BMI AND POPs:

ASSOCIATION BETWEEN PERSISTENT ORGANIC POLLUTANTS

AND INCREASING OBESITY PREVALENCE IN THE UNITED STATES

by

JENNIFER DENISE BELL

(Under the Direction of Xiaobai Angela Yao)

ABSTRACT

Geospatial analysis was used to analyze obesity prevalence in the United States in 2010 while assessing the effects of income, race, education, and exposure to pollutants to account for the processes behind the socio-spatially uneven increase in obesity across the nation. Ordinary least squares (OLS) and geographically weighted regression (GWR) models were used to determine the influence of these variables on the prevalence of obesity. Similar methodologies were implemented for the state of Louisiana to provide a comparison to nation-wide observations. This research compliments individual-level studies by assessing the spatial interaction between bodies and the environment. Acknowledging health disparities in the United States, results of this work offer an insight into the racial, economic, and educational inequalities that lead to disproportionate exposure to toxins and prevalence of obesity.

INDEX WORDS: Obesity, Toxic Release Inventory (TRI) Sites, Health Disparities, Pollutants, Geographically Weighted Regression (GWR)

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DEDICATION

You showed me a world

of neither stranger nor foe.

Flew my winged imagination

to the mysterious and inviting.

Never ceasing, always believing

in the magic that could be.

To you, I dedicate this piece.

Your music

          of loving words

                    rings in my heart

with every memory.

-Charles Silas Bell, November 23, 1936 – March 27, 2005

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During both undergrad and grad school at the University of Georgia, I was exposed to a new way of seeing the world. I began to question accepted norms and started to fully process our multi-faceted society and its complex web of stories. Although critical thinking is a lifelong process, I have many people to thank for encouraging this type of engagement and for strengthening my mental, emotional, and spiritual health during the past 24 years of my life.

The professors in the Geography Department have shown genuine kindness and interest in my endeavors throughout my college career. Through Dr. Tommy Jordan's passion for music and art, along with his GIS expertise, he has been my example of what a well-rounded geographer should look like. Dr. Marguerite Madden's Aerial Photographs course developed my love for GIS and Dr. Tommy Jordan's LiDAR class (it's "da bomb") brought me back to grad school. My committee members, Dr. Jerry Shannon and Dr. Lan Mu, could not have been more supportive and encouraging. Dr. Lan Mu's creative thinking and tech savy skills along with Dr. Jerry Shannon's emphasis on quality over quantity in all aspects of life have greatly influenced how I approach my research. Finally, my advisor, Dr. Yao, has supported me every semester of the six years that I attended UGA. No matter how busy she was, Dr. Yao always made time to talk with me about the excitement of a new project or internship, the frustrations with schoolwork, and the joys of family and friendships. She taught me the art of setting priorities- that the precious time we have in a day should be experienced with thoughtful consideration. Dr. Yao's example of a knowledgeable instructor, thoughtful advisor, caring mother, and true friend will continue to inspire me as I move on to the next part of my life.

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Lastly, the influence that my mother, Kannika Bell, and departed father, Charles Bell, have had, and will have, on my life cannot be explained with words. Their unconditional love for each other and for me will forever be my source of confidence, stability, and encouragement. Thank you for believing in me so that I could believe in myself. I admire you, remember you, and will always love you.

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CHAPTER I

INTRODUCTION

Obesity has significantly increased in the United States in just the past few decades; according to the CDC, from 1980 to 2008, obesity prevalence doubled for adults and tripled for children (CDC, 2011). Media outlets and current scientific research emphasize the effects of obesity citing issues such as heart disease, cancer, and type 2 diabetes (Heindel, 2003). Doing so places obesity, and the people categorized as such, as the underlying issue, as a disease, when in actuality obesity is a symptom of a much larger issue. Although these side effects are indeed very important and serious, I will argue that the focus should not only be on the *effects* of obesity, but more importantly on the *causes* of this significant increase in size.

Geographers, epidemiologists, endocrinologists, and public health experts increasingly debate the causes of obesity. Some of these researchers have done an excellent job of integrating various fields into their work, but for the most part, major disciplines tend to follow a certain trajectory. In general, geographers and urban planners attribute obesity to the built environment which includes, for example, the number of grocery stores and a city's walkability (Chalkias et al, 2013, Chi et al, 2013), epidemiologists and endocrinologists claim that genetics and environmental factors such as toxic exposure play a large role in obesity (Valvi et al, 2013, Hong et al, 2011, Dirinck et al, 2010, Pereira-Fernandes et al, 2014), and many public health researchers point to individual diet and exercise (Natale et al, 2013, Singh, 2013, Chen and Truong, 2011, Swinburn, 2004).

The belief that built environments cause obesity implies that the built environment acts on the people who live within it, that the location (and attributes of that location such as number of grocery stores, food deserts, gyms, and parks to name a few) of one's home will dictate the size of one's girth (Guthman, 2011). This theory transforms individuals into objects by removing their agency, or power to decide one's life outcome, and gives determining power to the environment. This approach problematically emphasizes the supply side of the issue (i.e., the idea that simply adding, for example, more grocery stores in an area will decrease obesity) and understates the production side of the problem (i.e., where and how food is produced and the implication of that system on health, for instance, exposure to toxins used in production). Not only is the production side deemphasized, but income inequality is also disregarded. Policy makers of the "built environment" school sufficiently recognize the ways in which income levels affect health outcomes, but implement health programs addressing food supply without focusing on the deeper issue of income inequality. Programs aimed at income equality could provide low income individuals with greater access to health care as well as foods with less toxic exposure. These programs could also strive to increase financial literacy, decrease tax burdens on low-income families, and provide equal access to affordable social services. The "built environment" school of thought attributes the supply issue to the causes of obesity, but in doing so, removes individual agency and can lead to health programs that merely skim the surface of the problem.

On the other hand, epidemiologists and endocrinologists find that genetics and toxin exposure contribute to increased obesity. Their environmental obesogen hypothesis, that prenatal or lifetime exposure to toxins accounts for a large part of the obesity epidemic, removes blame from the individual while also taking away the power of the environment to act on said individuals. This approach retells the narrative in a way that acknowledges the inseparability of individuals and the environment. However, most of the research done in these fields analyzes space at the individual body level through the study of serum samples or single patient characteristics (Dirinck et al, 2010, Hong et al, 2011, Pereira-Fernandes et al, 2014, Valvi et al, 2013). It is important to acknowledge the value of researching both bodies and the environment. This study looks at space in a different way, more specifically, through the interaction *between* bodies and the environment, and compliments the current literature with a new spatial approach. As toxic levels and obesity prevalence vary across space, it is important to analyze the effects of persistent organic pollutants (POPs) on obesity by integrating a geographic component. Although epidemiology and endocrinology fields remove blame from the individual, they often disregard class and race elements found in health disparities.

Lastly, the diet and exercise school of thought criticizes obese individuals for lack of both self-control and personal responsibility. This approach is problematic in that it doesn't recognize the underlying causes that may be out of one's control. Instead, the diet and exercise viewpoint further contributes to the social stigma of obesity. It problematizes obese, or nonnormative, bodies and disproportionately focuses on individual choices without considering the economic, political, and environmental aspects in which they are made (Guthman, 2011). An argument against the calories in/calories out hypothesis can be seen in the increasing rates of infant obesity. Babies who are exposed to toxins either *in utero*, through breast milk or formula, or within the surrounding environment may be at greater risk of obesity during infancy or later in life (Valvi et al, 2013). Diet and exercise may contribute to weight loss, but blaming an individual for his or her weight is problematic in that there are numerous underlying causes which are not being addressed.

Each of these fields play a pivotal role in obesity research, and it is important to recognize that an integration of the strengths from each field should be utilized to fully understand the various processes behind the complex issue of obesity. More specifically, the strengths this study draws on are the methods of spatial analysts, the theories of social geographers, and the findings of epidemiologists and endocrinologists. This study is necessary because a spatial component in analyzing POPs is essential to the discovery of health disparities amongst minorities and low-income individuals. A spatial element allows researchers to determine which groups of people are affected by toxic exposure as well as where toxic effects are most influential. This study contributes to the current literature by providing a fresh outlook on the causes of obesity and views this important issue as a symptom of the larger problem of income inequality. As this method, to the best of my knowledge, has not been taken before, it will provide a starting point for future research into the effects of toxic release on obesity prevalence in the United States.

Objectives

The purpose of this research is to produce new findings that contribute to the current discussion of obesity and its related causes. I combined the methods of spatial analysts, the theories of social geographers, and the findings of epidemiologists and endocrinologists to further contribute to the overall picture of obesity. I utilized ordinary least squares (OLS) and geographically weighted regression (GWR) models to determine spatial relationships between obesity and the explanatory variables described below.

The independent variables used to explain the prevalence of obesity were: 1) Toxic Release Inventory (TRI) sites; 2) black or African American, Asian, and Hispanic race (Dunn, Sharkey, and Horel, 2012, Wen and Kowaleski-Jones, 2012); 3) percent under the poverty line in the past 12 months (Bennett, Probst, and Pumkam, 2011, Shih et al, 2012); and 4) education level (Wen and Kowaleski-Jones, 2012).

Despite the vast and growing amount of research dedicated to understanding obesity, uncertainty and disagreement of the true causes still exist. This study aimed to discover the possible relationship between toxic exposure and obesity prevalence while incorporating variables of inequality with the following objectives:

1) Identify a set of variables that may significantly relate to the distribution of obesity prevalence using Body Mass Index (BMI) as a proxy;
2) Test and quantify the spatial relationship between derived variables and obesity distribution utilizing ordinary least squares (OLS) and geographically weighted regression (GWR) models, and evaluate improvement upon the OLS model;
3) Compliment current studies analyzing the effects of persistent organic pollutants (POPs) on obesity at the individual level with a study that approaches space in a different way, more specifically, by assessing the interaction between bodies and the environment;
4) Produce new findings to contribute to the current discussion of obesity and its related causes.

CHAPTER II

LITERATURE REVIEW

Numerous epidemiology and endocrinology studies tie increasing obesity prevalence to the hormonal effects of environmental toxins. POPs such as polychlorinated biphenyl (PCB) cogeners 138, 153, 170, and 180, polybrominated diphenyl ether (PBDE) cogener BDE 153, dichlorodiphenyldichloroethylene (DDE), hexachlorobenzene (HCB), and β-hexachlorocyclohexane (βHCH) are implemented in varying industrial and agricultural applications such as dielectric and coolant fluids, flame retardants, fungicides, and pesticides. These toxins, also known as endocrine disrupting chemicals (EDCs), mimic hormones, prevent other hormones from functioning, and even cause an increase in fatty tissues in the human body, regardless of diet and exercise. EDCs can alter gene expressions which are imprinted and transferred into the next generation. Although POPs such as DDT and PCB were banned in the United States since 1970s, they remain in the environment and in human tissue due to its slow degradation and stable bioaccumulation. POPs have a half-life of a few years to even decades and metabolize in humans at an extremely slow rate (Hong et al, 2011).

According to Heindel (2003), obesity cannot be explained by just poor diet and exercise. A genetic predisposition component must be included when studying obesity. However, since it is highly unlikely that human genetics have changed over the past few decades along with increasing obesity, it is very possible that environmental changes may be the cause for at least a portion of the obesity epidemic through POP's ability to alter gene expression in individuals.

Gene alteration, and its effects, may also remain throughout following generations (Heindel, 2003).

Leptin, a hormone that regulates hunger, metabolism, and energy expenditure, tends to increase in obese bodies. Increased leptin leads to leptin resistance causing the brain to ignore regulatory messages that the body is full. One study that analyzes POPs and leptin in Belgian patients' serum and fat tissue found a positive correlation between leptin gene expression and POPs such as cogeners CB 180 and BDE 153 (Pereira-Fernandes et al, 2014). This means that as POPs in the body increases, the chances of leptin overproduction increases as well which may lead to the leptin resistance described above. Another similar study established a positive relationship between βHCH serum levels and BMI (Dirinck et al, 2011). As toxins increase in the body, an individual's weight may also increase. A study analyzing prenatal exposure to POPs found a positive correlation between DDE and HCB in maternal serum and infant rapid growth as well as overweight (Valvi et al, 2013). Rapid weight gain in infants has been shown to lead to greater risk of obesity in both child- and adulthood (Valvi et al, 2013). This helps to confirm the environment obesogen hypothesis which states that exposure to environmental chemicals, especially *in utero*, increases an individual's susceptibility to obesity.

Adipocytes, an endocrine organ that regulates the body's physiology, are smaller in lean individuals and enlarged in obese individuals (Greenberg and Obin, 2006). Large adipocytes lead to increased inflammation and can cause insulin resistance (Greenberg and Obin, 2006). POPs target the adipose tissue and cause inflammation, the same inflammation found in obese individuals. One study that analyzed the effects of POPs in mice adipose tissue observed increased inflammation in the adipose tissue after administering pollutant doses (Kim et al, 2012). Their study reveals that toxins may play a large role in obesity through POP's ability to trigger inflammation responses in adipose tissue.

Described above are various studies that analyze the effects of POPs on obesity. In order to determine why varying spatial patterns and clusters of obesity exist across the United States, it is crucial to analyze the interaction between bodies and the environment. It is important to analyze where POPs are most found in order to assess its effects on obesity prevalence within various groups of people. This study addresses POPs through the use of Toxic Release Inventory sites at the county level for the United States study and at the Census tract level for the Louisiana study. Proximity, or Euclidean distance, is an appropriate measure because it reflects decreasing exposure with increased distance. Future studies would benefit from an analysis of exposure to toxins at the scale of individual food consumption, but this data is not as readily available at the national level. The distance used in this study addresses exposure to toxins through air. Another issue with epidemiology and endocrinology research is that it rarely acknowledges income inequality, a major factor in the obesity epidemic. Sites containing hazardous chemicals such as Toxic Release Inventory facilities, Superfund sites, sewer and water treatment plants, and incinerators have been shown to disproportionately affect poor populations and people of color (Wilson, 2012). Exposure to these sites leads to adverse health effect, stressed neighborhoods, and lower quality of life. Structural inequalities prevent many low-income people from accessing health care and also expose them to proportionately more environmental toxins. The poor live in areas with higher exposure to toxic pollutants due in large part to corporations' strategic avoidance of pollution laws. In his book *Dumping in Dixie: Race, Class, and Environmental Equality*, Bullard argues that minorities and the poor are disproportionately subject to environmental racism. Large corporations choose to place power plants, toxic waste dump sites, and factories in minority and poor communities knowing that they could potentially avoid pollution laws due to the plight of the neighborhood (Bullard, 2008). Obesity is a symptom of complex, underlying issues such as race and class inequality; as Roberts states in *Killing the Black Body: Race, Reproduction, and the Meaning of Liberty*, "…health cannot be allowed to trump other concerns, precisely because it has never been wholly innocent of class, race, and other social projects" (Roberts, 1997). For these reasons, this study did not solely analyze obesity prevalence across the U.S., but also included important variables such as race, income, and education. The purpose of this research was to challenge past and current views of the causes of obesity. It further compliments the environmental obesogen hypothesis by implementing spatial analysis that included race and class inequalities.

CHAPTER III

STUDY AREA

United States Study Area

In order to visualize the bigger picture of increasing obesity prevalence, this study included all of the contiguous United States (Figure 3.1). The geographical unit of analysis for this study was the county because the Behavioral Risk Factor Surveillance System (BRFSS) only provides county level BMI data. As this study is an initial attempt at spatial analysis of POPs and obesity, this scale suggested broad relationships between these variables. Without individual level data, the county scale provided the best available alternative. This study analyzed a total of 3,109 counties.

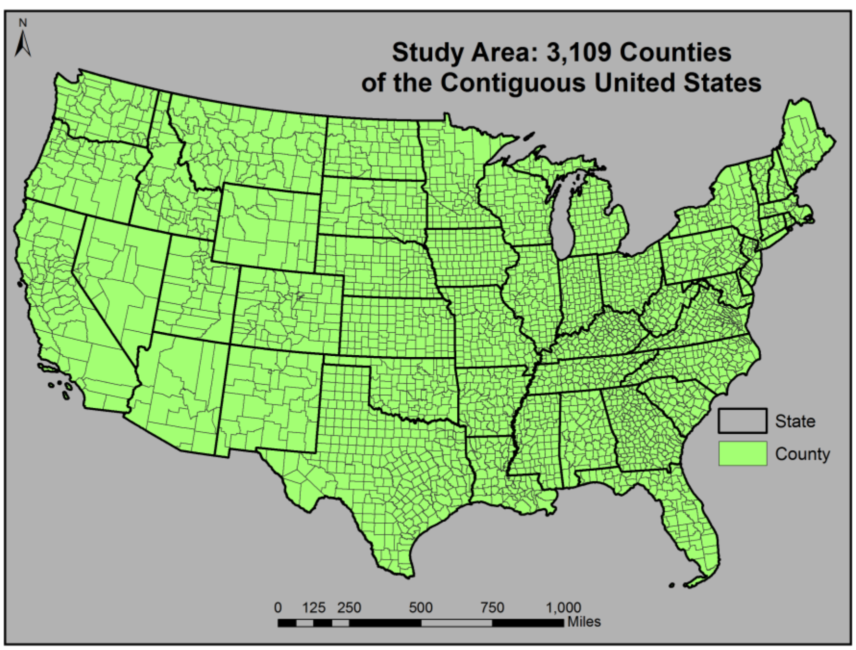

Figure 3.1: Study area including county level data for the contiguous United States.

Louisiana Study Area

To get a better understanding of state-wide patterns, a smaller study area of Louisiana was analyzed (Figure 3.2). To account for population density, this portion of the study utilizes data at the Census tract and block level. Louisiana was chosen for its high rates of obesity, and spatial distribution of Toxic Release Inventory sites. Of the contiguous states in the U.S., Louisiana ranked second highest in the average age-adjusted obesity rates in 2010 with about 35% of the population considered obese. The number one obese state was Mississippi with about 37% of its population estimated to be obese. Every state had at least 100 TRI sites and Louisiana, with its 1,926 sites, ranked 16th in number of TRI sites per state. There is also an abundance of Environmental Justice research relating to TRI sites in Louisiana (Wilson, 2012, Perlin, Sexton, and Wong, 1999, Mielke et al, 2002, Perlin, Wong, and Sexton, 2001). Additionally, Louisiana is a state that has already demonstrated an existing health issue; the area between Baton Rouge and New Orleans, known as "Cancer Alley", contains clusters of cancer patients that live near industrial plants. For the reasons listed above, the state of Louisiana was a good candidate for a smaller study area of research.

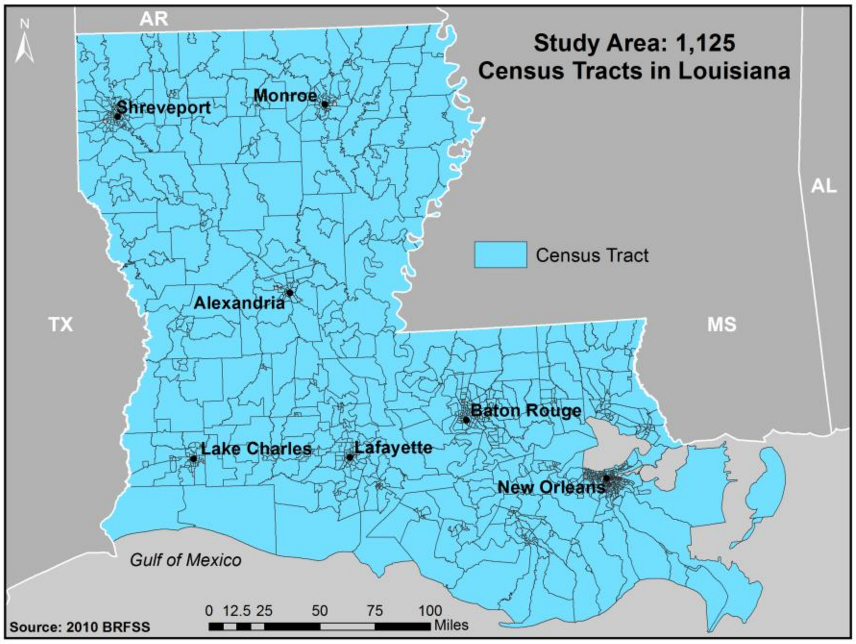

Figure 3.2: Study area including Census tract data for the state of Louisiana.

CHAPTER IV

METHODS

United States Datasets

The obesity data were obtained from the 2010 Center for Disease Control's (CDC's) Behavioral Risk Factor Surveillance System (BRFSS) (Figure 4.1). The BRFSS is a telephone-based survey collected monthly in every state. The Body Mass Index (BMI) (weight [kg] / height $[m]^2$) is calculated from self-reported height and weight. According to the Centers for Disease Control and Prevention, a person is considered obese if his or her BMI is greater than or equal to 30. The obesity rates are calculated to adjust for age; this is a mock estimate to allow for the comparison between populations of differing age distributions. This rate represents the rate of obese individuals in a certain area if the population in that location had the same age distribution of a "standard" population. A "standard" population is created from an area that has the exact age breakdown and is used as a comparison population when calculating age-adjusted rates.

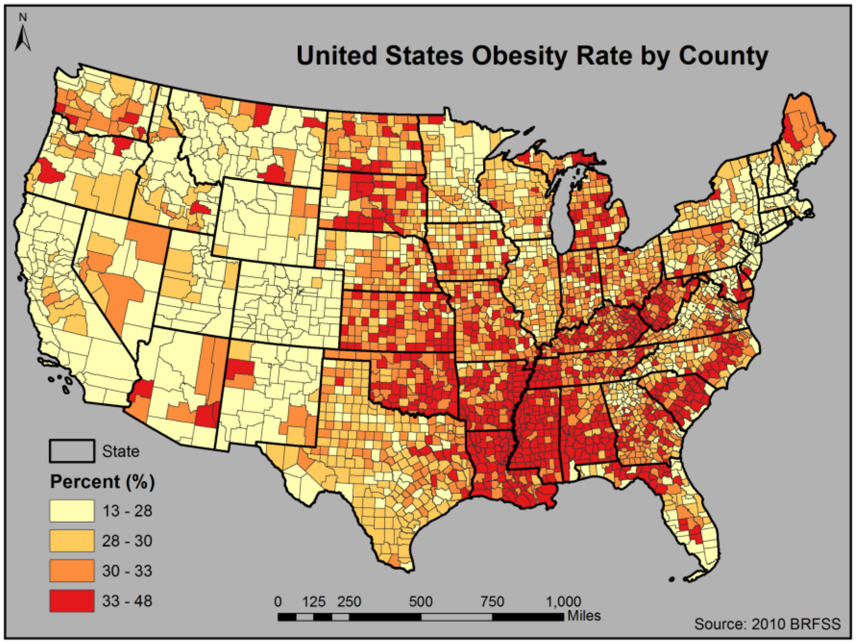

Figure 4.1: Percent obese (according to BMI) per county in the U.S. in 2010.

The 1990 Toxic Release Inventory (TRI) sites were downloaded from the U.S. National Library of Medicine and the U.S. Environmental Protection Agency (EPA) Toxic Release Inventory (TRI) (Figure 4.2). The 1990 dataset was chosen to account for the lag time in exposure and effect. The reasoning behind this choice is derived from epidemiology studies that have found that developmental exposure to toxins is related to obesity later in life (Gladen et al, 2000, Newbold, 2010). In order to achieve more conservative results, the 1990 dataset was utilized for lag time, but any year can be representative. This is justified by a comparison between 1990, 2000, and 2010 EPA TRI datasets which contain very similar TRI site counts as well as onsite release averages (Figure 4.2). The TRI site counts for the 1990, 2000, and 2010 TRI datasets are 88,550, 93,136, and 80,110, respectively. The onsite release (in pounds per square mile) for the 1990, 2000, and 2010 TRI datasets are 42,388, 60,320, and 31,750 lbs/sq mi, respectively. This study analyzes the onsite release in pounds per square mile of TRI chemicals in each county (Figure 4.3).

The Toxic Release Inventory (TRI) is a database managed by the EPA that includes sites that process more than 25,000 pounds or use more than 10,000 pounds of any one TRI chemical; it keeps track of over 650 types of toxic chemicals that may cause harm to human health and the environment. Each year, United States facilities producing above the established levels of toxic chemicals are mandated by the EPA to report the quantity of chemicals released into the air, water, and/or land disposal. POP exposure is difficult to measure because harmful chemicals can spread through the air, water, and food, but this study addressed the spread of POPs through close contact and through the air by analyzing areas with numerous Toxic Release Inventory sites which all contain traces of harmful chemicals. Since water is subjected to a more stringent cleaning process through water treatment facilities, transmission through air is a more likely culprit of toxin exposure. Persistent organic pollutants are hazardous organic chemicals that are resistant to biodegradation. Because of this, POPs remain in the environment for extended periods of time and continue to harm humans and animals who come into contact with them. Examples of POPs include insecticides, such as Aldrin, DDT, and chlordane, fungicide, industrial chemicals, and wood preservatives. Although numerous studies have attempted to understand the emission process, patterns, and effects of sites such as Toxic Release Inventory facilities, there is still some uncertainty as to how differing atmospheric conditions such as temperature affect the severity of toxic exposure. Quantitative knowledge of POP emission patterns is a necessary prerequisite for studying the distribution and effects of these emissions on the surrounding population (Breivik et al, 2004). Due to the current uncertainty of emission patterns, this study undertakes a preliminary analysis of the spatial effects of Toxic Release Inventory sites without said prerequisite knowledge in an attempt to visualize broader spatial patterns (Breivik et al, 2004). It is important to note that although emission patterns are not fully understood, numerous studies have utilized TRI sites as a proxy for chemical exposure (Fortunato et al, 2011, Palmer et al, 2004, Conley, 2011, Wilson et al, 2012).

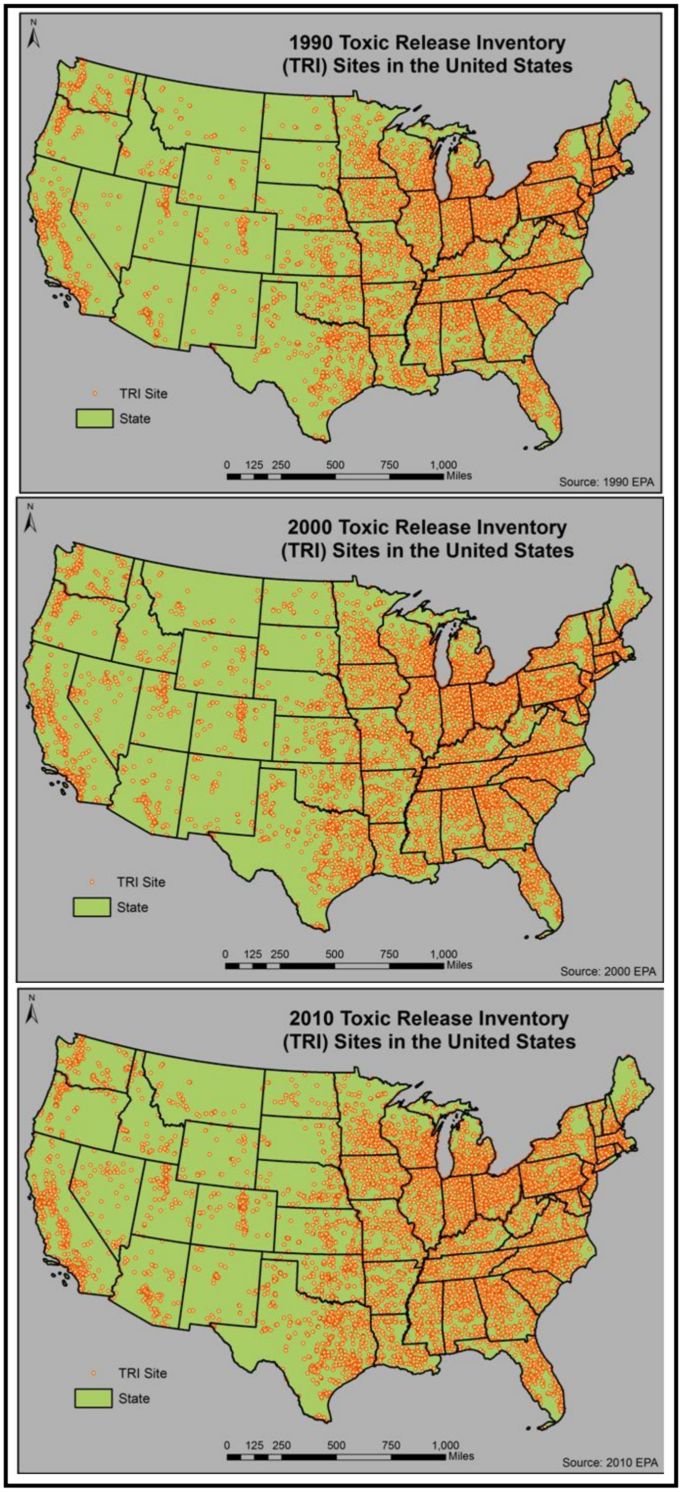

Figure 4.2: U.S. TRI site spatial distribution comparison for 1990, 2000, and 2010 datasets.

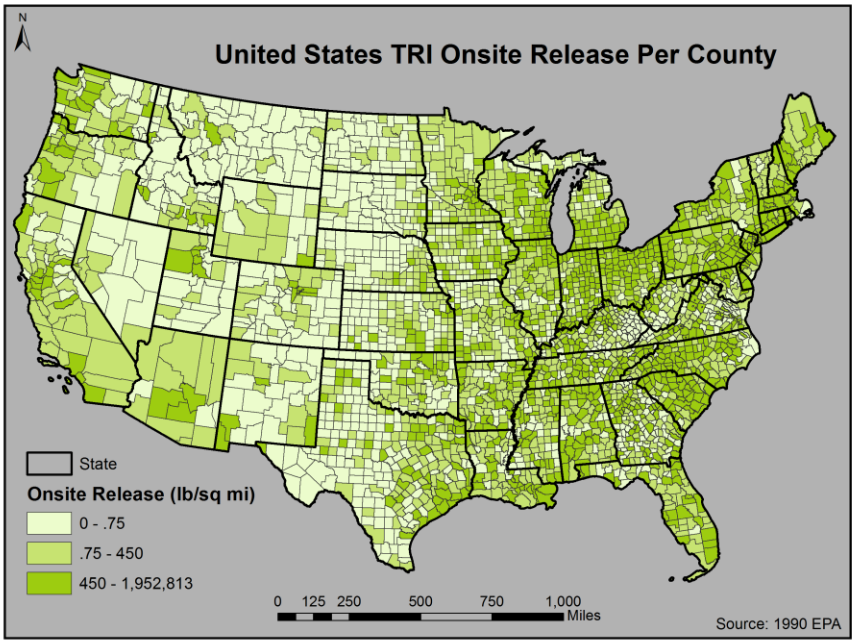

Figure 4.3: TRI onsite release per county in the U.S. in 1990.

The socioeconomic data were from the U.S. Census Bureau's Tiger Geodatabase which joins the geography from the TIGER/Line Shapefiles to the 2007-2011 American Community Survey 5-year estimates Data Profiles. The 2007-2011 data were used to coincide with the 2010 obesity data from BRFSS; using this dataset as opposed to the 2006-2010 dataset accounts for the 2008 recession and includes 2010 as more of a median. The county-level socioeconomic data contained the percentage of individuals whose income in the past 12 months was below the poverty level for all counties between 2007 and 2011 (Figure 4.4), the percentage of Black or African Americans (Figure 4.5), the percentage of Asians (Figure 4.6), the percentage of Hispanic or Latino of any race (Figure 4.7), and the low education rate, more specifically the rate of individuals who went through high school, but did not receive a diploma (Figure 4.8). The classification method for the socioeconomic data comprised of classes that included the spatial distribution of each variable.

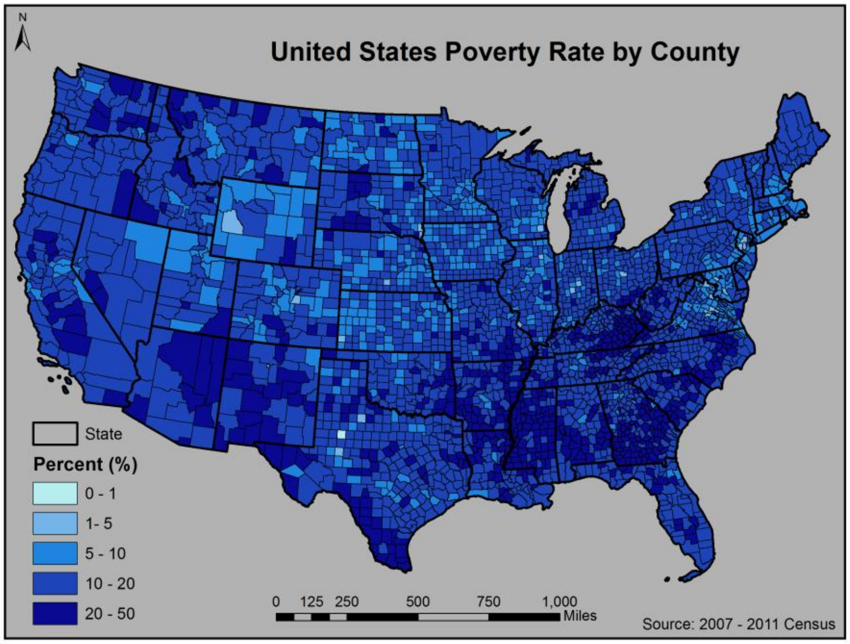

Figure 4.4: Percent of individuals whose income in the past 12 months is below the poverty level for all counties in the U.S. from 2007 - 2011.

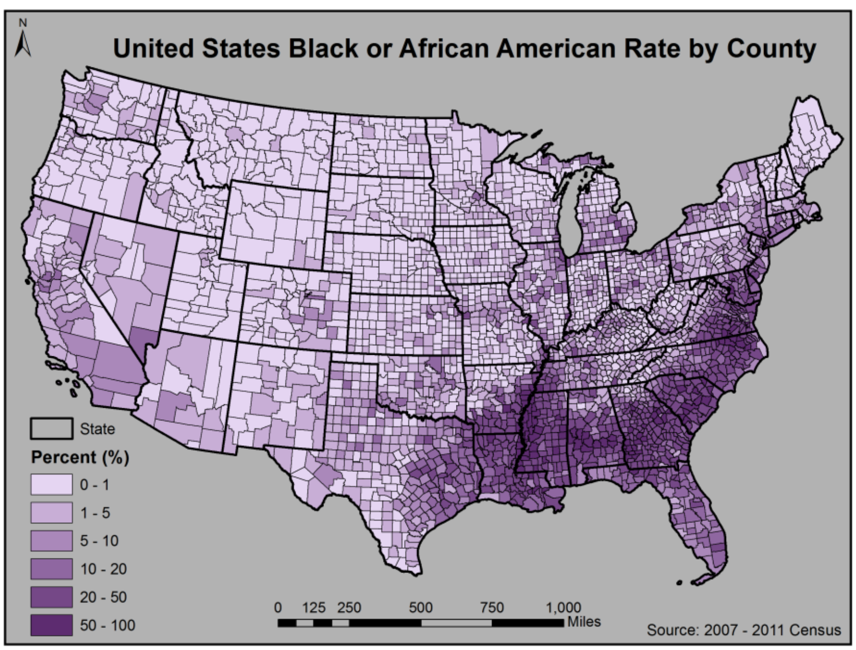

Figure 4.5: Percent black or African American per county in the U.S. from 2007-2011.

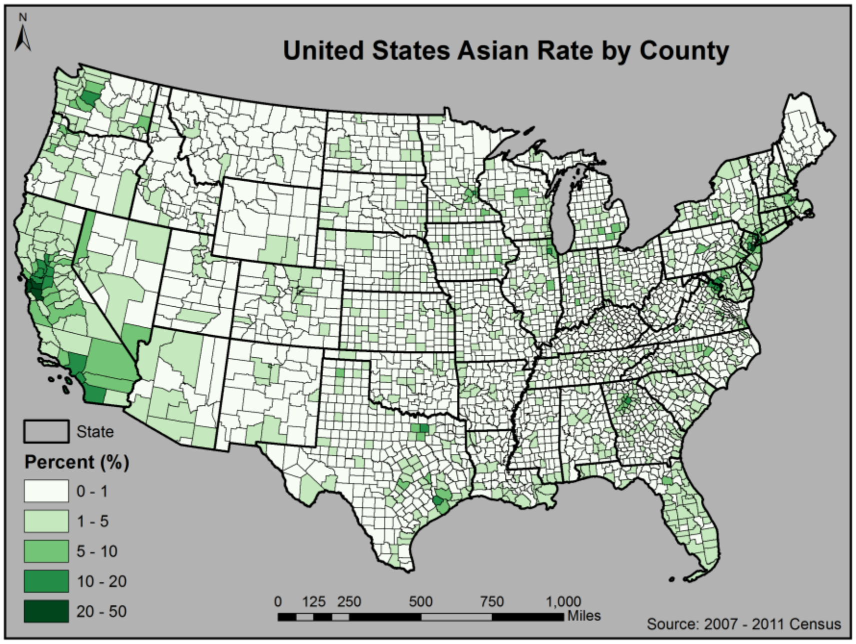

Figure 4.6: Percent Asian per county in the U.S. from 2007 - 2011.

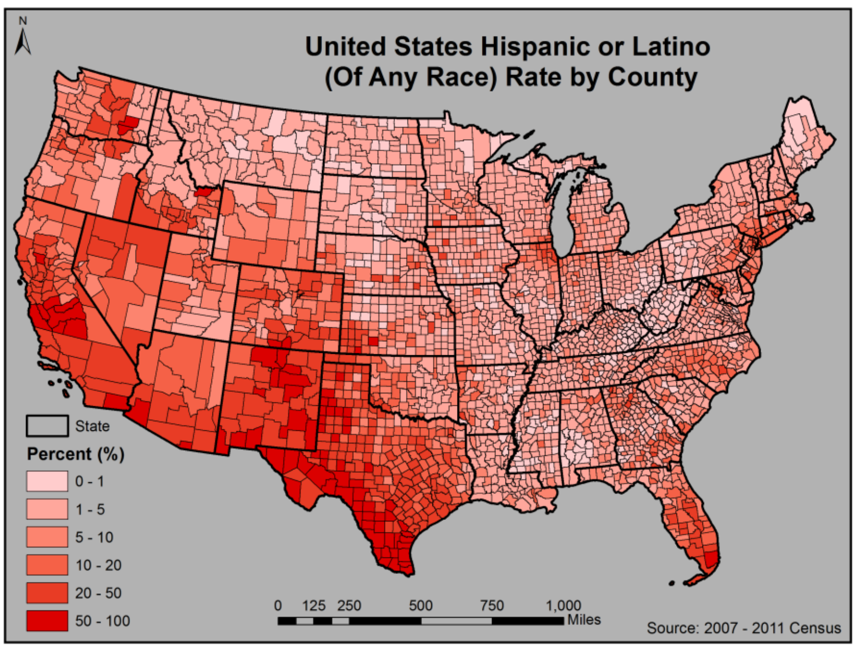

Figure 4.7: Percent Hispanic or Latino of all races per county in the U.S. from 2007 - 2011.

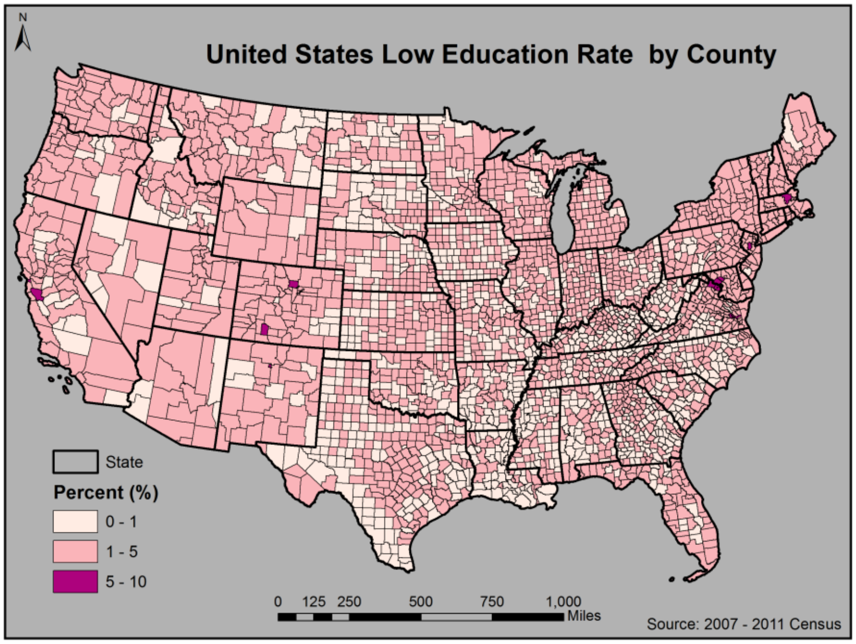

Figure 4.8: Percentage of people with some high school education and no degree per county in the U.S. from 2007 - 2011.

Since this study critiques the over-emphasis of the built environment as a cause of obesity, the food desert rate was tested to control for the built environment; however, OLS results revealed that this variable was not significant and was therefore dropped from the final model. The 2010 USDA food desert data that this study used considers someone to be low access if they are 1 or more miles away from a supermarket in the city and 10 or more miles away from a supermarket in a rural area. This rate was calculated by dividing the population living in a food desert by the county's total population. For visual purposes, the map in Figure 4.9 shows the number of low access tracts per county. The classification scheme used for this map was the Natural Breaks (Jenks) method.

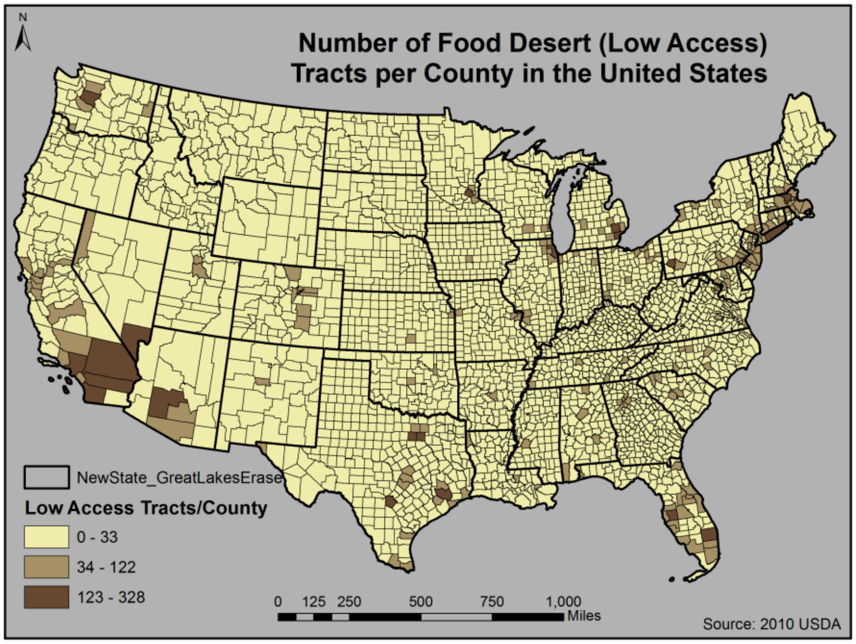

Figure 4.9: Food desert (low access) tracts per county in the United States.

A stepwise regression technique was applied to choose the best OLS model. One variable that was tested that was not included in the United States study was population density because it was not a significant input. Another variable not included in the final OLS model was the food desert variable calculated as the ratio of the population in a county living in food deserts to the total population of the county.

Louisiana Datasets

The Louisiana study's obesity data, EPA TRI site data, and socioeconomic data were obtained from the same sources as the United States study's data sets. The only difference was that the level of study was the Census tract. To do this, the BMI county data from BRFSS was copied into the Census tracts found within each Louisiana county (Figure 4.10). The socioeconomic data, which includes black or African American (Figure 4.11), Asian (Figure 4.12), Hispanic (Figure 4.13), percent under the poverty line (Figure 4.14), and low education levels (Figure 4.15), were obtained from the U.S. Census at the Census tract level. Since the

Geographically Weighted Regression tool in ArcGIS 10.2 does not do well with binary data, the food desert data from the USDA, a binary of whether or not populations in a Census tract are considered to have low access to food, could not be used in the GWR portion of the Louisiana study. However, the OLS portion of the Louisiana study included the food desert variable as a dummy variable (a value of 0 indicates that the tract is not considered a food desert and a value of 1 represents Census tracts that are considered food deserts by the USDA) (Figure 4.16).

The benefit of analyzing Louisiana at the Census tract level was that it considered population density when analyzing TRI sites. In the United States study, the onsite release per square mile was calculated; however, there was not a significant relationship between obesity rates and this variable because population density was not considered. Since including population data at the Census tract level for the contiguous United States would have been computationally intensive, I decided to study the patterns in one state. This study, like any geographical analysis that uses aggregation or grouping, is subject to the Modifiable Areal Unit Problem (MAUP) because only one scale of aggregation is considered. To address MAUP, which occurs in the United States study when aggregating point data (onsite release) to districts (county area in square miles), the Louisiana study utilizes the distance from each Census tract's population weighted center (calculated using block-level population data from the Census) to the nearest TRI site (Figure 4.17). The spatial distribution of TRI sites in Louisiana is seen in Figure 4.18. It was hypothesized that population weighted centers that were closer to TRI sites would have greater obesity rates. This method of distance based analysis was used in a study of Toxic Release Inventory sites and its relationship to poor and minority populations in Charleston, South Carolina (Wilson et al, 2012). However, the limitations of the Wilson et al study include the use of Census tract centroids as opposed to population weighted centers, their assumption that TRI sites only exposed people that lived within the same Census tract as the TRI site(s), and their use of logistic regression which does not account for Spatial Autocorrelation.

One other method of incorporating TRI sites, as opposed to the previously mentioned distance from population weighted center to nearest TRI site, is to analyze the average distance to the nearest TRI site per Census tract. This was completed by running the Euclidean Distance tool to create a raster in which the value of each pixel represented the distance from that pixel to the nearest TRI site. Then, using the Zonal Statistics as a Table tool, the average pixel distance per Census tract was calculated. This variable was tested in the OLS model in place of the previously mentioned population weighted center distance variable. Using the average distance to the nearest TRI site per Census tract slightly lowers the adjusted R^2 (by .01) and causes the Asian rate and food desert rate variables to be insignificant. For these reasons, the distance from the Census tract's population weighted center to the nearest TRI site was incorporated into the model as opposed to the average distance to the nearest TRI site variable. Population density was also included as a variable in the stepwise regression technique, but was removed from the final OLS model because it was weaker than the OLS model ultimately chosen for the study.

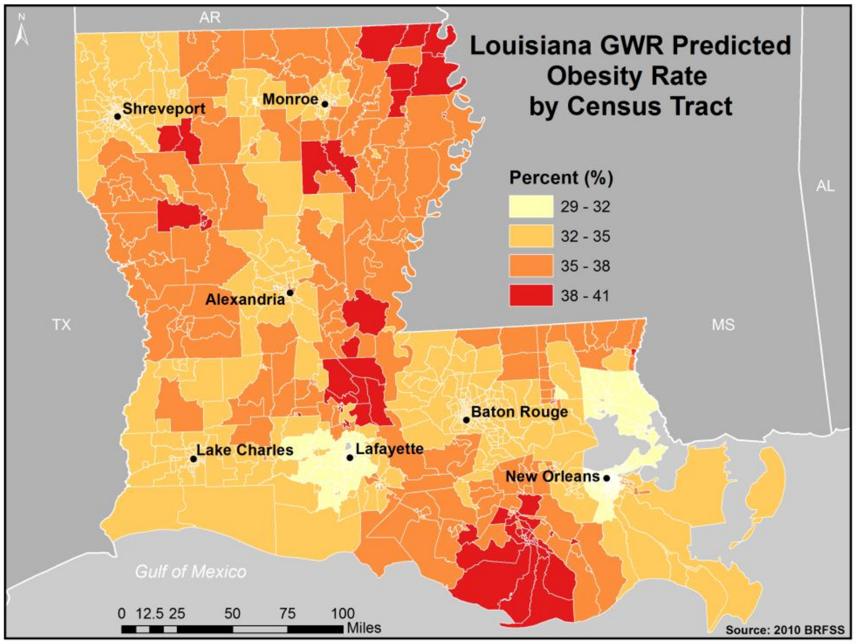

Figure 4.10: Percent obese (according to BMI) per Census tract in Louisiana in 2010.

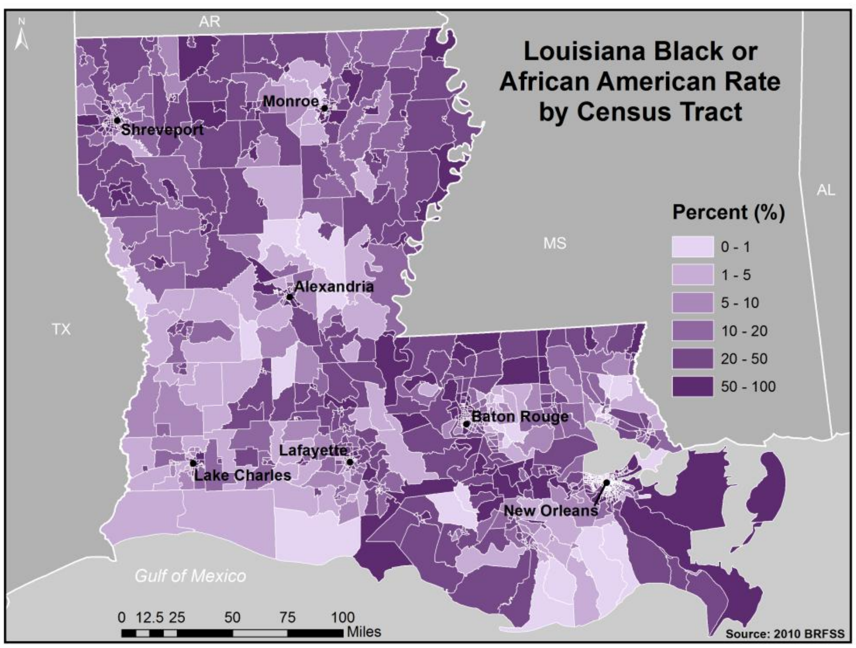

Figure 4.11: Percent black or African American per Census tract in Louisiana from 2007-2011.

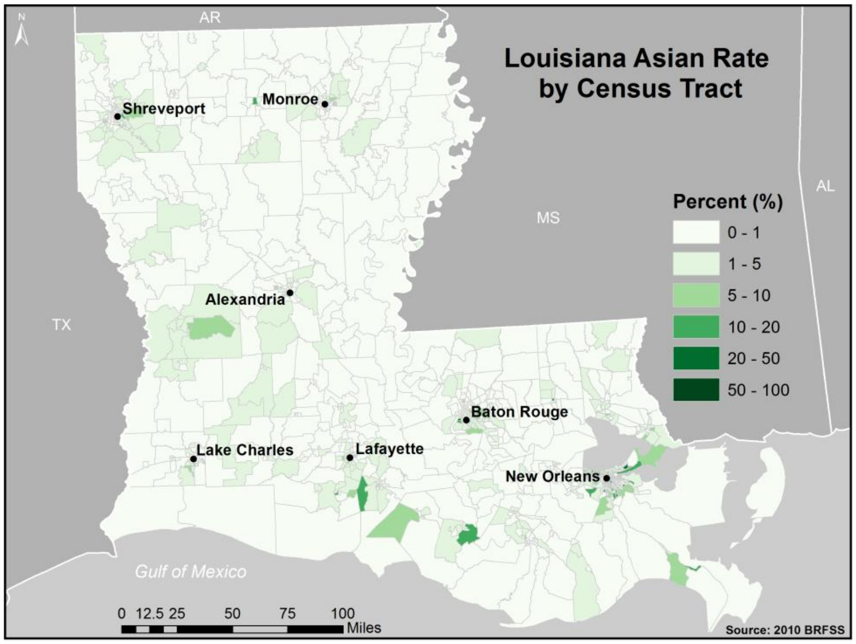

Figure 4.12: Percent Asian per Census tract in Louisiana from 2007 - 2011.

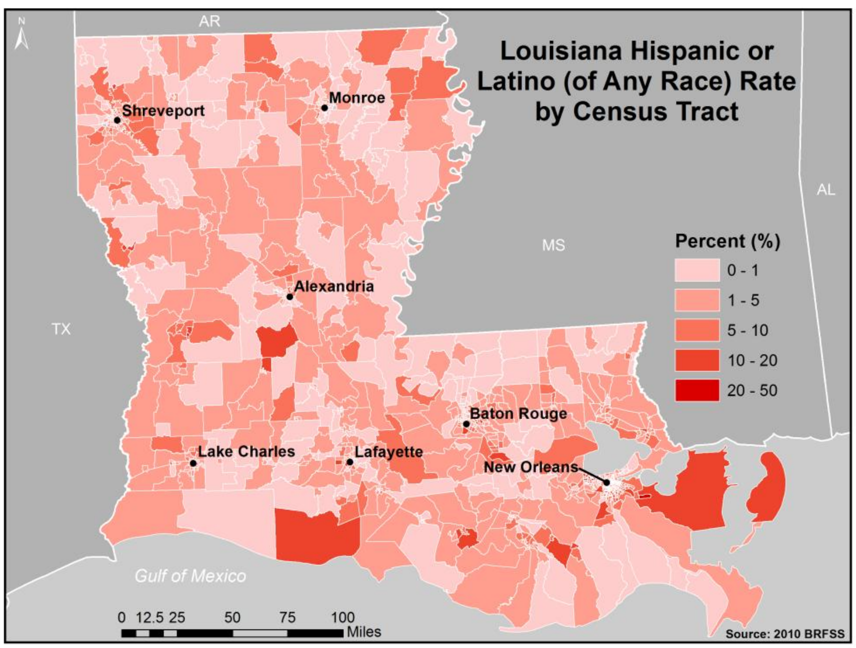

Figure 4.13: Percent Hispanic or Latino of all races per Census tract in Louisiana from 2007 - 2011.

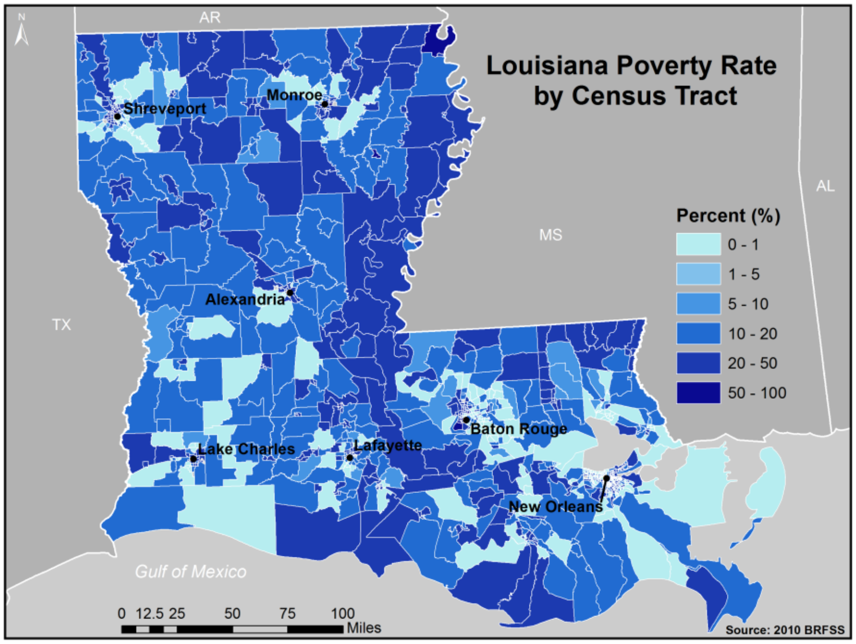

Figure 4.14: Percent of people whose income in the past 12 months is below the poverty level for all Census tracts in Louisiana from 2007 - 2011.

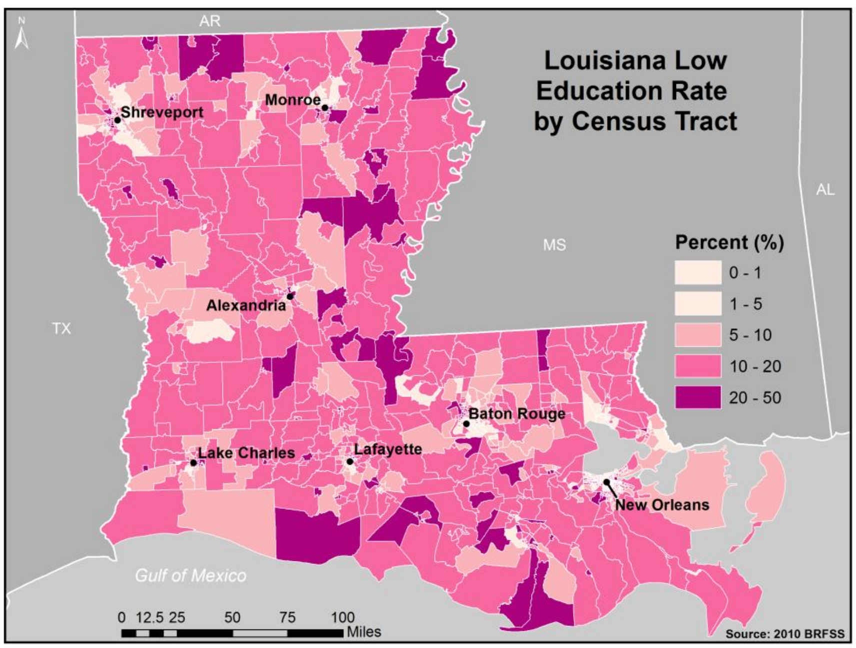

Figure 4.15: Percent people with some high school education and no degree per Census tract in Louisiana from 2007 - 2011.

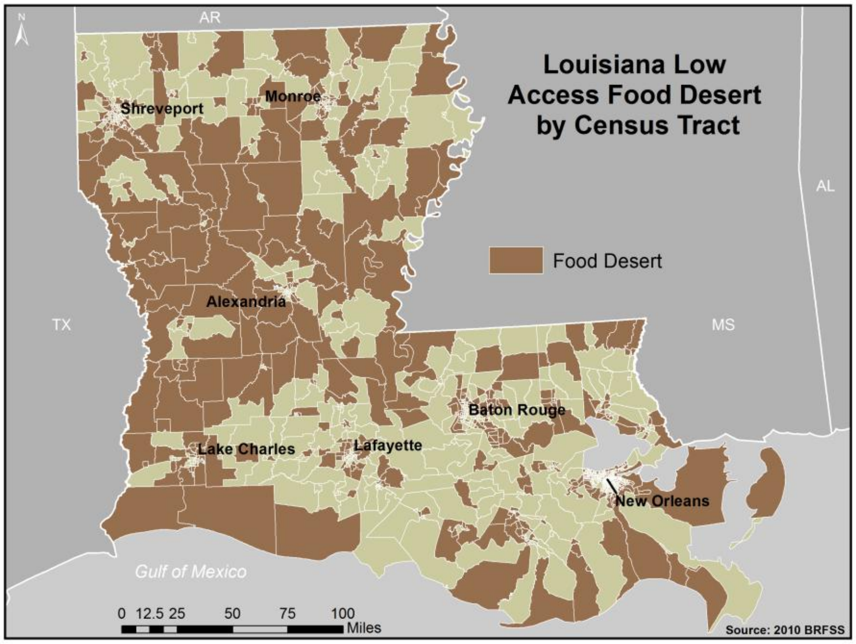

Figure 4.16: 2010 food deserts (low access) by Census tract in Louisiana.

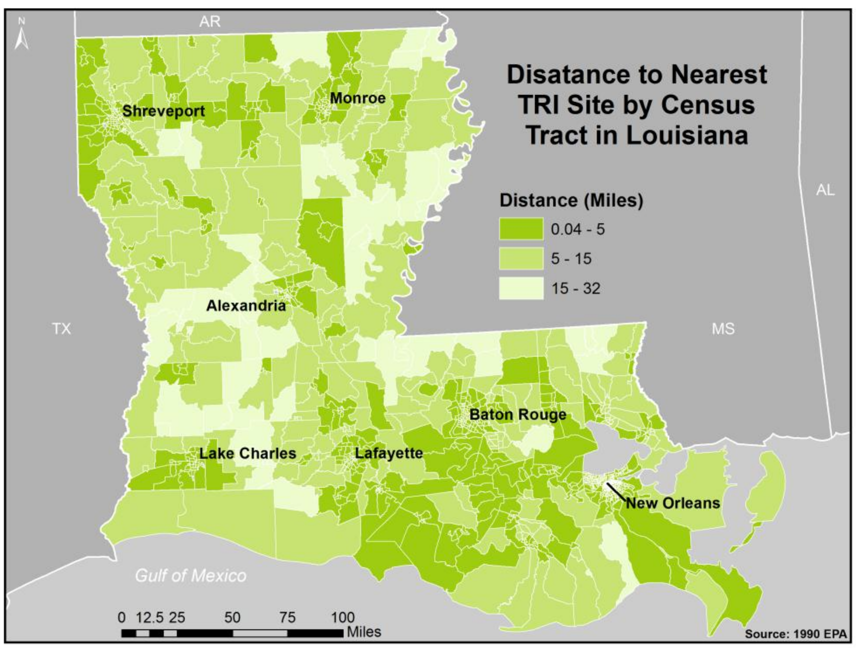

Figure 4.17: Distance from each Census tract’s population mean center to the nearest TRI site in Louisiana in 1990.

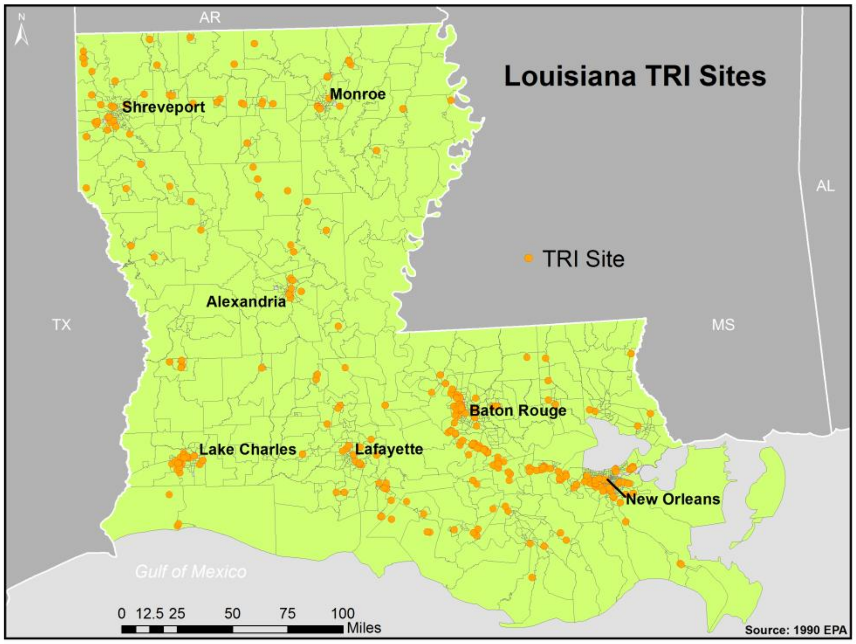

Figure 4.18: 1990 TRI site spatial distribution in Louisiana.

<u>Methods Background</u>

Global ordinary least squares regression, a regression method that assumes that all relationships are unchanging and constant throughout the study, is a widely-used method in epidemiology and endocrinology studies (Chalkias et al, 2013). Although a very popular method, ordinary least squares regression does not account for the spatial heterogeneity of variable relationships as well as spatial autocorrelation (the correlation of a variable with itself throughout space). Moran's I is used to determine whether or not spatial autocorrelation exists; if so, the geographically weighted regression model should be applied. Geographically weighted regression was utilized over other options because it takes into account the local relationships between variables and is also the most commonly used method in spatial obesity research.

In built environment studies that incorporate GIS, researchers commonly utilize the local geographically weighted regression to study the relationship between independent variables and explanatory variables. Since this relationship most likely changes over space, it is important to implement this modeling method to examine the influence and explanatory power of independent variables at every location (Chi et al, 2013). The geographically weighted regression model places different weights on observations that are closer than others using a spatial kernel. The two types of spatial kernels are fixed kernels and adaptive kernels. The fixed kernel maintains a constant-sized kernel across the study area, whereas the adaptive kernel takes into account the spatial distributions of the observations in determining kernel size. Chi et al (2013) analyzes the strength of geographically weighted regression to study obesity in U.S. counties and finds that the association between obesity and explanatory variables such as poverty and urban environments significantly varied across space. They found that urban environments, poverty rate, and higher ratios of convenience-to-grocery stores were positively association with obesity risk and locations with better physical environments were negatively associated with obesity risk (Chi et al, 2013). Their study applied the adaptive kernel method to account for the varying county sizes throughout the United States (Chi et al, 2013).

The Akaike Information Criterion, R^2, and adjusted R^2 determine the optimal regression method. This value measures the “relative distance” between the fitted model and the unknown “true” model. It is better to have a model with a smaller AIC value, but if the difference is less than about 3 or 4, then the two models are seen as equal in explanatory power. The R^2 and adjusted R^2 are also methods of determining which model maintains a better fit. The R^2 value indicates the model’s predictive performance; however, since adding more independent variables will always increase R^2, it is helpful to analyze the adjusted R^2 which takes the number of explanatory variables into account. For example, an adjusted R^2 of 0.40 indicates that the model accounts for forty percent of the variation in the dependent variable; this can mean that some variables are not included in the model that should be and that the model does not account for about sixty percent of the variation in the dependent variable. A study that looks at the relationship between place-level disadvantages and obesity in Taiwan compared the ordinary least squares results with those of the geographically weighted regression and found higher R^2 and lower Akaike Information Criterion values for the geographically weighted regression method; this proves that the relationship between disadvantages and obesity varied across geographical location (Chen and Truong, 2012). What separates my research from the two previously mentioned studies is the inclusion of the toxic release inventory variable. There is a need to further explore the heterogeneity of environmental causes of obesity across space which this study accomplished.

Geospatial Analysis

The first step in the research was to download the data from the multiple sources described earlier in the Datasets section (Figure 4.19). The dependent variable was the 2010 obesity rate by county and the independent variables were black or African American rate, Asian rate, Hispanic or Latino (of any race) rate, percent of individuals below the poverty line in the past 12 months, percent of adults with some high school education and no degree, TRI onsite release in pounds per square mile (for the United States study), USDA food deserts (for the Louisiana study), and distance from the population weighted mean center to the nearest TRI site (for the Louisiana study) (Figure 4.20).

After downloading the data, an intensive cleaning was applied which included deleting fields found outside of the study area and renaming boundary identifiers to match across all the datasets, Excel tables, and shapefiles. Then, using the Join function in ArcMap, the obesity file was merged with the TIGER county shapefile. Fields that were brought in as strings were converted to double by utilizing the field calculator and inputting CDbl([Name of String Field]).

The EPA data of the 1990 TRI sites were downloaded as an Excel file. A point shapefile of the TRI sites was created by running the Display XY Data tool in ArcMap. The desired fields from the socioeconomic Census data were chosen and joined. After all the necessary fields were joined to one shapefile, the data frame projection was changed to Albers Equal Area Conic to preserve the area of the counties.

For the Louisiana study, the methodology is the same except for the TRI data preparation methods. The population weighted center of each Census Tract was calculated with the Mean Center tool specifying the Census block population in the "weight" field and the Census Tract ID in the "case" field. Then, the distance (in miles) from the Louisiana Census tract population weighted center to the nearest TRI site was calculated using the Near tool in ArcMap. It would be beneficial to include weight by level of onsite release (in pounds per square mile), but the data is skewed with an over-abundance of zeroes in the Louisiana TRI site data. This is most likely due to three errors in the reporting system: 1) If the entry in a TRI site's reporting form is left blank, a zero is inputted, 2) all "N/A" (or not applicable) entries are replaced with zeroes, or 3) facilities that are not required to report onsite release are marked with zero onsite release. For these reasons, distance was used as a way to represent exposure to TRI site emissions.

After the data were cleaned and prepared, the first regression model used was the ordinary least squares (OLS) model. This study uses a stepwise regression technique to determine the best OLS model with the highest adjusted R^2. The independent variables for the United States study were the black or African American rate, Asian rate, Hispanic or Latino (of any race) rate, the percent of individuals under the poverty line in the past 12 months, the rate of individuals who completed some high school and did not receive a degree, and the onsite release (in pounds) per square mile. The independent variable for the Louisiana study were the black or

African American rate, Asian rate, Hispanic or Latino (of any race) rate, the percent of individuals under the poverty line in the past 12 months, the rate of individuals who completed some high school and did not receive a degree, USDA food deserts, and the distance from the population weighted center to the nearest TRI site.

After running the OLS regression, I analyzed the model coefficients, probability, variance inflation factor, and general patterns. Then I tested for spatial autocorrelation using Moran's I on the standard residuals. After determining that spatial autocorrelation existed with the OLS results, I performed the second model which was the geographically weighed regression (GWR) model. This study utilized an adaptive kernel type because the distribution varies across the U.S. meaning that some areas have higher obesity prevalence than others. The bandwidth method that was used was the AICc (Akaike Information Criterion) which finds the optimal distance/neighbor parameter. Next, I mapped the standard residuals from the GWR to make sure that the new model fixed the spatial autocorrelation issue. Finally, I analyzed the results and compared the global OLS with the local GWR model using the adjusted R^2 and AIC values.

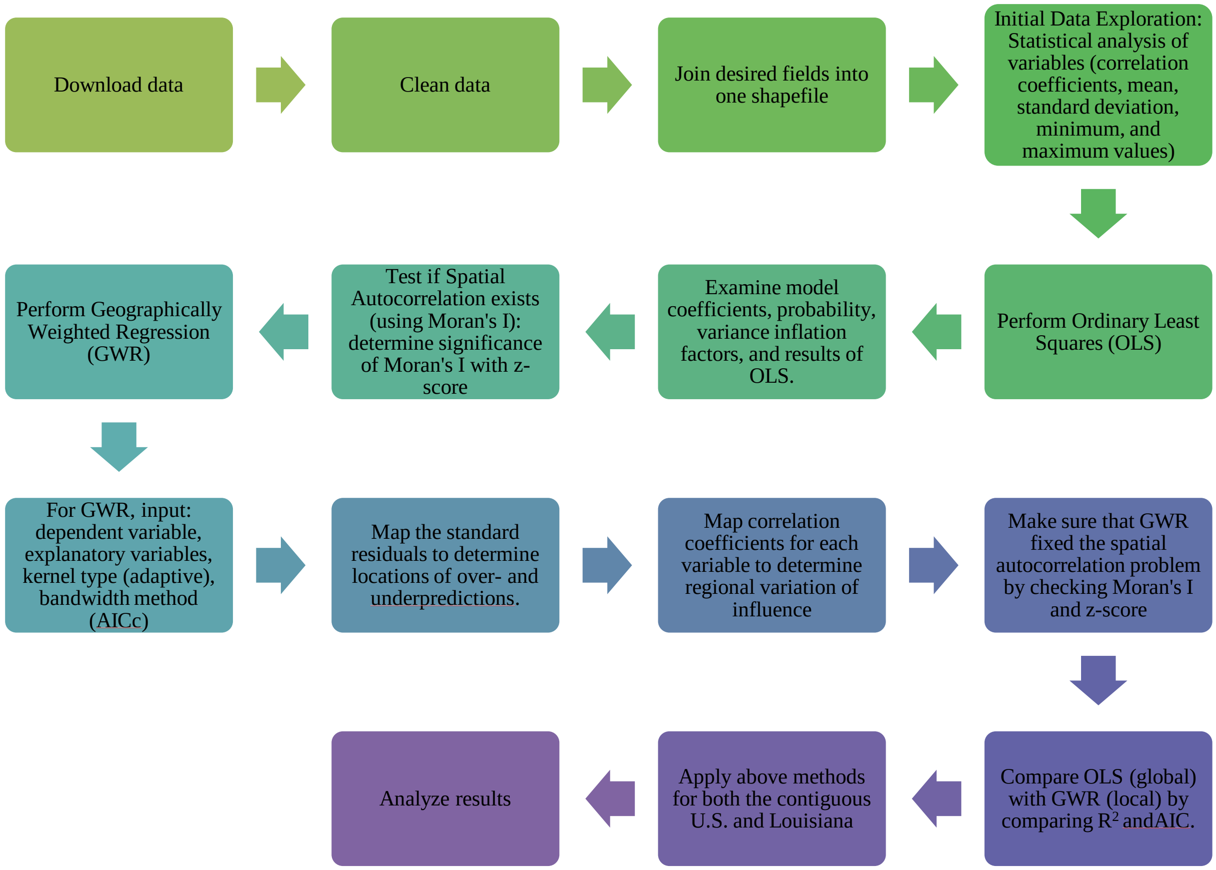

Figure 4.19: Methodology flowchart.

Dependent Variable	**Source**
Obesity Rate	*BRFSS*
Independent Variables	**Source**
Black or African American Rate	*U.S. Census*
Asian Rate	*U.S. Census*
Hispanic or Latino (of any race) Rate	*U.S. Census*
Low Education Rate (9^{th}-12^{th} grade and no diploma)	*U.S. Census*
Poverty Rate (income below the poverty line in the past 12 months)	*U.S. Census*
TRI onsite release in pounds per square miles (United States study)	*EPA*
Distance (in miles) from the Census tract population weighted center to the nearest TRI site (Louisiana study)	*EPA*
Food Desert (low access) (Louisiana study)	*USDA*

Figure 4.20: Dependent and independent variables.

CHAPTER V

RESULTS

United States Results

In this section, I compare the OLS and GWR model results for the United States study. The OLS model had an R^2 value of 0.50 and an adjusted R^2 value of 0.50, while the GWR model had an R^2 value of 0.73 and adjusted R^2 value of 0.69 (Table 5.1). The food desert variable was tested as a constant to account for the built environment, but was not significant. Because of this, it seems that the built environment, or the methods that the USDA employs when classifying Census tracts as food deserts, is not a strong explanatory variable for obesity. The USDA food desert metric is problematic in that it only analyzes the distance to the nearest food store and does not take into account the social variables such as where people prefer to shop.

Table 5.1: OLS and GWR results of the United States study.

Model	R^2	Adjusted R^2	AIC
OLS	0.50	0.50	-12,844.97
GWR	0.73	0.69	-14,119.69

The Akaike Information Criterion (AIC) was -12,844.97 for the OLS model and was -14,119.69 for the GWR model. Since the AIC for the GWR model was much lower, the GWR was more reliable than the OLS model. The R^2 is the proportion of the variation in the dependent variable that can be explained by the variation in the model. The adjusted R^2 accounts for the number of variables in the model. If the R^2 value is low in any models, it means that there could be some variable that is not included in the model, or it could mean that the form of the model is not ideal. The GWR model created the optimal adaptive number of neighbors; for the United States study, the number of neighbors used for each local estimation was 181 neighbors. It is important to note that the Akaike Information Criterion (AIC) is used after other models are run to compare for model sufficiency; the AIC is the measure of the relative distance between the fitted model and the unknown "true" model. An AIC value that is smaller and has a large (greater than 3 to 4) difference from other AIC values is wanted.

The OLS model revealed that income and the percent black or African American had a positive relationship with obesity while percent Hispanic or Latino (of all races) rate, Asian rate, education level, and onsite release per square mile of TRI sites had a negative association with obesity prevalence (Figure 5.1 and Figure 5.2). All of the variables were significant except for the onsite release per square mile input.

United States Study		
Independent Variables	**Coefficient**	**p-value**
Black or African American Rate	0.075	0.0000*
Asian Rate	-0.124	0.0001*
Hispanic or Latino (of any race) Rate	-0.070	0.0000*
Low Education Rate (9^{th}-12^{th} grade and no diploma)	-2.129	0.0000*
Poverty Rate (income below the poverty line in the past 12 months)	0.130	0.0000*
TRI onsite release in pounds per square miles	-0.000	0.4604

Figure 5.1: United States OLS coefficients and p-value. Asterisk (*) indicates a coefficient is statistically significant ($p < 0.05$).

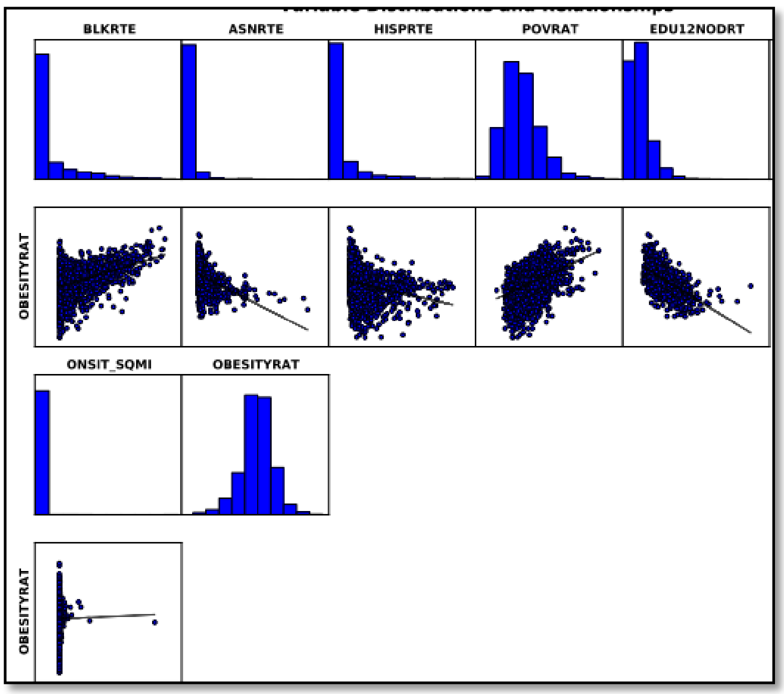

Figure 5.2: Histograms and scatterplots for each explanatory variable (from left to right: black or African American rate, Asian rate, Hispanic or Latino rate, poverty rate, education level, and onsite release per square mile).

The residual, which is the difference between observed values of the dependent variable and the fitted values, is another factor to analyze. The standardized value of the residual has a mean of zero and a standard deviation of 1; in this case, positive standard residuals indicate overpredictions while negative values indicate underpredictions. The standard residual map for the OLS model revealed that there are underpredictions in the Midwest and Southeast and overpredictions in the West and Southwest (Figure 5.3). To test if the OLS model should be used, it is necessary to determine if spatial autocorrelation exists in the residuals. If the residuals are spatially autocorrelated, then the results of the OLS are unreliable. The results of the Moran's I showed that the standard residuals of the OLS model were clustered with a z-score of 56.89 and a p-value of 0.000; this means that the GWR model should be used.

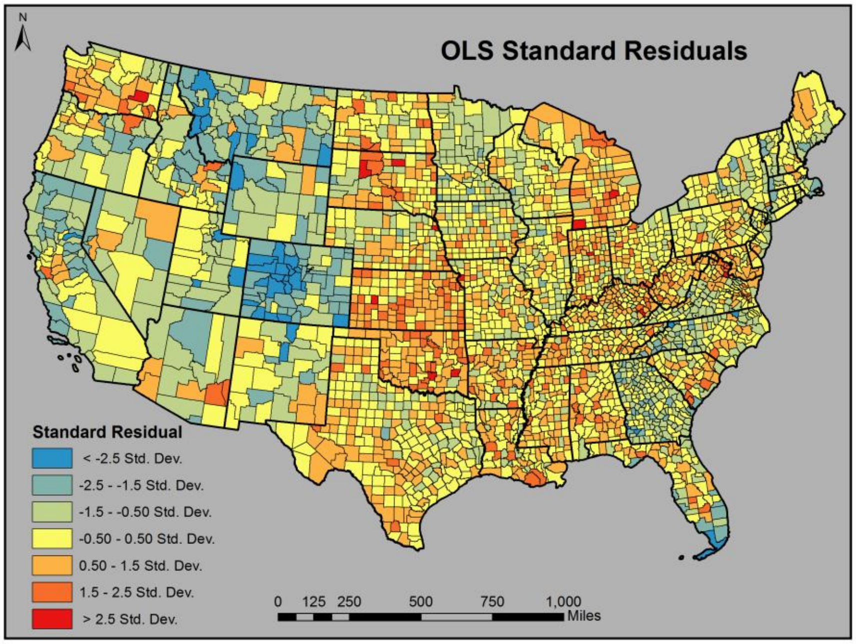

Figure 5.3: OLS standard residuals in the United States.

When testing for Spatial Autocorrelation of the GWR standard residuals, the GWR model standard residual outputs are indeed random. The standard residual map and the Moran's I Spatial Autocorrelation results (z-score of 1.44 and p-value of 0.15) for the GWR model demonstrated that the standard residuals are random (Figure 5.4).

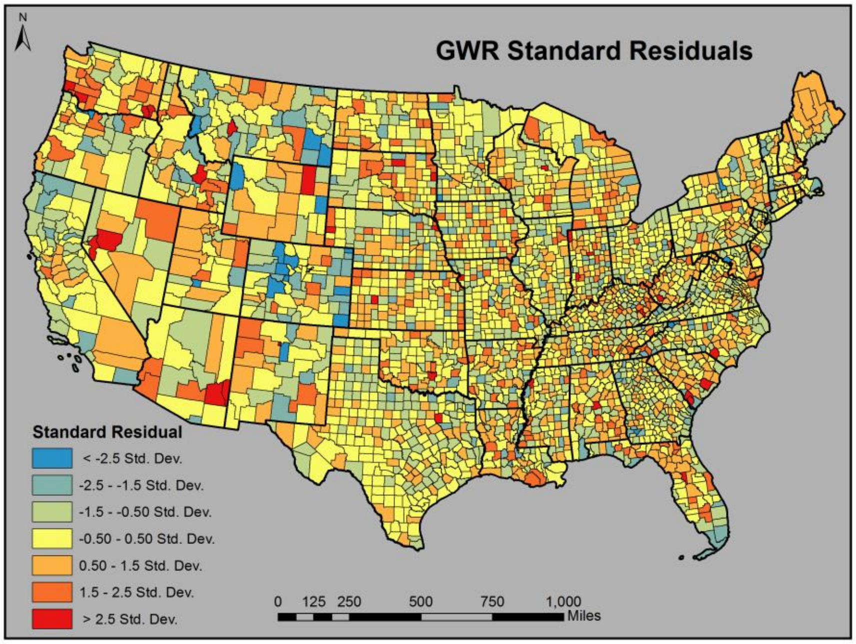

Figure 5.4: GWR standard residuals in the United States.

When comparing the GWR observed/predicted obesity rate distribution to the actual obesity rate distribution in 2010, one can see that the GWR model has high explanatory power (Figure 5.5 and Figure 5.6).

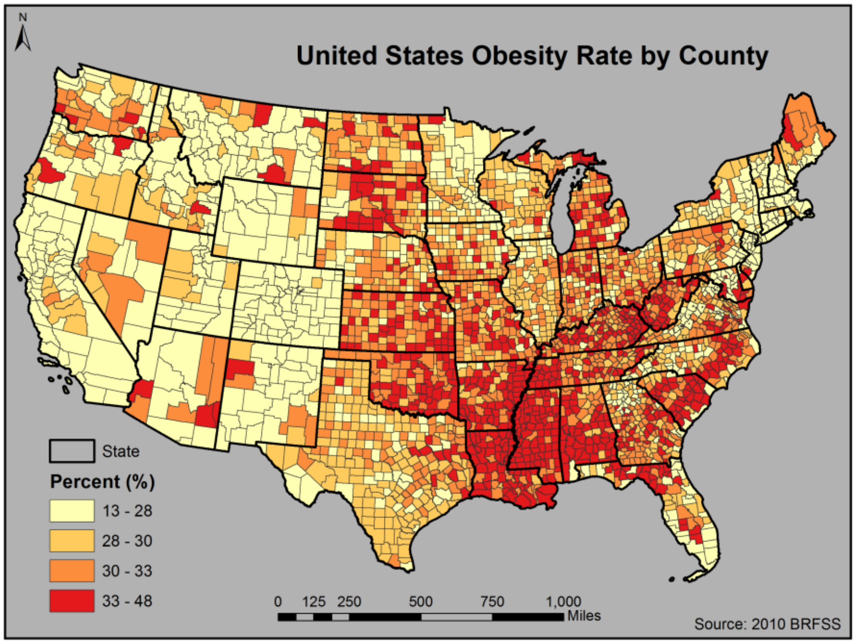

Figure 5.5: Observed obesity rates in the United States.

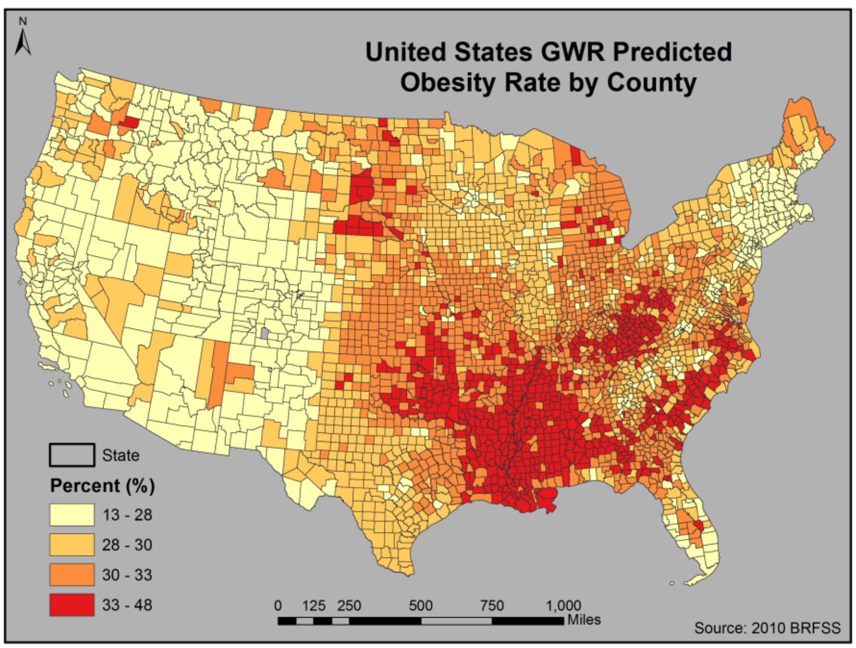

Figure 5.6: GWR predicted obesity rates in the United States.

By mapping the GWR coefficients for each independent variable, I was able to see the regional variance of the variable's influence. The areas shaded in green represent a negative relationship with obesity rate whereas the areas in purple represent a positive relationship with obesity rates. The classification method used to map the GWR coefficients was the Natural Breaks (Jenks) classification method which is based on natural groupings in the data and maximizes the difference between the classes. After assigning the Natural Breaks classification, I manually edited the central classes to differentiate between negative and positive values.

It is important to note that while testing OLS coefficients with a t-test is conventional, testing the significance of GWR coefficients remains contentious and also raises the issue of multiple significance testing (Charlton and Fotheringham, 2009). The Bonferroni correction can be used on the significance level, but it is suggested that this method may be too conservative; the p-values are computed in the software, but is not released in the GWR output because the developers and Esri believe that it is inappropriate to use this significance test in GWR (Charlton and Fotheringham, 2009). Determining the significance of the GWR coefficients still remains a subject of current research; in future research, this study will explore methods of calculating significance or will compare results with an alternative product that provides significance values (Charlton and Fotheringham, 2009). Although the p-values are not included in the GWR output, this study takes into account the possibility of local multicollinearity which is a redundancy of explanatory variables. When the values of the independent variables are spatially clustered, the issue of local multicollinearity arises. To test for this, the GWR outputs a field labeled "Condition"; values in this field that are larger than 30 indicate unstable results due to local multicollinearity. The highest "Condition", or count, value found in this study's output was 24.62 so it is safe to say that local multicollinearity does not exist in the output.

The TRI sites GWR coefficients map reveals positive GWR coefficients between the onsite release per square mile and obesity rates in the West, Midwest, Northeast, Texas, and

Florida. A positive association means that as the onsite release per square mile increases the obesity rate increases as well (Figure 5.7). This is probably because there numerous EPA sites in these regions due to the industrial center of the U.S. historically being in the Midwest. The Florida and Texas areas are affected by this variable most likely because of the shift in the industrial sites from the Midwest to the South in the late 1900s due to cheaper costs of operation. However, one must note that using onsite release values from the EPA TRI dataset is problematic in that there are numerous sites that report 0 pounds of onsite release. For this reason, the smaller study site of Louisiana was analyzed implementing the distance to the nearest TRI site based on population weighted centers.

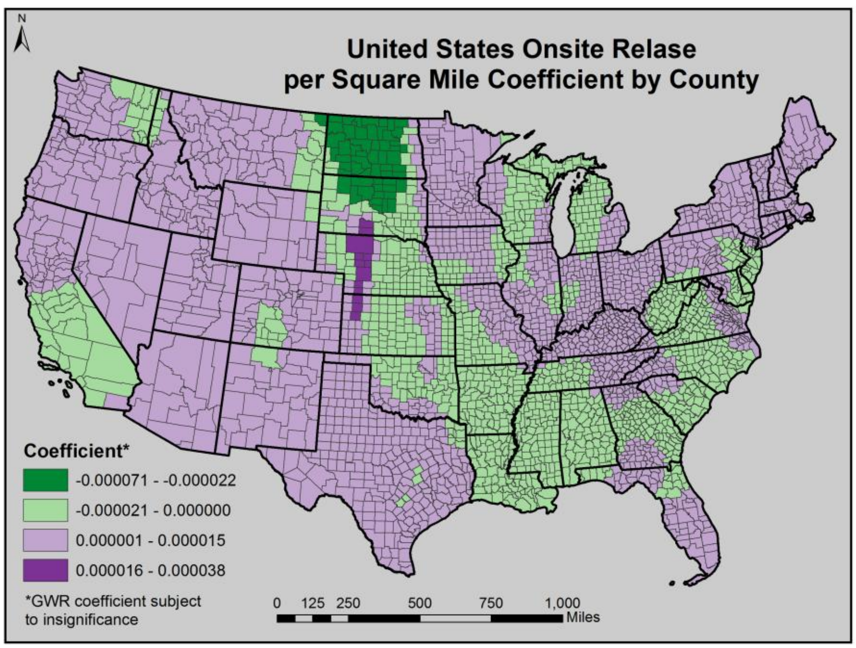

Figure 5.7: TRI site GWR coefficients in the United States.

The areas where the poverty variable has a positive relationship with obesity rates are seen in purple (Figure 5.8). It appears as if poverty is most influential in urban regions and major cities. Further research is needed to explain the high impact of poverty on obesity in the West, more specifically California.

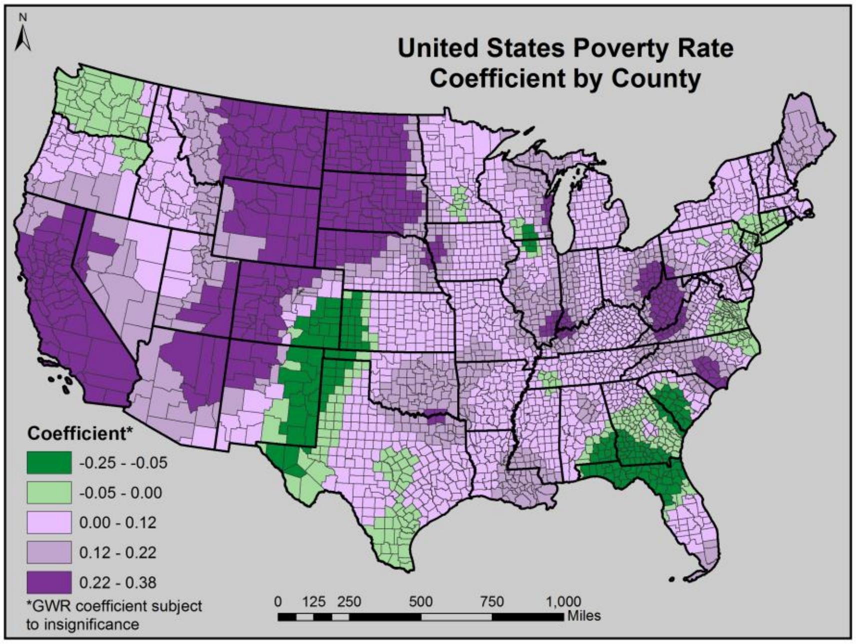

Figure 5.8: Percent under the poverty line GWR coefficients in the United States.

The black or African American rate GWR coefficients are positive in the South, Southwest, and Upper Midwest (Figure 5.9) and the Hispanic or Latino of any race rate GWR coefficients are positive in the Northwest, North Midwest, and some areas in the South (Figure 5.10). The Asian rate GWR coefficient is positive mostly in the West, in most or all of California, Washington, and Main, and on the tip of Florida (Figure 5.11). The low education rate GWR coefficient distribution is interesting in that there are only a few places in the United States where high rates of low education are correlated with obesity (Figure 5.12). This may suggest that education may not be a very influential factor in obesity rates.

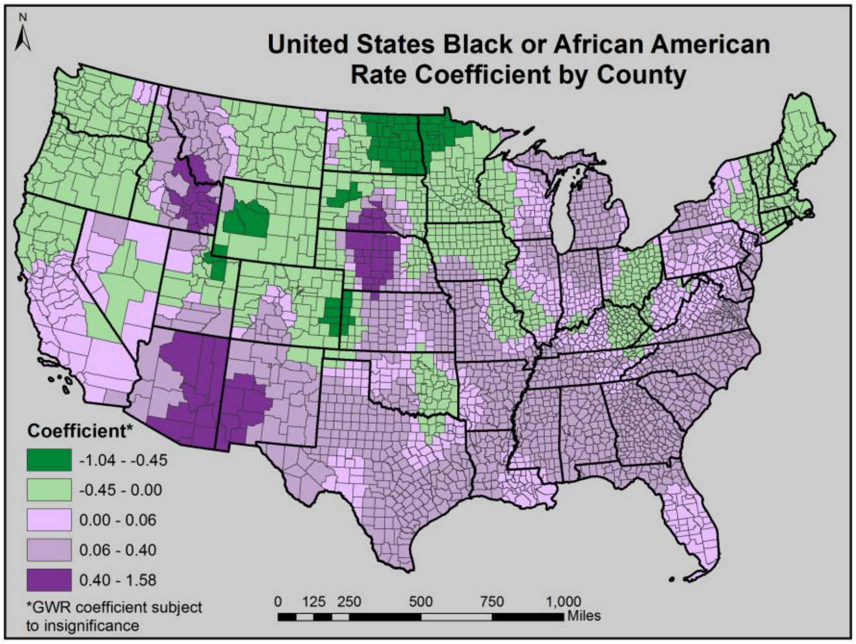

Figure 5.9: Percent black or African American GWR coefficients in the United States.

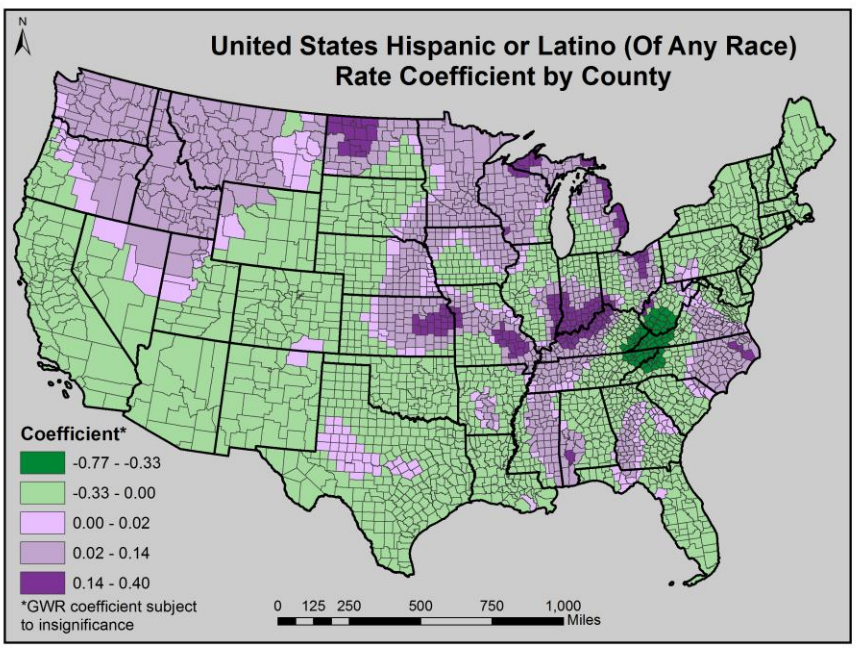

Figure 5.10: Percent Hispanic or Latino of all races GWR coefficients in the United States.

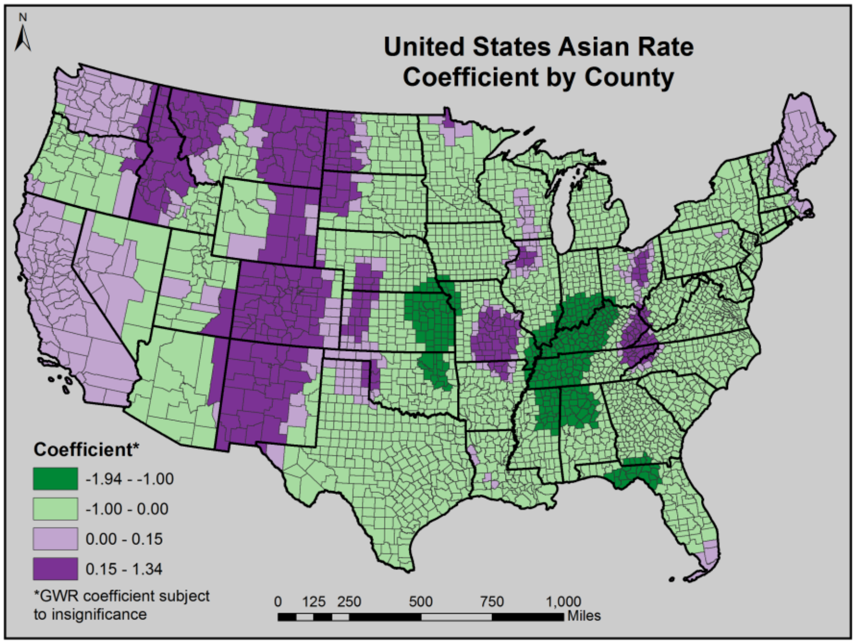

Figure 5.11: Percent Asian GWR coefficients in the United States.

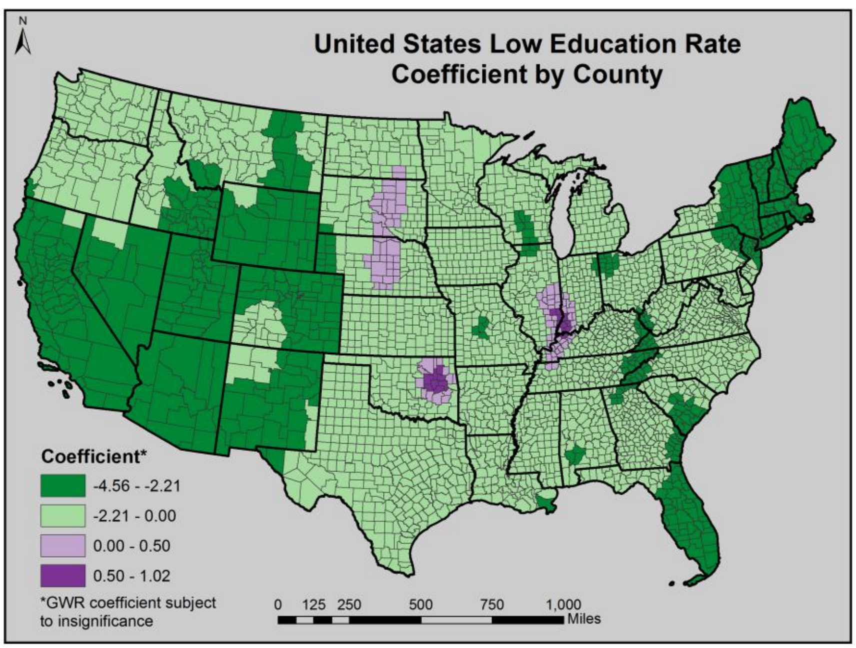

Figure 5.12: Low education GWR coefficients in the United States.

Louisiana Results

When compared to the United States study, the Louisiana study's OLS results were much lower, but the GWR results were slightly higher. The OLS R^2 and adjusted R^2 were both 0.18 and the GWR R^2 was 0.85 and the adjusted R^2 was 0.74 (Table 5.2). This means that the GWR model explains 74% of the total variation in the dependent variable, or obesity rate. Like the U.S. study, the AIC of the Louisiana study's GWR was much lower than the AIC of the OLS meaning that the GWR model was the superior tool. The number of neighbors used for each local estimation in the GWR model was 107 neighbors.

Table 5.2: OLS and GWR results of the Louisiana study.

Model	R^2	Adjusted R^2	AIC
OLS	0.18	0.18	-4,971.13
GWR	0.85	0.74	-6,168.78

All of the independent variables were significant in the OLS model. The black or African American, Hispanic or Latino of any race, and Asian rates had negative coefficients meaning that as the rates of these races increased the rates of obesity decreased (Figure 5.13 and Figure 5.14). The poverty rate, low education rate, food desert (low access), and the distance to the nearest TRI site inputs all had positive associations. These results were surprising in that I would have expected, based on current literature, a positive relationship between non-white rates and obesity rates as well as a negative association between the distance to the nearest TRI sites and obesity rates. However, this variation is most likely due to the issue of imputing county level obesity data to the Census tract level which could alter the regional influence of each Census tract variable inputted into the model. Imputing county level data to the tract level does not provide the same scale and spatial detail that tract level obesity data would. For this reason, a future study should include obesity data ideally at the individual level or at least at the tract level. Another method of addressing the distribution of race is to include a breakdown of each race by urban, suburban, or rural categories. As OLS only reports the overall association, GWR visualizes the regional variation in variable influence. Although the scatterplots in Figure 5.14 depict non-linear relationships, running a log, arcsine, or cube root transformation to create a linear relationship in the data only slightly lowers the adjusted R^2. For this reason, no transformations were performed.

Louisiana Study		
Independent Variables	**Coefficient**	**p-value**
Black or African American Rate	-0.019	0.0000*
Asian Rate	-0.056	0.0082*
Hispanic or Latino (of any race) Rate	-0.070	0.0000*
Low Education Rate (9^{th}-12^{th} grade and no diploma)	0.097	0.0000*
Poverty Rate (income below the poverty line in the past 12 months)	0.021	0.0180*
USDA Food Desert (low access 1 and 10)	0.004	0.0000*
Distance (in miles) from the Census tract population weighted center to the nearest TRI site	0.002	0.0000*

Figure 5.13: Louisiana OLS coefficients and p-value. Asterisk (*) indicates a coefficient is statistically significant ($p < 0.05$).

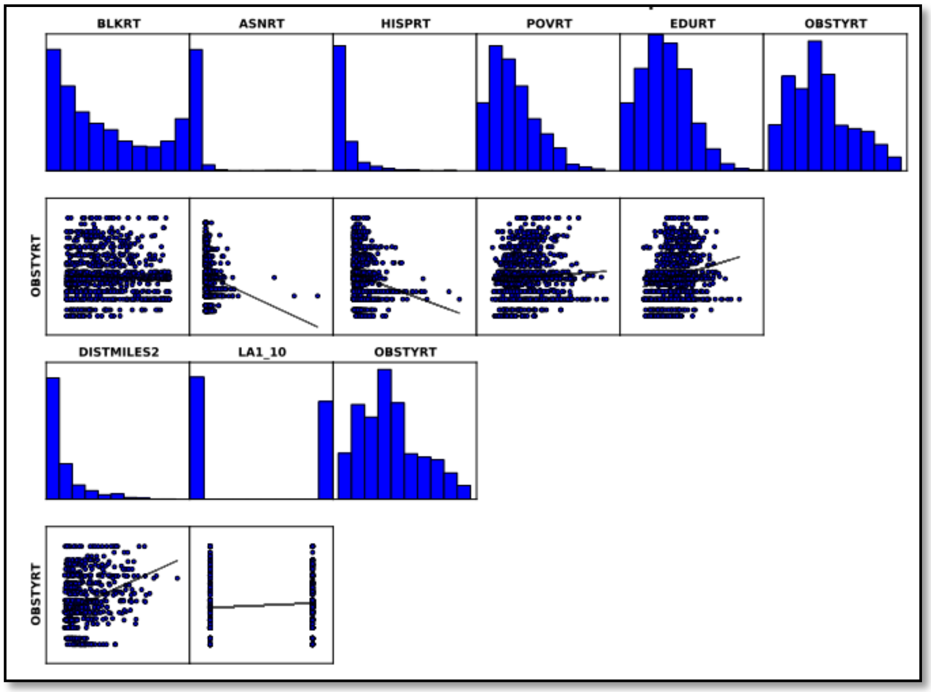

Figure 5.14: Histograms and scatterplots for each explanatory variable (from left to right: black or African American rate, Asian rate, Hispanic or Latino rate, poverty rate, education level, distance to nearest TRI site, and low access food desert).

After running the OLS regression model, it is important to check for Spatial Autocorrelation of the standard residuals (Figure 5.15). In order to test for clustering, the Moran's I tool was employed. The OLS standard residuals were clustered with a z-score of 101.47 and p-value of 0.00. The GWR model fixed the issue of Spatial Autocorrelation because the standard residuals were randomly distributed with a z-score of 0.45 and a p-value of 0.65 (Figure 5.16).

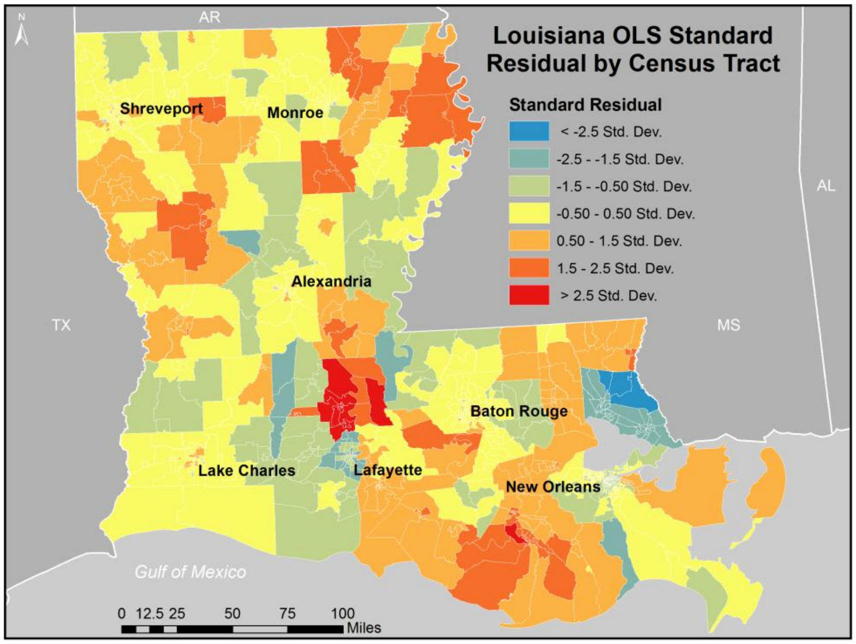

Figure 5.15: OLS clustered standard residuals in Louisiana.

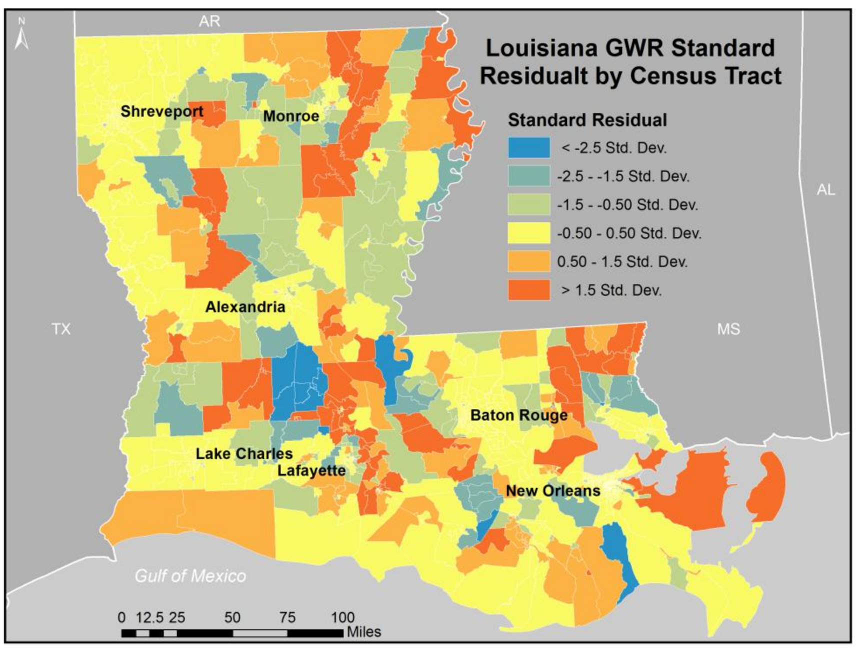

Figure 5.16: GWR randomly distributed standard residuals in the Louisiana.

When comparing the observed obesity rates in Louisiana (Figure 5.17) to the GWR's predicted obesity rates (Figure 5.18), one can see that the model predicts the distribution of obesity pretty well.

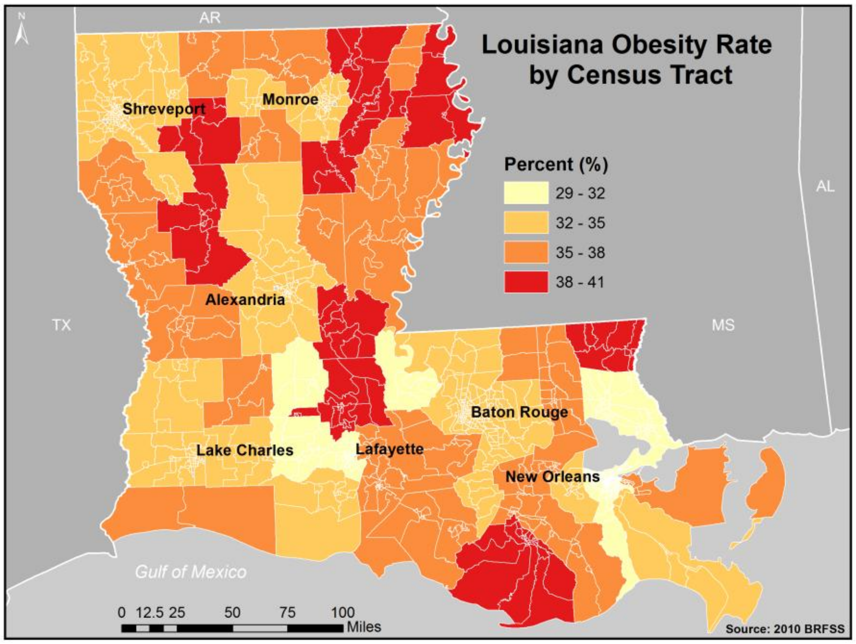

Figure 5.17: Observed obesity rates in Louisiana.

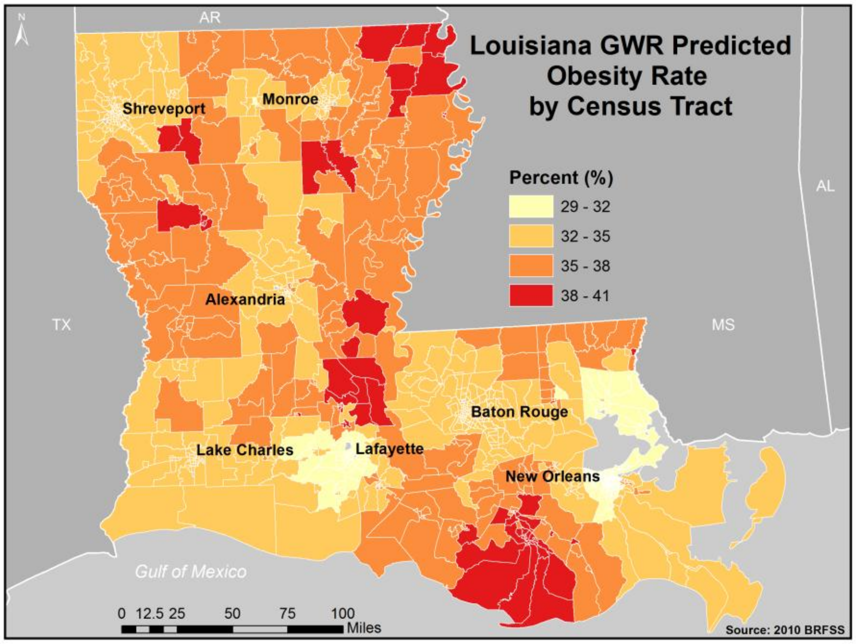

Figure 5.18: GWR predicted obesity rates in Louisiana.

The TRI site variable's GWR coefficient map can be seen in Figure 5.19. The areas of interest are the green shaded regions which represent a negative relationship between distance and obesity. In contrast, the purple areas indicate a positive relationship. The classification method used to map the GWR coefficients was the Natural Breaks (Jenks) classification method which is based on natural groupings in the data and maximizes the difference between the classes. After assigning the Natural Breaks classification, I manually edited the central classes to differentiate between negative and positive values. In these areas of negative GWR coefficients, the closer the population weighted center is to a TRI site, the greater the obesity rate. One reason why the TRI variable is negatively associated with obesity in these regions may be due to air stagnation which occurs when there are light winds and/or little precipitation. In these conditions, fine particles and air pollution remain in the air and are easily inhaled into the lungs. Future research is needed to further explore the relationship between the physical geography and atmospheric mechanisms that cause air stagnation and obesity.

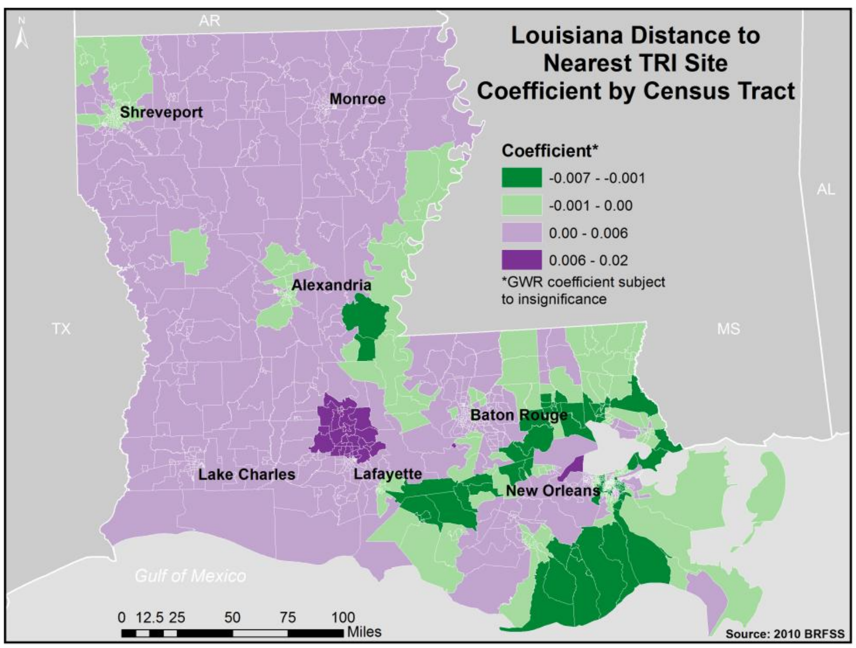

Figure 5.19: TRI site GWR coefficients in Louisiana.

Poverty is positively correlated with obesity in the Census tracts that are shaded purple (Figure 5.20). The areas of positive correlation are the Southeast, Northwest, and Mid-central portions of the state. The black or African American (Figure 5.21) and Hispanic or Latino (Figure 5.22) rate GWR coefficient maps have a similar pattern. They are both positively correlated in the Southwest, Northeast, Northwest, and scattered in the Southeast. The positive GWR coefficients in the Asian rate map (Figure 5.23) are found in the South and particularly in the Southwest. Low education levels seem to affect obesity rates in most areas of the state except for the Northwest near Shreveport (Figure 5.24).

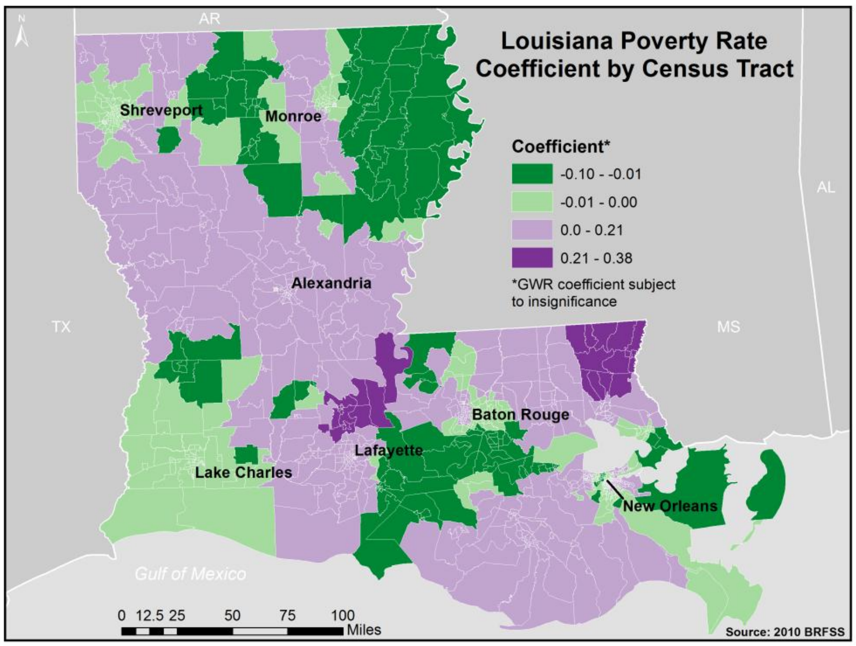

Figure 5.20: Percent under the poverty line GWR coefficients in Louisiana.

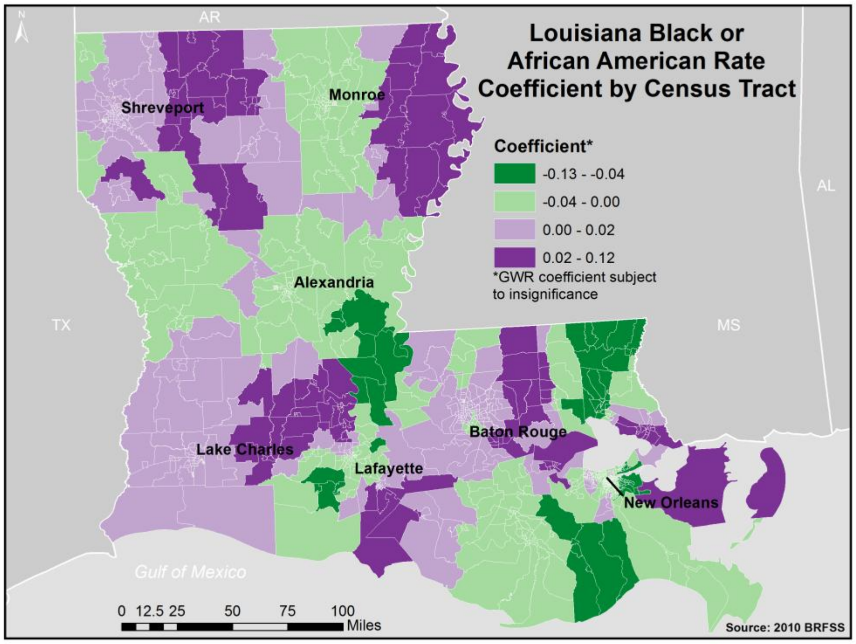

Figure 5.21: Percent black or African American GWR coefficients in Louisiana.

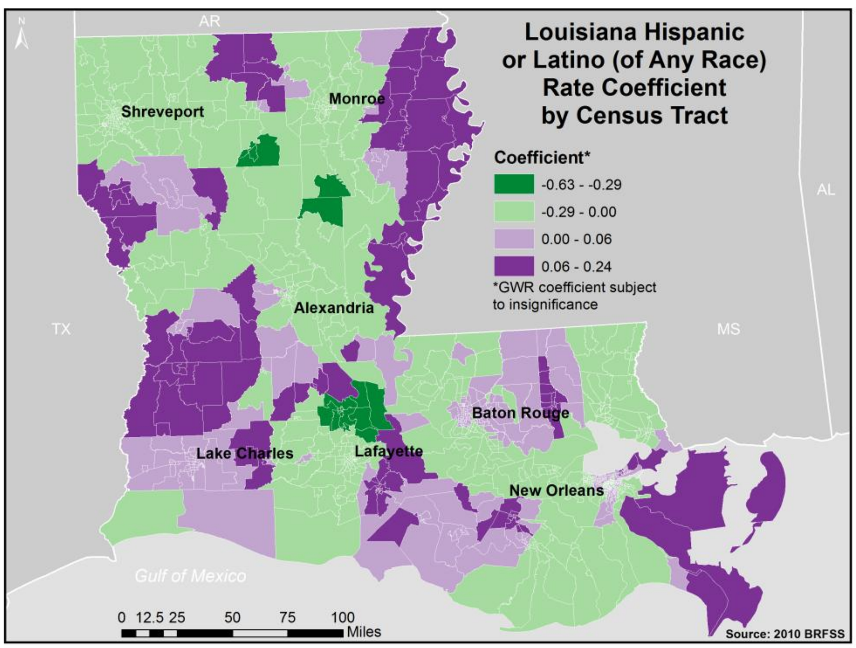

Figure 5.22: Percent Hispanic or Latino of all races GWR coefficients in Louisiana.

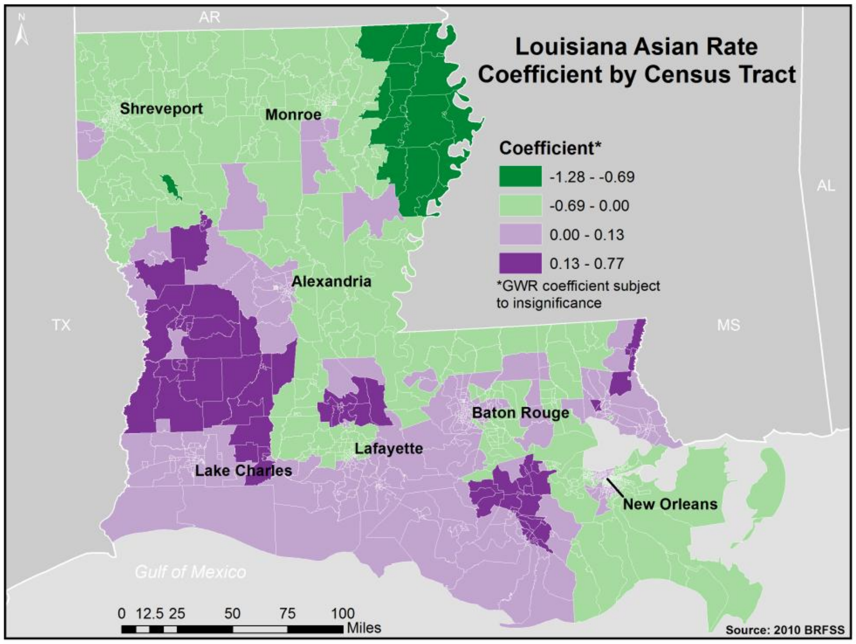

Figure 5.23: Percent Asian GWR coefficients in Louisiana.

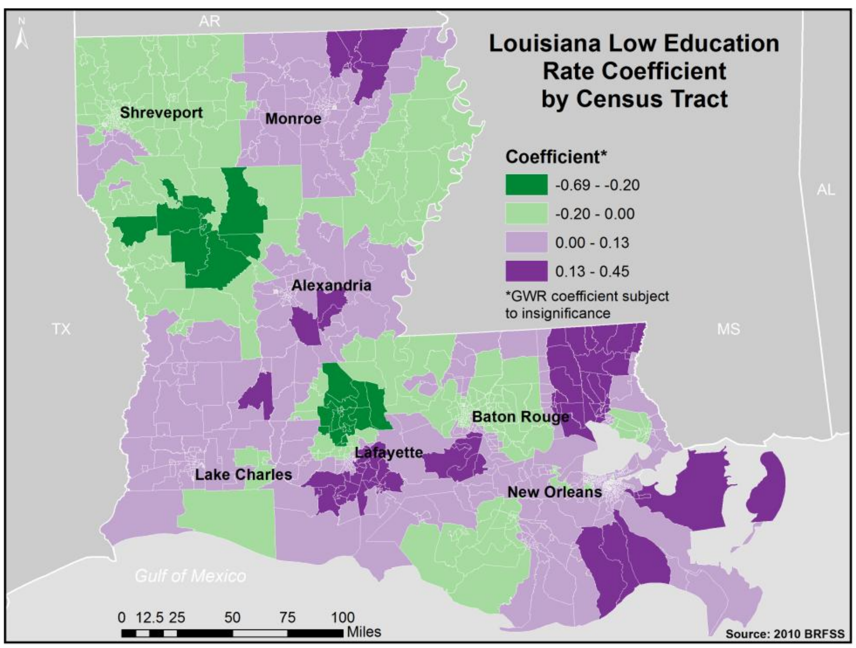

Figure 5.24: Low education GWR coefficients in Louisiana.

CHAPTER VI

CONCLUSION

This research was composed of two study regions: the United States and the state of Louisiana. The variables used to explain obesity rates were race, income, education, food deserts (in the Louisiana study) and exposure to chemicals from Toxic Release Inventory sites. In both study sites, the GWR model was far superior to the OLS model because it accounts for Spatial Autocorrelation. In the U.S. study, the black or African American and poverty rates had significant positive coefficients with obesity rates. The variable of TRI sites was the only insignificant input which might be due to the Modifiable Areal Unit Problem. When looking at a smaller scale of one state, the study was able to address this issue and supported the study's conjecture. In the Louisiana study, poverty, education, and Toxic Release Inventory sites had a significant and positive association with obesity rates. Although OLS results revealed a positive association between TRI sites and obesity, GWR was beneficial in that it was able to show where TRI sites had a negative relationship. These areas of negative TRI coefficients, in which close proximity to TRI sites leads to greater obesity rates, were found in the Southeast and Northwest portions of Louisiana. Further research is needed to fully understand the atmospheric conditions needed for populations to be exposed to TRI chemical emissions.

The limitations of this study include the following: (1) Until 2011, the BRFSS survey only called landlines which excludes people who only have cell phones and may only include individuals that do not have a typical "9 to 5" job; (2) using BMI as a metric for obesity can be problematic because it does not account for different body types, and when self-reported, there is a chance of underreporting; (3) since race is a social construct, one must be cautious when utilizing race categories in research; and (4) when using county-level data, there may be over-aggregation and results may not represent individual processes and characteristics.

In regards to the first and second limitations stated above, the CDC has tried to address the bias and the issue of individual misreporting while at the same time improving data quality through the careful selection and development of the questionnaire design and questions, data collection and editing procedures, and interviewing techniques. One method to correct the bias found in self-reported weight and height is to compare the BRFSS data to the National Health and Nutrition Examination Survey (NHANES) data. The BRFSS weight and height are self-reported from over 100,000 individuals a year across the U.S. and the NHANES data actually measures height and weight of 5,000 people a year. To correct for bias, the mean BMI from NHANES would be regressed on the mean BMI from BRFSS. Then, using the fitted coefficients from the model, the corrected BMI can be calculated. The third limitation about race is still a continuing struggle in GIS research which must continue to acknowledge such limitations. Finally, the fourth limitation about the issues of using county level data has been addressed by running the analysis at the Census tract level, but future study would greatly benefit from obesity data at a smaller scale. In order to obtain obesity data at a more precise level, individual weight and height from license data could be used to calculate BMI.

This research approach of combining various fields' strengths sets this study apart from others in that no other project has analyzed the relationship between persistent organic pollutants and obesity through geographic information systems. This study compliments the numerous epidemiology and endocrinology studies that prove the positive relationship between these two variables through i*n vitro* analysis. Geographers overemphasize the supply side of the argument, or the built environment, while deemphasizing the production side, more specifically the effects of environmental toxins on obesity. Lastly, public health officials mainly point to individual diet and exercise which also overlooks the possible environmental effects on obesity. This study compliments individual level epidemiology and endocrinology findings by assessing the interaction between bodies and the environment. Not only has this study tried to determine the relationship between these important variables, but it did so considering the regional variation of influence as well as the effects of spatial autocorrelation using geographically weighted regression. Results demonstrated that race, income, education, and TRI sites regionally impact obesity throughout the U.S. and Louisiana.

As the use of Toxic Release Inventory sites is steadily rising in the Public Health, Epidemiology, Endocrinology, and Geography research, it is important to understand and address statistical issues such as Spatial Autocorrelation and MAUP. Not only should quantitative limitations be acknowledged, future studies should also recognize issues of structural inequality. This study's approach contributes to the current discussion of obesity and its related causes while suggesting an integration of various fields to further understand the obesity issue in the United States.

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