.52	0.81	1.17	0.07	3.58	3,767	1,885	3,551,601
22	1,860	3.52	0.81	1.55	0.19	3.67	4,731	2,871	8,241,915
23	4,637	3.52	0.81	2.64	0.42	3.86	7,283	2,646	7,001,645
24	3,288	3.52	0.81	1.64	0.21	3.69	4,950	1,662	2,760,758
25	4,707	3.52	0.81	1.80	0.25	3.73	5,341	634	402,450
26	12,998	3.52	0.81	3.43	0.53	3.95	8,987	-4,011	16,089,890
27	3,830	3.52	0.81	2.20	0.34	3.80	6,274	2,444	5,973,780
28	31,877	3.52	0.81	9.59	0.98	4.31	20,623	-11,254	126,662,78
29	3,315	3.52	0.81	0.87	-0.06	3.47	2,964	-351	123,288
30	10,795	3.52	0.81	3.10	0.49	3.92	8,294		
31	3,002	3.52	0.81	1.30	0.11	3.61	4,101	1,099	1,207,437
32	7,601	3.52	0.81	1.77	0.25	3.72	5,283	-2,318	5,372,831
33	3,003	3.52	0.81	0.84	-0.07	3.46	2,897	-106	11,314
34	3,133	3.52	0.81	1.13	0.05	3.56	3,661	528	278,434
35	3,578	3.52	0.81	1.73	0.24	3.71	5,166	1,588	2,521,568
36	6,887	3.52	0.81	2.18	0.34	3.79	6,237	-650	422,841
37	4,671	3.52	0.81	1.42	0.15	3.64	4,408	-263	68,969
38	5,521	3.52	0.81	2.27	0.36	3.81	6,442	921	847,783
39	9,382	3.52	0.81	4.87	0.69	4.08	11,932	2,550	6,500,520
40	4,022	3.52	0.81	1.09	0.04	3.55	3,554		
41	12,636	3.52	0.81	4.25	0.63	4.03	10,698	-1,938	3,754,567
42	3,573	3.52	0.81	0.83	-0.08	3.46	2,874	-699	488,413
43	9,262	3.52	0.81	3.09	0.49	3.92	8,260	-1,002	1,005,002
44	2,925	3.52	0.81	0.95	-0.02	3.50	3,185	260	67,844
45	4,507	3.52	0.81	3.73	0.57	3.98	9,616	5,109	26,101,547
46	12,423	3.52	0.81	4.01	0.60	4.01	10,202	-2,221	4,931,955
47	7,772	3.52	0.81	3.13	0.50	3.92	8,364	592	350,832
48	11,075	3.52	0.81	2.91	0.46	3.90	7,872	-3,203	10,256,475
49	13,865	3.52	0.81	2.67	0.43	3.87	7,355	-6,510	42,378,891
50	7,276	3.52	0.81	1.24	0.09	3.60	3,955		
51	14,633	3.52	0.81	4.24	0.63	4.03	10,665	-3,968	15,741,631
52	13,734	3.52	0.81	3.65	0.56	3.98	9,464	-4,270	18,234,175
53	14,347	3.52	0.81	2.97	0.47	3.90	8,014	-6,333	40,110,725
54	2,909	3.52	0.81	2.21	0.34	3.80	6,311	3,402	11,576,816
55	4,960	3.52	0.81	1.28	0.11	3.61	4,059	-901	811,050
56	5,391	3.52	0.81	1.47	0.17	3.66	4,550	-841	707,041
57	5,111	3.52	0.81	1.81	0.26	3.73	5,361	250	62,399
Total	355,673			132.99			368,178	**RMSE**	**3,460.02**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.124: Allometric Growth Model and RMSE for Sim 2020 Smart in Santa Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,113	3.52	0.81	1.05	0.02	3.54	3,468	-645	415,813
92	4,325	3.52	0.81	1.78	0.25	3.72	5,303	978	955,550
93	11,750	3.52	0.81	1.88	0.27	3.74	5,535	-6,215	38,629,617
94	1,737	3.52	0.81	0.55	-0.26	3.31	2,056	319	101,637
95	12,226	3.52	0.81	3.52	0.55	3.96	9,192	-3,034	9,205,384
96	9,529	3.52	0.81	1.64	0.22	3.70	4,969	-4,560	20,790,708
97	5,830	3.52	0.81	3.84	0.58	3.99	9,851	4,021	16,172,128
98	7,206	3.52	0.81	2.49	0.40	3.84	6,957	-249	62,114
99	13,293	3.52	0.81	3.86	0.59	4.00	9,902	-3,391	11,500,610
100	5,582	3.52	0.81	1.95	0.29	3.76	5,707		
101	4,332	3.52	0.81	1.90	0.28	3.75	5,573	1,241	1,540,577
102	9,933	3.52	0.81	3.30	0.52	3.94	8,711	-1,222	1,492,202
103	20,362	3.52	0.81	2.89	0.46	3.89	7,837	-12,525	156,875,25
104	8,827	3.52	0.81	1.43	0.15	3.65	4,429	-4,398	19,345,054
105	15,693	3.52	0.81	3.55	0.55	3.97	9,243	-6,450	41,601,384
106	22,046	3.52	0.81	9.71	0.99	4.32	20,833	-1,213	1,471,057
107	16,193	3.52	0.81	5.40	0.73	4.11	12,978	-3,215	10,334,460
108	17,853	3.52	0.81	5.35	0.73	4.11	12,868	-4,985	24,847,769
109	6,103	3.52	0.81	2.59	0.41	3.86	7,175	1,072	1,148,530
Total	196,933			58.69			152,588	**RMSE**	**3,460.02**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.125: Allometric Growth Model and RMSE for Sim 2020 Smart in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,888	3.52	0.81	1.78	0.25	3.72	5,303	-3,585	12,855,649
59	2,159	3.52	0.81	0.55	-0.26	3.31	2,056	-103	10,649
60	13,918	3.52	0.81	2.40	0.38	3.83	6,737		
61	7,232	3.52	0.81	3.54	0.55	3.97	9,226	1,994	3,976,246
62	6,933	3.52	0.81	3.64	0.56	3.97	9,430	2,497	6,234,848
63	8,402	3.52	0.81	2.89	0.46	3.89	7,837	-565	319,208
64	13,614	3.52	0.81	3.86	0.59	4.00	9,902	-3,712	13,780,836
65	7,432	3.52	0.81	3.52	0.55	3.96	9,192	1,760	3,097,468
66	6,771	3.52	0.81	1.83	0.26	3.73	5,419	-1,352	1,828,114
67	21,299	3.52	0.81	2.79	0.45	3.88	7,624	-13,675	187,013,05
68	4,074	3.52	0.81	2.22	0.35	3.80	6,330	2,256	5,090,089
69	9,052	3.52	0.81	2.28	0.36	3.81	6,479	-2,573	6,621,061
70	8,836	3.52	0.81	3.75	0.57	3.99	9,667		
71	8,548	3.52	0.81	1.59	0.20	3.68	4,831	-3,717	13,819,312
72	9,946	3.52	0.81	2.93	0.47	3.90	7,925	-2,021	4,082,527
73	2,052	3.52	0.81	0.73	-0.14	3.41	2,578	526	276,290
74	2,929	3.52	0.81	1.24	0.09	3.60	3,955	1,026	1,053,553
75	8,772	3.52	0.81	1.47	0.17	3.66	4,530	-4,242	17,994,934
76	8,214	3.52	0.81	1.98	0.30	3.76	5,765	-2,449	5,999,442
77	8,069	3.52	0.81	3.07	0.49	3.92	8,224	155	24,179
78	8,071	3.52	0.81	2.45	0.39	3.84	6,865	-1,206	1,453,252
79	3,606	3.52	0.81	1.38	0.14	3.63	4,306	700	490,634
80	2,757	3.52	0.81	1.15	0.06	3.57	3,724		
81	4,490	3.52	0.81	1.77	0.25	3.72	5,264	774	598,437
82	4,503	3.52	0.81	2.56	0.41	3.85	7,102	2,599	6,756,010
83	3,417	3.52	0.81	1.54	0.19	3.67	4,711	1,294	1,674,112
84	4,068	3.52	0.81	1.81	0.26	3.73	5,380	1,312	1,721,841
85	2,606	3.52	0.81	0.83	-0.08	3.46	2,874	268	71,896
86	4,911	3.52	0.81	3.04	0.48	3.91	8,154	3,243	10,519,477
87	11,521	3.52	0.81	2.53	0.40	3.85	7,030	-4,491	20,172,739
88	2,208	3.52	0.81	1.64	0.21	3.69	4,950	2,742	7,516,112
89	16,605	3.52	0.81	6.07	0.78	4.15	14,251	-2,354	5,539,942
90	4,782	3.52	0.81	3.13	0.50	3.92	8,364		
Total	240,685			77.96			215,985	**RMSE**	**3,460.02**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM20smart	Pop		Area		AntilogPop		
	793,291		269.64		736,751	**RMSE**	**3,460.02**

Table A-V.126: Allometric Growth Model and RMSE for Sim 2020 Normal in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,531	3.41	0.91	1.91	0.28	3.67	4,632	3,101	9,617,613
1	2,523	3.41	0.91	3.14	0.50	3.86	7,279	4,756	22,617,814
2	2,710	3.41	0.91	1.49	0.17	3.57	3,694	984	968,849
3	1,379	3.41	0.91	0.92	-0.03	3.38	2,391	1,012	1,023,696
4	1,338	3.41	0.91	1.43	0.16	3.55	3,566	2,228	4,965,420
5	4,040	3.41	0.91	3.94	0.60	3.95	8,932	4,892	23,934,992
6	2,284	3.41	0.91	1.36	0.13	3.53	3,401	1,117	1,247,906
7	6,673	3.41	0.91	3.21	0.51	3.87	7,415	742	550,733
8	3,074	3.41	0.91	1.22	0.09	3.49	3,087	13	163
9	7,522	3.41	0.91	2.80	0.45	3.82	6,559	-963	927,502
10	3,514	3.41	0.91	1.23	0.09	3.49	3,105		
11	7,938	3.41	0.91	3.25	0.51	3.88	7,500	-438	191,695
12	5,346	3.41	0.91	3.48	0.54	3.90	7,992	2,646	6,999,391
13	3,948	3.41	0.91	2.53	0.40	3.78	5,970	2,022	4,089,878
14	4,189	3.41	0.91	2.23	0.35	3.73	5,323	1,134	1,286,229
15	6,682	3.41	0.91	2.69	0.43	3.80	6,317	-365	133,050
16	6,742	3.41	0.91	5.05	0.70	4.05	11,194	4,452	19,824,255
17	930	3.41	0.91	1.29	0.11	3.51	3,235	2,305	5,313,320
18	2,501	3.41	0.91	1.66	0.22	3.61	4,076	1,575	2,479,530
19	2,575	3.41	0.91	3.23	0.51	3.87	7,466	4,891	23,923,438
20	1,846	3.41	0.91	1.57	0.20	3.59	3,876		
21	1,882	3.41	0.91	1.41	0.15	3.55	3,511	1,629	2,654,729
22	1,860	3.41	0.91	1.77	0.25	3.63	4,310	2,450	6,002,138
23	4,637	3.41	0.91	3.10	0.49	3.86	7,194	2,557	6,535,719
24	3,288	3.41	0.91	1.96	0.29	3.68	4,739	1,451	2,105,855
25	4,707	3.41	0.91	2.11	0.33	3.71	5,076	369	136,312
26	12,998	3.41	0.91	3.60	0.56	3.92	8,245	-4,753	22,594,353
27	3,830	3.41	0.91	2.61	0.42	3.79	6,144	2,314	5,354,770
28	31,877	3.41	0.91	12.04	1.08	4.39	24,686	-7,191	51,716,344
29	3,315	3.41	0.91	1.13	0.05	3.46	2,882	-433	187,781
30	10,795	3.41	0.91	4.01	0.60	3.96	9,083		
31	3,002	3.41	0.91	1.70	0.23	3.62	4,166	1,164	1,354,694
32	7,601	3.41	0.91	2.32	0.37	3.74	5,534	-2,067	4,273,102
33	3,003	3.41	0.91	1.08	0.03	3.44	2,750	-253	63,813
34	3,133	3.41	0.91	1.19	0.08	3.48	3,012	-121	14,558
35	3,578	3.41	0.91	1.98	0.30	3.68	4,793	1,215	1,475,083
36	6,887	3.41	0.91	2.72	0.43	3.81	6,386	-501	250,613
37	4,671	3.41	0.91	1.70	0.23	3.62	4,166	-505	255,113
38	5,521	3.41	0.91	2.81	0.45	3.82	6,576	1,055	1,113,363
39	9,382	3.41	0.91	5.94	0.77	4.11	12,978	3,596	12,927,912
40	4,022	3.41	0.91	1.40	0.15	3.54	3,493		
41	12,636	3.41	0.91	5.30	0.72	4.07	11,700	-936	876,742
42	3,573	3.41	0.91	1.03	0.01	3.42	2,637	-936	875,410
43	9,262	3.41	0.91	3.88	0.59	3.95	8,815	-447	199,527
44	2,925	3.41	0.91	1.14	0.06	3.46	2,900	-25	607
45	4,507	3.41	0.91	4.77	0.68	4.03	10,638	6,131	37,585,466
46	12,423	3.41	0.91	5.24	0.72	4.06	11,586	-837	700,955
47	7,772	3.41	0.91	3.91	0.59	3.95	8,882	1,110	1,232,557
48	11,075	3.41	0.91	3.55	0.55	3.91	8,127	-2,948	8,692,625
49	13,865	3.41	0.91	3.39	0.53	3.89	7,806	-6,059	36,716,516
50	7,276	3.41	0.91	1.51	0.18	3.57	3,731		
51	14,633	3.41	0.91	5.42	0.73	4.08	11,943	-2,690	7,234,356
52	13,734	3.41	0.91	4.69	0.67	4.02	10,473	-3,261	10,631,511
53	14,347	3.41	0.91	3.86	0.59	3.94	8,765	-5,582	31,157,444
54	2,909	3.41	0.91	2.77	0.44	3.81	6,490	3,581	12,823,338
55	4,960	3.41	0.91	2.09	0.32	3.70	5,023	63	3,987
56	5,391	3.41	0.91	2.28	0.36	3.74	5,446	55	3,041
57	5,111	3.41	0.91	2.37	0.38	3.75	5,639	528	278,694
Total	355,673			163.44			377,336	**RMSE**	**3,095.31**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.127: Allometric Growth Model and RMSE for Sim 2020 Normal in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,113	3.41	0.91	1.93	0.29	3.67	4,668	555	307,912
92	4,325	3.41	0.91	2.59	0.41	3.79	6,109	1,784	3,183,865
93	11,750	3.41	0.91	2.58	0.41	3.78	6,092	-5,658	32,013,167
94	1,737	3.41	0.91	0.90	-0.05	3.37	2,334	597	355,836
95	12,226	3.41	0.91	4.66	0.67	4.02	10,408	-1,818	3,306,547
96	9,529	3.41	0.91	2.23	0.35	3.73	5,323	-4,206	17,689,422
97	5,830	3.41	0.91	4.52	0.66	4.01	10,128	4,298	18,468,730
98	7,206	3.41	0.91	3.67	0.56	3.92	8,379	1,173	1,376,561
99	13,293	3.41	0.91	4.98	0.70	4.04	11,064	-2,229	4,969,782
100	5,582	3.41	0.91	2.58	0.41	3.78	6,075		
101	4,332	3.41	0.91	2.30	0.36	3.74	5,481	1,149	1,320,765
102	9,933	3.41	0.91	4.45	0.65	4.00	9,979	46	2,110
103	20,362	3.41	0.91	4.60	0.66	4.01	10,292	-10,070	101,397,38
104	8,827	3.41	0.91	1.94	0.29	3.67	4,686	-4,141	17,150,179
105	15,693	3.41	0.91	4.64	0.67	4.02	10,375	-5,318	28,284,344
106	22,046	3.41	0.91	12.64	1.10	4.41	25,785	3,739	13,978,348
107	16,193	3.41	0.91	7.07	0.85	4.18	15,212	-981	961,776
108	17,853	3.41	0.91	6.92	0.84	4.17	14,911	-2,942	8,655,098
109	6,103	3.41	0.91	3.31	0.52	3.88	7,636	1,533	2,350,275
Total	196,933			78.50			174,936	**RMSE**	**3,095.31**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.128: Allometric Growth Model and RMSE for Sim 2020 Normal in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,888	3.41	0.91	2.58	0.41	3.78	6,075	-2,813	7,915,106
59	2,159	3.41	0.91	0.79	-0.10	3.32	2,084	-75	5,669
60	13,918	3.41	0.91	3.60	0.56	3.92	8,228		
61	7,232	3.41	0.91	4.46	0.65	4.00	9,995	2,763	7,636,683
62	6,933	3.41	0.91	4.71	0.67	4.02	10,506	3,573	12,768,333
63	8,402	3.41	0.91	3.80	0.58	3.94	8,648	246	60,451
64	13,614	3.41	0.91	5.10	0.71	4.05	11,309	-2,305	5,314,317
65	7,432	3.41	0.91	3.65	0.56	3.92	8,346	914	834,728
66	6,771	3.41	0.91	2.24	0.35	3.73	5,358	-1,413	1,995,722
67	21,299	3.41	0.91	3.69	0.57	3.92	8,413	-12,886	166,051,81
68	4,074	3.41	0.91	2.54	0.40	3.78	5,988	1,914	3,662,388
69	9,052	3.41	0.91	2.89	0.46	3.83	6,748	-2,304	5,307,470
70	8,836	3.41	0.91	4.16	0.62	3.97	9,399		
71	8,548	3.41	0.91	1.86	0.27	3.66	4,525	-4,023	16,184,118
72	9,946	3.41	0.91	3.45	0.54	3.90	7,924	-2,022	4,088,356
73	2,052	3.41	0.91	1.02	0.01	3.42	2,618	566	320,903
74	2,929	3.41	0.91	1.49	0.17	3.57	3,694	765	585,686
75	8,772	3.41	0.91	1.66	0.22	3.61	4,076	-4,696	22,055,680
76	8,214	3.41	0.91	2.41	0.38	3.76	5,709	-2,505	6,275,786
77	8,069	3.41	0.91	3.68	0.57	3.92	8,396	327	106,982
78	8,071	3.41	0.91	2.83	0.45	3.82	6,611	-1,460	2,132,754
79	3,606	3.41	0.91	1.53	0.18	3.58	3,785	179	32,200
80	2,757	3.41	0.91	1.34	0.13	3.53	3,364		
81	4,490	3.41	0.91	2.03	0.31	3.69	4,899	409	167,363
82	4,503	3.41	0.91	2.80	0.45	3.82	6,559	2,056	4,226,852
83	3,417	3.41	0.91	1.73	0.24	3.63	4,220	803	644,770
84	4,068	3.41	0.91	2.14	0.33	3.71	5,129	1,061	1,126,176
85	2,606	3.41	0.91	0.92	-0.04	3.38	2,372	-234	54,893
86	4,911	3.41	0.91	3.50	0.54	3.90	8,025	3,114	9,699,593
87	11,521	3.41	0.91	3.17	0.50	3.87	7,330	-4,191	17,564,823
88	2,208	3.41	0.91	2.04	0.31	3.69	4,917	2,709	7,337,808
89	16,605	3.41	0.91	7.89	0.90	4.23	16,804	199	39,606
90	4,782	3.41	0.91	3.60	0.56	3.92	8,245		
Total	240,685			95.29			220,299	**RMSE**	**3,095.31**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM20norm	Pop 793,291		Area 337.23		AntilogPop 772,571	**RMSE** **3,095.31**

Table A-V.129: Allometric Growth Model and RMSE for Sim 2020 Sprawl in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,531	3.34	0.94	1.98	0.30	3.62	4,162	2,631	6,922,352
1	2,523	3.34	0.94	3.35	0.52	3.84	6,840	4,317	18,637,931
2	2,710	3.34	0.94	1.55	0.19	3.52	3,303	593	351,620
3	1,379	3.34	0.94	1.00	0.00	3.34	2,197	818	668,875
4	1,338	3.34	0.94	1.53	0.18	3.51	3,270	1,932	3,733,848
5	4,040	3.34	0.94	4.21	0.62	3.93	8,502	4,462	19,908,730
6	2,284	3.34	0.94	1.47	0.17	3.50	3,139	855	731,855
7	6,673	3.34	0.94	3.57	0.55	3.86	7,277	604	364,968
8	3,074	3.34	0.94	1.40	0.15	3.48	3,008	-66	4,313
9	7,522	3.34	0.94	3.12	0.49	3.81	6,402	-1,120	1,255,420
10	3,514	3.34	0.94	1.43	0.15	3.49	3,058		
11	7,938	3.34	0.94	3.69	0.57	3.87	7,495	-443	196,234
12	5,346	3.34	0.94	3.96	0.60	3.90	8,023	2,677	7,164,413
13	3,948	3.34	0.94	2.92	0.46	3.78	6,008	2,060	4,245,281
14	4,189	3.34	0.94	2.51	0.40	3.72	5,217	1,028	1,057,635
15	6,682	3.34	0.94	2.95	0.47	3.78	6,071	-611	372,820
16	6,742	3.34	0.94	5.68	0.75	4.05	11,271	4,529	20,513,067
17	930	3.34	0.94	1.29	0.11	3.44	2,778	1,848	3,415,021
18	2,501	3.34	0.94	1.70	0.23	3.56	3,612	1,111	1,235,007
19	2,575	3.34	0.94	3.34	0.52	3.83	6,825	4,250	18,058,516
20	1,846	3.34	0.94	1.73	0.24	3.57	3,677		
21	1,882	3.34	0.94	1.49	0.17	3.50	3,189	1,307	1,707,162
22	1,860	3.34	0.94	1.94	0.29	3.61	4,081	2,221	4,934,965
23	4,637	3.34	0.94	3.31	0.52	3.83	6,778	2,141	4,582,217
24	3,288	3.34	0.94	2.06	0.31	3.64	4,323	1,035	1,070,971
25	4,707	3.34	0.94	2.36	0.37	3.69	4,915	208	43,270
26	12,998	3.34	0.94	3.66	0.56	3.87	7,448	-5,550	30,798,527
27	3,830	3.34	0.94	2.82	0.45	3.76	5,819	1,989	3,956,777
28	31,877	3.34	0.94	13.77	1.14	4.42	26,011	-5,866	34,412,352
29	3,315	3.34	0.94	1.38	0.14	3.47	2,959	-356	126,694
30	10,795	3.34	0.94	4.63	0.67	3.97	9,302		
31	3,002	3.34	0.94	1.85	0.27	3.59	3,904	902	813,451
32	7,601	3.34	0.94	2.35	0.37	3.69	4,899	-2,702	7,300,430
33	3,003	3.34	0.94	1.08	0.03	3.37	2,347	-656	430,246
34	3,133	3.34	0.94	1.22	0.08	3.42	2,629	-504	253,715
35	3,578	3.34	0.94	2.21	0.34	3.67	4,628	1,050	1,101,472
36	6,887	3.34	0.94	3.03	0.48	3.79	6,229	-658	433,298
37	4,671	3.34	0.94	1.76	0.24	3.57	3,726	-945	893,268
38	5,521	3.34	0.94	3.21	0.51	3.82	6,574	1,053	1,108,950
39	9,382	3.34	0.94	6.76	0.83	4.12	13,295	3,913	15,310,024
40	4,022	3.34	0.94	1.53	0.18	3.51	3,270		
41	12,636	3.34	0.94	5.99	0.78	4.07	11,847	-789	622,443
42	3,573	3.34	0.94	1.16	0.06	3.40	2,513	-1,060	1,122,930
43	9,262	3.34	0.94	4.26	0.63	3.93	8,594	-668	445,562
44	2,925	3.34	0.94	1.25	0.10	3.43	2,695	-230	52,699
45	4,507	3.34	0.94	5.34	0.73	4.03	10,633	6,126	37,522,439
46	12,423	3.34	0.94	5.99	0.78	4.07	11,862	-561	314,516
47	7,772	3.34	0.94	4.33	0.64	3.94	8,718	946	894,610
48	11,075	3.34	0.94	3.89	0.59	3.90	7,883	-3,192	10,187,698
49	13,865	3.34	0.94	4.03	0.61	3.91	8,162	-5,703	32,524,688
50	7,276	3.34	0.94	1.84	0.26	3.59	3,888		
51	14,633	3.34	0.94	6.16	0.79	4.09	12,165	-2,468	6,092,991
52	13,734	3.34	0.94	5.39	0.73	4.03	10,739	-2,995	8,969,183
53	14,347	3.34	0.94	4.34	0.64	3.94	8,749	-5,598	31,341,438
54	2,909	3.34	0.94	3.15	0.50	3.81	6,464	3,555	12,640,240
55	4,960	3.34	0.94	2.95	0.47	3.78	6,071	1,111	1,235,232
56	5,391	3.34	0.94	3.09	0.49	3.80	6,354	963	928,228
57	5,111	3.34	0.94	2.88	0.46	3.77	5,930	819	670,107
Total	355,673			182.79			371,730	**RMSE**	**3,027.78**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.130: Allometric Growth Model and RMSE for Sim 2020 Sprawl in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,113	3.34	0.94	2.29	0.36	3.68	4,787	674	454,764
92	4,325	3.34	0.94	3.61	0.56	3.87	7,355	3,030	9,180,827
93	11,750	3.34	0.94	3.19	0.50	3.82	6,543	-5,207	27,115,772
94	1,737	3.34	0.94	1.52	0.18	3.51	3,254	1,517	2,301,228
95	12,226	3.34	0.94	5.44	0.74	4.03	10,815	-1,411	1,990,261
96	9,529	3.34	0.94	2.83	0.45	3.77	5,835	-3,694	13,646,013
97	5,830	3.34	0.94	5.17	0.71	4.01	10,312	4,482	20,092,086
98	7,206	3.34	0.94	3.94	0.60	3.90	7,976	770	593,164
99	13,293	3.34	0.94	5.49	0.74	4.04	10,922	-2,371	5,623,011
100	5,582	3.34	0.94	3.16	0.50	3.81	6,480		
101	4,332	3.34	0.94	2.62	0.42	3.74	5,440	1,108	1,226,705
102	9,933	3.34	0.94	5.58	0.75	4.04	11,089	1,156	1,336,125
103	20,362	3.34	0.94	5.63	0.75	4.05	11,180	-9,182	84,308,316
104	8,827	3.34	0.94	2.32	0.36	3.68	4,835	-3,992	15,934,027
105	15,693	3.34	0.94	5.20	0.72	4.02	10,373	-5,320	28,297,687
106	22,046	3.34	0.94	14.68	1.17	4.44	27,626	5,580	31,131,562
107	16,193	3.34	0.94	8.29	0.92	4.21	16,104	-89	7,930
108	17,853	3.34	0.94	8.12	0.91	4.20	15,792	-2,061	4,248,942
109	6,103	3.34	0.94	3.55	0.55	3.86	7,230	1,127	1,270,997
Total	196,933			92.62			183,948	**RMSE**	**3,027.78**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.131: Allometric Growth Model and RMSE for Sim 2020 Sprawl in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	$(PopEst-PopAct)^2$
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	8,888	3.34	0.94	3.54	0.55	3.86	7,215	-1,673	2,799,596
59	2,159	3.34	0.94	1.02	0.01	3.35	2,230	71	5,081
60	13,918	3.34	0.94	4.66	0.67	3.97	9,348		
61	7,232	3.34	0.94	4.95	0.69	4.00	9,900	2,668	7,117,928
62	6,933	3.34	0.94	5.32	0.73	4.03	10,602	3,669	13,462,236
63	8,402	3.34	0.94	4.38	0.64	3.95	8,826	424	179,503
64	13,614	3.34	0.94	5.77	0.76	4.06	11,438	-2,176	4,734,875
65	7,432	3.34	0.94	3.85	0.59	3.89	7,806	374	139,608
66	6,771	3.34	0.94	2.55	0.41	3.72	5,297	-1,474	2,173,214
67	21,299	3.34	0.94	4.18	0.62	3.93	8,440	-12,859	165,349,51
68	4,074	3.34	0.94	2.75	0.44	3.75	5,677	1,603	2,569,587
69	9,052	3.34	0.94	3.28	0.52	3.83	6,715	-2,337	5,461,469
70	8,836	3.34	0.94	4.57	0.66	3.96	9,179		
71	8,548	3.34	0.94	2.02	0.30	3.63	4,243	-4,305	18,537,314
72	9,946	3.34	0.94	3.72	0.57	3.88	7,557	-2,389	5,706,356
73	2,052	3.34	0.94	1.22	0.09	3.42	2,646	594	352,650
74	2,929	3.34	0.94	1.64	0.22	3.54	3,499	570	324,369
75	8,772	3.34	0.94	1.73	0.24	3.57	3,677	-5,095	25,956,710
76	8,214	3.34	0.94	2.52	0.40	3.72	5,233	-2,981	8,884,570
77	8,069	3.34	0.94	4.10	0.61	3.92	8,286	217	46,948
78	8,071	3.34	0.94	3.11	0.49	3.81	6,386	-1,685	2,839,739
79	3,606	3.34	0.94	1.67	0.22	3.55	3,547	-59	3,443
80	2,757	3.34	0.94	1.48	0.17	3.50	3,172		
81	4,490	3.34	0.94	2.26	0.35	3.67	4,723	233	54,503
82	4,503	3.34	0.94	2.95	0.47	3.78	6,071	1,568	2,459,910
83	3,417	3.34	0.94	1.82	0.26	3.59	3,855	438	192,200
84	4,068	3.34	0.94	2.17	0.34	3.66	4,547	479	229,884
85	2,606	3.34	0.94	0.90	-0.05	3.30	1,979	-627	393,421
86	4,911	3.34	0.94	3.76	0.58	3.88	7,635	2,724	7,419,581
87	11,521	3.34	0.94	3.44	0.54	3.85	7,028	-4,493	20,190,357
88	2,208	3.34	0.94	2.20	0.34	3.66	4,596	2,388	5,700,161
89	16,605	3.34	0.94	9.11	0.96	4.25	17,616	1,011	1,021,345
90	4,782	3.34	0.94	3.95	0.60	3.90	8,007		
Total	240,685			106.59			216,976	**RMSE**	**3,027.78**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM20spraw	Pop 793,291		Area 382.00		AntilogPop 772,655	**RMSE**	**3,027.78**

Table A-V.132: Allometric Growth Model and RMSE for Sim 2025 Smart in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,402	3.53	0.83	1.70	0.23	3.72	5,245	3,843	14,765,845
1	2,364	3.53	0.83	2.77	0.44	3.90	7,866	5,502	30,266,584
2	2,514	3.53	0.83	1.34	0.13	3.63	4,292	1,778	3,162,004
3	1,302	3.53	0.83	0.82	-0.09	3.46	2,855	1,553	2,410,502
4	1,199	3.53	0.83	1.34	0.13	3.63	4,292	3,093	9,567,902
5	3,746	3.53	0.83	3.39	0.53	3.97	9,293	5,547	30,767,453
6	2,170	3.53	0.83	1.11	0.05	3.57	3,678	1,508	2,272,892
7	6,644	3.53	0.83	2.59	0.41	3.87	7,443	799	637,926
8	3,040	3.53	0.83	1.13	0.05	3.57	3,722	682	465,358
9	7,774	3.53	0.83	2.35	0.37	3.84	6,858	-916	838,874
10	3,602	3.53	0.83	0.97	-0.01	3.52	3,294		
11	8,155	3.53	0.83	2.81	0.45	3.90	7,961	-194	37,656
12	5,290	3.53	0.83	2.95	0.47	3.92	8,284	2,994	8,962,461
13	3,899	3.53	0.83	2.19	0.34	3.81	6,463	2,564	6,572,584
14	4,014	3.53	0.83	1.84	0.26	3.75	5,595	1,581	2,499,905
15	6,870	3.53	0.83	2.35	0.37	3.84	6,858	-12	142
16	6,792	3.53	0.83	4.03	0.61	4.03	10,749	3,957	15,654,044
17	834	3.53	0.83	1.14	0.06	3.58	3,767	2,933	8,600,277
18	2,386	3.53	0.83	1.47	0.17	3.67	4,657	2,271	5,155,694
19	2,412	3.53	0.83	2.63	0.42	3.88	7,539	5,127	26,288,333
20	1,695	3.53	0.83	1.37	0.14	3.64	4,378		
21	1,777	3.53	0.83	1.17	0.07	3.59	3,855	2,078	4,318,950
22	1,737	3.53	0.83	1.59	0.20	3.69	4,952	3,215	10,338,807
23	4,423	3.53	0.83	2.64	0.42	3.88	7,558	3,135	9,831,279
24	3,062	3.53	0.83	1.64	0.22	3.71	5,099	2,037	4,149,142
25	4,471	3.53	0.83	1.80	0.25	3.74	5,493	1,022	1,043,470
26	13,497	3.53	0.83	3.44	0.54	3.97	9,422	-4,075	16,605,775
27	4,090	3.53	0.83	2.21	0.34	3.81	6,522	2,432	5,916,188
28	36,385	3.53	0.83	9.66	0.99	4.35	22,215	-14,170	200,799,13
29	3,492	3.53	0.83	0.88	-0.05	3.48	3,041	-451	203,173
30	11,419	3.53	0.83	3.13	0.50	3.94	8,716		
31	3,013	3.53	0.83	1.30	0.12	3.62	4,206	1,193	1,422,188
32	7,886	3.53	0.83	1.79	0.25	3.74	5,472	-2,414	5,827,704
33	3,008	3.53	0.83	0.84	-0.07	3.47	2,925	-83	6,912
34	3,107	3.53	0.83	1.13	0.05	3.57	3,722	615	378,436
35	3,385	3.53	0.83	1.73	0.24	3.73	5,328	1,943	3,773,375
36	6,720	3.53	0.83	2.20	0.34	3.81	6,502	-218	47,323
37	4,534	3.53	0.83	1.43	0.15	3.66	4,529	-5	28
38	5,601	3.53	0.83	2.30	0.36	3.83	6,740	1,139	1,297,275
39	9,562	3.53	0.83	4.89	0.69	4.10	12,618	3,056	9,339,531
40	4,327	3.53	0.83	1.12	0.05	3.57	3,700		
41	13,490	3.53	0.83	4.28	0.63	4.05	11,302	-2,188	4,788,778
42	3,850	3.53	0.83	0.84	-0.07	3.47	2,925	-925	855,876
43	9,815	3.53	0.83	3.09	0.49	3.93	8,604	-1,211	1,466,554
44	3,064	3.53	0.83	0.95	-0.02	3.51	3,226	162	26,122
45	4,393	3.53	0.83	3.76	0.58	4.01	10,135	5,742	32,971,566
46	13,016	3.53	0.83	4.07	0.61	4.03	10,838	-2,178	4,743,151
47	8,095	3.53	0.83	3.18	0.50	3.94	8,810	715	511,105
48	11,524	3.53	0.83	2.92	0.46	3.91	8,208	-3,316	10,995,720
49	15,159	3.53	0.83	2.70	0.43	3.89	7,693	-7,466	55,739,443
50	7,910	3.53	0.83	1.25	0.10	3.61	4,053		
51	16,271	3.53	0.83	4.26	0.63	4.05	11,248	-5,023	25,226,653
52	15,241	3.53	0.83	3.72	0.57	4.00	10,044	-5,197	27,006,240
53	15,720	3.53	0.83	2.99	0.48	3.92	8,378	-7,342	53,902,243
54	2,765	3.53	0.83	2.24	0.35	3.82	6,602	3,837	14,719,795
55	4,994	3.53	0.83	1.30	0.12	3.62	4,206	-788	621,645
56	5,368	3.53	0.83	1.48	0.17	3.67	4,678	-690	476,283
57	5,030	3.53	0.83	1.81	0.26	3.74	5,534	504	253,605
Total	369,305			134.04			384,185	**RMSE**	**4,074.41**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.133: Allometric Growth Model and RMSE for Sim 2025 Smart in Santa Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,010	3.53	0.83	1.06	0.03	3.55	3,543	-467	217,843
92	4,129	3.53	0.83	1.78	0.25	3.74	5,451	1,322	1,748,617
93	12,807	3.53	0.83	1.92	0.28	3.76	5,799	-7,008	49,109,478
94	1,540	3.53	0.83	0.56	-0.25	3.32	2,080	540	291,452
95	12,801	3.53	0.83	3.58	0.55	3.99	9,734	-3,067	9,405,717
96	10,075	3.53	0.83	1.68	0.23	3.72	5,203	-4,872	23,735,467
97	5,443	3.53	0.83	3.86	0.59	4.02	10,371	4,928	24,280,286
98	7,490	3.53	0.83	2.54	0.41	3.86	7,327	-163	26,716
99	14,186	3.53	0.83	3.89	0.59	4.02	10,425	-3,761	14,147,567
100	5,882	3.53	0.83	1.96	0.29	3.77	5,901		
101	4,431	3.53	0.83	1.91	0.28	3.76	5,779	1,348	1,816,682
102	10,327	3.53	0.83	3.36	0.53	3.97	9,237	-1,090	1,187,262
103	22,892	3.53	0.83	2.91	0.46	3.91	8,189	-14,703	216,176,17
104	10,346	3.53	0.83	1.47	0.17	3.67	4,635	-5,711	32,611,595
105	17,149	3.53	0.83	3.60	0.56	3.99	9,771	-7,378	54,439,105
106	25,525	3.53	0.83	9.83	0.99	4.35	22,539	-2,986	8,915,534
107	18,509	3.53	0.83	5.46	0.74	4.14	13,822	-4,687	21,969,002
108	20,054	3.53	0.83	5.45	0.74	4.14	13,805	-6,249	39,051,925
109	5,869	3.53	0.83	2.62	0.42	3.88	7,520	1,651	2,725,579
Total	213,465			59.45			161,130	**RMSE**	**4,074.41**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.134: Allometric Growth Model and RMSE for Sim 2025 Smart in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	9,186	3.53	0.83	1.80	0.25	3.74	5,493	-3,693	13,641,914
59	2,179	3.53	0.83	0.55	-0.26	3.31	2,055	-124	15,430
60	15,189	3.53	0.83	2.43	0.39	3.85	7,054		
61	7,460	3.53	0.83	3.59	0.55	3.99	9,752	2,292	5,255,205
62	7,095	3.53	0.83	3.66	0.56	4.00	9,917	2,822	7,962,495
63	9,067	3.53	0.83	2.94	0.47	3.92	8,265	-802	643,491
64	15,113	3.53	0.83	3.92	0.59	4.02	10,497	-4,616	21,309,163
65	7,773	3.53	0.83	3.54	0.55	3.98	9,643	1,870	3,495,153
66	7,203	3.53	0.83	1.87	0.27	3.75	5,677	-1,526	2,328,927
67	25,032	3.53	0.83	2.84	0.45	3.91	8,037	-16,995	288,825,43
68	4,140	3.53	0.83	2.22	0.35	3.82	6,542	2,402	5,770,417
69	9,226	3.53	0.83	2.31	0.36	3.83	6,760	-2,466	6,082,658
70	8,881	3.53	0.83	3.76	0.58	4.01	10,135		
71	8,569	3.53	0.83	1.60	0.20	3.70	4,973	-3,596	12,928,414
72	10,156	3.53	0.83	2.96	0.47	3.92	8,322	-1,834	3,365,235
73	2,033	3.53	0.83	0.75	-0.13	3.42	2,642	609	370,332
74	2,898	3.53	0.83	1.26	0.10	3.61	4,075	1,177	1,385,088
75	9,598	3.53	0.83	1.49	0.17	3.67	4,699	-4,899	23,999,224
76	8,919	3.53	0.83	2.00	0.30	3.78	6,002	-2,917	8,509,999
77	8,278	3.53	0.83	3.10	0.49	3.94	8,642	364	132,134
78	8,066	3.53	0.83	2.47	0.39	3.85	7,152	-914	836,097
79	3,581	3.53	0.83	1.41	0.15	3.65	4,486	905	818,805
80	2,771	3.53	0.83	1.16	0.06	3.58	3,811		
81	4,446	3.53	0.83	1.80	0.25	3.74	5,493	1,047	1,095,170
82	4,450	3.53	0.83	2.58	0.41	3.87	7,404	2,954	8,726,275
83	3,442	3.53	0.83	1.54	0.19	3.68	4,826	1,384	1,915,701
84	4,020	3.53	0.83	1.82	0.26	3.74	5,554	1,534	2,353,503
85	2,672	3.53	0.83	0.83	-0.08	3.46	2,901	229	52,659
86	4,937	3.53	0.83	3.07	0.49	3.93	8,566	3,629	13,172,814
87	12,400	3.53	0.83	2.57	0.41	3.87	7,385	-5,015	25,153,500
88	2,234	3.53	0.83	1.67	0.22	3.71	5,161	2,927	8,570,171
89	18,519	3.53	0.83	6.12	0.79	4.18	15,206	-3,313	10,978,828
90	5,102	3.53	0.83	3.17	0.50	3.94	8,791		
Total	254,635			78.79			225,916	**RMSE**	**4,074.41**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM25smart	Pop 837,405			Area 272.28			AntilogPop 771,231	**RMSE**	**4,074.41**

Table A-V.135: Allometric Growth Model and RMSE for Sim 2025 Normal in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,402	3.36	1.00	1.96	0.29	3.65	4,513	3,111	9,675,615
1	2,364	3.36	1.00	3.25	0.51	3.87	7,466	5,102	26,031,547
2	2,514	3.36	1.00	1.51	0.18	3.54	3,490	976	951,952
3	1,302	3.36	1.00	0.99	-0.01	3.36	2,280	978	955,719
4	1,199	3.36	1.00	1.45	0.16	3.52	3,341	2,142	4,587,425
5	3,746	3.36	1.00	4.11	0.61	3.97	9,433	5,687	32,342,627
6	2,170	3.36	1.00	1.41	0.15	3.51	3,248	1,078	1,161,619
7	6,644	3.36	1.00	3.45	0.54	3.90	7,930	1,286	1,654,160
8	3,040	3.36	1.00	1.26	0.10	3.46	2,894	-146	21,274
9	7,774	3.36	1.00	2.94	0.47	3.83	6,761	-1,013	1,026,941
10	3,602	3.36	1.00	1.33	0.12	3.49	3,062		
11	8,155	3.36	1.00	3.39	0.53	3.89	7,800	-355	125,868
12	5,290	3.36	1.00	3.74	0.57	3.93	8,598	3,308	10,944,196
13	3,899	3.36	1.00	2.71	0.43	3.79	6,222	2,323	5,396,647
14	4,014	3.36	1.00	2.38	0.38	3.74	5,479	1,465	2,146,245
15	6,870	3.36	1.00	2.79	0.45	3.81	6,408	-462	213,637
16	6,792	3.36	1.00	5.39	0.73	4.09	12,381	5,589	31,239,358
17	834	3.36	1.00	1.33	0.12	3.49	3,062	2,228	4,962,529
18	2,386	3.36	1.00	1.71	0.23	3.60	3,936	1,550	2,402,896
19	2,412	3.36	1.00	3.47	0.54	3.90	7,986	5,574	31,067,463
20	1,695	3.36	1.00	1.63	0.21	3.57	3,750		
21	1,777	3.36	1.00	1.44	0.16	3.52	3,322	1,545	2,387,703
22	1,737	3.36	1.00	1.81	0.26	3.62	4,159	2,422	5,867,503
23	4,423	3.36	1.00	3.26	0.51	3.88	7,503	3,080	9,487,863
24	3,062	3.36	1.00	2.09	0.32	3.68	4,810	1,748	3,055,478
25	4,471	3.36	1.00	2.24	0.35	3.71	5,163	692	479,025
26	13,497	3.36	1.00	3.65	0.56	3.92	8,394	-5,103	26,039,699
27	4,090	3.36	1.00	2.67	0.43	3.79	6,148	2,058	4,234,438
28	36,385	3.36	1.00	13.15	1.12	4.48	30,092	-6,293	39,605,272
29	3,492	3.36	1.00	1.23	0.09	3.45	2,838	-654	427,329
30	11,419	3.36	1.00	4.34	0.64	4.00	9,971		
31	3,013	3.36	1.00	1.81	0.26	3.62	4,178	1,165	1,356,965
32	7,886	3.36	1.00	2.45	0.39	3.75	5,628	-2,258	5,100,179
33	3,008	3.36	1.00	1.17	0.07	3.43	2,708	-300	90,019
34	3,107	3.36	1.00	1.22	0.09	3.45	2,820	-287	82,554
35	3,385	3.36	1.00	2.11	0.32	3.69	4,847	1,462	2,137,933
36	6,720	3.36	1.00	2.84	0.45	3.81	6,519	-201	40,314
37	4,534	3.36	1.00	1.77	0.25	3.61	4,066	-468	218,732
38	5,601	3.36	1.00	3.07	0.49	3.85	7,058	1,457	2,121,959
39	9,562	3.36	1.00	6.51	0.81	4.17	14,938	5,376	28,904,109
40	4,327	3.36	1.00	1.51	0.18	3.54	3,490		
41	13,490	3.36	1.00	5.62	0.75	4.11	12,900	-590	347,916
42	3,850	3.36	1.00	1.09	0.04	3.40	2,503	-1,347	1,814,064
43	9,815	3.36	1.00	4.09	0.61	3.97	9,396	-419	175,596
44	3,064	3.36	1.00	1.19	0.08	3.44	2,745	-319	101,630
45	4,393	3.36	1.00	5.05	0.70	4.06	11,603	7,210	51,979,596
46	13,016	3.36	1.00	5.71	0.76	4.12	13,104	88	7,745
47	8,095	3.36	1.00	4.26	0.63	3.99	9,785	1,690	2,857,739
48	11,524	3.36	1.00	3.73	0.57	3.93	8,580	-2,944	8,669,218
49	15,159	3.36	1.00	3.74	0.57	3.93	8,598	-6,561	43,044,078
50	7,910	3.36	1.00	1.74	0.24	3.60	4,011		
51	16,271	3.36	1.00	5.76	0.76	4.12	13,215	-3,056	9,337,948
52	15,241	3.36	1.00	5.18	0.71	4.08	11,899	-3,342	11,167,035
53	15,720	3.36	1.00	4.18	0.62	3.98	9,600	-6,120	37,454,377
54	2,765	3.36	1.00	2.99	0.48	3.84	6,872	4,107	16,867,670
55	4,994	3.36	1.00	2.46	0.39	3.75	5,665	671	449,972
56	5,368	3.36	1.00	2.62	0.42	3.78	6,018	650	422,181
57	5,030	3.36	1.00	2.57	0.41	3.77	5,906	876	767,905
Total	369,305			174.54			401,091	**RMSE**	**3,529.62**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.136: Allometric Growth Model and RMSE for Sim 2025 Normal in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,010	3.36	1.00	2.32	0.37	3.73	5,349	1,339	1,792,763
92	4,129	3.36	1.00	2.89	0.46	3.82	6,649	2,520	6,351,437
93	12,807	3.36	1.00	2.90	0.46	3.82	6,668	-6,139	37,690,083
94	1,540	3.36	1.00	1.13	0.05	3.42	2,615	1,075	1,155,334
95	12,801	3.36	1.00	5.05	0.70	4.06	11,584	-1,217	1,480,726
96	10,075	3.36	1.00	2.45	0.39	3.75	5,646	-4,429	19,614,084
97	5,443	3.36	1.00	4.80	0.68	4.04	11,028	5,585	31,191,753
98	7,490	3.36	1.00	4.07	0.61	3.97	9,359	1,869	3,492,629
99	14,186	3.36	1.00	5.24	0.72	4.08	12,029	-2,157	4,652,457
100	5,882	3.36	1.00	2.79	0.45	3.81	6,426		
101	4,431	3.36	1.00	2.46	0.39	3.75	5,665	1,234	1,522,261
102	10,327	3.36	1.00	4.90	0.69	4.05	11,250	923	852,749
103	22,892	3.36	1.00	5.41	0.73	4.09	12,418	-10,474	109,698,66
104	10,346	3.36	1.00	2.11	0.33	3.69	4,866	-5,480	30,033,096
105	17,149	3.36	1.00	5.03	0.70	4.06	11,547	-5,602	31,381,593
106	25,525	3.36	1.00	13.63	1.13	4.49	31,201	5,676	32,214,459
107	18,509	3.36	1.00	7.70	0.89	4.25	17,642	-867	751,535
108	20,054	3.36	1.00	7.49	0.87	4.24	17,179	-2,875	8,264,490
109	5,869	3.36	1.00	3.53	0.55	3.91	8,116	2,247	5,047,796
Total	213,465			85.93			197,238	**RMSE**	**3,529.62**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.137: Allometric Growth Model and RMSE for Sim 2025 Normal in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	9,186	3.36	1.00	2.90	0.46	3.82	6,668	-2,518	6,341,457
59	2,179	3.36	1.00	0.90	-0.05	3.32	2,075	-104	10,887
60	15,189	3.36	1.00	4.07	0.61	3.97	9,359		
61	7,460	3.36	1.00	4.85	0.69	4.05	11,139	3,679	13,536,532
62	7,095	3.36	1.00	5.14	0.71	4.07	11,807	4,712	22,199,205
63	9,067	3.36	1.00	4.20	0.62	3.98	9,656	589	346,506
64	15,113	3.36	1.00	5.56	0.74	4.11	12,752	-2,361	5,574,820
65	7,773	3.36	1.00	3.73	0.57	3.93	8,561	788	621,088
66	7,203	3.36	1.00	2.48	0.39	3.76	5,702	-1,501	2,253,134
67	25,032	3.36	1.00	3.87	0.59	3.95	8,895	-16,137	260,400,63
68	4,140	3.36	1.00	2.64	0.42	3.78	6,073	1,933	3,738,340
69	9,226	3.36	1.00	3.05	0.48	3.85	7,021	-2,205	4,863,956
70	8,881	3.36	1.00	4.26	0.63	3.99	9,785		
71	8,569	3.36	1.00	1.93	0.29	3.65	4,438	-4,131	17,063,515
72	10,156	3.36	1.00	3.57	0.55	3.91	8,209	-1,947	3,792,680
73	2,033	3.36	1.00	1.15	0.06	3.42	2,652	619	383,293
74	2,898	3.36	1.00	1.57	0.20	3.56	3,620	722	521,155
75	9,598	3.36	1.00	1.73	0.24	3.60	3,992	-5,606	31,428,105
76	8,919	3.36	1.00	2.48	0.39	3.76	5,702	-3,217	10,349,375
77	8,278	3.36	1.00	3.84	0.58	3.95	8,821	543	294,689
78	8,066	3.36	1.00	2.96	0.47	3.83	6,798	-1,268	1,608,444
79	3,581	3.36	1.00	1.65	0.22	3.58	3,806	225	50,594
80	2,771	3.36	1.00	1.41	0.15	3.51	3,248		
81	4,446	3.36	1.00	2.12	0.33	3.69	4,884	438	192,143
82	4,450	3.36	1.00	2.88	0.46	3.82	6,612	2,162	4,674,533
83	3,442	3.36	1.00	1.78	0.25	3.61	4,104	662	437,589
84	4,020	3.36	1.00	2.18	0.34	3.70	5,014	994	988,914
85	2,672	3.36	1.00	0.92	-0.04	3.32	2,112	-560	313,682
86	4,937	3.36	1.00	3.66	0.56	3.92	8,413	3,476	12,080,111
87	12,400	3.36	1.00	3.30	0.52	3.88	7,596	-4,804	23,077,947
88	2,234	3.36	1.00	2.09	0.32	3.68	4,810	2,576	6,635,738
89	18,519	3.36	1.00	8.48	0.93	4.29	19,438	919	844,136
90	5,102	3.36	1.00	3.80	0.58	3.94	8,728		
Total	254,635			101.16			232,488	**RMSE**	**3,529.62**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM25norm	Pop 837,405			Area 361.63			AntilogPop 830,817	**RMSE**	**3,529.62**

Table A-V.138: Allometric Growth Model and RMSE for Sim 2025 Sprawl in Escambia

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
0	1,402	3.29	1.01	2.00	0.30	3.59	3,927	2,525	6,377,289
1	2,364	3.29	1.01	3.41	0.53	3.83	6,741	4,377	19,153,885
2	2,514	3.29	1.01	1.62	0.21	3.50	3,171	657	432,057
3	1,302	3.29	1.01	1.02	0.01	3.30	1,986	684	467,802
4	1,199	3.29	1.01	1.56	0.19	3.48	3,043	1,844	3,399,755
5	3,746	3.29	1.01	4.31	0.63	3.93	8,544	4,798	23,017,513
6	2,170	3.29	1.01	1.55	0.19	3.48	3,027	857	734,087
7	6,644	3.29	1.01	3.73	0.57	3.87	7,390	746	556,006
8	3,040	3.29	1.01	1.43	0.15	3.45	2,786	-254	64,456
9	7,774	3.29	1.01	3.33	0.52	3.82	6,578	-1,196	1,429,575
10	3,602	3.29	1.01	1.55	0.19	3.48	3,027		
11	8,155	3.29	1.01	3.88	0.59	3.89	7,682	-473	223,714
12	5,290	3.29	1.01	4.24	0.63	3.92	8,414	3,124	9,756,400
13	3,899	3.29	1.01	3.07	0.49	3.78	6,060	2,161	4,668,969
14	4,014	3.29	1.01	2.71	0.43	3.73	5,348	1,334	1,778,712
15	6,870	3.29	1.01	3.08	0.49	3.78	6,076	-794	630,473
16	6,792	3.29	1.01	6.26	0.80	4.10	12,474	5,682	32,290,155
17	834	3.29	1.01	1.30	0.12	3.41	2,546	1,712	2,929,971
18	2,386	3.29	1.01	1.73	0.24	3.53	3,380	994	988,456
19	2,412	3.29	1.01	3.63	0.56	3.86	7,179	4,767	22,720,507
20	1,695	3.29	1.01	1.77	0.25	3.54	3,461		
21	1,777	3.29	1.01	1.54	0.19	3.48	3,011	1,234	1,522,105
22	1,737	3.29	1.01	2.03	0.31	3.60	3,992	2,255	5,083,958
23	4,423	3.29	1.01	3.53	0.55	3.84	6,984	2,561	6,557,972
24	3,062	3.29	1.01	2.12	0.33	3.62	4,169	1,107	1,225,505
25	4,471	3.29	1.01	2.49	0.40	3.69	4,895	424	179,908
26	13,497	3.29	1.01	3.69	0.57	3.86	7,308	-6,189	38,297,853
27	4,090	3.29	1.01	2.89	0.46	3.76	5,704	1,614	2,603,670
28	36,385	3.29	1.01	14.95	1.17	4.48	30,129	-6,256	39,134,658
29	3,492	3.29	1.01	1.59	0.20	3.49	3,107	-385	148,173
30	11,419	3.29	1.01	5.03	0.70	4.00	9,993		
31	3,013	3.29	1.01	1.96	0.29	3.59	3,847	834	695,233
32	7,886	3.29	1.01	2.54	0.41	3.70	5,008	-2,878	8,281,508
33	3,008	3.29	1.01	1.20	0.08	3.37	2,338	-670	449,434
34	3,107	3.29	1.01	1.26	0.10	3.39	2,450	-657	432,129
35	3,385	3.29	1.01	2.32	0.36	3.66	4,556	1,171	1,371,497
36	6,720	3.29	1.01	3.20	0.51	3.80	6,319	-401	160,803
37	4,534	3.29	1.01	1.85	0.27	3.56	3,621	-913	832,735
38	5,601	3.29	1.01	3.60	0.56	3.85	7,114	1,513	2,288,198
39	9,562	3.29	1.01	7.24	0.86	4.16	14,454	4,892	23,935,630
40	4,327	3.29	1.01	1.73	0.24	3.53	3,380		
41	13,490	3.29	1.01	6.44	0.81	4.11	12,834	-656	430,135
42	3,850	3.29	1.01	1.30	0.11	3.40	2,530	-1,320	1,743,194
43	9,815	3.29	1.01	4.55	0.66	3.96	9,032	-783	613,275
44	3,064	3.29	1.01	1.31	0.12	3.41	2,562	-502	252,271
45	4,393	3.29	1.01	5.74	0.76	4.06	11,429	7,036	49,502,233
46	13,016	3.29	1.01	6.71	0.83	4.13	13,390	374	140,118
47	8,095	3.29	1.01	4.87	0.69	3.99	9,667	1,572	2,471,425
48	11,524	3.29	1.01	4.16	0.62	3.92	8,235	-3,289	10,819,939
49	15,159	3.29	1.01	4.54	0.66	3.95	8,999	-6,160	37,941,632
50	7,910	3.29	1.01	2.08	0.32	3.61	4,088		
51	16,271	3.29	1.01	6.83	0.83	4.13	13,619	-2,652	7,030,869
52	15,241	3.29	1.01	6.00	0.78	4.08	11,951	-3,290	10,821,036
53	15,720	3.29	1.01	4.88	0.69	3.99	9,683	-6,037	36,440,890
54	2,765	3.29	1.01	3.52	0.55	3.84	6,968	4,203	17,662,080
55	4,994	3.29	1.01	3.81	0.58	3.88	7,536	2,542	6,460,843
56	5,368	3.29	1.01	3.99	0.60	3.90	7,893	2,525	6,376,898
57	5,030	3.29	1.01	3.22	0.51	3.80	6,351	1,321	1,746,123
Total	369,305			197.86			391,985	**RMSE**	**3,483.53**

Note: Total results are calculated for Escambia county. The only exception is RMSE, based on all 3 counties.

Table A-V.139: Allometric Growth Model and RMSE for Sim 2025 Sprawl in Sta. Rosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
91	4,010	3.29	1.01	2.88	0.46	3.75	5,687	1,677	2,813,688
92	4,129	3.29	1.01	4.44	0.65	3.94	8,804	4,675	21,855,624
93	12,807	3.29	1.01	3.72	0.57	3.87	7,357	-5,450	29,700,502
94	1,540	3.29	1.01	2.11	0.32	3.62	4,137	2,597	6,743,311
95	12,801	3.29	1.01	6.15	0.79	4.09	12,246	-555	308,464
96	10,075	3.29	1.01	3.30	0.52	3.81	6,514	-3,561	12,684,278
97	5,443	3.29	1.01	5.42	0.73	4.03	10,776	5,333	28,439,407
98	7,490	3.29	1.01	4.44	0.65	3.94	8,804	1,314	1,726,596
99	14,186	3.29	1.01	6.15	0.79	4.09	12,246	-1,940	3,765,133
100	5,882	3.29	1.01	3.52	0.55	3.84	6,951		
101	4,431	3.29	1.01	2.90	0.46	3.76	5,720	1,289	1,660,937
102	10,327	3.29	1.01	6.32	0.80	4.10	12,589	2,262	5,116,109
103	22,892	3.29	1.01	6.72	0.83	4.13	13,407	-9,485	89,971,185
104	10,346	3.29	1.01	2.64	0.42	3.72	5,202	-5,144	26,458,961
105	17,149	3.29	1.01	5.61	0.75	4.05	11,168	-5,981	35,777,687
106	25,525	3.29	1.01	16.13	1.21	4.51	32,528	7,003	49,039,019
107	18,509	3.29	1.01	9.10	0.96	4.26	18,227	-282	79,372
108	20,054	3.29	1.01	8.95	0.95	4.25	17,915	-2,139	4,574,527
109	5,869	3.29	1.01	3.82	0.58	3.88	7,552	1,683	2,832,695
Total	213,465			104.30			207,829	**RMSE**	**3,483.53**

Note: Total results are calculated for Santa Rosa county. The only exception is RMSE, based on all 3 counties.

Table A-V.140: Allometric Growth Model and RMSE for Sim 2025 Sprawl in Okaloosa

Tract ID	Log Pop = a + b * Log Area							Pop Est-PopAct	(PopEst-PopAct)^2
	Pop	a	b	Area	Log Area	Log_Pop	AntilogPop		
58	9,186	3.29	1.01	4.50	0.65	3.95	8,934	-252	63,399
59	2,179	3.29	1.01	1.31	0.12	3.41	2,562	383	146,485
60	15,189	3.29	1.01	5.67	0.75	4.05	11,282		
61	7,460	3.29	1.01	5.58	0.75	4.05	11,102	3,642	13,266,058
62	7,095	3.29	1.01	5.74	0.76	4.06	11,429	4,334	18,781,669
63	9,067	3.29	1.01	4.92	0.69	3.99	9,765	698	486,991
64	15,113	3.29	1.01	6.34	0.80	4.10	12,638	-2,475	6,125,965
65	7,773	3.29	1.01	4.00	0.60	3.90	7,926	153	23,335
66	7,203	3.29	1.01	2.79	0.45	3.74	5,493	-1,710	2,923,260
67	25,032	3.29	1.01	4.50	0.65	3.95	8,934	-16,098	259,138,88
68	4,140	3.29	1.01	2.88	0.46	3.75	5,671	1,531	2,344,641
69	9,226	3.29	1.01	3.59	0.55	3.85	7,097	-2,129	4,530,728
70	8,881	3.29	1.01	4.75	0.68	3.97	9,423		
71	8,569	3.29	1.01	2.10	0.32	3.61	4,121	-4,448	19,787,627
72	10,156	3.29	1.01	3.92	0.59	3.89	7,763	-2,393	5,725,244
73	2,033	3.29	1.01	1.34	0.13	3.42	2,626	593	351,435
74	2,898	3.29	1.01	1.73	0.24	3.53	3,380	482	232,528
75	9,598	3.29	1.01	1.81	0.26	3.55	3,557	-6,041	36,492,424
76	8,919	3.29	1.01	2.61	0.42	3.71	5,138	-3,781	14,299,609
77	8,278	3.29	1.01	4.27	0.63	3.93	8,462	184	33,974
78	8,066	3.29	1.01	3.20	0.51	3.80	6,319	-1,747	3,052,018
79	3,581	3.29	1.01	1.73	0.24	3.53	3,380	-201	40,316
80	2,771	3.29	1.01	1.56	0.19	3.48	3,043		
81	4,446	3.29	1.01	2.33	0.37	3.66	4,588	142	20,274
82	4,450	3.29	1.01	3.02	0.48	3.78	5,963	1,513	2,287,988
83	3,442	3.29	1.01	1.85	0.27	3.56	3,621	179	32,205
84	4,020	3.29	1.01	2.28	0.36	3.65	4,475	455	207,417
85	2,672	3.29	1.01	0.92	-0.04	3.25	1,779	-893	798,270
86	4,937	3.29	1.01	3.99	0.60	3.90	7,893	2,956	8,739,426
87	12,400	3.29	1.01	3.64	0.56	3.86	7,195	-5,205	27,093,738
88	2,234	3.29	1.01	2.28	0.36	3.65	4,492	2,258	5,096,599
89	18,519	3.29	1.01	10.04	1.00	4.30	20,118	1,599	2,555,580
90	5,102	3.29	1.01	4.14	0.62	3.91	8,202		
Total	254,635			115.30			228,371	**RMSE**	**3,483.53**

Note: Total results are calculated for Okaloosa county. The only exception is RMSE, based on all 3 counties.

TOTAL SIM25spraw	Pop 837,405			Area 417.47			AntilogPop 828,185	**RMSE**	**3,483.53**