ESTIMATING LAND USE CHANGE AND ECONOMIC VALUE OF WATER QUALITY IN A NORTH GEORGIA ECOSYSTEM

by

DANIEL GEORGE NGUGI

(Under the Direction of Jeffrey Mullen)

ABSTRACT

This study seeks to forecast land use change in an ecosystem in the Upper Chattahoochee River Basin, model associated water quality changes and estimate the economic value of the same using Benefit Transfer. The basin is of significant source of water, recreational and other ecological amenities, but encroachment by urban development is a major threat to the ecosystem. Econometric, vector autoregressive and structural time series models are applied to land use data and the best forecasting model is selected. Land use change and resulting water quality changes are modeled under different scenarios and the public’s willingness to pay for improving and maintaining the quality of fishing and drinking water supply is estimated.

INDEX WORDS: Ecosystem, Economic Valuation, Watershed, Willingness to pay, benefit transfer, Chattahoochee River, Land use, Fish, Forecasting, Water quality, Value, urban growth, Georgia, structural time series, vector autoregressive models, land use change, land use modeling

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DANIEL GEORGE NGUGI

BS., University of Nairobi, Kenya, 1993

MS., University Of Malawi, Malawi, 1998

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DANIEL GEORGE NGUGI

Major Professor: Jeffrey Mullen

Committee: John Bergstrom
Jack Houston
Jimmy Bramblett

Electronic Version Approved:

Maureen Grasso
Dean of the Graduate School
The University of Georgia
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DEDICATION

To “the King eternal, immortal, invisible, the only wise God, be honor and glory for ever and ever. Amen”. 1 Tim 1:17.

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CHAPTER I

INTRODUCTION

Problem Statement and Justification of Study

An ecosystem is defined as “a geographic area and all its living components (e.g., people, plants, animals, and microorganisms), their physical surroundings (e.g., soil, water, and air), and the natural cycles that sustain them (e.g., precipitation, drought, fire, grazing)” (United States Fish and Wildlife Service (USFWS), 2007). The USFWS also describes a watershed as “the drainage basin contributing water, organic matter, dissolved nutrients, and sediments to a water body”. Thus a watershed or watershed ecosystem is a special type of ecosystem that drains into a single water body.

Watershed ecosystems play an important role in providing functions and services that are beneficial to society. Ecologists see ecosystems as having functions and providing services (including goods). Ecosystem functions are the physical, chemical, and biological processes or attributes that contribute to the self-maintenance of an ecosystem (Saplaco and Herminia, 2003). Watershed ecosystem functions include provision of wildlife habitat, carbon cycling, trapping of nutrients, regulation of hydrologic flows and soil formation processes.

Ecosystem services result from ecosystem functions as the beneficial outcomes of the same to humans and the natural environment. Watershed ecosystem services include support of the food chain, harvesting of animals or plants, provision of clean water, and scenic views.

Ecosystem Valuation: An Overview

Valuing environmental impacts has become increasingly important with the increase in public awareness of environmental issues, government requirements such as executive order 12291 that required assessment of benefits and costs of environmental regulations with major impacts on the economy, and the rising scarcity of environmental commodities. The impact of land use change could be negative or positive, depending on which land use takes what portion of the land. Normally though, land moves from farms and forests to urban and industrial areas, with negative consequences for runoff, and biological and chemical pollutants.

Economic valuation of ecosystems has often been criticized as putting a price tag on nature. But ecosystems do not exist in a vacuum; they are daily impacted upon by human activity. Decisions that touch on ecosystems are made daily by governments, corporations, private property owners, communities etc. These decisions are based on implicit or explicit valuation of the ecosystems, so that whether we like it or not, some form of ecosystem valuation is taking place on a daily basis.

Without some estimate of value, it is possible for decision makers and society to assume that ecosystem services are valueless and therefore not provide for them during tight government budgeting. Without a sense of what ecosystem services are worth, society is likely to dispose of them without any regard. It may be that this is the kind of reasoning that has facilitated environmental and resource degradation in many countries over the years.

Economic valuation of watersheds and other ecosystems is complicated by market failure and characterized by three main factors. For one, the services are public goods in that their use by one person does not hinder use by another, so no one has the incentive to pay for them. Secondly, they are affected by externalities – negative outcomes of people's activities such as raw sewage disposal into a river that affect others that are not party to the negative activities often without compensation. Thirdly, property rights for most watersheds are not properly defined or are so broadly defined that there is no incentive for conservation.

Economists have used diverse approaches to valuing ecosystems in the past. Many have used a combination of methods, including market prices, to value marketed components of ecosystem services and direct and indirect techniques of valuing public goods. Except for market prices, other methods of valuing ecosystem components or entire ecosystems are costly both in time and money.

Benefit (or benefits) transfer is a set of techniques used for estimating the value of public goods whenever it is not practical to collect primary data on which to base economic valuation (Bergstrom and Civita, 1999). Benefits Transfer has been used to value ecosystems in numerous studies, including Constanza et al (1997), Verna (2000), Toras (2000) and Kramer et al (1997). We apply benefit transfer techniques to the valuation of a watershed ecosystem within the Upper Chattahoochee River Basin in North Georgia.

Resource Constraints in the Chattahoochee River Basin

This study focuses on Habersham and White, two counties within the Upper Chattahoochee River basin above Lake Lanier in North Georgia. For the purpose of this study, this ecosystem is referred to as the Policy Site or Policy Area.

The Chattahoochee River (CR) rises in the Blue Ridge Mountains about 12 miles south of the Tennessee border (Georgia

Environmental Protection Division (GAEPD), 1997). The river flows for a total of 434 miles through Georgia to its confluence with the Flint River near Columbia, Alabama, and further south to terminate in Lake Seminole at the Georgia-Florida border. The river is part of the Apalachicola-Chattahoochee-Flint River basin (ACF), which covers about 20,400 sq mi of land (American Rivers, 1996). The entire Chattahoochee River Basin (CRB) on its own covers about 8770 square miles.

The policy site contributes to provision of water for drinking, irrigation, animal, industrial and sewage disposal purposes to residents of the counties located on the basin. Additionally, the watershed contributes to quantity and quality of waters downstream; a variety of recreational uses including hiking, fishing, sightseeing, bird watching, swimming camping and game hunting and a variety of ecosystem functions.

The Chattahoochee is the primary source of drinking water for the city of Atlanta and more than 4.1 million people from three states (Georgia, Florida, Alabama) drink water from the Chattahoochee. The United States Geological Survey (USGS) observes that water withdrawals in Georgia increased by close to nine percent between 1990 and 1995 (USGS, 2000). Ground water withdrawals in the state rose by about 240 % between 1970 and 1990, while surface water withdrawals rose by about 29% over the same period (GAEPD, 2000).

Recreation water demand has been markedly high. Lake Lanier, situated on the river, is the most visited federal recreation lake in the U.S., generating billions of dollars in tourism money (Riverkeeper, 1998). The river also provides flow regulation because of three reservoirs located on the river besides providing sewage disposal services, hydroelectric power, supporting recreational activities.

In North Georgia, the UCRB incorporates the Chattahoochee National Forest, the headwaters of the CR, various creeks and the 11,200 acre Mark Trail Wilderness (United States Department of Agriculture, Forest Services (USDAFS), 1992). Complemented by altitude and its rugged terrain, the Chattahoochee National Forest has, over the last decade, become a place of growing attraction to people from all over Georgia and beyond. The once forgotten city of Helen in White county has come alive; various sites like the Unicoi State Park, the Mark Trail Wilderness and Yonah Mountain have become major attractions (Georgia Conservancy, 2003).

Data provided by the National Resources Spatial Analysis Laboratory (NARSAL), shows that in 1974 only 3% of the non-government forest land in the policy area was under residential/urban use. But thirty years later in 2005, 13% of the land was under urban development. Additionally, the proportion of land taken over by urban growth has doubled every

10 years between 1984 and 2005 (NARSAL, 2007). In the greater CRB, total farmland has decreased over the years, while poultry production has increased, particularly in North Georgia counties (GAEPD, 2000). The Georgia County Guide reports confined/concentrated animal operations (poultry, cattle, pigs), pasture and hay production as the dominant agricultural activities in North Georgia. The data indicates poultry production has been increasing over the years. In addition to increasing the demand for water (quantity wise), increased concentrated animal production raises the risk of water contamination with nitrogen and fecal coliform bacteria (FCB). Over the last decade, Georgia has experienced long periods of drought that have become both frequent and prolonged to the extent that in the later part of 2007, the state Governor declared a state of emergency and imposed water-use restrictions. All these factors have worked together to exacerbate the strain on Georgia water resources.

In the future, as population pressure and the demand for affordable meats increases, people, animal agriculture, and recreation activities will undoubtedly continue moving further north of Atlanta, stretching land and natural resources and increasing the economic value of the policy site.

Although quantity and quality are two different things, there is a simple connection between the two – assuming constant amounts of, say, dissolved substances, the quality of water is lower if the quantity is low. The water quality picture in Georgia may be worse than that of quantity. In 1995, for example, 49% of assessed stream miles in the entire UCRB were contaminated with fecal coliform bacteria to a partially-supporting or non-supporting level (GAEPD, 2000). With regard to metals (copper, zinc, lead), 24% of assessed miles were contaminated (GAEPD, 2000). Both fecal coliform bacteria and metal violations are associated with urban runoff as a primary source of non-point source pollution.

The prevailing population trends, growing water use, deteriorating water quality and land use trend (particularly the growth of the poultry industry), are likely to result in continued deterioration of environmental recourses. Further, as conversion of land away from "environment friendly uses" (such as forestry) continues, there will be an inevitable loss of ecosystem functions and services. Models of future land use and land use change could provide information on how the aforesaid changes would affect the value of ecosystem services and functions in this key watershed. The next section outlines the objectives of this study and the layout of the rest of the document.

Objectives

This study seeks to model land use change in the Upper Chattahoochee River above Lake Lanier and to provide economic valuation of watershed ecosystem services and functions. Specifically, the study will seek to:

1. Simulate three likely land use and land cover scenarios (or changes) and resulting changes in ecosystem services and functions for the policy site, using the current population and land use pattern as the benchmark. Projections will be done to the year 2030. The simulations of population and land use scenarios will be based on the following projections:
    a. The "High Growth" scenario, for instance assuming a high population growth rate for the site;
    b. The moderate growth scenario, say with continuation of "recent past trends" in population and land use;
    c. The "Managed Growth" scenario, e.g. with limited population growth.
2. Estimate economic value of the changes in the watershed ecosystem (services and functions) using benefits transfer techniques, with special emphasis on water quality.

The remainder of this dissertation is arranged as follows: In the following chapter we discuss theoretical framework and techniques for valuing environmental (ecosystem) commodities with emphasis on benefit transfer. We review existing literature on benefit transfer, and propose an empirical methodology and a road map for applying benefit transfer to measuring the economic value of the UCRB ecosystem.

In chapter three, we discuss the theory of modeling land use change and propose a methodology for estimating and forecasting land allocation in the ecosystem. Chapter four is a presentation of the empirical analysis of land use and a discussion of results of the land use model. In chapter five, we discuss the Long-Term Impact Assessment (L-THIA) model and its application to water quality assessment in an ecosystem. We also discuss water quality standards, forecast water quality in the UCRB based on land use change (discussed in chapter four), and apply benefit transfer to value water quality in the UCRB. Chapter six has the summary of our findings, conclusions and recommendations.

CHAPTER II

LITERATURE REVIEW: ECOSYSTEM VALUATION AND BENEFIT TRANSFER

Ecosystem Valuation: Review of Literature

There has been a major movement towards ecosystem-based (including watershed-based) management of natural resources over the last decade (Lambert, 2003). This can be attributed to the realization that ecosystems functions and services are so intertwined that human activities on one service affect another. In line with this trend, economists have in the last decade begun to place emphasis on valuing entire ecosystems as opposed to individual services. This shift seems to be prompted by the growing awareness that ecosystem and watershed services are seldom provided in isolation. Fragmenting ecosystem services might lead to overvaluation or under-valuation of the ecosystem.

A number of studies have attempted to place value on ecosystems. The most notable and ambitious attempt was by Constanza et al. (1997). The authors used existing studies (BT) to estimate the value of the world’s ecosystem services and natural capital (stock that provides these services). Their estimates covered only non-renewable services, and although the study does not value watersheds separately, it is critical in that it provides “a minimum value” of the world’s ecosystems, watersheds and watershed services and functions included.

The Constanza study used 100 past studies as a basis for estimation. As expected for a study of such magnitude, the study sites are diverse and are not provided in the paper. It is not clear whether it was values or functions that were transferred but one would imagine that it would be almost unrealistic to transfer functions for such a study. Also, one would imagine that requirements for carrying out BT were not necessarily strictly adhered to, as it would be impossible to carry out such a study while adhering to such requirements to the letter. For instance the question of correspondence between study and policy sites would be a real challenge in such a situation.

The said study estimates that the world’s ecosystem services are on average worth US$ 33 trillion (between US$ 16-54 trillion) annually about 1.8 times the current global Gross National Product(GNP) at 1994 US prices. The authors advocate for giving the natural capital stock adequate weight in the decision making process to avoid the detriment of current and future human welfare.

Verma (2000) used benefits transfer to value forests of the Himalal Pradesh state of India. The study used forest valuation in India and other countries to come up with economic values for the state forests. Available study details are sketchy, but although the emphasis is on forests, watersheds values are specified separately. To estimate watershed values, the study used the average value of all India watersheds based on case studies as an estimate for the value of the state's watersheds. The sketchy details do not allow for a serious critique of this study.

Toras (2000) estimated the economic value of the Amazonian deforestation using data from past studies. The original studies the author adopted used a mixture of market prices, direct and indirect methods. For instance, market prices were used to value marketable commodities like timber and foodstuffs; replacement costs were used to value nutrient loss due to soil erosion; TCM was used to value recreational benefits, CVM for valuing existence benefits etc. The author came then discounted the TEV of the Amazonian forest and arrived at a Net Present Value (NPV) of $1175/ha/yr at 1993 prices.

Kramer et al (1997) estimated the value of flood control services resulting from protection of upland forests in Madagascar. They used averted flood damage to crops to estimate the value of the service. They placed the flood protection value of the watershed at $ 126700.00, the amount of losses the community avoided from the presence of the forest park.

Alp et al (2002) applied BT to the estimation of the value of flood control and ecological risk reduction services provided by the Root River watershed (as the policy site) in Wisconsin. The study sites included Oak Creek and Menomonee River watershed both located in Milwaukee County, Wisconsin, most of which neighbors the policy site to the North. They observe that the sites are very close (geographically), were almost identical and were affected by the same problem. The authors suggest that their study findings could be used for the purpose of screening related projects.

Bouma and Schuijt (2001) documented a case study conducted by the World Wide Fund for Nature (WWF) to estimate the economic values of the natural Rhine River basin functions. The authors used market prices to estimate losses in fish production; and shadow pricing techniques to estimate losses in provision of clean drinking water, existence values and natural retention capacity. The total economic value of the four ecosystem functions was estimated at USD 1.8 billion per year.

In their study based a county in the Hubei province of China, Guo et al (2001) applied GIS and simulation models to estimate the value of some forest ecosystem functions and services. They used the TCM to estimate the economic value of forest tours; soil conservation was valued using replacement cost techniques; timber and marketable forest products, electricity generation and water retention and storage were valued using market prices; reservoir siltation control benefits were valued avoidance cost; carbon fixation and oxygen supply were valued using cost avoidance.

Loomis et al (2000) estimated the total economic value of restoring ecosystem services in an impaired river basin using CVM. The services in question were dilution of waste water, natural purification of water, erosion control, fish and wildlife habitat, and recreation. Results form contingent valuation interviews suggested a willingness to pay for additional ecosystem services ranging from $ 25.00 per month to $252 per year.

The range of approaches to estimating ecosystem services is almost as wide as the studies. Benefits transfer seems to be a common threat that links studies that estimate the value of entire ecosystems.

Theoretical Measures of Economic Value

Total Economic Value (TEV) can be viewed as the value of environmental resources, goods or benefits generated as determined by peoples' preferences. It is the sum of "Active use" and "passive-use" values. Watershed ecosystem active use values (AUV) are values derived from use of a natural resource. They include option, direct and indirect use values. Direct use values entail actual use of the ecosystem e.g. as a source of drinking water, site for bird watching, etc. Indirect use values are unrelated to current use but nonetheless linked to the ecosystem, e.g. ecosystem functions such as watershed protection and carbon sequestration by the soil and the forest. Option values are related to the option of using the site in the future.

Passive-use values (PUV) on the other hand include existence, altruistic and bequest values. Existence values have to do with the 'existence' of part of an ecosystem even though it has nothing to do with current or future use – many people derive satisfaction simply from knowing that an ecosystem exists. Altruistic values refer to values of ecosystem services that may accrue to other people in the current generation. Bequest values are related to value of ensuring that future generations will be able to enjoy ecosystem services.

Most environmental "commodities" (goods, services, functions) can be viewed as public goods with no real market transactions take place. This makes it difficult to measure changes in the quantities of such commodities. Such commodities are mostly available in fixed unalterable quantities. Policy changes affecting such commodities result in changes in the consumer's bundle hence the consumer's welfare.

There are two major approaches to measuring changes in consumer welfare i.e., Marshallian and Hicksian measures. Marshallian measures are useful when constant marginal utility of income assumption holds. In such cases, change in Marshallian Surplus (MS) accurately reflects ordinal changes in utility. Also, constant marginal utility of income implies path independence (uniqueness) i.e. that the final value will not depend on the order (path) in which the changes in price or quantity are evaluated for multiple changes. The assumption of constant marginal utility of income only holds in rare circumstances where individuals have homothetic preferences and changes in utility are very small. Moreover MS is not easy to measure.

Hicksian (exact) welfare measures (figure 2.1 – 2.4) are often preferred because they hold utility constant so that the money metric will always accurately reflect ordinal utility changes. Equivalent Surplus (ES) and Compensating Surplus (CS) are two exact welfare measures for imposed or rationed quantity changes (Freeman, 1993).

Equivalent Surplus can be defined as "The amount of money, paid or received, which places an individual at his or her subsequent utility level if the imposed quantity change does not occur, and optimizing adjustments are not allowed" (Bergstrom, 2002). The same source defines Compensating Surplus as "The amount of money, paid or received, which places an individual at his or her initial utility level after a restricted or rationed change in quantity where optimizing adjustments are not allowed".

Depending on the assumption we make about property rights of the individual, we could use either WTP or Willingness to Accept Compensation (WTA) to measure welfare changes. Eliciting realistic responses on WTA has been proven to be a difficult task so that often WTP approaches are used to measure WTA indirectly (Freeman, 1993).

The following discussion of measures of economic value follows Freeman (1993). Suppose we want to measure the value of an increase in environmental quality. We could assume a two commodities, economy and the environmental resource, Q and a "numeraire" commodity Y representing "all other goods", with a price P^0 = \$1.00. We could further assume that the individual has implicit or presumed rights to an initial (pre-policy/program) quantity Q^0 and utility level U^0 derived from the bundle (Q^0, Y^0) with Y^0 as the initial income level (recall P^0 = \$1.00) as depicted in figure 2.1. Let us assume also that a new policy results in increase of Q to Q^1. The individual's initial and subsequent (post-policy) utility levels can be expressed respectively as:

$$U^0 = V(P^0, Q^0, M^0) \tag{2.1}$$

$$U^1 = V(P^0, Q^1, M^0) \tag{2.2}$$

where $U^1 > U^0$, U^1 is post-policy utility level and M^0 is initial income. If we were to bring the individual back to the initial utility level U^0, we would need to take away from them income equivalent to:

$$CS = Y^0 - Y^1 \qquad (2.3)$$

where, Y^1 is the subsequent income level. In other words,

$$V(P^0, Q^1, M^0 - CS) = V(P^0, Q^0, M^0) = U^0 \qquad (2.4)$$

or $$U(Q^1, Y^0 - CS) = U(Q^0, Y^0) = U^0 \qquad (2.5)$$

The right hand side of equation 2.1 is the same as the left hand side of equation 2.4 and is represented by point A in figure 2.1. The left hand side in equation 2.2 is represented by point B. The right hand side in equation 2.4 is represented by point C in the same figure.

The implication here is that the individual is indifferent between subsequent (higher) level of Q and subsequent (lower) income, and initial (lower) level of Q and initial (higher) income. For our quantity increase scenario, CS is an income decrement corresponding to the Hicksian Compensating welfare measure (WTP^c) for the quantity increase, that is:

$$WTP^c = CS = Y^0 - Y^1 \qquad (2.6)$$

Now, suppose there is a decrease in the amount of environmental resource so that Q^1 is a lower quantity. If we continue to assume that the individual has implicit rights to the initial (pre-policy/program) higher quantity Q^0 and higher utility level U^0 derived from the bundle (Q^0, Y^0) with Y^0 as the initial income level as depicted in figure 2.3. The individual's initial and subsequent (post-policy) utility levels can be expressed respectively as:

$$U^0 = V(P^0, Q^0, M^0) \tag{2.7}$$

$$U^1 = V(P^0, Q^1, M^0) \tag{2.8}$$

where $U^1 < U^0$, Q^1 is post-policy quantity. If we were to bring the individual back to the initial utility level U^0, we would need to compensate them with income equivalent to:

$$CS = Y^0 - Y^1 \tag{2.9}$$

In other words,

$$V(P^0, Q^1, M^0 + CS) = V(P^0, Q^0, M^0) = U^0 \tag{2.10}$$

or $$U(Q^1, Y^0 + CS) = U(Q^0, Y^0) = U^0 \tag{2.11}$$

The right hand side in equation 2.7, which is the same as the middle term in equation 2.10 is represented by point A in figure 2.2. The right hand side in equation 2.8 is represented by point B and the first term in equation 2.10 is represented by point C in the same figure.

Thus the individual is indifferent between subsequent (lower) level of Q with subsequent (higher) income, and initial (higher) level of Q with initial (lower) income. Now, CS is an income increment corresponding to the individual's willingness to accept compensation for the lower level of Q or the Hicksian Compensating Surplus (WTA^c), that is:

$$WTA = CS = Y^1 - Y^0 \tag{2.12}$$

One could define CS in terms of the expenditure (instead of utility) function. Thus for a quantity increase, CS is an income decrement, representing WTP^c for the quantity increase.

$$WTP^c = CS = |e(P^0, Q^1, U^0) - e(P^0, Q^0, U^0)| \tag{2.13}$$

$$WTP^c = CS = |M^1 - M^0| \tag{2.14}$$

where $M^0 > M^1$ since it would cost less (therefore less income) to achieve U^0 with a higher level of $Q = Q^1$.

For a quantity decrease, CS is an income increment, representing WTA^c for the quantity decrease.

$$WTA^c = CS = |e(P^0, Q^1, U^0) - e(P^0, Q^0, U^0)| \tag{2.15}$$

$$WTA^c = CS = |M^1 - M^0| \tag{2.16}$$

where $M^1 > M^0$ since it takes more expenditure (therefore more income) to achieve U^0 with a lower level of $Q = Q^1$.

Now, if instead of assuming that the individual has implicit rights to the initial quantity we assumed s/he has rights to subsequent quantity, we would approach the analysis from the perspective of the other Hicksian measure of welfare change, i.e. the Equivalent Variation (EV).

Examining the scenario where a new policy results in an increase in amount of environmental resource from an initial quantity Q^0 to a subsequent quantity Q^1. When the change is an increase, i.e. $Q^0 < Q^1$, the individual's initial and subsequent (post-policy) utility levels can be expressed respectively as:

$$U^0 = V(P^0, Q^0, M^0) \tag{2.17}$$

$$U^1 = V(P^0, Q^1, M^0) \tag{2.18}$$

where $U^1 > U^0$, U^1 is post-policy utility level. In order to bring the individual to the subsequent utility level U^1, we would need to compensate them by an amount equal to:

$$ES = Y^1 - Y^0 \tag{2.19}$$

where, Y^1 is the subsequent income level, to bring them up to the subsequent utility level U^1 if the quantity change does not actually take place. In other words,

$$V(P^0, Q^0, M^0 + ES) = V(P^0, Q^1, M^0) = U^1 \tag{2.20}$$

or $$U(Q^0, Y^0 + ES) = U(Q^1, Y^0) = U^1 \tag{2.21}$$

The second term in equation 2.18 is the same as the second term in equation 2.20 and is represented by point B in figure 2.3. The second term in equation 2.17 is represented by point A. The first term in equation 2.20 is represented by point C. Thus the individual is indifferent between subsequent (higher) level of Q with initial (lower) income, and initial (lower) level of Q with subsequent (higher) income. In this case ES represent an is income increment corresponding to WTA^c to forego quantity increase.

Lets now assume that a new policy results in a decrease in amount of environmental resource from an initial quantity Q^0 to a subsequent quantity Q^1 so that $Q^0 > Q^1$. The individual's initial and subsequent (post-policy) utility levels can be expressed respectively as:

$$U^0 = V(P^0, Q^0, M^0) \qquad (2.22)$$

$$U^1 = V(P^0, Q^1, M^0) \qquad (2.23)$$

This is similar to equation 2.17 and 2.18 above except now $U^1 < U^0$. In order to bring the individual to the subsequent utility level U^1, we would need to take away from them an amount equal to:

$$ES = Y^0 - Y^1 \qquad (2.24)$$

to bring them up to the subsequent utility level U^1 if the quantity decrement does not actually take place. Thus,

$$V(P^0, Q^0, M^0 - ES) = V(P^0, Q^1, M^0) = U^1 \qquad (2.25)$$

or $$U(Q^0, Y^0 - ES) = U(Q^1, Y^0) = U^1 \qquad (2.26)$$

The second term in equation 2.23 is the same as the second term in equation 2.25 and is represented by point B in figure 2.4. The second term in equation 2.22 is represented by point A. The first term in equation 2.25 is represented by point C. The individual is indifferent between subsequent (lower) level of Q with initial (higher) income, and initial (higher) level of Q with subsequent (lower) income. Now ES represents an income decrement corresponding to WTP^e to prevent quantity decrease.

Another, more complex way to look at this is to derive the inverse Hicksian demand function or the Marginal WTP function (MWTP). For example maintaining the assumption that the individual has a right to the initial quantity (as in CS) and assuming an increase in quantity of the commodity as in equation 2.1 through 2.6, the inverse demand function can be presented as:

$$W_Q = b(P, Q, U^0) \qquad (2.27)$$

where W_Q is MWTP for Q; P is the price vector; U is utility. The expected value of WTP can be presented as:

$$EWTP = E[CS] = \int_{Q^0}^{Q^1} (W_Q) dQ \qquad (2.28)$$

Equation 2.28 is equivalent to equation 2.13 and integrating provides the area below the MWTP between the two quantities – figure 2.5. Similar models can be written for a decrease in quantity and under the ES approach. The parameter estimates of equation 2.28 can be arrived at by specifying and estimating the functional form for the observable components of utility.

Most ecosystem values, both active passive use, render themselves to measurement by ES or CS. Most direct use values can be measured using market prices since they are marketable. Moreover, measurement is relatively easy for commodities whose preference is readily revealed through expenditure eg camping, hunting, sight seeing, bird-watching which are often measured using Marshallian Surplus.

In regard to producers, changes in welfare can be measured using producer surplus. Suppose the environmental resource in question is used in the production of other goods e.g. wood/lumber; changes in a watershed ecosystem might entail increasing the wilderness area and therefore reducing access to wood for lumbering. This would adversely affect economic rents accruing to lumbering firms. Total Economic Value for such an ecosystem would be incomplete without taking to account such changes.

Economic rent is an economic surplus or excess of benefits over costs. Producer surplus (PS) is a good measure of the firm's economic rent. $PS = TR - TVC$, where TR is total revenue, TVC is total variable cost. The producer surplus (A in figure 2.5) can be presented as:

$$\begin{aligned} PS &= TR - TVC \\ &= \Pr ofit + TFC \\ &= (P_1 Q_1) - \int (MC) dQ_1 \end{aligned} \tag{2.29}$$

where TFC = total fixed costs.

Now suppose that for some reason there is a decrease in lumber from the watershed ecosystem from Q_2. to Q_1(figure 2.6),there will be a loss in producer surplus to the firm equal to area A1.

This is a CS measure that assumes the firm has rights to the higher initial Q, Q_2. The same loss can be equated to A1 = WTP^e, i.e., the firms willingness to pay to prevent quantity decrease to Q_1. This is an ES measure that assumes the firm has rights to the subsequent quantity of Q, Q_1. Conversely, for a quantity increase from Q_1 to Q_2, the gain in producer's surplus to the firm is Area A1 = WTP^c (CS measure) = WTA^e (ES measure).

Considering figure 2.7, if there is a reduction in lumber from X_0 to X_1, say due to an expansion of the wilderness area in an ecosystem, lumbering firms may have to depend on other more expensive sources of lumber; log prices rise from W_0 to W_1. The loss in producer welfare to lumbering firms (now viewed as consumers) is really an increase in variable costs which, assuming perfect elasticity of the input, can be represented by area A2 in figure 2.7.

Now, for a price increase from W_0 to W_1, the loss in producer welfare (“consumer surplus”, since the firm is here viewed as a consumer of inputs) is area A2 = WTA^c (CV measure, assuming the firm has rights to the lower initial Price, W_0) = WTP^c (EV measure, assuming the firm has rights to the higher subsequent price, W_1).Most marketable services of the ecosystem such as agricultural values like provision of irrigation and livestock water, and lumbering would be easily valued using producer surplus.

Conventional Environmental Valuation Techniques

Ecosystem valuation has for a long time been done using traditional techniques of valuing non-marketed goods and services including direct and indirect techniques. Direct (revealed preference) techniques rely on actual expenditure to ***reveal*** the preferences of individuals for environmental goods or services associated with the expenditure (e.g. the added value of a house near a forest, or the cost of traveling to a national park). These techniques include hedonic pricing (HPM) and travel cost method (TCM). These methods are limited in that they can only capture use values.

Hedonic pricing is based on the assumption that people value the characteristics of a good, or the services it provides, rather than the good itself. It is mostly used to measure the effect of natural amenities on property hence the value that people attach to the amenity. For instance the prices of residential property near a lake reflect the value of a set of property characteristics, including distance from the lake; structural characteristics of the house; neighborhood characteristics etc. When factors other than proximity to the lake are controlled for, any remaining differences in price can be attributed to differences in proximity to the lake.

With TCM, a survey is used to capture information for all people visiting a particular site say each year. Data collected covers distance traveled; cost of travel, county and state of residence of the visitor; socio-economic characteristics of the visitor; direct travel-related expenditures.

The correct multiplier is used to isolate travel cost due to visitation to the site other from all the other purposes of visit to the area, mostly from a regression equation. Demand for visits to the site and consumer surplus per person per trip are estimated and aggregation is done to arrive at the total value.

Indirect (stated preference) techniques rely on questionnaires to elicit participant’s response to questions that simulate a market situation. Indirect techniques have the advantage of being able to capture non-use values. The major one of these techniques is Contingent Valuation Method (CVM).

The Contingent Valuation Method (CVM) seems to be the most commonly used techniques of measuring the value of improvements in ecosystem or resource quality. The CVM adopts survey and questioning techniques to estimate individual's expressed preferences (willingness to pay) for changes in the level of public resources contingent upon a hypothetical market situation (Jordan and Elnagheeb, 1993). It is assumed that people will respond to the contingent market as if it were a real market situation.

Table 2.1 outlines various watershed ecosystem commodities, types of economic valuation measures that could or have been used to value the commodities and the respective valuation methods. The list is not intended to be exhaustive.

Benefit Transfer Estimation

In the recent past, "benefit transfer" (BT), sometimes called "benefits transfer", is becoming increasingly useful as an approach to valuation of non-marketed public goods and service. Brookshire and Neill (1992) suggest that, "A benefit transfer is the application of monetary values obtained from a particular nonmarket goods analysis to an alternative or secondary policy decision setting".

Table 2.1: Ecosystem commodities, Measurement techniques and Valuation methods

Benefit/Commodity provided by ecosystem	Type of Economic Value Measure	Valuation Method	Reference
Forest products – fuel wood, timber, poles	Producer surplus – EV, CS	Demand/supply analysis; market prices; surrogate market prices	Guo et al (2001)
Agricultural Land (Productivity)	Producer Surplus – ES, CS	Market Prices; Rental Rates; demand/supply analysis; Production Function Approach/Productivity Analysis	Kramer et al (1995); Guo et al (2001);
Livestock Water Demand	Consumer Surplus – CS, ES	CVM; avoidance costs	*Adhikari(2004)*
Irrigation Water Demand	Producer Surplus – ES, CS	Market prices; rental Rates; Supply and demand (Marginal cost/Marginal Benefits) Analysis; Production Function	Acharya (2000); Banerjee (2004)
Real Estate Values	Consumer Surplus – CS	Revealed through Property/ Values – HPM	Hanson and Hatch (1998); Mahan (1997);
Water Quality - drinking water;	Consumer Surplus – CS, ES	CVM; avoidance costs; Shadow Prices	Bouma and Schuijt (2001); Kask et al(1994)
Water Quality for fishing	Consumer Surplus – CS, ES	CVM; avoidance costs; Market Prices	Bouma and Schuijt (2001)
Water Quantity – municipal water demand	Consumer Surplus – CS, ES	CVM; avoidance costs; Market Prices	Misra S. (2002); Guo et al(2001); Acharya (2000)
Existence Values; option values; bequest values	Consumer Surplus – CS, ES	CVM; Shadow Prices	Bouma and Schuijt (2001)

Benefit/Commodity provided by ecosystem	**Type of Economic Value Measure**	**Valuation Method**	**Reference**
Carbon sequestration; Nutrient Cycling Air Pollution reduction Micro-climate regulation Clean Air Climatic Change	CS; ES; producer surplus	Avoidance costs; Market prices; CVM; Production Function Approach	Tri et al (1996); Guo et al (2001)
Flood control	Consumer surplus - CS	CVM; Avoidance costs; demand/supply analysis; HPM	Alp et al(2002); Kramer et al (1995)
Siltation control, reduction in water storage capacity – e.g. for downstream dams	Consumer surplus – CS, ES	Avoidance costs;	Guo et al (2001)
Hydroelectric Power Generation	Consumer surplus – CV, EV	Avoidance costs; Market Prices	Guo et al (2001)
Recreation values i.e Camping Days; bird watching; fishing; hunting	Consumer surplus – CS; ES; MS	TCM; CVM	Hanson and Hatch (1998); Bowker, English and Donovan(1996)
Biological Diversity and Nature Conservation	Consumer surplus – CS; ES	CVM	White and Lovett(1197);
Eco-tourism	Consumer surplus – CS; ES	TCM	Menkhaus and Lober (1995);

Rosenberger and Loomis (2000) add one of the basic tenets of benefits transfer, that is, the sites have to be similar. They define Benefits Transfer as - "The adaptation and use of economic information derived from specific site(s) under certain resource and policy conditions to a site with similar resources and conditions". In BT literature, the site that provides data is referred to as the study site, while the site to which data is transferred is called the policy site.

Benefits Transfer Estimation (BTE) is gaining importance because of its usefulness whenever it may not be practical for an organization to collect data on which to base economic value estimation at short notice (Bergstrom and Civita, 1999), and in cases where a high degree of precision is not critical (Du, 1998). This approach reduces costs (Kask and Shogren, 1994) and is therefore important during times of public funding cuts. It enables estimation within a shorter time than traditional methods, reducing the time it takes for policy makers to make informed decisions (Bingham, 1992). Economists realize that benefits transfer estimates can, in the best case scenario, be only as good as the original studies. Thus benefits transfer is regarded as a "second best" approach to measuring economic value (Resenberger and Loomis, 2000) basically because it relies on secondary data.

Benefits Transfer Estimation has been applied in many areas including valuation of forest and rangeland resources (USDA forest Service, 1990; Verna, 2000) outdoor recreational services including recreational water quality (Du, 1999; Rosenberger and Loomis, 2000; Mitchell and Carson, 1984), flood control and ecological risk reduction services (Alp, Clark and Novotny, 2002) ecosystems (Constanza et al, 1999), ground water quality (Bergstrom, Kevin and Boyle, 1992; Denevan and Alp, 2001); cancer and smog reduction (Caulkins and Sessions, 1997).

Moreover it is evident that BTE will continue to play a key role in the policy arena with state and government agencies using, recommending or allowing use of the technique in public policies and policies that impact on natural resources and the environment (NOAA, 1996; USEPA, 1983; US Water resource Council, 1983; USDA Forest Service, 1990; Bergstrom and Civita).

Literature provides a number of types of BT including expert judgment, value transfer, benefits function transfer, and meta analysis (Bergstrom and Cavita; Rosenberger and Loomis; Brookshire and Neill; Loomis, 1992; US Water resource Council, 1983).

Value transfer entails transfer of a single point estimate or the transfer of a measure of central tendency, e.g. the mean or median WTP. Single point estimate transfer is based on estimate from one study or a range of estimates if there are a number of studies. Expert judgment entails aggregating values derived from an expert or a panel of experts with the relevant adjustments.

Transfer of benefits function or value estimator model entails using the benefits function derived from the study site together with explanatory variable data derived from the policy site to estimate the total number of units and value per unit at the policy site. Benefits function transfer enables accounting for differences in physical and demographic characteristics between study and policy sites and is considered superior to fixed value transfer (Loomis, 1992).

In the context of BT, Meta analysis can be viewed as the statistical summarization of results of individual valuation studies to be and using the summarized findings to value changes at a policy site. Thus data for meta analysis is mostly summary statistics including population characteristics, environmental resources of study site, and valuation methodology use. In most cases, meta regression analysis is applied to a benefits function based on data from previous studies to estimate the value of the policy site (Poe, Boyle and Bergstrom, 2001; Rosenberger and Loomis). Although Meta analysis has been used in BT, a number of authors including Poe, Boyle and Bergstrom; Delevan and Epp, 2001 do not view meta analysis as a suitable tool for BT. Delevan and Epp view Meta analysis as an unsatisfactory transfer tool and argue that summarizing a number of studies and methodologies may lead to erroneous coefficients.

The authors Poe, Boyle and Bergstrom argue that Meta analysis is based on a number of studies with different methodologies and resulting values that vary systematically across the studies. They urge caution in using Meta analysis to provide value estimate for policy analysis. Given these misgivings and the trend away from Meta analysis in the recent past, we opt not to use Meta analysis as a method of BT in this study. Understandably, the literature seems to lean toward two major methods of BT namely, value transfer and benefits function transfer (Bergstrom and Cavita; Rosenberger and Loomis; Brookshire and Neill; Loomis).

Rosenberger and Loomis outline a number of problems related to Benefits transfer. The quality of original data affects quality of process, and data documentation is often insufficient. In addition there are not many existing studies and those that are available will not have been conducted with benefit transfer in mind so the data they provide is not necessarily amenable to benefit transfer.

Given these problems there has been quite some controversy surrounding the technique. Brookshire (1992) recommends that the final use of benefit estimate should determine its required accuracy and proposes a continuum from “Gains in Knowledge” at the lowest end through "Screening of projects", "Policy decision" and "compensating damages/utility externality costs" at the highest end. Brookshire and Neill (1992) suggest that BT estimates should only be used towards the low end of the continuum. Devouges et al (1992) offers a similar continuum but is more optimistic about potential uses of BT.

It appears as suggested by Smith (1992) and by Bergstrom and Boyle (1992) that economists are divided into two camps over the issue of Benefits transfer; those who would rather wait for the ideal data (idealists) on one hand, and those who believe that some information is better than none (pragmatists) on the other.

Protocol for Meaningful Benefit Transfer

A number of conditions necessary to ensure effective and efficient benefits transfer estimation are discussed by several authors including Rosenberger and Loomis.

First the policy context should be thoroughly defined to identify three issues namely: impact of proposed action, relevant population to be affected and data needs.

Second, the study site data should meet certain conditions for critical benefits transfer. It should have adequate data, methods, and empirical analysis; information on benefits/costs and characteristics of affected pop; information on statistical relationship between benefits/costs and physical characteristics of the site; and adequate number of individual studies for credible inference.

Third, there has to be correspondence between study and policy sites with regard to environmental resources and changes; markets, population demographics and cultural aspects; conditions and quality of resource use activities and experiences.

There seems to be a general consensus that benefits transfer should be done systematically. Rosenberger and Loomis; Desvousges, Naughton and Parson (1998); Saplaco and Herminia(2003) identify a set of steps that should form the necessary procedure to BTE. From an examination of the two sources, the procedure can be summarized as follows:

1. Identify the resources (forests, wetlands, wildlife etc) affected by the proposed action;
2. Translate resource impacts to changes in commodity (goods, services, functions) use ;
3. Measure commodity use changes;
4. Conduct a literature search for relevant study sites;
5. Assess relevance and applicability of study site data;
6. Depending on the approach selected (value transfer, function transfer or expert opinion) identify or

forecast a benefit measure from the study site to the policy site.

7. Adjust the benefits measure for any differences in site characteristics between the study and policy site. These may not be easy to make, particularly where the benefits function approach is not feasible. Adjustment for per capita income or Gross Site Product (GSP) which is the Gross Domestic Product (GDP) of study site, and the price level are most common and are discussed later.
8. Determine total number of affected units (e.g. households, individuals) in the policy site, Aggregate the benefits over the entire policy site by multiplying the benefit measure by affected population.

Empirical Methodology and Data Issues

This research took place in stages. The first stage was to establish a benchmark for simulation of land use change, by taking stock and creating an inventory of resources at the policy site. In taking stock, an attempt was be made to map out the current land use (and land cover) patterns. Data and information for this exercise were sought mainly from NARSAL (2007).

Stock taking was done simultaneously with creating an inventory of past studies that have measured values that could be derived from similar ecosystems and ecosystem resources. These studies were later used for benefit transfer.

The second stage entailed developing a land use and land use change model for the area, and postulating different land use scenarios as discussed in chapters three and four. Land use determines the level of ecosystem services and functions provided by the watershed. Land use changes therefore precede changes in ecosystem functions and services.

The third stage entailed quantifying changes in underlying ecosystem services, specifically water quality, for various land use scenarios. For instance suppose the amount of land under forest decreases by a certain amount, and the amount of land under commercial land use increases by the same amount, we would at this stage estimate the extent of say an increase in runoff and subsequent concentration of suspended solids in the streams in the ecosystem, etc.

The fourth stage entailed quantifying and measuring the economic value of the aforesaid changes in ecosystem services and functions resulting from changes in land use. Such effects will be reflected by changes in value of amenities, services and functions e.g. change in price/cost of drinking water in the neighboring counties, changes in number of fish caught in the area streams the and the value of the same, increase in number of sick-off days, etc. Measurement of the economic values resulting from the identified economic effects was done using Benefits Transfer. This study closely followed the procedures for benefits transfer outlined earlier with regard to valuation. Below is an hypothetical example of how the protocol would be (and was) applied.

Benefit Transfer Analysis: A Hypothetical Case

One of the major ecosystem services provided by our policy site is drinking water quality. Over time, there will be changes in land use which will cause changes in this service. Let us postulate a high growth scenario, and imagine that during the second stage of our study, land use models lead us to believe that there will be a takeover of some of the wetlands in the UCRB (identified during the first stage of research) by real estate developers. Scientific knowledge tells us that such takeovers will most likely lead to a deterioration of drinking water quality due to the reduction in runoff sinks so that more nutrients end up in drinking water sources. This knowledge is further established in the third stage of our research. In the fourth stage of the study we ask what people, both within and outside the policy site, would be willing to pay to fund a program that forestalls the wetland takeover and therefore protects drinking water quality. Benefits transfer will be used to value drinking water quality changes, following these general steps:

The resource affected by the proposed action is identified as the wetlands;

Translating the impact on wetlands to changes in water quality is the second step, which is carried out as outlined above;

Measuring change (reduction) in drinking water quality at the policy site is the third step – Assuming that the individual has a right to the initial situation (higher drinking water quality, with the wetlands), a decrease in drinking water quality could be measured using CS which represents an income increment corresponding to the individuals willingness to accept compensation (WTA^c) for the lower level of water quality. Given the difficulties of measuring WTA^c discussed earlier, we will follow Freeman (1993) and measure WTA^c indirectly through WTP^c . In essence this means that we will assume that the individual has a right to the subsequent lower quality. Thus we will use ES, representing an income decrement corresponding to the individual's willingness to pay (WTP) to prevent a water quality decrease.

The fourth step entails conducting a search for relevant study sites – we will search for published and unpublished articles that have carried out similar studies. Such studies will most likely use the CVM to value drinking water quality in relation to wetland removal/sustenance.

The fifth step will entails assessing relevance and applicability of study site data – This step will involve identifying and isolating studies based on sites that are as similar as possible to the policy site with respect to geography, income, preferences, culture, substitution, social characteristics.

The next step will entail identifying or forecasting a benefit measure from the study site to the policy site – This will depend on the approach we find to be most suitable. Our method of choice will be the functions transfer approach given its advantages discussed earlier. To perform this sixth step, the fifth step, above, would of necessity entail finding out whether the benefits transfer functions have been specified in the sources. This step will then entail adapting the benefits function(s) to the policy site characteristics and forecasting the benefit measure. For instance where the primary study is based on CVM the model could be as follows:

$$WTP = \alpha + \beta_{1*}Q + \beta_2 SEC + \beta_3 SC \qquad (2.30)$$

where α, β_1, β_2 and β_3 are coefficients from the primary study, Q represents (perceived) quality of drinking water, SEC is a vector of socioeconomic characteristics of the user population, while SC is a vector of other characteristics of the site. Incorporating SEC and SC allows us to adjust for differences in the study and policy sites.

In case there are no relevant and applicable studies where the benefits functions are specified, then the value transfer will be our second choice method. In that case we will use the single unit value for this step where there is only one relevant study or an average over the several relevant studies. In the rare event that there are absolutely no relevant studies, the opinion of a panel of experts will be sought as a last resort. Such a panel could be composed of persons familiar with the site and with valuation sourced from academia, USDA, USFS, and USFWS.

Adjusting the benefits measure for any differences in site characteristics will be done as provided for in the preceding step. This is not possible for value transfer. Whatever the transfer method, adjustment for income and time will be done following the procedure presented below.

The last step will entail determining total number of units (individuals or households) affected by the reduction in water quality. This will be done using population data for the area and the surrounding areas that could be affected. Aggregate the benefits over the affected population by multiplying the benefit measure by total number of individuals affected by the wetland takeover and subsequent water quality change.

Adjustments for per capita income represented hereafter as Gross Site Product (GSP) which is the Gross Domestic Product (GDP) of study site, and the price level will follow Saplaco and Herminia (2003).

Income (GSP) adjustment is as follows:

$$A_{1i} = \frac{X_{i,ss}^{o}\{GSP_{ps}^{t}\}}{GSP_{ss}^{t}} \tag{2.31}$$

where,

A_{1i} = i[th] study site value after first adjustment;

$X_{i,ss}^{o}$ = Initial i[th] Study site value

GSP_{ps}^{t} = GSP of the Policy site for the current year

GSP_{ss}^{t} = GSP of Study site for the current year.

The second step will entail adjustment of the price index will be to offset the inflation effects between the time the study was carried out and the present time. This adjustment will be as follows:

$$A_{2v} = A_{1i}\{\frac{CPI_{ps,o}^{t}}{CPI_{ps,o}^{o}}\} \tag{2.32}$$

where, A_{2v} = ith study site value after second adjustment - this is essentially the policy site value;

A_{1i} = ith study site value after first adjustment;

$CPI^{t}_{ps,o}$ = CPI of the policy site for the current year using study year as a base year

$CPI^{o}_{ps,o}$ = CPI of the policy site for the study year using the study year as a base year. Thus the final term, A_{2v}, will have undergone the following adjustment:

$$X^{t}_{i,ps} = A_{2v} = X^{o}_{i,ss} \left\{\frac{GSP^{t}_{ps}}{GSP^{t}_{ss}}\right\} \left\{\frac{CPI^{t}_{ps,o}}{CPI^{o}_{ps,o}}\right\}, \qquad (2.33)$$

where, $X^{t}_{i,ps}$ is the value of policy site.

For each ecosystem commodity, benefits transfer estimates will be discounted to come up with the Present Value (PV) of the resource. The total ecosystem value will be arrived at by aggregating over all the commodities that the site has to offer. Care will be taken to avoid double or even multiple counting.

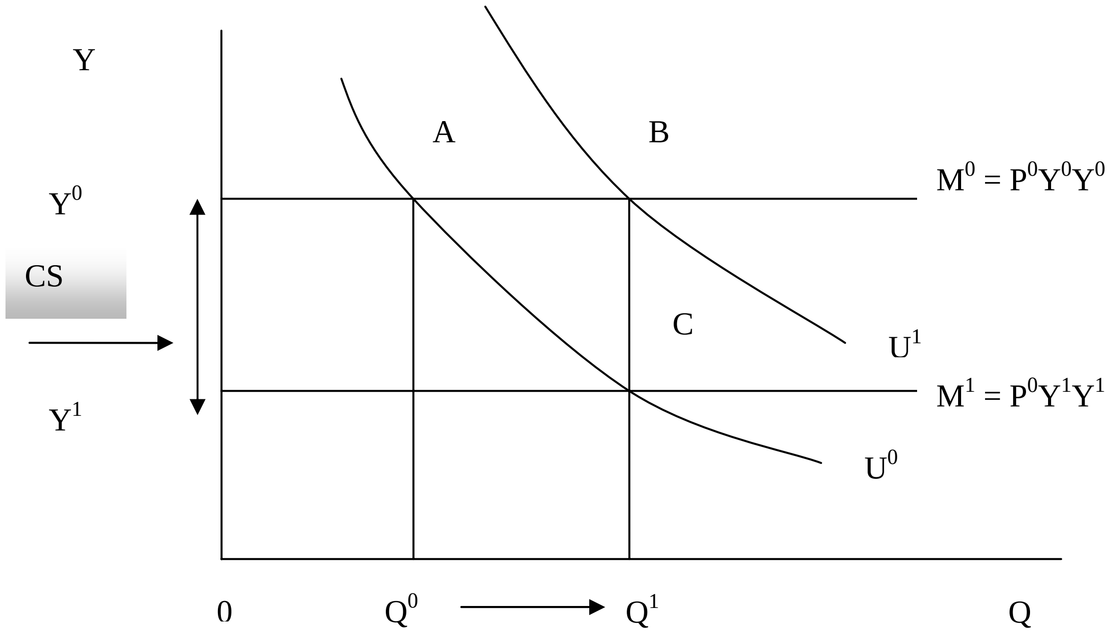


Figure 2.1 Compensating Surplus with Quantity Increase

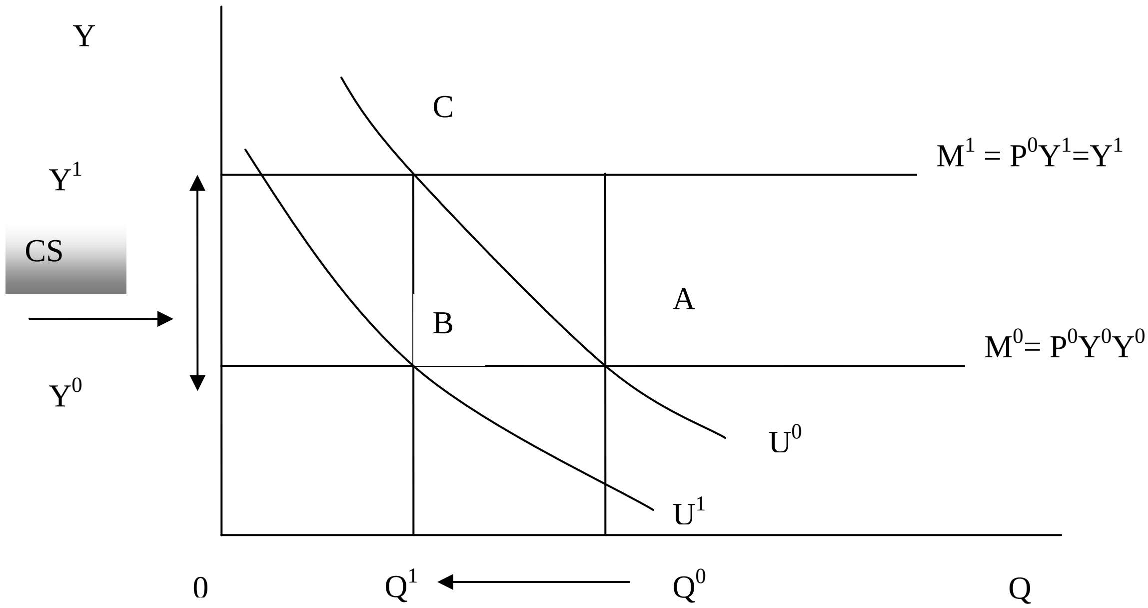


Figure 2.2 Compensating Surplus with Quantity Decrease

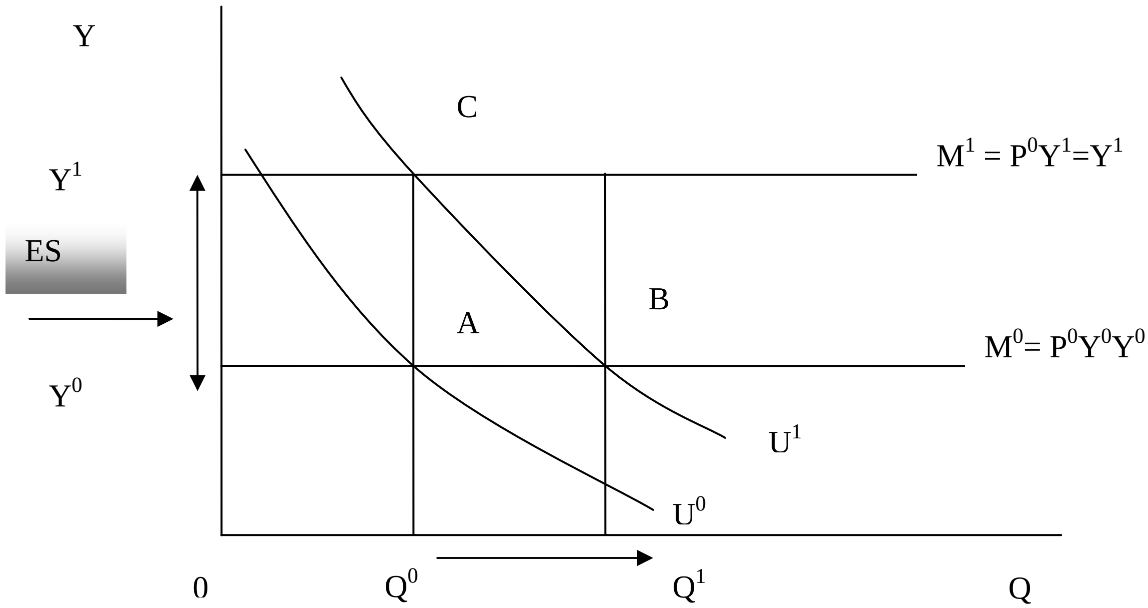


Figure 2.3: Equivalent Surplus with Quantity Increase

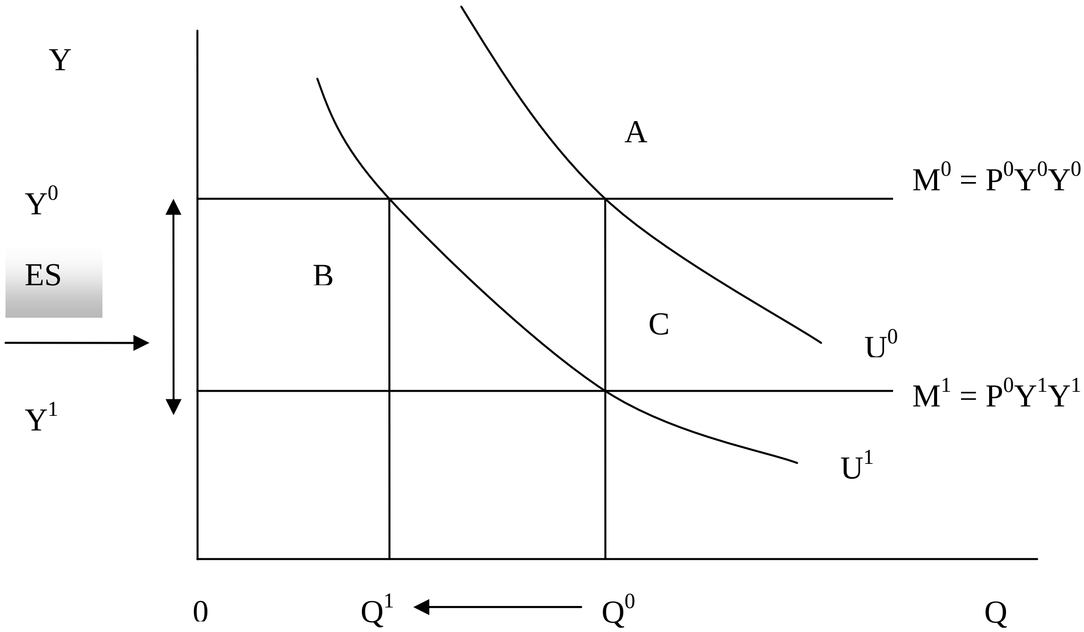
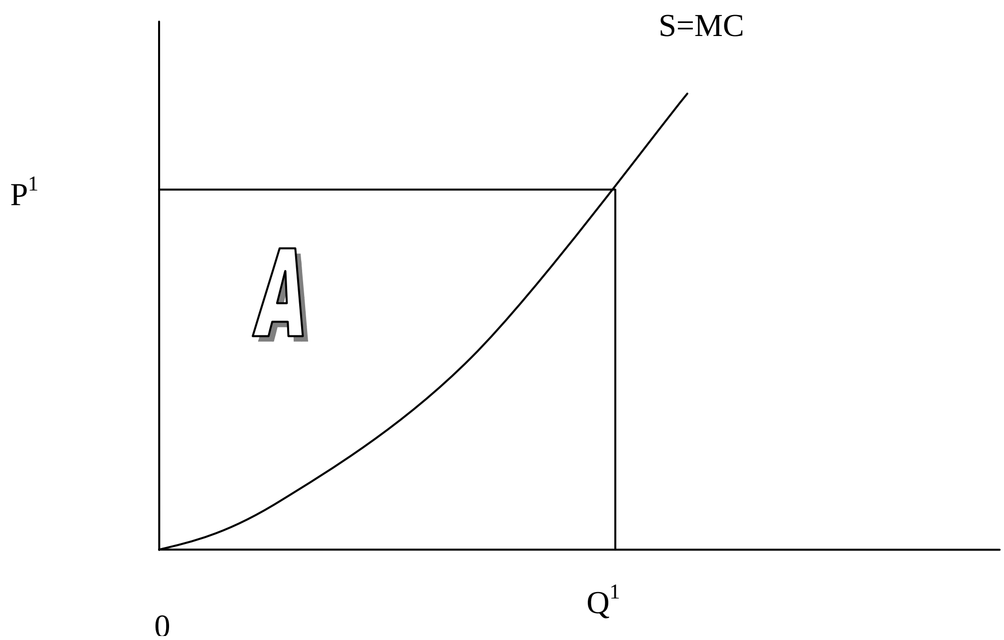


Figure 2.4: Equivalent Surplus with Quantity Decrease



2.5 The Producer Surplus

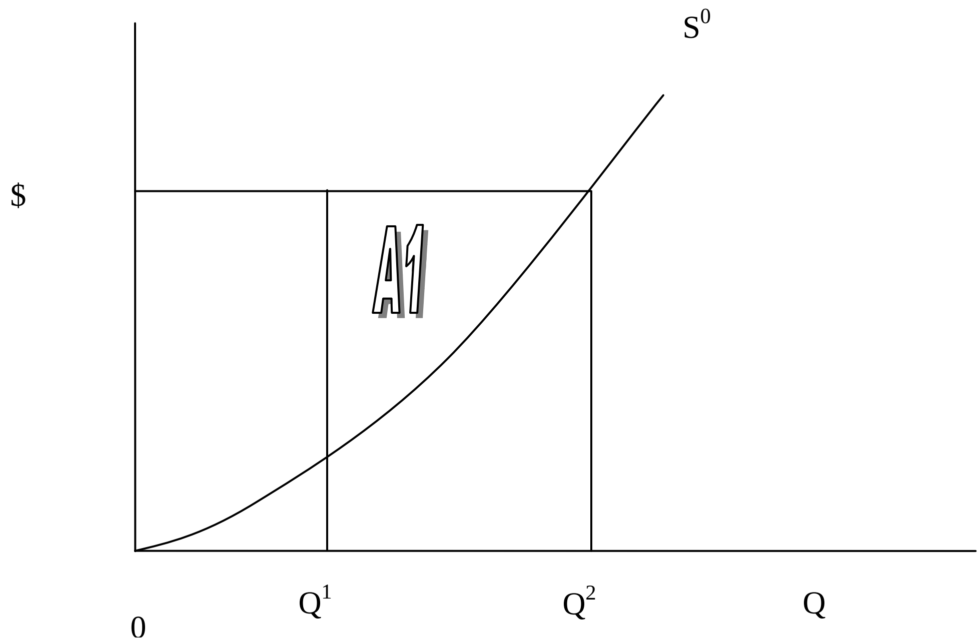


Figure 2.6: Changes in Producer Surplus With Quantity Change

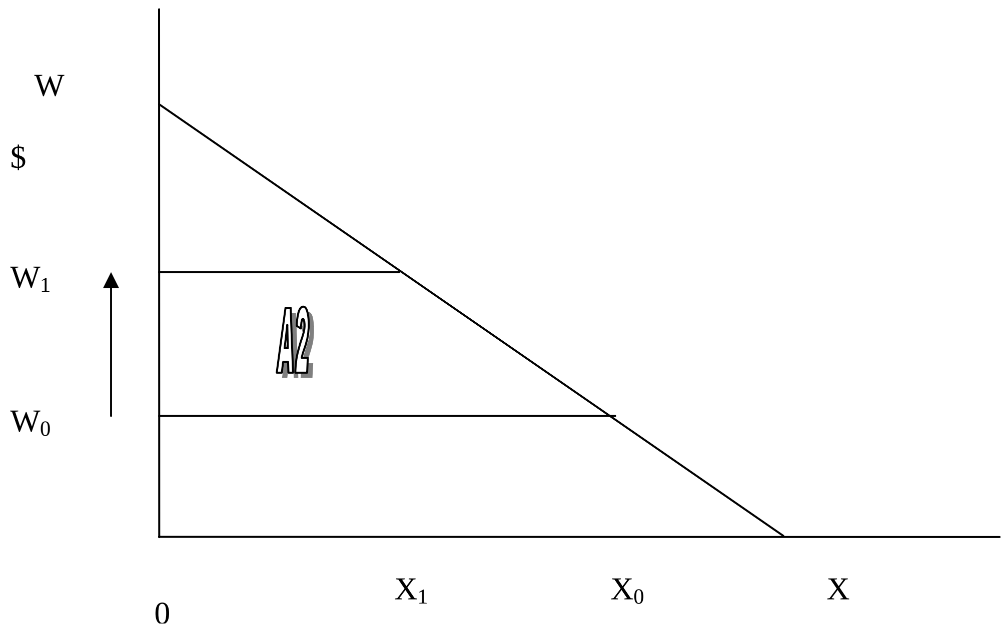


Figure 2.7: Changes in Producer Welfare with Price Change

CHAPTER III

THEORETICAL LAND USE MODEL

Overview

In this section we discuss theoretical land use modeling under the assumption of risk neutrality. The risk neutrality assumption is found to provide the best estimates of acreage allocation, and, it is simple in the sense that there is no need of incorporating risk taking/aversion behavior of the economic agent (Miller and Plantinga, 1999; Ahn, Plantinga and Alig, 2000).

Analysis of optimal land allocation has been carried out by a number of authors including Miller and Plantiga (1999); Plantinga, Maulding and Miller (1999). The aforesaid studies have applied econometric models to estimate aggregate (such as farm and forest as opposed to crop level) land allocation. Land allocation, and the many factors affecting it, change over time. This makes land use (and land use change)a suitable candidate for time series and structural time series modeling.

Farm acreage response/farm land allocation among (different) crop enterprises have been estimated using econometric and time series models (Duffy, Shaishali, and

Kinnucan 1994; Houston et al., 1999; Wu and Segerson, 1995; Plantiga, 1996; Lichtenberg, 1989; Banerjee, 2004). Structural Time Series Models (STSM) pioneered by Harvey (1989) have seen recent use in estimating farm acreage response models (Houston et al., 1999; Adhikari, 2004). The STSM has the advantage of being able to capture structural and technological change, which are either overlooked or assumed to be deterministic in conventional econometric and time series modeling. Despite these benefits, the STSM has not been exploited much in aggregate acreage response modeling.

This study pursues three approaches to modeling aggregate land use, namely, econometric, time series and structural time series analysis. Based on the forecasting ability, we choose the best model from the three, and apply it to forecast land allocation in the upper Chattahoochee river basin, in North Georgia.

Theoretical Econometric Model

Following Wu and Segerson (1995) and Miller and Plantinga(1999) we develop a model of land allocation at the aggregate watershed (two-county) level, assuming profit or net benefit maximization under risk neutrality. Consider a land manager/owner who maximizes total restricted returns to A acres of land, by allocating the land optimally among i alternative uses (i= 1,…n). We use discounted (present value) benefits approach to account for the fact that returns to forestry are realized over long periods of time. The land allocation process can then be expressed as:

$$\max_{Ai} \sum_{i=0}^{n} \prod_i (X) \qquad (3.1)$$

Subject to,

$$\sum_{i=0}^{n} A_i = A \qquad (3.2)$$

Where X = Matrix of exogenous variables

A_i = Acreage of the i^{th} land use

A = Total available acreage

$\prod_i$= expected returns from land use i.

Solving the constrained profit maximization problem above gives us the optimal allocation to land use i, denoted by

$$A_i^* = f_i(X) \text{ for all i=1,…,n} \qquad (3.3)$$

We can rewrite equation 3.3 from the land share perspective as follows:

$$S_i^* = \frac{A_i^*}{A} = \frac{f_i(X)}{A} \qquad (3.4)$$

$$S_i^* = S_i(X) \qquad (3.5)$$

where S_i^* = optimal expected share of land use i.

Analytically, equation 3.5 can be estimated as a flexible functional form for the restricted benefits function or for the acreage function and the implied share equations can then be derived (Moore and Negri, 1992; Shumway, 1983; Wu and Segerson, 1995). Alternatively one can estimate such a functional form for the share equations themselves.

We choose this (share equation) approach as it best represents the way we view land allocation. The extent of land is static but over time land is allocated across different uses depending on the use that maximizes the land owner's welfare. We follow Wu and Segerson(1995) and estimate the share equations assuming a logistic distribution of the error terms. This assumption has the advantage of ensuring the shares lie in the zero-one range. The approach is fairly common in the literature including Lichtenberg (1989) and Plantinga(1996). As Wu and Segerson (1995) observe, the logistic distribution outperforms other functional forms such as the Almost Ideal Demand System (AIDS) and the translog model.

Again given equation 3.5 and using county averages, the share of use i at time t, can be written as follows:

$$S_{it}^{*} = \frac{\exp\left[f_i(X_t)\right]}{\sum_{i=0}^{n}\exp\left[f_i(X_t)\right]} \qquad (3.6)$$

where exp[ ] is the exponential function.

We sum up over 3 land use types namely farming, forestry and urban (industrial, commercial and residential). We select the "urban" category as the normalizing land use alternative and rewrite the share equations as:

$$\ln(S_{it}^*/S_{0t}^*) = f_i(X_t) - f_0(X_t) \qquad (3.7)$$

Since i=0 is the normalizing land use, equation 3.7 reduces to

$$\ln(S_{it}^*/S_{0t}^*) = f_i(X_t) \qquad (3.8)$$

which can be estimated as:

$$Y_{it}^* = \alpha_0 + \mu_t + \beta_i^{'} X_{it} + e_{it} \qquad (3.9)$$

where α_0 is the intercept; Y_{it} is the land share of use i, (over share of use 0); $\beta_i^{'}$ is a vector of parameters to be estimated; X_{it} is a vector of independent variables for land use i, μ_t is the time trend variable which could be deterministic, stochastic or absent altogether, and e_{it} is the error term.

Equation 3.9 is a typical econometric model representation. If the vector of dependant variables is made up of lagged dependant variables, then we have a time series model. Structural time series analysis on the other hand views changes in the dependant variables as resulting from structural or technological change. We can model these kinds of changes using elements of time such as trend and seasonality.

Structural Time Series Modeling

A Structural Time Series Model (STSM) of land use is estimated in order to incorporate existing structural or technological change. The issue of structural/technological change seems to have been overlooked in most of the literature on land use change including crop acreage response models.

Most authors incorporate trend dummy variables in their models to capture the impacts of technological progress (Chavas and Holt, 1990; Shideed et al., 1987). However, one limitation of these studies is that they assume a deterministic trend component in acreage response and specify the model with a time trend.

We choose to let the data tell us the nature of the trend, and by implication the structural/technological change. We do so by estimating three options that incorporate trend components in our land use share equations, that is, stochastic trend no seasonality(STNS); fixed trend no seasonality (FTNS); no trend no seasonality (NTNS). We assume "no seasonality" because we are using annual data without the possibility of capturing seasonality.

The Structural Time Series (STS) Model was first proposed by Harvey in 1989. Unlike traditional ARIMA models, the STSM is developed directly in terms of components of interest, such as trend, seasonal, cyclical, and residual or irregular components. The model allows the unobservable components to change stochastically over time. In the absence of the unobserved components, the STSM reverts to the classical regression model.

Structural time series modeling can also be carried out primarily as time series modeling, without including explanatory variables. Incorporating explanatory variables with the stochastic components results in a mixture of time series and econometric model(Koopman et al., 2000), which broadens the scope of the STSM. Given that our purpose is forecasting, but sticking with the Basic STSM framework, without explanatory variables, allows one to avoid using forecasted explanatory variables in forecasting the dependant variable, which should reduce forecasting error.

Three versions of acreage allocation are specified for forest and farm acreage: no trend, no seasonality (NTNS); deterministic trend no seasonality (DTNS) and stochastic trend no seasonality (STNS). The classical STSM contains a seasonality component which we have ignored since it is not relevant to our annual data based model.

Consider the following STS land allocation model:

$$Y_{it} = \nu_t + \delta_{it}^{'} X_{it} + \varepsilon_{it} \tag{3.10}$$

Where α_0 is the intercept; Y_{it} is the land share of use i; $\delta_i^{'}$ is a vector of parameters to be estimated; X_{it} is a vector of explanatory variables for land use i, ν_t is the trend component, and ε_{it} is the white noise disturbance term.

The simple STSM without explanatory variables may be represented by,

$$Y_{it} = \nu_t + \varepsilon_{it} \tag{3.11}$$

If the trend is stochastic, the trend component may be represented by,

$$\nu_t = \nu_{t-1} + \beta_{t-1} + \eta_t \tag{3.12}$$

$$\beta_t = \beta_{t-1} + \xi_t \tag{3.13}$$

where $\eta_t \sim NID\ (0,\ \sigma_\eta^2)$ and $\xi_t \sim NID\ (0,\ \sigma_\xi^2)$

Equations (3.12) and (3.13) represent the level and the slope of the trend, respectively; ν_{t-1} is a random walk with a drift factor, β_t. The drift factor follows a first-order autoregressive process as provided in equation 3.13. The stochastic trend variable (ν_t) captures the technological progress and structural change in the farm and forestry sectors over the past years.

The form that the trend takes depends on whether the variances, σ_η^2 and σ_ξ^2 (hyper parameters) are zero or not. If either σ_η^2 or σ_ξ^2 or both are non-zero, then the trend is said to be stochastic; STNS is the way to go. Otherwise, if both are zero, the trend is linear; the model reverts to a deterministic linear trend (DTNS),

$$Y_{it} = \nu_t + \varepsilon_{it} \qquad (3.14)$$

where, $\nu_t = \nu_{t-1} + \beta_t$, with β_t being a fixed slope component, or, if the slope component is zero, then the expression reduces to, $\nu_t = \nu_{t-1}$.

If ν_t is zero, there is no trend; the STS model reverts to a simple classical regression model without a trend term and the STS model may not be the way to go. Our third approach to estimating land use is time series analysis.

The Vector Autoregressive Model

Vector Autoregressive (VAR) models are the multivariate estimation equivalent of Autoregressive Integrated Moving Average (ARIMA) models in univariate estimation. Various criticisms of VAR models have been put forward, the major ones being that they are not based on economic theory, that individual coefficients of the model estimates are difficult to interpret, and that they can not be used for policy analysis (Gujarati, 2003; Kennedy, 1998).

Proponents of VAR approach argue that the models are useful for forecasting as they often outperform econometric models;

they are also useful for describing various relationships in the data, and testing certain hypothesis and theories (Gujarati, 2003; Kennedy, 1998). Thus the VAR methodology has remained a line of choice for many economists particularly when the goal is forecasting as opposed to policy analysis. The basic VAR model can be represented as follows:

$$Y_t = \mu + \delta_1 Y_{t-1} + ... + \delta_p Y_{t-p} + \nu_t \qquad (3.15)$$

where, Y_t is a vector of endogenous variables; δ is a vector of parameters to be estimated, p is the number of lags, and for all i and t, ν_t is a vector of uncorrelated error terms; $\nu_t \sim (0,\Omega)$, and Ω is a diagonal matrix. The representation could also include a trend term.

Individually for two endogenous variables Y_1 andY_2, based on two lags (p=2), the equations can be represented as:

$$\begin{aligned} Y_{1t} &= \mu_1 + \delta_{11} Y_{1t-1} + \delta_{12} Y_{1t-2} + \delta_{13} Y_{2t-1} + \delta_{14} Y_{2t-2} + \nu_{1t} \\ Y_{2t} &= \mu_2 + \delta_{21} Y_{1t-1} + \delta_{22} Y_{1t-2} + \delta_{23} Y_{2t-1} + \delta_{24} Y_{2t-2} + \nu_{2t} \end{aligned} \qquad (3.16)$$

where the δs are parameter estimates; $\nu_{1t} \sim (0,\sigma_1^2)$ and $\nu_{2t} \sim (0,\sigma_2^2)$ for all t.

Given the challenge in interpreting VAR parameter estimates, proponents of the model recommend inducing shocks or innovations to the error terms and using an “impulse response function” to map out the response of the endogenous variables. We do not need to follow this path to the end since our goal is simply forecasting the endogenous variables – we will stop at deriving the best forecasting fit for the data. In the next chapter, we estimate land allocation using the three approaches, namely econometrics, time series analysis and structural time series analysis. Our goal in estimation was basically forecasting land use and land use change. Without a priori knowledge of the type of model that would perform better in forecasting land use, between econometric, STS and VAR models, we opted to run the three types and let the data decide. We would then select the model with the best forecasting accuracy and utilize the same to forecast the water quality. Thus, in addition to the econometric and STSM, we estimated a VAR model to forecast forest and farm acreage in UCRB.

CHAPTER IV

LAND USE MODEL ESTIMATION AND RESULTS

Factors Influencing Land Allocation

A number of studies on aggregate level land use change have documented factors thought to determine or influence land allocation. Time trend is one variable that would intuitively feature in land allocation models so that structural time series analysis majors on trend as a measure of structural and technological change. Land allocation from one use to another changes over time so that as a variable time may capture the unknown causes of land use change.

In addition to time trend, other factors have been thought to impact on land use and been used in econometric modeling to explain land allocation and land use change. It can be postulated that one major driver of conversion of land to urban use is population density. As population grows and, people push into the forest and farmland simply to acquire room for settlement or to find quality settlement further and further away from the cities. This urban sprawl like behavior is a major factor in land allocation. Virtually all studies on land allocation use population density as an exogenous variable including Plantinga and Miller(1999), Ahn, Plantinga and Alig (2000), Wu and Sergerson(1995).

Ahn, Plantinga and Alig (2000), document a comprehensive model of land use at the aggregate level. They assume that land shares follow a logistic distribution and estimate three panel data models (OLS, fixed effects, random effects) of land use shares, normalizing over forest. Independent variables used in their model include revenues (real and discounted), population density, and measures of land quality. Using net revenues for competing land uses makes intuitive sense. Since we assume profit (or utility or net benefit) maximization, land will move from lower net revenue uses to higher net revenue uses. In regard to land quality, we expect that fertile land is most likely going to be allocated to agriculture over forestry since will still do better than the former even in land of poor quality and higher marginal returns to fertile land are likely to be achieved with farming that forestry (Plantinga, Maulding and Miller, 1999).

The later study estimates a SURE model (assuming logistic distribution of share allocations) for forestry and farms (and normalizing on “other” land use). They estimate three separate models for South, Carolina, Maine and Wisconsin, using county level data. The independent variables applied include land quality, population density, net farm and forest revenues, and for Maine, travel time between the county center to the port. Higher quality land and shorter travel time (for Maine) tended to favor/increased allocation to farms.

Miller and Plantinga (1999) estimated least square (assumed a logistic distribution of share allocations), and maximum entropy models (of share equations), for the allocation of cropland between corn and soybean, in three Iowa counties. They used government payments, fertilizer prices (production costs) and payment in kind (PIK) dummy variable, farmer prices, cost of inputs, and wages as independent variables.

Direct government payments to farmers, PIK, Conservation Reserve Program (CRP), and Wetland Reserve Program (WRP) incentives all contribute to increasing farm net revenue and the attractiveness of agriculture over other land uses.

Costs of inputs on the other hand are constraints to net revenue while producer prices are an addition to the same. These prices would therefore be applied in the absence of net revenues. Other prices that could impact on conversion include interest rates which would mirror the cost of capital. We envisage that higher interest rates would push allocation of land to uses with higher returns as cost of capital and acceptable returns rise.

Wages add to the total revenue available to the land owner. Higher Off-farm/forest wages as compared to net farm/forest revenues could be an incentive to “sell the land and take a job” or at some higher levels to keep the farm/forest for non-use purposes. Ordinarily though, higher wage income in an area attracts people looking for jobs, increasing population pressure and conversion of the farm/forest to urban. High wages may also imply higher cost of production and lower net returns which would push allocation to urban development as land owners sell out the land.

Wu and Segerson (1995) estimated a similar model, albeit covering six major crops (wheat, corn, soybean, Oat, hay and silage), for 57 Wisconsin counties. They assumed a logistic form for the shares equations and estimated a SURE-panel data model. Independent variables for their model included expected prices of commodities, number of cattle, population density, input prices, farm wage, and land quality classifications.

The number of cattle and other large animals like hogs and horses can reduce conversion of farmland to urban development particularly if large animals are a profitable enterprise. Large animals normally require a certain amount of land (carrying capacity)which limits the extent to which urban encroachment can occur without wiping out farming altogether.

Land quality indices can come in handy in a panel data estimation setting or in models using geographical information systems (GIS) whereby land quality can vary across counties. In our kind of scenario however, land quality is assumed to be constant across the watershed and is therefore not an important variable.

Farm equity has been applied as an exogenous variable in modeling allocation among crop enterprises (Banerjee, 2004; Adhikari, 2004). Wealthier farmers may have higher investments in the farm and choose to keep it longer hoping for better days, hence positive effect on farmland; But higher wealth may imply higher expectations on returns forcing conversion away from farming if incomes consistently fail to meet expectations.

Per capita income is another factor that may be important in modeling land allocation. High per capita incomes may create an incentive for migration of population to counties with higher incomes, increasing pressure on land. High incomes may also increase pressure on suburbs to encroach on agricultural and forest land as richer citizens demand higher quality of life away from the city core. But like extremely high wages, extremely high incomes may cause citizens to keep land unspoiled for aesthetic purposes. Table 4.1 provides a summary of explanatory variables and the expected signs.

Table 4.1: Expected Signs: Farm and Forest Econometric Equations

Variable	**Expected Sign**	**Comments**
Time	-	General decreasing trend with increasing urbanization
Expected Returns	+ or -	Net returns drive enterprises and lead to increased acreage on associated enterprise acreage. If farming and forestry are competing enterprises, increase in returns of forestry versus farming will lead to increased forest acreage and reduced farm acreage; the reverse also being true.
Per Capita Income	-	High per capita incomes may attract population to the counties and increase pressure on land; high incomes may also increase pressure on suburbs to encroach on agricultural and forest land as richer citizens demand higher quality of life away from the city core.
Large livestock Numbers	+(farm)	Need for more land as numbers increase.
CRP/WRP	-(farm); +(forest)	Forest and farm land increases;
Pop	-	Farm and forest decrease with urban encroachment
Gov Payments (farm)	+ or - (farm)	Farm land increases to take advantage of government payments; or decreases if payments are a sign of falling farm incomes
PIK	+(forest); -(farm)	Increases for; decreases farm
Farm Wealth	effect Unknown	Wealthier farmers may have higher investments in the farm and choose to keep it longer hoping for better days, hence positive effect on farmland; But higher wealth may imply higher expectations on returns forcing conversion away from farming if incomes consistently fail to meet expectations.

Econometric Model Estimation

We estimate the land allocation model under the assumption of risk neutrality. This simplifying assumption allows us to ignore the effects of the variance and covariance of returns to various land uses. Since data is not available at the individual land owner level, we aggregate county level data to arrive at ecosystem figures.

The theoretical model in equation 3.9 could be further simplified to:

$$\ln(S_{it}/S_{0t}) = \mu_t + \beta_i^{'} X_{it} + e_{it} \qquad (4.1)$$

Where, $\beta_i^{'}$ is a vector of parameters to be estimated; X_{it} is a vector of independent variables for land use; μ_t is the intercept, e_{it} is random white noise disturbance term; the model is identified if we set $\beta_0 = 0$.

Empirically the econometric model could be represented as:

$$A_{it} = \alpha_i + \theta T_t + \sum_i \beta_i \pi_{it} + \zeta \; EQ_t + \delta AN_t + \phi Pop_t + \ell INC_t + \gamma WAGE_t + \kappa INT_t + \sum_i \eta_i Z_{it} + \varepsilon_{it}$$
(4.2)

where, A_{it} = log of share of (land)acreage allocated to use i over acreage allocated to use 0, at time t,

T = time variable,

π_{it} = present discounted value of a stream of real revenues per acre = net returns, for i^{th} land use per acre at time t, (i=1 for farm and i=2 for forest)

EQ_t = real farm wealth measured as average state level farm equity per acre at time t,

Wage = real average wage per job at time t,

INT = Interest rate (20 year constant Treasury bill) rate at time t,

AN_t = Number of large animal(cattle and pig)units per acre,

Pop_t = Population density at time t.

INC_t = real per Capita income at time t,

Z_i = matrix of policy variables; including CRP/WRP (CWRP), PIK, Government payments per acre(GOV),

ε_{it} = Gaussian white noise error terms

Wealth, Wage, Interest rate, government payments, and all income and return variables were deflated/normalized using Consumer Price Index for the south (CPI), (1982=100). Table 4.1 below outlines the independent variables used in the model and expected signs.

Data and Policy Site

The policy site (our area of study) area covers two counties of North Georgia, namely, Habersham and White. Since data is not available at the individual land owner level, we aggregate at the county level to get data for the policy site. Data covering Habersham and White counties, for the period 1974 – 2005 were sourced from various publication and websites including the Georgia county Guide and Georgia Agricultural Facts. Land use data was compiled from the University of Georgia (UGA) Odum School of Ecology, Natural Resources Spatial Analysis Laboratory (NARSAL) database.

Acreage data was available for only six years, 1974, 1985, 1991, 1998, 2001, and 2005. Missing observations were filled-in using the SAS interpolation "JOIN" method which connects data points with a straight line by averaging between successive points. We used this as the best method for filling missing values, after comparing graphs of interpolated and actual data derived by various methods.

Timber revenues streams were calculated as weighted averages of three major types of timber occurring in the policy site, namely, Oak-Pine, Oak-Hickory and Pine. Rotation rates are from Griffin (2007), a Georgia Forestry Commission specialist, based on his field experience. Timber yields are from Birdsey(1992), Birdsey(2003) and Plantinga (2007). Stumpage prices are from the Center for Forest Business at the University of Georgia. Management of forests in North Georgia is not intense.

Forest management costs were minimal and were compiled from Dubois, Eric and Straka (1982) based on information provided by Griffin (2007). Final forest revenue was therefore present discounted value of streams of real timber revenues per acre.

Forest revenues were basically timber revenues discounted at a rate of 5% as is the practice among studies applying forest returns as a variable (Plantinga, Maulding and Miller, 1999; Ahn, Plantinga and Alig, 2000). The choice of discount rates for valuing natural and environmental resources is subject to debate. Some economists are of the opinion that high discount rates may cause environmental degradation. They argue that low discount rates encourage investment in environmental projects with even low return rates. Others argue that using very low rates makes environmental investments unattractive. Federal discount rates for environmental projects normally vary between 3% and 7%. We chose to follow the most of the authors cited above and stick to a reasonably low discount rate of 5%, which ensures comparison purposes.

Population data was compiled from the website of the US Census Bureau. The Bureau conducts population census every 10 years and provides estimates for the intermediate year. These estimates and census data covering 1974 to 2005, were used for this analysis.

Data on government payments, net farm revenue and per capita income were compiled from the Georgia statistical system database available online. Data covered the years 1974 Livestock numbers (cattle, poultry, pigs) were compiled from the various issues of the Georgia County Guide. These data covered the years between 1974 and 2005. Georgia farm equity data (1974-2005) were, interest rate (1974-2005) data were from the St Luis reserve bank. Average wage per job as well as data on the Consumer Price Index (CPI) were from the Bureau of Labor Statistics. State Gross Domestic Product (GDP) data (2004-2006) were compiled from the website of the US Bureau of Economic Analysis.

Preliminary Model Examination

Preliminary estimation using Ordinary Least Squares (OLS) and Seemingly Unrelated Regression (SUR) models was done. Problems of residual autocorrelation are common in OLS estimation of time series data violating OLS assumption of uncorrelated error terms. This problem was tested for using conventional tests, that is, the Durbin Watson (DW) and Breusch-Godfrey, Lagrange multiplier Test (LM). The later is more appropriate when lagged dependant variables are included in the model making DW a weak test, or there is likely to be contemporaneous correlation in the model (Hendry and Doornik, 2001; Green, 2000). There are χ^2 and F forms of the test; the F-version is shown under the null hypothesis of no autocorrelation. The null hypothesis is would be rejected if the test statistic is too high. The residual autocorrelation function plots were used for the same purpose.

Contemporaneous correlation may be a problem in our model since decisions made for one land use alternative affects the others. The common solution to this problem is to estimate the equations in an SUR framework. In this case, equation by equation OLS is the efficient estimator so long as the independent variables are the same for all equations in the system.

Logarithmic transformation of data as in equation 4.1 and 14 is known to induce heteroskedasticity in the model (Ahn, Plantinga and Alig, 2000), rendering OLS estimates inefficient. We will test for the same using the F-form of the Breusch-Pagan Test(BP). High values of the test statistic (low p-values) cause us to reject the null hypothesis of homoscedasticity.

Although we had no reason to suspect absence of normality in the distribution of residuals we examined the various residual plots (including density function and QQ plots) and applied the Jarque-Bera normality test (N) to the model residuals. The statistic follows a χ^2 distribution with two degrees of freedom under the null hypothesis of normality (Gujarati, 2003). The 5% critical value for a $\chi^2_{(2)}$ is 5.99, and the 1% critical value is 9.22; N values larger than these may signify absence of normality.

Econometric Model Fitness and General Forecasting

In addition to the R^2, and the F-test are useful measures of how well the model fits the data and to select between competing econometric models. Chow's forecast test also referred to as Chow's predictive failure test measures the predictive power of a regression model. The forecast failure chi-square is another test similar to the Chow test is test in terms of testing the constancy of parameters between the sample and post-sample periods.

For both tests, the null hypothesis is no structural change in parameter values, meaning there are constant parameters between the sample and the forecast period. Significantly large values imply the equation may not provide very accurate ex-ante predictions.

Whereas the forecast failure chi-square and the Chow test leans more towards measuring parameter constancy/structural change in the model, the Root Mean Square Error (RMSE) and the Mean Absolute Percentage Error (MAPE) are two measures of the model forecasting accuracy. Higher values imply poor forecasting performance of the model.

Results of the Econometric Model

We started out with the comprehensive model as outlined in equation 4.2 and estimated the model by OLS. The results are provided in table 4.2 and 4.3. The all-inclusive model satisfies most OLS requirements except that it has highly collinear dependant variables. This is evidenced by the very high R^2 (at least 0.98), and the fact that other than the constant, few variables are significant at the 5% level. In addition there are wrong signs on three variables namely per capita income (INC), PIK, and wage (WAGE).

Examining the independent variables shows a number of variables have high pair-wise correlation coefficients. Time trend variable (T), WAGE and INC are highly correlated with POP, which may explain the source of multicollinearity. As proposed by Gujarati (2003) we dropped groups of variables with pair-wise correlation coefficients exceeding 0.8, leaving about two per "group", and applied stepwise regression as determined by the value of partial R^2, to settle on the list of variables ultimately included in the model. We put off other measures of model suitability till we come up with a model that meets the requirements of OLS. The final forest acreage model results are provided in table 4.4.

Table 4.2: Forest Acreage Comprehensive Model Estimates

Parameter	Estimate	SE	t-value	p-value
Constant	2.6981**	0.7936	3.4000	0.0050
POP	-0.0349	0.0173	-2.0200	0.0650
INC	0.0183	0.0119	1.5400	0.1480
WAGE	0.0020	0.0100	0.1960	0.8480
PIK	-0.0303	0.1009	-0.3000	0.7690
CWRP	-0.1384	0.1199	-1.1500	0.2690
INT	1.4443	2.3330	0.6190	0.5470
Π1	4.9459**	0.7501	6.5900	0.0000
GOV	-0.0201**	0.0085	-2.3600	0.0350
AN	0.6794	0.3786	1.7900	0.0960
Π2	-0.0519**	0.0220	-2.3600	0.0350
EQ	-0.0665	0.0308	-2.1600	0.0500
T	-0.0048	0.0484	-0.0989	0.9230
RSS		0.0511		
R^2		0.9920		
F(12,13)		134.4 [0.000]**		
DW		2.07		
LM, F(2,11)		0.2043 [0.8182]		
Normality,Chi^2(2)		1.5808 [0.4537]		

Note: ** - implies significant at 5%;

Table 4.3: Farm Acreage Comprehensive Model Estimates

Parameter	Estimate	SE	t-value	p-value
Constant	1.2111	0.8505	1.4200	0.1780
POP	-0.0378	0.0185	-2.0400	0.0620
INC	0.0202	0.0128	1.5800	0.1390
WAGE	0.0017	0.0107	0.1540	0.8800
PIK	-0.0359	0.1082	-0.3320	0.7460
CWRP	-0.1496	0.1285	-1.1600	0.2650
INT	1.4100	2.5000	0.5640	0.5820
Π1	5.3784**	0.8039	6.6900	0.0000
GOV	-0.0214**	0.0091	-2.3500	0.0350
AN	0.7306	0.4057	1.8000	0.0950
Π2	-0.0568**	0.0236	-2.4100	0.0310
EQ	-0.0728**	0.0330	-2.2000	0.0460
T	0.0097	0.0519	0.1870	0.8550
RSS		0.0587		
R^2		0.9874		
F(12,13)		85.16[0.000]**		
DW		2.08		
LM, F(2,11)		0.2299[0.7984]		
Normality Chi^2(2)		1.5056[0.4711]		

Note: ** - implies significant at 5%;

Both the forest and farm acreage equations meet the requirements of OLS. The models do not fail the normality, homoscedasticity and no autocorrelation tests. There are no signs of multicollinearity in the model and coefficients of determination for both models are high (0.97 and above).

The F-values are significant (even at 1% level) implying parameter estimates do not equal zero. In addition to the intercept that is significant (at 1% level), for both land use equations, the forest acreage equation yields negative but not significant signs for farm government payments and wage and negative and significant signs for farm wealth and population.

The negative sign for population is as expected; as population density increases there is likely to be increased encroachment of urban development on forests. The negative sign on farm wealth may not have a clear-cut explanation. It may be that higher investment in the farm serves as an incentive to move land from forestry to agriculture, hence the negative sign.

The equation yields a positive and significant sign for forest returns implying, in line with expectations, that increased forest revenue is likely to be an incentive for land owners to increase forest acreage.

Table 4.4: Forest Acreage Selected Model Estimates

Parameter	Estimate	SE	t-value	p-value
Intercept	4.1770**	0.3657	11.4000	0.0000
POP	-0.0249**	0.0021	-12.1000	0.0000
WAGE	-0.0002	0.0031	-0.0796	0.9370
Π1	4.8519**	0.4904	9.8900	0.0000
GOV	-0.0108	0.0070	-1.5500	0.1370
EQ	-0.0675**	0.0193	-3.5000	0.0020
Mean(LFORESr)		2.9104		
Variance(LFORESr)		0.2457		
RSS		0.1132		
R^2		0.9823		
F(5,20)		221.664[0.0000]**		
LM, F(2,18)		3.1679[0.0663]		
N, Chi^2(2)		0.5843[0.7467]		
Chow, F(6,20)		4.0977 [0.0077]**		
BP, F(10,9)		0.5849 [0.7924]		

Note: ** - implies significant at 1%; * - significant at 5%

The results of the final farm acreage model are provided in tables 4.5. The equation yields significant (at 1% level), estimates for the intercept, population, and farm wealth. The equation yields negative but not significant (at 5%) estimates for farm government payments and wage, and positive and significant estimates for forest revenue.

As is the case with the forest acreage equation, increased population is likely to result in increased encroachment of urban development on farm land hence the negative sign on population. The negative sign on farm wealth implies increased farm wealth leads to increased conversion of farms to urban development. It may be that richer resource farmers have higher expectations of profits forcing conversion away from farming when returns fail to meet expectations.

The farm equation yields a positive and significant sign on forest returns, implying that increased returns from forestry are likely to be an incentive for land owners to increase farm acreage.

Table 4.5: Farm Acreage Selected Model Estimates

Parameter	Estimate	SE	t-value	p-value
Intercept	2.8282**	0.4071	6.9500	0.0000
POP	-0.0189**	0.0023	-8.2600	0.0000
WAGE	-0.0028	0.0034	-0.8370	0.4120
Π1	4.7909**	0.5459	8.7800	0.0000
GOV	-0.0049	0.0078	-0.6380	0.5310
EQ	-0.0802**	0.0215	-3.7400	0.0010
Mean(LFARMr)		1.5941		
Variance(LFARMr)		0.1796		
RSS		0.1403		
R^2		0.97		
F(5,20)		129.19	[0.0000]**	
Chow, F(6,20)		3.5229	[0.0152]*	
LM, F(2,18)		3.4671	[0.0532]	
N, Chi^2(2)		0.6539	[0.7211]	
BP, F(10,9)		0.8048	[0.6321]	

Note: ** - implies significant at 1%; * - significant at 5%

Whereas one would expect this to be the case in regard to forest acreage, assuming the two land uses are competing, the reasons for this positive effect on farm acreage is not fully clear. It may mean that the two are actually complimentary, as would be the case if, say, land converts to farming first them to forestry. But the effect may also be simply coincidental given the high (0.99) correlation between farm and forest acreage variables. Model diagnostic graphics support the diagnostic tests outline earlier.

The literature examining cropland allocation across different crop enterprises is fairly common. But studies of land allocation at the level of forest versus farm and other uses, based on economic theory or even time series analysis, are scarce. In the overall, it is not uncommon for land use models to fail to provide substantial evidence as to factors that contribute to land use changes.

Ahn, Plantinga and Alig (2000), document a comprehensive model of land use at the aggregate level. They take the common approach of assuming a logistic distribution of share equations (normalize over forest) and estimate three panel data models (OLS, fixed effects, random effects) of land use shares. Independent variables used are revenues (real and discounted), population density, and measures of land quality. Their models yield expected signs – farm revenue yields significant and positive signs on the farm equation, while forest revenue yields a negative and significant sign. They conclude that revenues tend to "allocate" land to the land use generating the most of it. Population density does not yield a significant sign suggesting it affects farm and forest the same way (forest is the normalizing factor). Land quality yields a positive and significant sign on farm supporting the notion that fertile land is most likely going to be allocated to agriculture over forestry.

Plantinga, Maulding and Miller (1999), estimate a SURE model (assuming logistic distribution of share allocations) for forestry and farms (and normalizing on "other" land use). They estimate three separate models for South, Carolina, Maine and Wisconsin, using county level data. The independent variables applied include land quality, population density, net farm and forest revenues, and for Maine, travel time between the county center to the port. Unlike, our results that yielded the same (positive) sign on farm revenue with both equations, they found farm and forest revenues to have the expected signs (negative and significant sign on farm revenue in the forest equation; negative sign on forest revenue in the farm equation). These results point to the competing nature of the two land uses, farm and forest. The population variable had expected (and significant) signs, which tallied with our results. Higher quality land and shorter travel time (for Maine) tended to favor/increased allocation to farms.

Miller and Plantinga (1999) estimated least square (assumed a logistic distribution of share allocations), and maximum entropy models (of share equations), for the allocation of cropland between corn and soybean, in three Iowa counties. They found that government payments, fertilizer prices (production costs) and PIK are significant and negatively related to acreage. All other factors including farmer prices, cost of inputs, and wages were not significant. The government payment variable had a negative but not significant sign in our model.

Wu and Segerson (1995) estimated a similar model, albeit covering six major crops (wheat, corn, soybean, Oat, hay and silage), for 57 Wisconsin counties. They assumed a logistic form for the shares equations and estimated a SURE-panel data model. Independent variables for their model included expected prices of commodities, number of cattle, population density, input prices, farm wage, and land quality classifications. Population density yielded a negative and significant sign for some of the crop enterprises (corn and silage) and a positive sign for others (soybean, wheat). Farm wage, expected commodity prices, input prices gave mixed signals with significant and negative sign for some of the crops and positive signs for others.

The overall picture that we got from comparison of the results of our econometric model with those from other studies is that, aggregate land use models (forest-farms-other, etc) seem to provide results, consistent with expectation that cropland share models. One possible explanation for the differences between our results and past studies could very well be the kind of data available to us. In regard to land use, we had only six data points spread over 30 years, and we had to resort to interpolation to fill in the gaps. Estimating a more comprehensive model with county level data, in a panel data framework, would be the better way to go in the future. Even with six data points, not having to interpolate will most likely create a data set that would provide more agreeable results, *ceteris paribus*.

Econometric Model Forecasting Results

The econometric model (both equations) fails to pass the Chow forecasting parameter constancy test, meaning there may be structural change in the data that the model fails to capture. Structural change is better captured by the Structural Time Series models results of which are provided later. The RMSE and MAPE statistics are provided in table 4.6 and 4.7 as well as the ex ante forecast of the dependant variables.

Both equations yield substantially large RMSE and MAPE values which was not entirely unexpected given the significant Chow prediction failure test values. The forest acreage equation yields smaller values for both the RMSE and the MAPE compared to the farm acreage equation, implying better forecasting accuracy for that equation.

The MAPE value on the farm acreage equation is particularly large at 101.68 implying that the equation misses the actual data values by more than 100 %. We will compare these results with the STSM and choose the better model for forecasting purposes.

Structural Time Series Model Estimation

We used the Structural Time Series Analyzer, Modeller, and Predictor (STAMP) version 6.0 program (Koopman, et. al., 2000) for STS analysis. The program carries out maximum likelihood estimation using numerical optimization procedure.

Table 4.6: Econometric Model Forecasted Values of Log of Farm Shares

Period	Forecast	Actual	Error
2000	1.147	0.845	-0.302
2001	1.174	0.738	-0.437
2002	1.212	0.638	-0.574
2003	1.176	0.546	-0.631
2004	1.097	0.460	-0.637
2005	1.027	0.379	-0.648
Mean(Error)	-0.538	RMSE	0.553
SD(Error)	0.128	MAPE	101.680

Table 4.7: Econometric Model Forecasted Values of log of Forest Shares

Period	Forecast	Actual	Error
2000	2.304	2.028	-0.276
2001	2.254	1.917	-0.337
2002	2.351	1.814	-0.537
2003	2.299	1.718	-0.581
2004	2.234	1.629	-0.605
2005	2.114	1.545	-0.569

Mean(Error)	-0.484	RMSE	0.501
SD(Error)	0.128	MAPE	28.114

Model diagnostic tests are similar to those of the OLS (econometric) model and all statistics are as explained earlier including the Jarque and Bera normality test and the Durbin-Watson (DW) test. A few diagnostic tests are introduced; Rd^2, the Q statistic and the H statistic.

The STS analysis software, STAMP, uses Rd^2 instead of R^2 as the coefficient of determination whenever the model incorporates trend of seasonality components. The former is a better measure of goodness of fit where the series appears stationary with no trend or seasonality (Koopman et al, 2000; Harvey, 1989). This said alternative coefficient of determination (Rd^2) has deviation of first difference (from its mean) in the denominator, where R^2 uses deviation from the levels. The value of Rd^2 may be negative indicating a worse fit than a simple random walk plus drift model.

In STS analysis, STAMP uses the Box-Ljung Q statistic, Q(p,q) as a measure of serial correlation. The Q statistic is based on the first p residual autocorrelations and distributed as a χ^2(q). We reject the null hypothesis of no autocorrelation if the p-value is smaller than 0.05, (the test statistic is larger than the critical value). The Q statistic is asymptotically equivalent to the Breusch-Godfrey LM test when there are no lag dependant variables among the set of explanatory variables.

The H(g)test is an F(g,g) non-parametric test of heteroskedasticity (Koopman, et al, 2000). A large F-value calls for rejection of the null hypothesis of homoscedasticity.

Results of the Structural Time Series Model

For both the forest and farm equations, we estimated two versions of the simple STS model (without explanatory variables), that is, DTNS, and STNS. As with the econometric model, we assume farm and forest acreage models follow the same processes and estimate a seemingly unrelated structural time series equations (SUTSE), which is the same as equation-by-equation STSM.

The first step is to find the best fit among basic models, STNS, and DTNS. The next step was to introduce interventions in the best-fit-model to take care of any poor diagnostics. Typical interventions in STSM include dummy variables for slope, trend irregularities or outliers. Such interventions would signal structural or technological change or simply abnormally large values.

Diagnostic tests are performed to gauge the goodness of fit of the model; results are presented in table 4.8 and table 4.9 below.

Table 4.8: Diagnostic Summary of the STNS Model

Statistic	forest	farm
Std.Error	0.0509	0.0544
Normality	10.681	10.915
H(8)	123.93	137.33
DW	0.9748	0.9812
Q(8,6)	19.435	19.356
Rd^2	0.3450	0.3558

Table 4.9: Diagnostic Summary of DTNS

Statistic	forest	farm
Std. Error	0.0786	0.0827
Normality	1.1054	1.0214
H(8)	136.1200	140.8500
DW	0.3918	0.4061
Q(7,6)	35.4390	34.9900
Rd^2	-0.5590	-0.4912

Neither the farm nor the forest equation passes the normality, homoscedasticity, and DW and Q(no autocorrelation)tests at 5% and 1% levels.

Results of the DTNS model seem better in regard to some of the statistics but worse for others. The normality (N) values are below the 5% critical value of 5.99 so we fail to reject the null hypothesis of normality. Other tests of homoscedasticity, no autocorrelation are rejected at 5% and 1% levels.

Since both models (STNS and DTNS) fail most diagnostics test, we select the better of the two and subject it to interventions to see if it is worth considering versus the econometric model.

The coefficient of determination (Rd^2 version) is the one thing that separates the two models. We observe that the stochastic trend (STNS) model explains the variations in the dependant variables better than the deterministic trend model. The negative value of Rd^2 in the DTNS model is of particular concern as it implies the model is a worse fit that a simple random walk with a drift factor.

In STS model interventions include indicator (dummy) variables to account for outliers and structural breaks. Outliers can be incorporated as impulse variables which take the value of one when the outlier occurs and zero elsewhere. Structural breaks represent instances where the level of the series shifts up or down. Indicator variables taking the value of one after the break and zero before the break are used to capture this kind of changes. Structural breaks can also occur in the slope of the series. Such changes are captured by a “staircase” intervention in which the trend variable takes the values, one, two, three, and so on, beginning after the change in the slope (Koopman, et al, 2000).

The final STSM had a STNS structure and included interventions for change in the slope (structural breaks) of the dependant variables. The results of the final STSM are presented in table 4.10 below.

The diagnostic tests suggest the STNS model explains the data adequately. The DW statistics are around 1.5 which falls within the region of indecision but below the 5% (d) critical value of 1.553, so we fail to reject the hypothesis of no autocorrelation. The p-values for our Q statistic are 0.0283 for the forest equation and 0.0279 for the farm equation which suggests we fail to reject the null hypothesis of no serial correlation at 1% although the same is not the case at 5% significance level. Since there were no lagged dependant variables in the model (we can comfortably use the DW), and both the DW and the Q statistic support the no residual autocorrelation hypothesis generally, we conclude that this may not be a significant problem in the model.

Table 4.10 Diagnostic summary of the STS model

Statistic	forest	farm
Std. Error	0.0149	0.0149
Normality	3.873	3.7856
H(8)	1.1001	1.1936
DW	1.5052	1.5151
Q(8,6)	14.119	14.164
Rd^2	0.9440	0.9514
R^2	0.9991	0.9988
Forecast Chi2(6)	2.0926[0.9110]	1.8313[0.9345]

The normality statistics are below 5.99 (and 9.22) the 5% and 10% critical values; we do not reject the null hypothesis of normality distribution of the model residuals. The heteroskedasticity H(g)test critical values with 8 degrees of freedom are 3.44 for 5% and 6.03 for 1% significance levels. The statistics exhibited by our models fall below these cut-offs, so fail to reject the null hypothesis of homoscedasticity.

The both coefficients of determination, R^2 and the preferred Rd^2 are high; at a minimum of 94% and 99% respectively meaning the model explains at least 94% of the variation in the dependant variables. For both farm and forest equations, the forecast failure chi-square statistics are not significant at 5% so we do not reject the hypothesis of parameter constancy between the sample and pos-sample periods.

The major purpose of carrying out STS analysis was to determine if the STSM would provide a better tool for forecasting land use in the upper Chattahoochee river basin, particularly when compared to the econometric model. Table 4.11 and 4.12 below provide the forecasted values for and tests for evaluating of the forecasting accuracy of the model.

Table 4.11: STSM Forecasted Values of Log of Forest Shares

Period	Forecast	Actual	Error
2000	2.0159	2.0276	1.9770
2001	1.8816	1.9167	1.8630
2002	1.7441	1.8137	1.7565
2003	1.6027	1.7182	1.6574
2004	1.4579	1.6290	1.5647
2005	1.3116	1.5451	1.4776
Mean (Error)		0.1061	RMSE 0.0322
SD (Error)		0.0846	MAPE 6.4305

Table 4.12: STSM Forecasted Values of Log of Farm Shares

Period	Forecast	Actual	Error
2000	0.8337	0.8454	0.7919
2001	0.7022	0.7377	0.6808
2002	0.5675	0.6379	0.5774
2003	0.4287	0.5456	0.4816
2004	0.2867	0.4596	0.3924
2005	0.1430	0.3789	0.3088
Mean(Error)		0.1072	RMSE 0.0322
SD(Error)		0.0855	MAPE 23.0913

Both equations yield substantially smaller RMSE and MAPE values, particularly when compared to the econometric model. This causes us to select the STSM as the preferred approach to forecasting land use in our policy site.

The RMSE statistic yielded by the STSM is 0.0322 for both farm and forest equation. This is about fifteen times smaller than the RMSE values from the econometric model which were between 0.553 (for farm equation) and 0.502 (for forest equation). The MAPE statistics for the two models are similarly divergent. The MAPE values of 23.0913, for the farm equation, and 6.4305, for the forest equation, are about 4 times smaller than corresponding values from the econometric model; 101.68 for the farm equation and 28.114 for the forest equation.

The STSM outperforms the econometric model in regard to forecasting accuracy. In the next chapter, we use the STSM model to forecast future land use, then model resulting, water quality changes and assign economic value to the later.

Vector Autoregressive Model Estimation

The VAR model is similar to an econometric simultaneous equation model, except that all the variables are endogenous. The assumption is that lagged values of a variable should be able to explain the variation in the variable. In estimating the VAR model, we started out with equation 3.15.

One critical decision in regard to VAR estimation is the lag length - including too many lags would reduce degrees of freedom and induce multicollinearity while too few lags could results in specification errors (Gujarati, 2003). Use of decision tools like the Akaike (AIC) and Schwarz (sic) information criteria is common with smaller values indicating a better fit for the data. We followed this approach in our analysis. Because of the expected problem of multicollinearity (given the use of lags of the same variables), parameters estimates may not be statistically significant even when a variable does contribute to the model. We adopted the F-test on the retained regressors which seems a better tool in making the decision to drop or keep a variable.

Given that our dependant variables are in logs, we expect to encounter the problem of heteroskedasticity. To counter this we will use White (1980) estimation method and estimate heteroskedasticity consistent standard errors (HCSE).

As in the SURE approach, the problem of identification is overcome by using the same number of right hand side variables in all equations in the model. Contemporaneous correlation could be a problem in VAR model estimation. To circumvent this problem, we apply equation by equation OLS which is also the efficient estimation method in a SURE framework.

Other problems such as autocorrelation and lack of normality were tested for using the conventional OLS strategies discussed earlier.

Results of the Vector Autoregressive Model

We started with a general VAR model based on 4 lags, for each endogenous variable LFARM (log of farm to urban acreage ratio) and LFOREST (log of forest to urban acreage ratio). The results of the VAR model are provided in tables 4.13 and 4.14 below.

The discussion that follows applies to both farm and forest equations. The Breusch Pagan heteroskedasticity test is omitted as we applied heteroskedasticity consistent standard errors in estimation. The R^2 (0.99) and overall equation F-statistic (p-values equal zero) are high suggesting the model may be a good fit for the data. The DW and LM tests autocorrelation tests statistics are not significant even at 10% level. The Jarque-Bera (normality tests) statistic is not significant at 5% level. These results suggest we can not reject either the normality or the no autocorrelation (null) hypotheses. The chow parameter consistency/prediction failure test statistic is not significant at 5%, suggesting we can not reject the null hypothesis of no structural change in parameter values.

Table 4.13: Farm Acreage VAR Estimation Based on 4 Lags

Parameter	Estimate	Std Error	t-value	p-value
LFOREST_1	-5.6501	25.9700	-0.2180	0.8310
LFOREST_2	-3.6529	11.8900	-0.3070	0.7890
LFOREST_3	-6.5167	9.7420	-0.6690	0.7640
LFOREST_4	1.9680	8.5020	0.2310	0.5160
LFARM_1	6.6660	24.3500	0.2740	0.8210
LFARM_2	2.9415	11.3000	0.2600	0.7990
LFARM_3	6.2167	9.1180	0.6820	0.5080
LFARM_4	-2.3440	8.1350	-0.2880	0.7780
Trend	-0.2221	0.3129	-0.7100	0.4910
Constant	23.9142	34.8100	0.6870	0.5050
Mean(LFARM)		1.5768		
Variance(LFARM)		0.1791		
RSS		0.0377		
R^2		0.99		
F(9,12)		134.1[0]**		
DW		2.18		
Chow, F(6,12)		0.0780[0.9974]		
N, Chi^2(2)		5.1355[0.0767]		
LM, F(2,10)		3.1159[0.0887]		
AIC		-2.6232		
SIC		-2.5064		

Note: X_i implies ith lag of variable X; ** - implies significant at 1%; * - implies significant at 5%

Table 4.14: Forest Acreage VAR Estimation Based on 4 Lags

Parameter	Estimate	Std Error	t-value	p-value
LFOREST_1	-4.3659	24.1600	-0.1810	0.860
LFOREST_2	-3.7311	11.0100	-0.3390	0.816
LFOREST_3	-6.3239	9.1710	-0.6900	0.741
LFOREST_4	2.1236	7.9930	0.2660	0.504
LFARM_1	5.3740	22.6500	0.2370	0.795
LFARM_2	3.0428	10.4600	0.2910	0.776
LFARM_3	6.0259	8.5860	0.7020	0.496
LFARM_4	-2.4572	7.6560	-0.3210	0.754
Trend	-0.2128	0.2901	-0.7330	0.477
Constant	22.9245	32.2600	0.7110	0.491
Mean(LFOREST)		2.8164		
Variance(LFOREST)		0.2244		
RSS		0.0330		
R^2		0.99		
F(9,12)		197.9[0.000]**		
DW		2.18		
Chow, F(6,12)		0.0824[0.9970]		
LM, F(2,10)		3.0129[0.0946]		
N, Chi^2(2)		5.6583[0.0591]		
AIC		-2.9903		
SIC		-2.7953		

Note: X_i implies ith lag of variable X; ** - implies significant at 1%; * - implies significant at 5%

Despite apparent good performance for the two equations, none of the equations has a single significant parameter estimate, which may suggest the model in its aforesaid form is mis-specified.

The next step in our analysis was to examine simpler equations including shorter lags of the endogenous variables and find model that better fits the data. In addition to examining conventional diagnostic tests of the Classical Linear Regression Model (CLRM), we examined the AIC and SIC both of which are common criteria for model selection. We also looked at F-test on retained regressors to see if they contribute to the model; under the null hypothesis that coefficients are equal to zero, significant values suggest we may reject the null and retain the variables in subsequent steps. Results of the final model are provided in table 4.15 and 4.16 below.

As is the case with the initial (4 lag) VAR model, we applied White’s heteroskedasticity consistent standard errors to circumvent the problem of non-constant variance in the model – the Breusch Pagan heteroskedasticity test is therefore omitted from the results.

Table 4.15: Farm Acreage Selected VAR Model Estimation

Parameter	Estimate	Std Error	t-value	p-value
LFOREST_1	12.2257	2.7130	4.5100**	0.0000
LFARM_1	-10.4162	2.4900	-4.1800**	0.0000
Trend	0.1725	0.0419	4.1100**	0.0000
Constant	-20.0108	4.5510	-4.4000**	0.0000
Mean(LFARM)		1.57682		
Variance(LFARM)		0.179105		
RSS		0.0608		
R^2		0.99		
F(3,21)		508.1[0.000]**		
DW		1.2		
Chow, F(6,21)		2.0852[0.0986]		
LM, F(2,19)		1.6139[0.2252]		
N, Chi^2(2)		5.4651[0.0651]		
AIC		-2.8604		
SIC		-2.6654		

Note: X_i implies ith lag of variable X; ** - implies significant at 1%; * - implies significant at 5%

Table 4.16: Forest Acreage Selected VAR Model Estimation

Parameter	Estimate	Std Error	t-value	p-value
LFOREST_1	12.2121	2.5090	4.8700**	0.0000
LFARM_1	-10.4746	2.3040	-4.5500**	0.0000
Trend	0.1580	0.0387	4.0800**	0.0010
Constant	-18.3559	4.2090	-4.3600**	0.0000
Mean(LFARM)		2.8939		
Variance(LFARM)		0.2415		
RSS		0.0534		
R^2		0.9911		
F(3,21)		784[0.000]**		
DW		1.2		
Chow, F(6,21)		1.9559[0.1184]		
LM, F(2,19)		1.6414[0.2200]		
N, Chi^2(2)		5.3485[0.0690]		
AIC		-2.9903		
SIC		-2.7953		

Note: X_i implies ith lag of variable X; ** - implies significant at 1%; * - implies significant at 5%

The final VAR model meets CLRM requirements. For both farm and forest equations, the DW test yields a d-value of 1.2, which falls within the indecision region for the 5% level of significance (1.038 to 1.767) for N=25 and k=4. This implies we can not conclusively reject the null hypothesis of no autocorrelation based on this statistic. Nevertheless, for both equations, the LM autocorrelation tests statistics is not significant at 5% level. As indicated earlier this is a more appropriate test when lagged dependant variables are present in the model as is the case here, so we may not reject the null hypothesis and conclude that autocorrelation may not be a problem in the model.

The Jarque-Bera normality tests statistic N is not significant at 5% level. These results suggest we can not reject either the normality hypotheses. The chow parameter consistency/prediction failure test statistic is not significant at 5%, suggesting we can not reject the null hypothesis of no structural change in parameter values.

The final model is also a reasonably good fit for the data with R^2 values of 0.99 and above. The overall equation F-statistics are significant at 1% level which suggests we may reject the null hypothesis that the coefficients are collectively equal to zero.

As compared to the initial model where none of the parameter estimates were significant, the final model had all parameter estimates being significant at 1% suggesting more appropriate specification and further strengthening our perspective that the later model should be preferred. The AIC and SIC values were about the equal for the initial (-2.5064 to – 2.9903) and final models (-2.6654 to -2.9903), so we could not use these criteria to pick the better model.

As discussed above, both the initial and final models met the CLRM requirements. Additionally, similarity of the initial and final models in regard to fitness (R^2, overall F value, information criteria, parameter consistency) reduced the criteria for choosing the final model to its simplicity and the significance of the parameter estimates. Model diagnostic graphics for the selected (final) model are provided below.

Vector Autoregressive Model Forecasting Results

None of the equations in the selected model failed the Chow forecasting parameter constancy test. This means that there may be no structural change in the parameter estimated between the in-sample and post-sample period.

The RMSE and MAPE statistics are provided in table 4.17 and 4.18 below as are the ex ante forecast of the dependant variables.

Table 4.17: VAR Model Forecast Values of Log of Farm Share

Period	Forecast	Actual	Error
2000	0.9597	0.8454	-0.1143
2001	0.9557	0.7377	-0.2179
2002	0.9499	0.6379	-0.3120
2003	0.9408	0.5456	-0.3952
2004	0.9271	0.4596	-0.4676
2005	0.9081	0.3789	-0.5291
Mean (Error)		-0.3394	RMSE 0.3680
SD(Error)		0.1424	MAPE 67.6320

Table 4.18: VAR Model Forecast Values of log of Forest Share

Period	Forecast	Actual	Error
2000	2.1312	2.0276	-0.1037
2001	2.1132	1.9167	-0.1965
2002	2.0934	1.8137	-0.2797
2003	2.0704	1.7182	-0.3522
2004	2.0431	1.6290	-0.4141
2005	2.0107	1.5451	-0.4656
Mean (Error)		-0.3020	RMSE 0.3266
SD(Error)		0.1244	MAPE 17.8070

The model yielded RMSE values of 0.3680 and 0.3266 and MAPE values of 67.632 and 17.807 for the for the farm and forest equations respectively. Given the negative mean error, the MAPE values indicate that model overestimates the farm and forest acreage shares by about 67% and 17% respectively.

Forecasting Ability: Comparing VAR, STS and Econometric Models

Table 4.19 compares the three land use models, econometric, VAR and STSM in regard to forecasting ability. Overall, the VAR model RMSE and MAPE values were smaller than the corresponding values yielded by the econometric model but smaller than the STSM. Thus, in terms of model forecasting accuracy, the STSM would be most preferred followed by the VAR time series model, with the econometric model being the worst performer. Although this is as expected, many econometricians are of the opinion that wherever time series models outperform econometric models, the econometric model may be miss-specified (Green, 2000; Kennedy, 2001). It may be important for future research to examine the validity of this notion in regard to land use modeling.

Table 4.19: Forecasting Ability of the Land Use Models

	RMSE		MAPE	
Model	Farm	Forest	Farm	Forest
Econometric	0.55	0.50	101.68	28.11
VAR	0.37	0.33	67.63	17.81
STSM*	0.03	0.03	23.09	6.43

*: The STSM has the smallest RMSE and MAPE

Whereas both econometric and the VAR models yielded negative mean error values, the STSM yielded a positive value. This suggests that the first two models would likely overestimate land acreages allocated to farms and forests, where the STSM would likely underestimate these allocations. We selected the STSM for forecasting on the basis of RMSE and MAPE statistics.

Forecasting Land Use and Land Use Change

A key objective of our study was to forecast land use in the Upper Chattahoochee River Basin (UCRB) in North Georgia, in order to forecast changes in water quality and economic value of this environmental good. We focused in the are of the basin north of Lake Lanier, particularly the area covered by Habersham and white counties. Two approaches to forecasting land use were applied namely the Seemingly Unrelated Regression, and a Structural Time Series Model. The STSM results seemed a better choice for forecasting as evidenced by smaller RMSE and MAPE statistics.

We proceed to forecast land acreage for farm and forest uses for the years 2006 to 2030 under three scenarios, that is, Scenario I, the highest rate of conversion (to urban land use) as forecasted by the STSM; Scenario III, limited or managed conversion represented by average growth rate between 1974 and

2005; Scenario II, moderate conversion represented by the average growth rate between the two scenarios above. We would not expect conversion rates to fall below scenario III levels, as urbanization and deforestation have been rising steadily over the years.

Land Use Change Scenario I: The STSM Highest Conversion Rate

The results of the first scenario are presented in table 4.20. Figures in the table are in percentage of land under indicated use and do not cover government land (about 80,000 acres of forest) and lakes (about 2100 acres) all of which we assumed would remain unchanged.

The STSM provides us with estimated ratios of the logs of shares of non-urban to urban land uses, that is, forest to urban and farm to urban. We used Microsoft Excel software to compute acres and percentages for the respective land uses.

Only farm and forest figures were actually forecasted; urban figures were computed as the difference between the total and the sum of farm and forest acreage proportions. The values for year 2005 are from actual baseline data and are included here for comparison purposes. Forecasted values are for selected years between 2006 and 2030.

Table 4.20: Scenario I, Percentage Land Use With Highest conversion Under STSM

Period	Forest	Farm	Urban	Total
2005	66	20	14	100
2006	65	20	15	100
2010	61	19	20	100
2015	53	17	30	100
2020	43	14	43	100
2025	33	11	56	100
2030	24	8	68	100

The above results indicate that in 2005, about 66% of the land was under forestry, 20% was under farms and 14% was under urban development. It seems that ten years later by the year 2015, the percentage of land under various uses will have changed to about 53%, 17% and 30% for the forest, farm and urban categories respectively and by the year 2030, urban development will have increased to cover about 68% of available land with forests and farms taking a backseat at 24%, and 8% respectively.

The STSM does not tell us why these changes would take place; it simply provides the best fit for the data and the better model for forecasting compared to the econometrics model. Intuitively, the high population growth rate may have had a major impact on conversion of farms and forests to urban development, as human settlement has pushed into forests and farmlands in the watershed. In the space of about three decades covered by the data, annual population growth rate averaged 2.2% increasing over the decades from a low of 1.23% in the first decade (1974-1984), and a high of 2.99% in the last decade (1995 and 2005). The notion of a strong relationship between population growth and urbanization is further supported by the large, negative and significant coefficient on population density in the econometric model. These forecasts may seem incredible and we consider that the STSM had significantly large forecasting error statistics.

Scenario II, (Table 4.21) is an average of the two extreme situations, the highest conversion under STSM, and the limited growth conversion. Under this scenario, about one half of the forest cover and one third of farmland are lost to urban development. By 2030 the proportion of land in forests has reduced to 37%; farmland has lost 7% to stand at 13%; urban development space has quadrupled to take a share of 50%.

Table 4.21: Scenario II, Percentage Land Use Based On Moderate Conversion

Period	Forest	Farm	Urban	Total
2005	66	20	14	100
2006	64	20	16	100
2010	58	19	23	100
2015	52	17	31	100
2020	46	16	38	100
2025	41	15	44	100
2030	37	13	50	100

These figures may still seem incredible, but this is by no means a far fetched scenario. Examining existing data for the last decade or so, the annual rate of loss of forests between 1998 and 2005 was about 1.1%, while farmland was being lost at a rate of 0.83%. If land conversion continued at these rates, by 2030, forests would cover 53%, farms would cover 15% and urban development would take over 32% of the ecosystem.

Under scenario III - forecasts are presented in table 4.22 the limited/managed conversion, we assume that land acreage will change at a rate equivalent to the average growth between 1974 and 2005. During this period forest is lost at a compounded annual growth rate of 0.61%, farmland increases by about 0.37% and urban development increases by a 1.7%. By 2030, forest covers 56% of the land down from 66% in 2005, farmland increases marginally from 21% to 22%, while commercial and residential development increases by about 50% from to cover 21% of available ecosystem land up from 14%. Examining the data, urban growth was very limited in the 1970s and 1980s but shot up in the last one and a half decades. Moreover, the 1998 to 2005 growth rates give us a markedly higher conversion rates, than the managed growth scenario. We therefore have reason to consider this as a realistic best case land allocation scenario for this ecosystem. The implications of these changes for water quality are explored in the next chapter.

Table 4.22: Scenario III, Managed Growth, Percentage Land Use Forecasts Based On 1974-2005 Growth Rate

Period	Forest	Farm	Urban	Total
2005	66	20	14	100
2006	65	21	14	100
2010	64	21	16	100
2015	62	21	17	100
2020	60	22	19	100
2025	58	22	20	100
2030	56	22	21	100

Land Use Change Forecasting

Table 4.23 provides land use shares under different scenarios from baseline through scenario III. Table 4.24 provides the baseline land use allocations (acreage) and percentage change in individual land use categories under different scenarios. The tables depicts the extent to which land allocation changes (for each category of use) between year 2005 (baseline) and 2030 under different scenarios. This conversion is discussed in greater detail in the previous chapter. Summarily, Scenario I (STSM) represents highest conversion. Under this scenario, urban growth (commercial and residential areas) encroaches on farms and forests to increase by 390 % as the later two reduce by about 63 %. In scenario II, moderate growth, urban growth takes over from farms and forests to increase by a lower but significant magnitude of 258 %. Land in farms drops by 35 % while forestry loses 44 %. Under scenario III with mitigating action/managed growth, urban growth increases by 53 %, farm acreage increases by 10 %, and forestry loses 14 %. In the next chapter we explore the implications of these land use change for water quality.

Table 4.23: Land Use Shares Under Different Scenarios

Scenario	Forest	Farm	Urban
Baseline 2005	66	20	14
I. STSM highest growth	24	8	68
II. Moderate growth	37	13	50
III. Managed growth	56	22	21

Note: Values are percentages

Table 4.24 Land Use Change Between 2005 And 2030

Land Use	Curve Number	Baseline Acreage	Scenario I	II	III
Commercial	92	1738	390%	258%	53%
Residential High Density	75	1738	390%	258%	53%
Residential Low Density	65	31278	390%	258%	53%
Agricultural	61	50765	-62%	-35%	10%
Forest	55	162939	-64%	-44%	-14%
Total Acreage	NA	248458	0%	0%	0%

* The baseline values represent acreage (allocation) in year 2005 prior to the postulated land use changes. Percentage changes represent year 2030 values relative to the baseline.

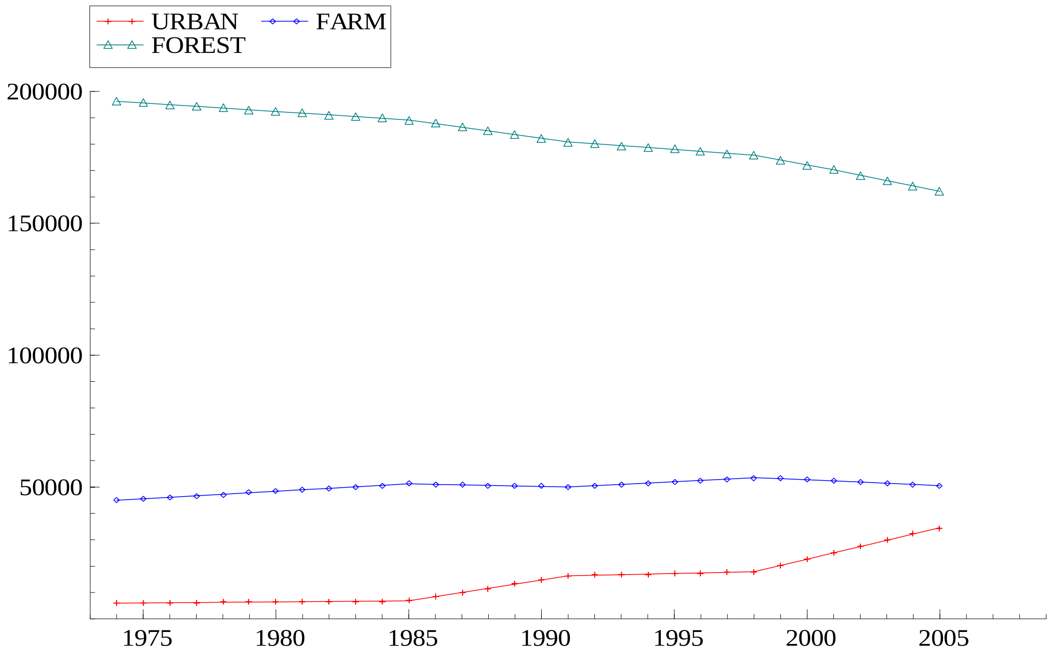


Figure 4.1 Land acreage levels

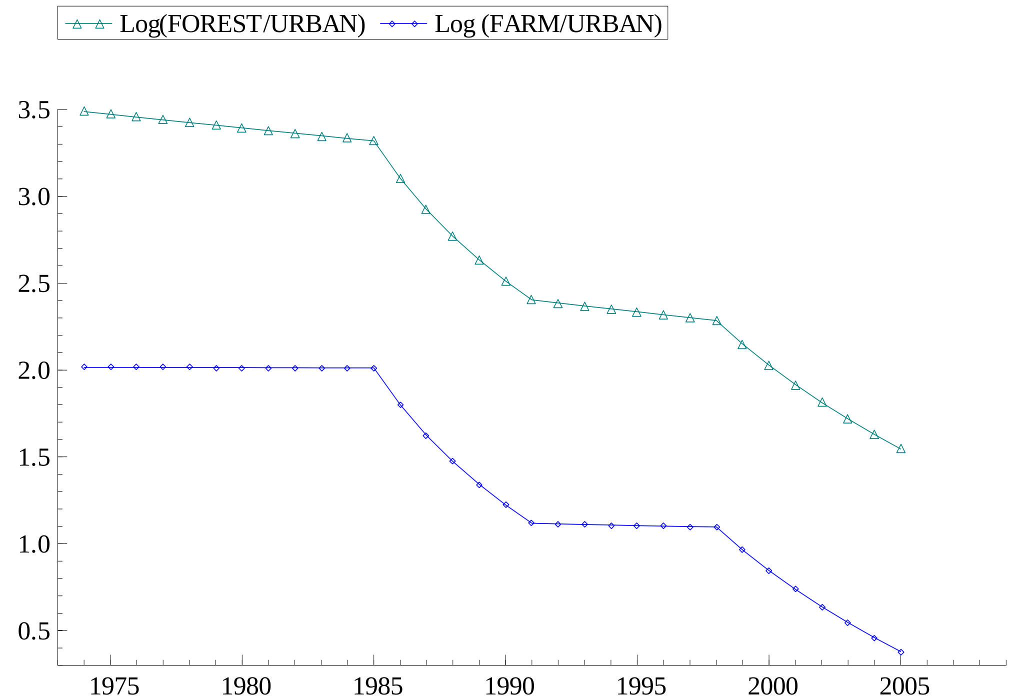


Figure 4.2: Log of Farm and forest (to urban) acreage shares

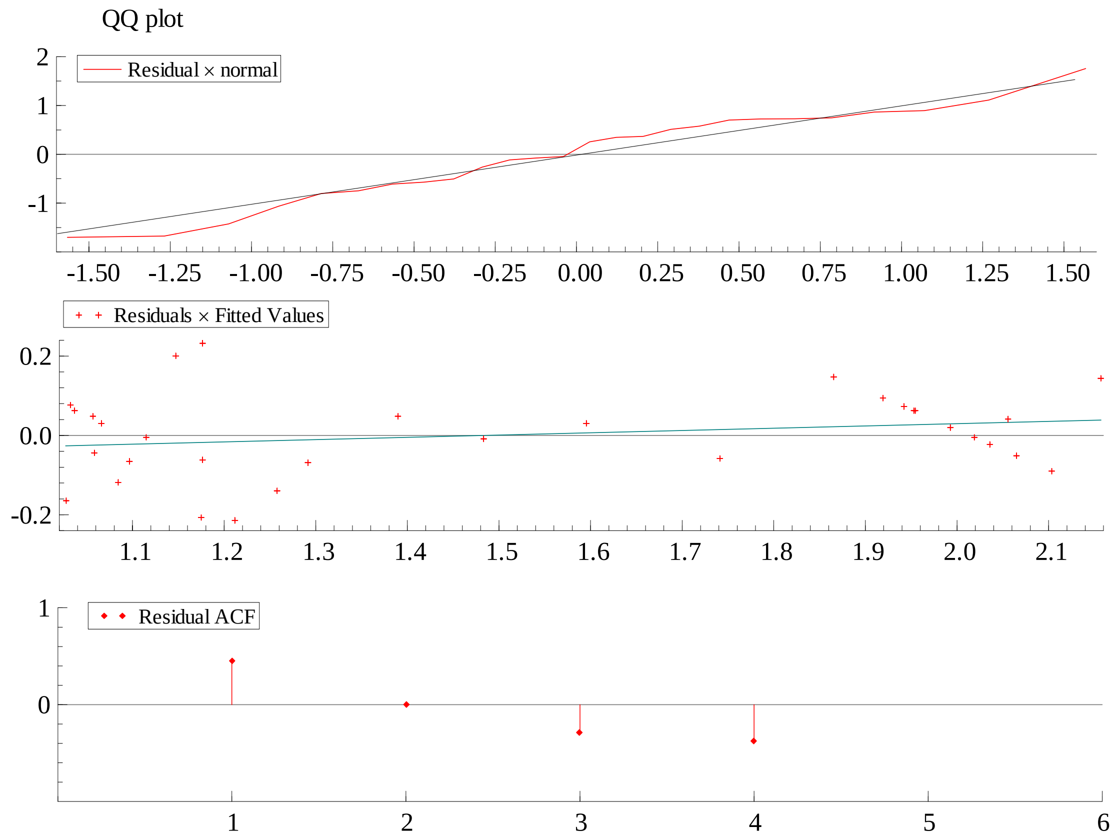


Figure 4.3: Econometric model residual graphics - farm equation

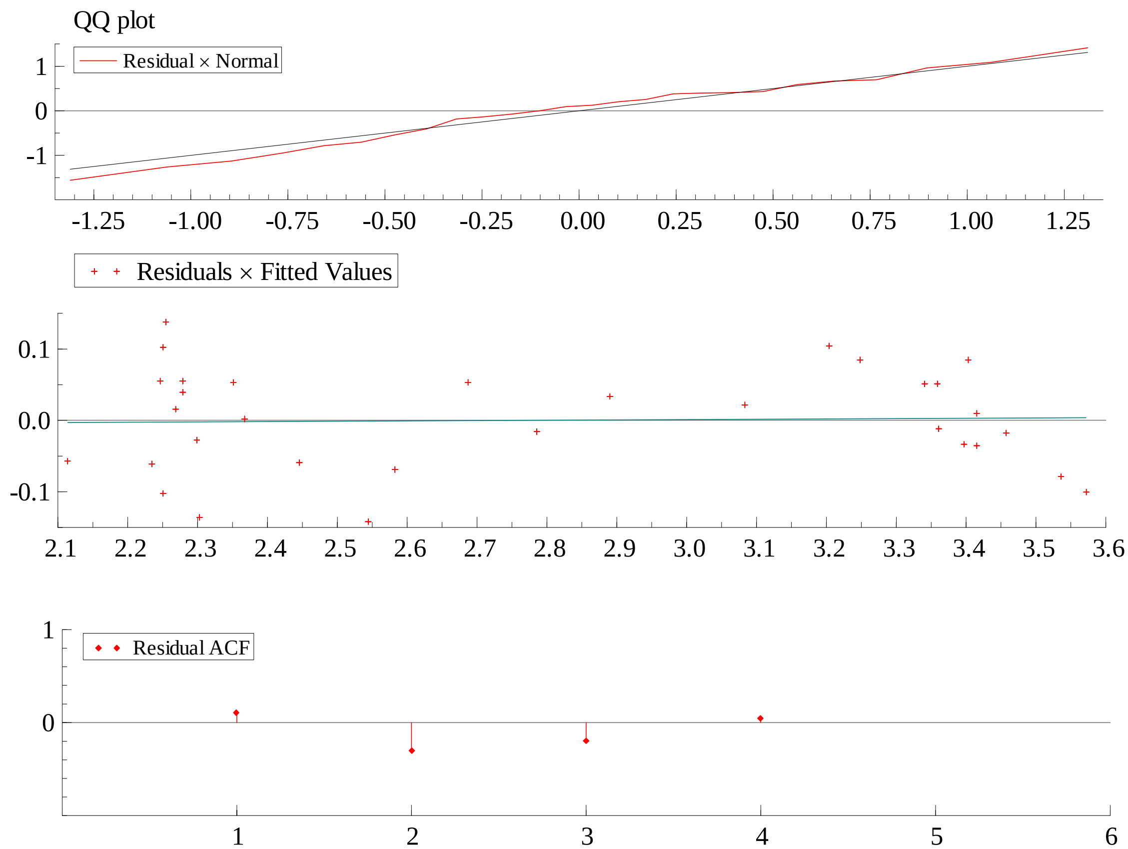


Figure 4.4: Econometric model residual graphics - forest equation

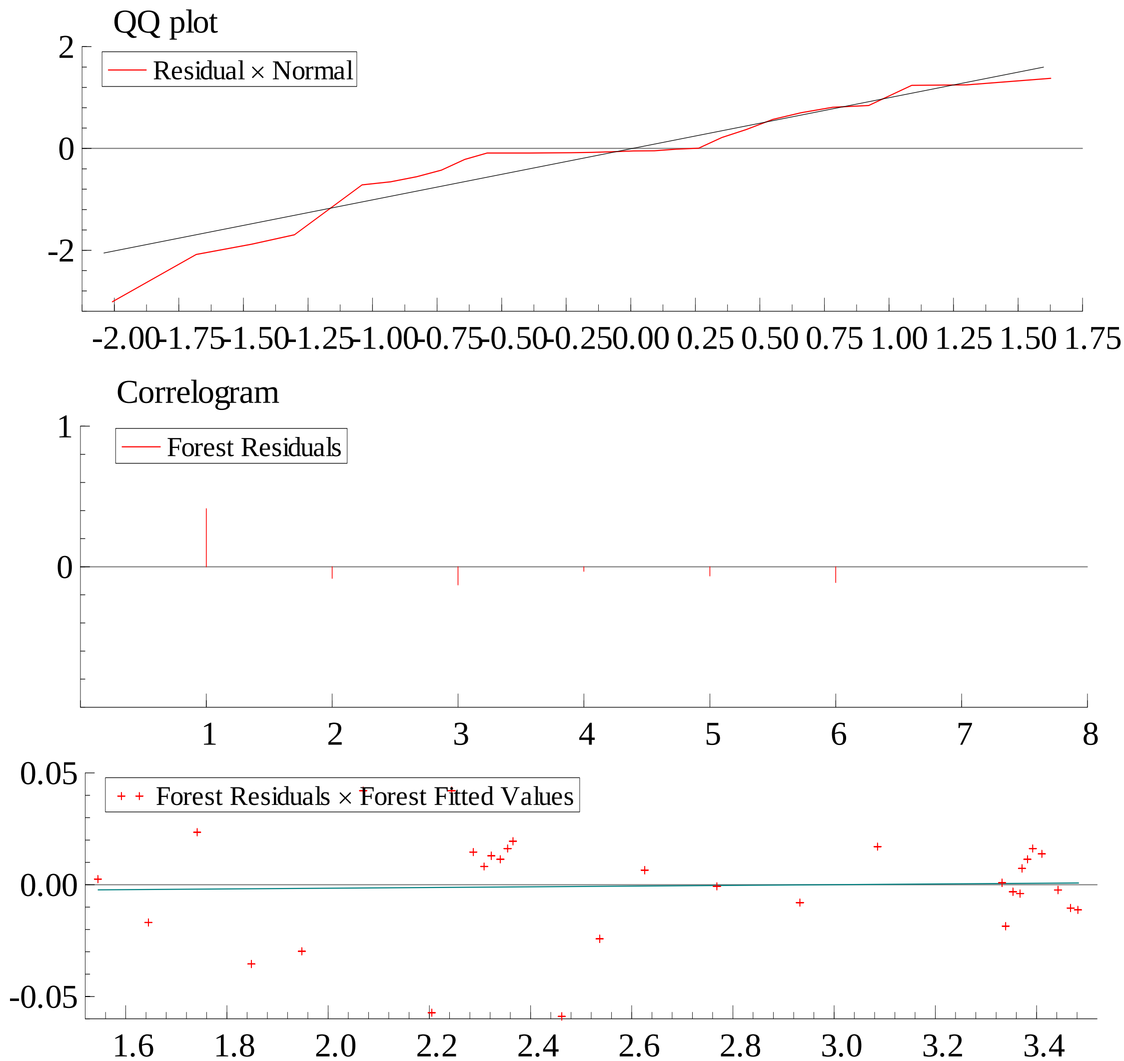


Figure 4.5 STSM forest equation residual graphics

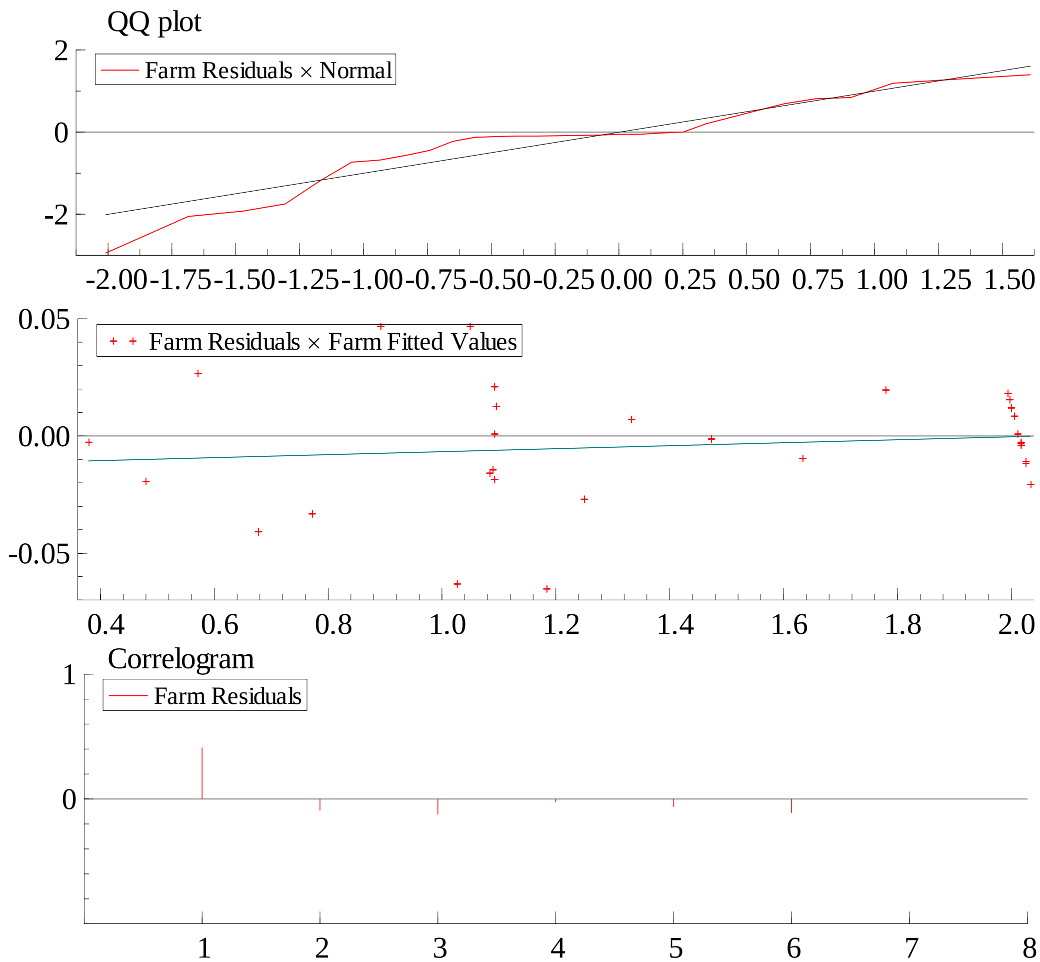


Figure 4.6: STSM farm equation residual graphics

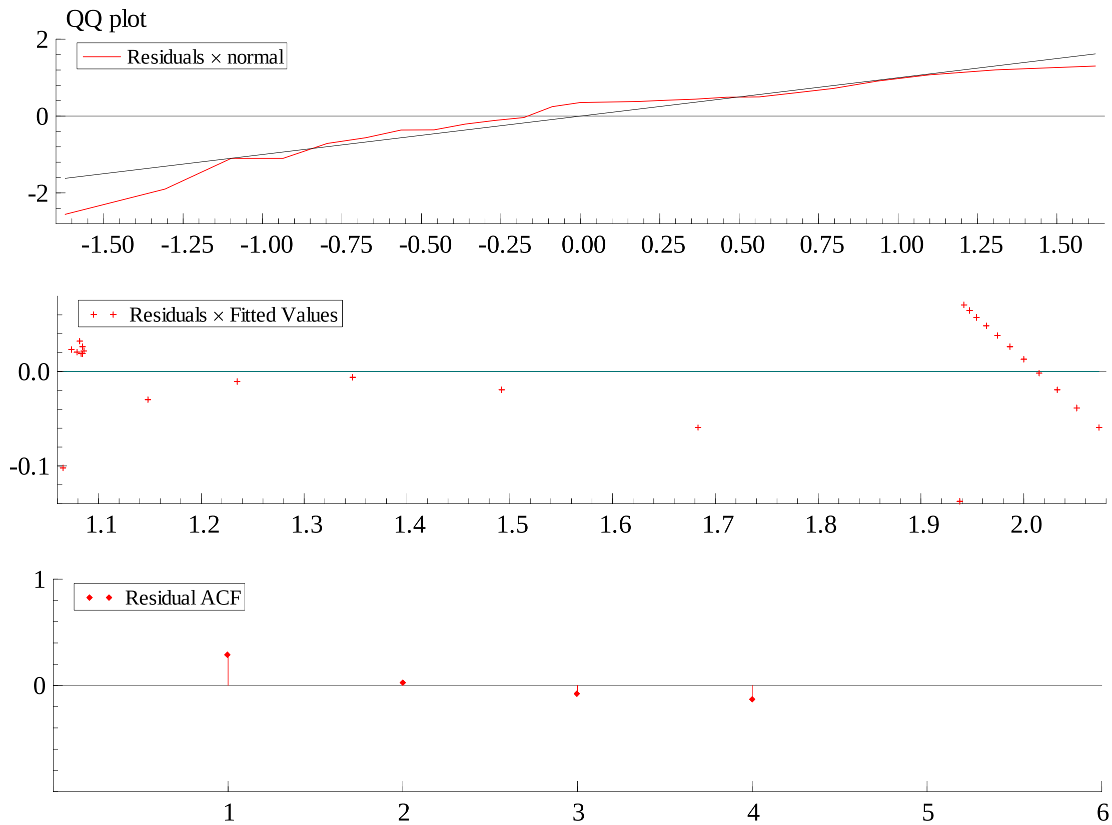


Figure 4.7: Selected VAR model residual graphics - farm equation

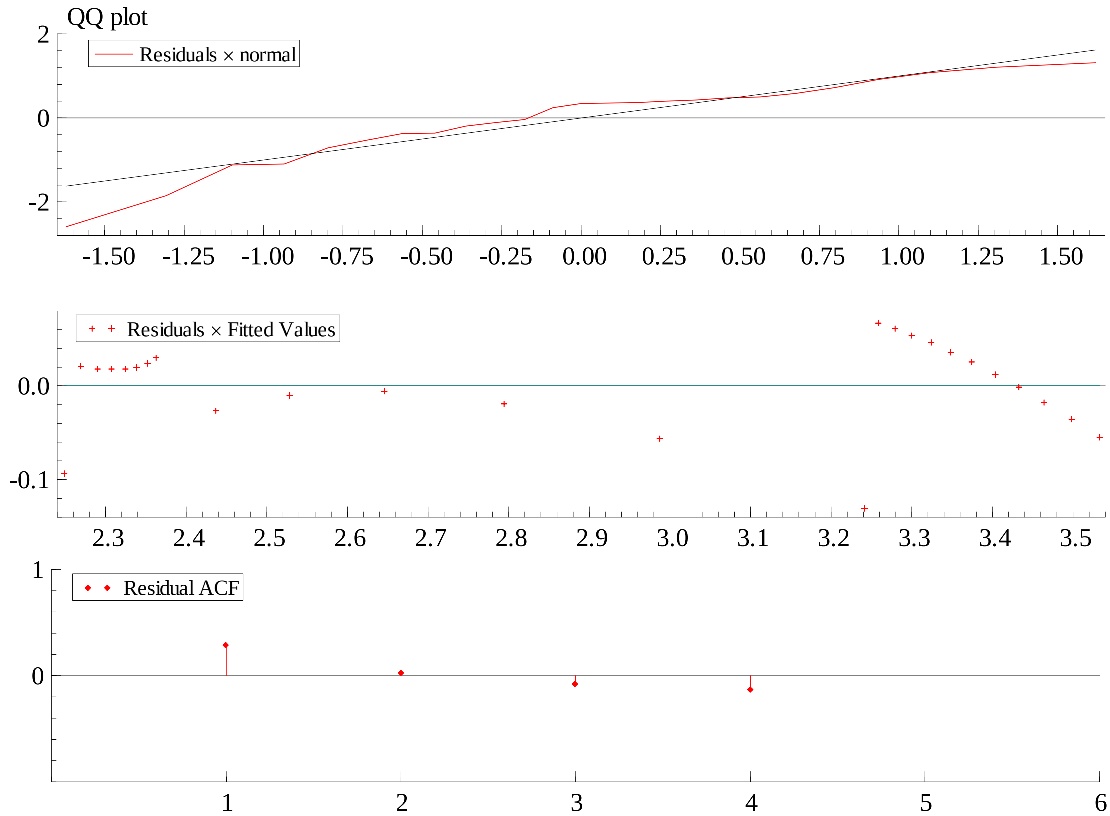


Figure 4.8 Selected VAR model residual graphics - forest equation

CHAPTER V

LAND USE CHANGE, WATER QUALITY AND ECOSYTEM VALUATION

Land use change affects the quality and quantity of environmental commodities (goods and services), and functions. In our study we zeroed down on water quality as an environmental commodity. We sought to model land use change, examine how it would affect water quality in the study area, and finally assess the economic value that society would attach to the resulting change in water quality. In the last subsection we modeled and forecasted land use and postulated three different future (up to 2030) land use scenarios, that is, highest, limited and moderate conversion to urban development. In this chapter we present the Long-Term Hydrologic Impact Assessment (L-THIA) procedure and forecast water quality in the study area under the aforesaid land use scenarios. We then estimate the value of water quality in respect to a number of Non Point Source (NPS) Pollutants and assess the economic value of the ecosystem service.

The Long-Term Hydrologic Impact Assessment Procedure

The L-THIA model was developed by the Purdue Research Foundation as a tool for mapping out changes in run off, recharge and nonpoint source pollution (NPSP) resulting from land use changes (Purdue Research Foundation, 2004; Engel, et.al., 2003; Bhaduri, et. al.,1999). The L-THIA software, available online, computes long term average annual estimates of the aforesaid hydrological parameters for specified land use scenarios, based on long term historical climatic data at county level.

The software allows one to input data at two levels of complexity, basic and detailed. The basic option allows input of up to eight land use categories, namely, commercial, industrial, high density residential, low density residential, grass/pasture, forest, water/wetland, and agriculture. The detailed option allows input of up to fourteen land use categories including open spaces, parking/paved spaces, six lot sizes for residential housing, and the possibility of adding a custom land use. Irrespective of the option selected, L-THIA requires input of at least one hydrological soil group, A to D. These categories are from the National Resource Conservation Service (NRCS) classifications of soils, and represent indicators of runoff potential. Group A has the lowest potential while group D has the highest.

Once the level of complexity is selected, the next step is to select the location (state and county) of interest. The software requires selecting the hydrological soil group or groups and an input of the type and size (acres, hectares, square miles, square kilometers) of land use change. The software then computes expected runoff depths and volumes and nonpoint source pollution loadings to waterbodies, based on the selected hydrological groups and proposed land use and land use changes. The pollutants covered by the model include chemicals such as nitrogen, phosphorous, lead and other inorganic compounds, suspended solids, dissolved oxygen, microbes such as fecal coliform and fecal streptococcus, urban wastes such as oil and grease. We zeroed down on nitrogen, total bacteria (fecal Coliform plus fecal streptococcus), and dissolved oxygen as they are the most commonly studied pollutants, which would give us most access to benefit transfer data.

Hydrological Soil Types

The major soils of Habersham and White counties of North Georgia range from deep fairly well drained sandy loams to poorly drained sandy clay loams (McIntyre, 1972; Robertson, McIntyre, and Ritchie, 1963). The deep, well drained Cecil and Madison, group A like, soils cover about two thirds of Habersham County. The remaining one third is covered by various poorly drained sandy clays loams (Robertson, McIntyre, and Ritchie, 1963) that would fall under hydrological soil group C.

About a half of White county is covered by deep and well drained Tallapoosa, Tusquitee, Ashe and Edneysville loam soils

(McIntyre, 1972), which would fall under category A. The other half of the County is covered deep to moderately deep, well drained to moderately well drained soils of various associations, including, Hayesville-Fannin-Wickam and Hayes-Rubin-Hiwassee (McIntyre, 1972) which would fit in hydrologic soil group B. To simplify the analysis we make a compromise and classify the entire study area under hydrological soil group B.

Water Pollution and Quality Standards

Different land uses are associated with different levels of nutrient and contaminant loading into ground and surface water. Under most natural land cover types, a certain (normally limited) level of nutrients occurs naturally based on the type of underlying rock, soils, atmospheric and hydrologic conditions.

Living things (life), both plants and animals are adapted to survive under varied but often limited concentrations of nutrients such as nitrogen (for plants), phosphorous (for plants and animals), etc. In limited amounts many nutrients are beneficial and often required to sustain life. In high concentrations however, nutrients become poisonous contaminants that may impair proper functioning of an organism or even destroy life. The EPA has developed recommendations (criteria) that states and local authorities should use as a guide to ensure water quality in their areas (USEPA, 1986a).

There are numerous environmental stressors and sources of associated pollution with potential to impair water quality. Attempts to ameliorate nutrient levels in ecosystems naturally lean toward cultural or “human-made” sources of nutrient loading/injection as these are often the cause of excessive loadings as well as being the easiest to control. For the purpose of this study and given our need for previous studies with benefit transfer data, we zeroed down on major stressors identified in the literature and for which the United States Environmental Protection Agency (USEPA) and the Georgia Environmental Protection Division (GAEPD have provided protection guidance criteria. These stressors include Nitrates, Phosphorous, Total Suspended Solids (TSS), Dissolved oxygen (DO), Turbidity, and Fecal Coliform (bacteria). The literature also provides guidelines for other NPS pollutants including Biochemical Oxygen Demand (BOD).

Nitrates, as nitrogen or otherwise, are about the most discussed contaminants of drinking water in the literature. Together with phosphorous, nitrates and nitrites are associated with agriculture (fertilizers and animal waste) and human residential waste disposal. Nitrate concentration in ground water unaffected by human activities is about 2 mg/L (Nolan and

Stoner, 2000). In reasonable amounts nitrogen (from nitrates and nitrites) and phosphorous are needed for plant growth hence the extensive use in agriculture. But excess and unutilized nutrients from farms, byproducts of animal waste and poorly disposed human waste end up in ground and surface water mainly through leaching and runoff. Pollution by nitrates is especially a problem with ground water as 22 per cent of domestic wells in agricultural areas, in the US, report nitrogen contamination. About 22 % of Georgians including 98 % living in rural areas of the state (GAEPD, 1997) and about 46 % of all Americans, use ground wells, as their main source of water supply (Ward, et., al., 2005).

In humans, excess nitrogen (more than 10 mg/L) is associated with blue baby syndrome or Methemoglobinemia (Ward, et. al.) a situation where the capacity of the blood to transport oxygen is impaired. In both animals and humans, nitrogen related compounds can also be transformed into carcinogenic compounds (Ward, et. al.).

Digestive problems can occur in animals and humans ingesting high levels of phosphorous (phosphates, etc) but toxic effects of phosphorous in humans is not common. Excessive levels of phosphorous and/or nitrates in water bodies stimulates accelerated growth of planktons and other aquatic plants (eutrophication) resulting in chocking of the waterways, diminished oxygen (hypoxia) and death of aquatic life (USEPA, 1986a). There is not a major phosphorous pollution in Georgia waterways and the state has no numeric MCL for phosphorous (GAEPD, 1997).

In addition to blocking waterways and hindering navigation of vessels and animals in the water, solids (dissolved and suspended) lower the level of Dissolved Oxygen (DO) in the water with associated implications for aquatic life. Among other problems, sediments (solids, etc), also serve as anchors for bacteria, increase water treatment costs, damage plant and animal habitats, destroy fish spawning areas, contribute to flooding and may change entire aquatic ecosystems (GAEPD, 1997).

Regarding dissolved and suspended solids, the EPA has a secondary criterion for water quality. Secondary criteria are more of recommendations than primary enforceable targets. The EPA’s Total Dissolved Solid (TDS) criterion is 500 mg/L (USEPA, 2000). On the other hand, a Total Suspended Solid (TSS) concentration of 50 mg/L has been used by some states as a threshold for potential impairment of water bodies (NEGRDC, 2004). The EPA has minimum in-stream water standard for the DO level of drinking, recreation, and fishing waters set at 4.0 mg/L. The standard for trout fishing waters is higher at 5.0 mg/L.

The amount of oxygen in water (dissolved oxygen) is important for the survival of aquatic life. Levels of in the water are dependant on temperature and the level of nutrients and solids in the water (GAEPD, 1997). Dissolved oxygen criteria are therefore meant to be lower limits below which aquatic life is impaired. A low level of DO indicates high levels of nutrients and solids without specificity as to type. But DO criteria are not covered by L-THIA making it hard for us to estimate the levels and changes in dissolved oxygen.

An alternative indicator of DO is Biochemical Oxygen Demand (BDO). This measures the amount of oxygen that bacteria will require to decompose organic matter. If runoff or effluence entering a river is rich in organic matter, there will be intensive bacterial decomposition organic matter; BOD will be high resulting in competition, for oxygen, with aquatic life. This will decrease the amount of DO, at, and downstream of the point of discharge to the extent that in-stream life could die (CRC, 2000). High levels of BOD are accompanied by low levels of DO. Accordingly, BOD is a good indicator of the health of a stream, river or other water body. Recommendations for BOD are scarce, but the Australian government recommendation for BOD for protecting freshwater aquatic life is a maximum of 15 mg/L (CRC, 2000). We adopted this criterion for the purpose of this study.

Contamination of drinking water by bacteria, particularly the Fecal Coliforms group (including the infamous *Escherichia coli),* is a major water quality concern. Bacteria are mainly associated with human and animal waste that finds its way into ground or surface water. In low levels, fecal coliform bacteria (FCB) may cause no harm, but high levels they are considered an indicator of potential health risk to humans.

The GAEPD has water quality standards consisting of two groups of criteria; the general criteria that apply to all waters and the specific criteria that vary with the intended use of the water. Table 5.1 shows various (USEPA, GAEPD, other states) water quality criteria for some of the stressors, for drinking water (USEPA,2000; GAEPD,2004). For ease of presentation, only stressors covered by the L-THIA software are included in the table.

Although there are not many primary (enforceable) numeric criteria for pollutants like total nitrogen, in regard to rivers and streams with fishing as designated use, NPS pollutants do affect aquatic life in general and fish in particular. For instance, levels of TN in excess of 0.5 mg/L are toxic to rainbow trout (North East Georgia Regional development Center (NEGRDC), 2004). Available water quality criteria for fishing and recreation are presented in table 5.2.

Table 5.1 Water Quality Criteria for Rivers and Streams and drinking water quality standards

Intended Use	TN	TP	Total Suspended Solids	Fecal Coliform	Dissolved Oxygen(minimum)
Drinking water supply (not treated)	0.69 mg/L	0.57 mg/L	50 mg/L	200 colonies /L	>4.0 mg/L
Portable drinking water	0.10 mg/L	NA	NA	</=5% of samples per month	NA

Figures represent Maximum Contaminant Level (MCL). Figures are from USEPA (2000) and GAEPD (2004). TN and TP stand for Total Nitrogen and Total Phosphorous respectively; figures are based on the 25th percentile. Fecal coliform figures are based on 30 day geometric mean. BOD criterion is from the literature (CRC, 2002) and can be assumed to be secondary.

Table 5.2 Water Quality Criteria for Rivers and Streams for non-human uses

Intended Use	Fecal Coliform (30 day geometric mean)	BOD (maximum)	Dissolved Oxygen (minimum)
Fishing(all species)	200 colonies/L	> 15 mg/L	>4.0 mg/L
Fishing(trout)	200 colonies/L	> 15 mg/L	>5.0 mg/L
Recreation	200 colonies/L	NA	>4.0 mg/L

Source: CRC, (2002) for BOD; GAEPD (2004)for all other data.

Land Use Change: Implications for Water Quality

For the purpose of this study the baseline year for land use change will be the latest year for which land use data exists, which is 2005. Although L-THIA software provides up to 12 land use types including industrial, commercial, and high density residential, our data groups together these three under high intensity urban. Given the rural nature of the study area, we assumed that half of the area so classified was under commercial land use while the remainder was put to high density residential use. About 40 % of the study area is in White county while the remaining 60 % is in Habersham, yet the L-THIA model runs at county level. Nevertheless so long as one has the curve numbers (CNs), which is are measures of hydrologic soil groups, one could create run the model on either county. We begun by running the model at each county level with respective acreages, then combined the acreages and used weighted averaging to arrive at CNs for the entire ecosystem. Finally we applied the model to Habersham county (yields the same results with White county so long as the CNs are uniform) to come up with runoff, and level of Non Point Source (NPS) pollutants in the waters within the ecosystem.

In addition, we assumed that the ratio of high density urban to low density urban acreage would remain as it was in

2005, which is about 10% high density and 90% low density. If this assumption changes, the higher the proportion of high density urban acreage the lower the water quality situation and vis versa.

Table 5.3 provides the L-THIA program output of average annual water quality parameters for the study area under the different scenarios - the table covers only major NPS pollutants.

From the table, it is apparent that runoff levels under scenario I, II and III exceed baseline levels. Additionally, the findings seem to suggest that although the level of TSS, BOD and FCB increase across all scenarios, only fecal coliform and BOD criteria are likely to be violated in the study area. The BOD criterion of 15 mg/L is exceeded in scenario I and II. The FCB criterion of 200 colonies/100 ml is exceeded under all scenarios including current (2005) baseline land distribution. Current bacteria violations may be as a result of poor human waste disposal systems but more likely livestock waste is the culprit as chicken, hog and cattle farming are the main agricultural enterprises in the study area.

Table 5.3: Runoff and NPS Pollutant Loadings in 2030

Pollutant	Baseline	Scenario I	Scenario II	Scenario III
Runoff depth (in)	69555.99	111088.40	97399.67	76246.05
Nitrogen (mg/L)	0.99	1.57	1.43	1.10
Phosphorous (mg/L)	0.15	0.44	0.37	0.20
BOD (mg/L)	7.25	21.19	17.75	9.90
Fecal Coliform (col/100ml)	483.04	1439.50	1203.11	664.57
TSS (mg/L)	12.91	37.47	31.40	17.57

Future violations of biotic criterion may be related to increased urban development and accompanying problems with human waste disposal such as untreated/poorly treated waste and seepage from malfunctioning septic systems. The violations may also be related to loss of forest cover and increase in impervious (urban) surfaces, both of which may result in excess runoff and deposition of solids (TSS increase) and microbes in the water bodies.

Although farm acreage increases in scenario III, this happens at the expense of forests which reduce by 14%. The resulting reduction in land cover and animal waste may be responsible for increased levels of FCB and TSS. In the next section we estimate the value of water quality changes discussed above.

Benefit Transfer: Empirical Application

As discussed in chapter one, we apply Benefit Transfer method to the valuation of water quality as an ecosystem service. The BTE protocol (outlined in chapter one) allows us to estimate what the public would be willing to pay to mitigate some projected environmental quality violations in an area without carrying out actual interviews as in HPM, CVM, TCM, etc. The lands of Habersham and White counties in the UCRB are the affected area. Land reallocation causes changes to water quality which is manifested by changes in biological oxygen demand (proxy for dissolved oxygen) and fecal coliform bacteria levels.

We start by assuming the individual has a right to the initial situation (higher drinking water quality). A decrease in drinking water quality could be measured using CS which represents an income increment corresponding to the individuals willingness to accept compensation (WTA^c) for the diminished level of water quality.

Given the difficulties of measuring WTA discussed in chapter one, we follow Freeman (1993) and measure WTA indirectly through WTP. We assume the individual has a right to the subsequent lower quality. We proceed to measure the welfare change using ES representing an income decrement corresponding to the individuals willingness to pay to prevent a water quality decrease.

In the next step of our BTE we searched for studies conducted on relevant study sites. Two main sources of the studies were the Environmental Valuation Database (ENVALUE) of the Department of Environment and Conservation of the province of New South Wales province of Australia (ENVALUE, 2007), and the Environmental Valuation Reference Inventory (EVRI) a Canadian based research initiative (EVRI, 1999). Other sources of relevant studies included the online environmental science and economic journals. The BT protocol requires that only studies with relevance and applicability to the study site be used for benefit transfer. Accordingly, the Policy site (new study area) and the study site (past actual valuation area) should be as similar as possible with respect to geography, income, preferences, culture, substitution, social characteristics.

Numerous studies on water quality valuation have been documented. Nevertheless most studies cover nitrate (nitrogen) contamination and studies on water quality as measured by BOD and FCB are not plentiful.

Transferring Benefits, Valuing the Ecosystem

In the USA, documented past studies on FCB contamination are few and those that exist offer limited use for BT. This is so because the in most relevant studies Fecal coliform is but one of the problems addressed so that it becomes impossible to extract values that would apply solely to the FCB problem.

Collins and Steinback (1993) apply the cost of averting behavior to study rural household willingness to pay for reduced water contamination by FCB, organic chemicals and minerals, in West Virginia. Average averting expenditure for activities conducted by individuals and households to realize the state water quality standards such as boiling or otherwise treating the water, using alternative or new sources of water, are computed. One important aspect of the study is that unlike others, this study clearly categorizes the costs for overcoming the different problems, with drinking water, FCB, organic chemicals and minerals. Estimates of WTP in this study are considered lower bounds as actual WTP is likely to be higher than defensive expenditures (Bartik, 1988) used to estimate WTP for this study. The study estimates WTP to eliminate FCB problem in drinking water to be USD 320 per household per year.

Table 5.4 compares the study and policy sites. Surface water is the predominant source of drinking water north of the Georgia fall line in the Piedmont province of the Chattahoochee River Basin (GAEPD, 1997). We can therefore make the assumption that 100% of the public in the policy site use surface water and have interest in local surface water quality. In addition, most agricultural water, used in the UCRB (mainly for livestock and aquaculture) is surface water. Additionally, rivers and streams North of Lake Lanier are host to recreational cold-water trout fisheries (GAEPD, 1997).To transfer this value to the UCRB study site, we adjust for income and time as outlined in chapter one.

Table 5.4: FCB Comparison Between Study and Policy Sites

	Study Site	**Policy Site**
Place	West Virginia	UCRB, Georgia
Authors	Collins and Steinback(1993)	Ngugi, D. G.
Problem	FCB in drinking water	FCB in drinking water
Per Capita Income(2005)	$27215.00	$24726.87
Water Source	98%	100%
Data Source	Survey, mail and personal	Benefit transfer
Rural/urban	Rural	Rural
WTP/Capita/Year	$196.30	$248.00

The WTP for programs that would clear the waterways of FCB is estimated at USD 631.70 per household or USD 248.00 per capita per year in constant 2005 dollars. This amounts to USD 15,785,740.00 per year for the entire population of the policy site. The 2005 constant prices WTP for the West Virginia study site was about USD 196.30 per capita per year. The two values compare reasonably considering the differences in per capita income between the two areas. We note that these are lower bound WTP values since they are derived from defensive expenditures.

A similar limitation was encountered in regard to BOD and DO water quality benefit valuation. There exist a sizable number of studies dealing with BOD or DO, but most studies have valued water quality benefits associated with these parameters in combination with other parameters so that it is difficult to extract the share of benefits assignable to DO/BOD.

Russell and Vaughan (1982) applied the Travel Cost Model of the number of one day fishing trips made by anglers in Indiana and neighboring fish and wildlife recreation regions in, to estimate WTP for water quality due to BOD/DO. The authors obtained data from the 1975 National Survey of Fishing, Hunting and Wildlife Related Recreation which covered the 48 contiguous states and the District of Columbia.

Their estimation yields annual economic values of between USD 2.05 USD 4.56 per capita. These values represent WTP for increasing BOD/DO to national standards through Best Available Technology (BAT). In preparing the literature, WTP was adjusted to 1978 current prices. Table 5.5 compares the study and policy sites for BOD violation.

Transferring these values to the policy site with appropriate adjustments for income and time yields annual WTP of between USD 5.58 and USD 12.42 per capita, which translates to an aggregate WTP of USD 355490.10 and USD 790748.70, for the entire policy site. A summary of the benefits is provided in Table 5.6.

The benefits provided in Table 5.6 are really the lower bounds of the economic value of increasing water quality to drinking (and fishing) water standards in regard to fecal coliform bacteria (reducing loading to a maximum of 200 colonies/ 100 ml) and reducing BOD to fishable standards (<15 mg/l). Given that fishable and drinking supply water standards for BOD and DO standards are almost identical, we will make the simplifying assumption that waters satisfying BOD standards also satisfy DO standards, and this is the case for both fishing (including trout) and drinking water supply purposes. The water quality forecast results (Table 5.3) seem to suggest that we are likely to have existing FCB violations in the UCRB. We have therefore included a valuation for FCB control benefits in Table 5.6 for the baseline year.

Table 5.5: BOD/DO, Comparison Of Study Site and Policy Site

	Study Site	**Policy Site**
Place	National,48 states	UCRB, Georgia
Authors	Russel & Vaughan (1982)	Ngugi, D.G
Data Source	National Survey of Fishing (USFWS)	
Problem	Excess BOD/Low DO in fishing water	Excess BOD/Low DO in fishing water
Per Capita Income(2005)	$34,586	$24726.87
Rural/urban	Both	Rural
WTP/Capita/Year	$2.05-$4.56	$5.58-$12.42

Table 5.6: Economic Value of Water Quality in the UCRB

Pollutant	Baseline 2005	Scenario I	Scenario II	Scenario III
BOD/DO	NA	355.49	355.49	NA
Fecal Coliform	15785.74	15785.74	15785.74	15785.74
Total	15785.74	16141.23	16141.23	15785.74

Note: Values are in thousands of US dollars per year at constant 2005 prices.

Our results suggest that the lower bound WTP for creating and maintaining water quality standards for drinking water supply and fishing are about USD 15,785,740 under baseline and scenario III (managed growth) conditions and about USD 16,141,230 under scenarios I and II.

CHAPTER VI

SUMMARY CONCLUSIONS AND RECOMMENDATIONS

The rivers of the Chattahoochee basin are the primary source of drinking water for the city of Atlanta, a significant number of counties north of the Georgia fault line, and more than 4.1 million people from the three states of Georgia, Florida, and Alabama. The Basin's waters including Lake Sydney Lanier provide ampler recreational amenities and income to the Georgia. The river also provides flow regulation, sewage disposal services, hydroelectric power, and valuable wildlife habitat. The Upper Chattahoochee River Basin encompasses the headwaters of the Chattahoochee River and is most serene portion of the ecosystem including the Chattahoochee National Forest.

In this study, we sought to model land use change in the Upper Chattahoochee River Basin above Lake Lanier and to provide economic valuation of subsequent changes in watershed ecosystem services and functions. Towards this end, we developed three models of land use change, a Structural Time Series Model, an Econometric Model and a Vector Autoregressive Model. We selected the Structural Time Series Model for forecasting land use, based on conventional criteria, namely, Mean Absolute Percentage Error and Root Mean Square Error. We then proceeded to forecast three likely land use and land use change scenarios based on the aforesaid results and the resulting changes in ecosystem services, basically water quality for drinking and fishing, for the year 2030. We applied Benefit Transfer Techniques to estimate the economic value of water quality in the Upper Chattahoochee River Basin.

Summary of Findings

A model of land allocation at the aggregate watershed level was developed assuming profit/net benefit maximization under risk neutrality. We assumed a logistic distribution for farm to urban, and forest to urban, land share equations. The assumption has the advantage of ensuring the shares lie in the zero-one range.

The econometric land use model was analyzed as an equation by equation SURE model as all the independent variables were the same for both equations. In line with a logistic distribution assumption, log of land shares formed the dependent variables for the models. Independent variables in the econometric model included farm revenue, forest revenue, Georgia farm equity, average wage per job, interest rate, number of large animal units, population, per Capita income, government payment to farms, government conservation and wetland reserve program (years of operation dummy variable) and Payment in Kind (year of operation dummy variable). The income related variables and farm equity were deflated using CPI for the southern US.

The final equation retained (through stepwise regression) net farm revenue, Georgia farm equity, population, and government payments. The model also satisfied classical OLS requirements. A key result of the model is that both (farm and forest share) equations yielded negative and significant signs for population, showing as expected that increase population density will all things equal result in increased encroachment of urban development on forests and farms. The econometric model had the largest forecasting ability statistics meaning it was the worst model for forecasting land allocation.

The VAR model yielded significant signs on first lag and the trend variable. The model also satisfied classical OLS requirements and had showed better forecasting ability compared to the econometric model.

Econometric and conventional time series models will normally include one form of trend or no trend in a model. Additionally these models may include a dummy variable to cater for structural change depending on assumptions made about the same. The STSM has the advantage of allowing the data to reveal underlying structural and technological change without imposing such a priori. In our STS analysis we examined models with stochastic trend no seasonality (STNS) and fixed trend no seasonality (DTNS). Additionally, we assumed farm and forest acreage models follow the same processes and estimated a seemingly unrelated structural time series equations (SUTSE). The model with the best forecasting ability was a STNS model with structural breaks in the slope component. Ultimately the STSM seemed the best land use forecasting model among the three mainly by virtue of having the smallest RMSE and MAPE. The model also tracked the data well as evidenced by lack non-significant (at 5%) forecast failure chi-square statistic implying parameter constancy hypothesis was not rejected.

In analyzing effect of land use change on water quality, we took year 2005 as our baseline and postulated three land use scenarios. Forecasts of the STSM represented the highest growth rate in urban development; the average rate of land use change in existing data between 1974 and 2005 was taken to be the best case or limited/managed growth scenario and average of these two scenarios represented a third, moderate growth scenario.

We proceeded to input land allocations into the L-THIA model. Land allocations were as forecasted by the three scenarios above while year 2005 data formed the baseline. The L-THIA model output was in terms of levels of NPS pollutant loadings including runoff, TSS, BOD (for DO), FCB in the ecosystem surface waters. All future scenarios, except limited growth, showed excesses (worsening water quality) for BOD and

FCB and worsening (increasing) runoff. In addition the baseline also showed violations for FCB.

We applied Benefit Transfer techniques to value water quality changes resulting from land use change and estimated lower bounds for WTP to improve water quality to meet the FCB criterion for drinking water supply and fishing waters and BOD (DO) criteria for fishing waters.

Conclusions

The data related limitations of the study notwithstanding; the most important contribution of the econometric land allocation model was the negative and significant sign on population. This implies that, *ceteris paribus,* increased population density results in increased encroachment of urban development on forests and farms.

The STSM outperformed both the VAR and the econometric model in terms of forecasting ability. The presence of a stochastic trend in the model suggests that models of land use that ignore the trend variable might be miss-specified and might lead to erroneous conclusions. In spite of the state of our land use data, we were confident that the STSM yielded reasonable and results given the model forecasting ability as evidenced by small MAPE and RMSE. All land use forecasts pointed toward loss of forest land to urbanization. Farmland may or may not be spared the encroachment; it would all depend on interventions that the community takes to control urban growth.

Water quality modeling revealed that land use change would result in increased runoff, and associated increase in FCB and BOD/DO violations. But the BOD/DO violations could be curtailed by managing urban growth as evidenced absence of BOD violations in the managed growth scenario. Our study finds there may be problems of FCB under all postulated future land use scenarios. The findings also support existing literature that there are problems with FCB violation in the study area at the moment.

Finally, it seems that the people of UCRB would be willing to pay a lower bound value between USD 15,785,740 and USD 16,141,230 per year to create and maintain quality standards for fishing and drinking water supply.

Implications and Future Research Recommendations

Thus far, few economic and statistical based ecosystem and aggregate land use models exist. The few that have been estimated are based on conventional econometrics and there have been no significant attempts to apply structural and/or time series methods in estimating land use. Additionally literature forecasting land allocation is noticeably scarce and scarcer still is literature exploring land use change implications for water quality particularly in the setting of an ecosystem.

A key contribution of this study is to estimate land use model using VAR and STS models as past studies have relied solely on traditional econometric models. The advantage of STS models is that they can capture underlying trends, structural and technological changes that may be missed or miss-specified by other estimation methods. STSM are also better placed for ex-ante forecasting as there is a reduction in the number of variables to be forecasted.

This study was particularly constrained by scarcity of land use data. The land use component of this study was seriously impeded by lack of data. The fact that we had to interpolate to create more than 80% of the observations meant that we would not be very confident of getting really good results particularly with the econometric model.

Inconsistencies in farm and forest acreage data compiled by various bodies including the Census of agriculture, Georgia County Guide, Georgia Statistical System and the US Forestry Service, meant that we had to find a “more consistent” data source for land acreage. The final data set consisted of six observations spread over the period between 1974 and 2005 compelling us to interpolate between the observation to obtain sufficient data and degrees of freedom. This may explain which may explain some of the limitations of our results such as a not so robust econometric model. Since land use data were available at county level, future research could surmount this problem by covering using a panel data approach; covering a larger portion of the watershed, hence having more data points from more counties.

The L-THIA model made estimating water quality changes associated with land use change relatively fast and straight forward. We would recommend the use of this software for land use-water quality estimation. In estimating WTP for water quality, a key limitation was lack of similar enough studies. Many would be relevant studies lumped together numerous NPS pollutants and separating a few for estimation was not possible. The few relevant studies also applied diverse subjective measures of utility such as “concern for preserving an amenity” that would not be easy to formulate for a policy site. Ultimately whereas we would have preferred to apply function transfer we ended up using value transfer to estimate the benefits in the policy site.

Our study supports the literatures in finding problems of FCB in the Upper Chattahoochee River Basin. These and the problems of BOD/DO can be ameliorated by concerted efforts including introducing best management practices, reducing impervious surfaces, reducing urban sprawl so as to conserve the forest, and other activities that involve the community in watershed management. Efforts geared towards protecting forests and farms, preserving open spaces and riverbed buffer zones would preserve water quality as evidenced by a higher level of water quality during the baseline and limited growth scenarios when forests occupy a major portion of the ecosystem. Such approaches are likely to cost less than the cost of defensive behavior or ecosystem restoration after the fact.

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APPENDIX

Appendix 1 Tables

Table A: Data Needs and Sources

Data Needs	Data Sources
Population; Income;	United States Census Bureau
Land acreage	NARSAL (2007)
Livestock numbers	Georgia County Guide
Farm income	Georgia Statistics System
Timber yields	Birdsey(1992); Birdsey(2003); Plantinga (2007)
Timber prices	Center for Forest Business (2007)
Farm equity	USDA, Economic Research Service
Interest rates	US Reserve Bank
Wage; CPI	Bureau of Labor Statistics