THREE ESSAYS ON THE ECONOMICS OF LAND USE AND WATER QUALITY

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THREE ESSAYS ON THE ECONOMICS OF LAND USE AND WATER QUALITY

Gandhi Raj Bhattarai

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THREE ESSAYS ON THE ECONOMICS OF LAND USE AND WATER QUALITY

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Date of Graduation

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Gandhi Raj Bhattarai, son of Chhabilal Bhattarai and Januka Bhattarai, was born January 27, 1971, in Tanahun, Nepal. He graduated from Biswo Prakash High school, Chitwan, Nepal, in 1986. He attended Institute of Agriculture and Animal Science, Tribhuwan University, Nepal, for five years and graduated with a Bachelor of Science degree in Agriculture in September 1993. He worked as Outreach Research Officer in Pakhribas Agricultural Center's Outreach Research Division for five years. He obtained a Master of Science degree in Agricultural Development Economics from Reading University, UK, in September 1998. After returning to Nepal, he worked as a faculty in the Department of Agricultural Economics in the Institute of Agriculture and Animal Science for two years. He entered Graduate School, Auburn University in January 2001 and earned a Master of Economics (Non-Thesis) degree in May 2004. He married Rajani Sedhain, daughter of Late Giriraj and Ganga Sedhain, on November 26, 1996. He has two daughters Akriti, 7 and Asmita, 3.

DISSERTATION ABSTRACT

THREE ESSAYS ON THE ECONOMICS OF LAND USE AND WATER QUALITY

Gandhi Raj Bhattarai

Doctor of Philosophy, May 11, 2006
(M.S., Auburn University, 2004)
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Studies in natural resources economics apply different models ranging from a simple linear regression models to much more complex models requiring advance skills in Geographic Information Systems, statistics and computer programming to predict the effect of population and income on the demand for resources, to much more complex models requiring advanced skills in Geographic Information Systems, statistics and computer programming. The later kind of models are often developed and used to estimate the effect of human actions including land management practices on soil erosion, water quality and biodiversity. The results of such models have been instrumental in improving, among others, our understanding of causes of decline in environmental quality, formulating policies for pollution control, and conserving the natural environment.

This work, focused on water quality as a specific environmental quality indicator, demonstrates how different models can be applied to estimate the effects of (i) socioeconomic and demographic forces on land use distribution, (ii) land use distribution on water quality, and (iii) the value placed on environmental amenities.

This dissertation is divided into three essays. In the first, a multinomial logit model is used to estimate the effects of urbanization, demographic structure, personal income and spatial distribution of watersheds in the allocation of fixed proportion of land to developed, forest, agricultural and other land uses in a watershed. These results constitute a foundation for spatial and ecosystem models to predict long-term environmental impacts of land use change.

In the second essay, a simple bioeconomic model is used to determine how changes in land use distribution affect the water quality in a watershed. The BASINS-SWAT model is used to estimate environmental parameters, which will then be used in the economic model to examine optimal land use under environmental constraints. The results will inform policy decisions on land use in the watershed.

In the third essay, a hedonic model is applied to estimate the demand for public goods, including water quality, using housing market data from Ohio. The model derives implicit prices for neighborhood and environmental characteristics and estimates the demand for those qualities. This study estimates willingness to pay for individual house characteristic related to environmental quality, which helps environmental policy makers to assess the benefits and costs of environmental pollution control and streamline their resources.

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I would like to show my appreciation for all the support I have received from my family and friends. No words can express my gratitude to my aging parents for their sacrifices in their lives to make me stand where I am now. Finally, I would like to thank my wife Rajani for her love and support throughout the study. I appreciate the wonderful patience and understanding of two daughters Akriti and Asmita.

Style Journal Used:

Land Economics

Computer Software Used:

- Microsoft Office (Word and Excel)
- SAS, Version 9.1
- Maple, Version 9.5
- ArcView Geographic Information System, Version 3.2a
- BASINS (Better Assessment Science Integrating Point and Nonpoint Sources) Version 3.1
- SWAT (Soil and Water Assessment Tool) Version 2000

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INTRODUCTION

I. BACKGROUND

Studies in natural resources economics apply different models ranging from a simple linear regression models, for example, to predict the effect of population and income on the demand for resources, to much more complex models requiring advanced skills in Geographic Information Systems, statistics and computer programming. The latter variety of models are often developed and used to estimate the effect of human actions, including land management practices in soil erosion, on water quality and biodiversity. The results of such models have been instrumental in our understanding of the causes of decline in environmental quality, which in turn help in formulating policies for pollution control, to conserve the natural environment. Hedonic demand models can expand the economic analysis of such actions by estimating the existence and nature of demand for public goods. Demand curves can be used to estimate the willingness to pay for environmental amenities, which is useful for evaluation of alternative projects and policies.

The agricultural sector is alleged to be the largest contributor to NPP through runoff of herbicides, pesticides, sediment, and nutrients (USEPA, 1998). Crop cultivation requires more use of chemicals and nutrients than does natural vegetative cover like forest and grasslands. Tillage operations affect the soil structure and often make nutrient rich topsoil fragile and cause it to lose more chemicals and soil particles during rainfall.

Increasing land productivity and agricultural production while maintaining, if not improving, environmental quality, has been a challenge in recent years. On one hand, increasing population and economic growth has created increased demand for food production, while on the other hand it has encouraged conversion of forest and agricultural lands to developed uses. This has resulted in rapid land use change and unprecedented input use in agriculture, thus causing further deterioration of water quality through nonpoint source pollution. A study by the National Assessment Synthesis Team (2000) suggests that another factor affecting NPP is future climate change which will require higher use of chemicals, pesticides and nutrients to maintain the current level of productivity of most crops. This will further increase the rapid decline in the quality of water bodies for their intended uses.

Thus, on one hand, increased land use in agriculture results in larger quantities of chemicals and pesticides, causing higher non-point source pollution of ground and surface water. On the other hand, lands in residential and developed uses, such as lawns and gardens are managed more intensively than agricultural land encouraging the generation of even more pollutants. Clear cutting forests results in loss of wildlife habitat and increases runoff, as protective vegetative cover of the soil is lost. Urban development increases the amount of impervious surface and causes lower percolation and higher run-off. During precipitation, runoff carries more nutrients and sediments from agricultural and residential lands, resulting in higher chemical levels and turbidity in the water. Urban wastes such as in landfill sites also cause water pollution as water percolates through. Thus, increasing urbanization coupled with increasing use of nutrients and chemicals in agricultural lands creates significant challenges for water quality maintenance.

Ecosystem services in a watershed are affected by human impact on land and water. A combination of all the previously mentioned factors contributes to water stress, pollution, and loss of aquatic and terrestrial biodiversity. Understanding the effects alternative land management scenarios on environmental quality through simulations helps environmental policy planners to integrate efforts to effectively reduce the environmental pollution through the institutionalization of best management practices. A better understanding of the causes and effects of land use change helps in making public policy towards land development and planning.

Agricultural BMPs have been shown to reduce NPP by reducing runoff and/or capturing sediments, and can thus be helpful to maintain water quantity and improve water quality in streams and other water bodies. However, it is imperative to account for the effects that BMPs may have on farmers' profitability. Thus, watershed and farm level economic impacts must be evaluated to understand the magnitude of gains and losses to individual farmers through use of BMPs and provide institutional support when required.

Understanding people's willingness to pay to public goods will help to formulate policies towards institutional support for improvement in environmental quality and other publicly provided goods and services. Results from such studies help determine tax assessment policies by county and state legislatures, for example, abatement fees or environmental pollution taxes on different geographic regions. At the same time, this will provide the basis for benefit cost analysis for cleaning toxic substances, improving water quality, investing in school quality improvement or strengthening public safety.

This work focuses on water quality as a specific environmental quality indicator. The present study develops different models in stepwise fashion to examine three different areas of the economics of land use change and water quality. It demonstrates how different biophysical and econometric models can be applied, firstly, to estimate the demographic and socioeconomic influence on land use choice, secondly, to measure the effects of land use change on water quality, and finally, to estimate the value people place on environmental amenities.

II. DISSERTATION OUTLINE

This dissertation is divided into three essays. Each essay is designed as an independent study of a sequence of activities. Each essay focuses on a specific objective as explained in the following paragraphs. Each of these steps involves econometric models and makes use of geographic information system tools in data processing and analysis.

In the first, a multinomial logit model is used to estimate the effects of urbanization, demographic structure, personal income and spatial distribution of watersheds in the allocation of fixed proportion of land to different uses in West Georgia watersheds. Increasing population and economic activities demand more land for developed purposes, such as home sites, roads, airports, schools, parks, and industrial and commercial developments. The level of economic activities, demographic changes, and public policies related to land management are associated with the distribution of agricultural, forest, urban, and other lands. Individual landowners' decisions on land use conversion result in an aggregate pattern of regional land use distribution. The model estimates the effects of different socioeconomic variables on land use choice faced as a social planner's problem. These results constitute a foundation for spatial and ecosystem models to predict long-term environmental impacts of land use change.

In the second essay, a simple bioeconomic model is used to determine how changes in land use distribution affect water quality in an Alabama watershed with multiple land uses. The BASINS-SWAT model is used to estimate environmental parameters, which are in turn used in the economic model to examine optimal land use under environmental constraints. The results will inform policy decisions on land use in the watershed.

In the third essay, a hedonic model is applied to estimate the demand for public goods, including water quality, using housing market data from Ohio. The model derives implicit prices for neighborhood and environmental characteristics and which are used to estimate the demand functions for those qualities. This study estimates willingness to pay for individual house characteristic related to environmental quality, which helps environmental policy makers to assess the benefits and costs of environmental pollution control and streamline their resources.

III. SCOPE AND LIMITATIONS

The study has been guided by the availability of data and the location of related works in a wider project area. West Georgia, in which the first chapter of the dissertation is based, is a part of project area for Center of Forest Sustainability project. The Columbus, GA Metropolitan Area is among the rapidly growing urban areas in the State. While some areas within the state have gone through rapid transformation from rural to developed land in a short period of time, other parts of the state are still predominantly rural with low population growth and no urban development. Large urban areas have expanded significantly to the suburban areas, and small townships have developed into urban centers. Thus the pattern of land development in an area covering five counties in

West Georgia gives an excellent field for measuring effects of demographic and socioeconomic changes on different type of predominant land uses. However, spatial variations in some socioeconomic variables are limited because only five counties are considered. Nonetheless, this study provides a solid foundation for more complex regional analysis involving multiple states using county level information.

The second paper has few limitations in the analytical framework and model estimation. About two third of land surface in Alabama is covered with forest. The study area was selected based on the multiple land use criteria in predominantly agricultural production belt. While the share of cropland, pastureland and forestlands are substantial the share of developed land is relatively small. The model setup picks up major land use in each subbasin leaving out unique land uses with small land coverage. However, the effects of such an adjustment are likely to be minimal and insignificant.

Another limitation in this paper is the aggregation of land use categories to a few dominant land cover classes. The land use data used in this study come from the 1992 and 2001 National Land Cover Datasets. Although vegetative covers are broken down into different types of forestlands, pasture and rangeland, cropland, and different intensities of developed land, the maps do not disaggregate to crop level. Hence, simulations are limited to a single major row crop and a single forage crop grown in the study area.

The third paper is based on housing transaction prices in six metropolitan areas in the state of Ohio. Secondary data on housing and neighborhood characteristics for more than 45,000 house transactions within those metropolitan areas provides an excellent opportunity to estimate two stage hedonic demand models using multiple market data. This paper estimates demand for four public goods namely environmental quality as measured by the distance to hazardous site, school quality as measured by expenditure per student, public safety as measured by the index of crime ratio, and water quality as measured by the index of impaired water. First stage hedonic model helps to derive the marginal implicit prices of each of these neighborhood characteristics and a number of housing characteristics. The second stage demand model, which is estimated as a system of four simultaneous equations, derives the demand for each of these public goods. Joint estimation of four demand equations facilitates the estimation of cross-price elasticities of one public good with another public good.

All three papers are designed to demonstrate the use of specific a model within particular areas of environmental and natural resources economics. Though the studies are based on different geographic areas, the themes are connected because they related a number of economic activities to land use and water quality. While input data specific model results are valid for the geographic region of the study area and the time period included in the study, the tools used in the study have will be widely applicable to other regions and other types of environmental quality issues.

CHAPTER 1. ESTIMATING THE SOCIOECONOMIC INFLUENCES ON LAND USE CHOICE USING A MULTINOMIAL LOGIT MODEL

1.1 INTRODUCTION

Increasing population and economic activities demand more land home sites, roads, airports, schools, parks, and industrial and commercial developments. Population growth and increased per capita disposable income are important components of the economic demand for urban land uses (Reynolds 2001). As a result, more forestland has been cleared for cultivation, and more agricultural lands have been converted to satisfy increasing demand for urban development. Urban areas have become more intensified, and they have expanded into rural areas to accommodate the demand for urban land uses. This has created strong competition among urban expansion, agriculture, forestry and other rural land uses (Reynolds 2000).

The southeast region of the United States has experienced tremendous urban expansion and market influence in the past forty years. Georgia ranked 6th among the fastest growing states with a 26.4% increase in population between census years 1990 and 2000 (Census 2000). Columbus is among the most rapidly growing urban areas in Georgia. While the population of Columbus increased just 4.0% between census years 1990 and 2000, the population in neighboring Harris County increased by a record 33.2% (Census 2000). Some areas within the state have gone through rapid transformation from rural to developed land in a short period of time. However, some parts of the state are still predominantly rural with low population growth and no urban development. While large urban areas have expanded significantly to the suburban areas, more importantly, small townships have developed into urban centers. These discontinuous development and land use change are often regarded as urban sprawl (Carrion-Flores and Irwin 2004; Wu and Plantinga 2003).

Individual landowner's decision of land use conversion aggregate into a pattern in regional land use distribution. The level of economic activities, demographic changes, and public policies related to land management are associated with the distribution of agricultural, forest, urban, and other lands. The conversion of land use from forest or agricultural to residential development tends to be permanent and irreversible (Hite et al. 2003).

Increased land use in agriculture results in larger quantities of chemicals and pesticides in the environment causing higher non-point source pollution of ground and surface water. Clear cutting forests results in loss of wildlife habitat and increases runoff and sediment transport as protective vegetative cover of the soil is lost. Urban development increases the amount of impervious surface and causes higher run-off. Urban wastes such as in landfills also cause water pollution when water flows through wastes.

A combination of all these factors contributes to stress on water quality and quantity, and loss of aquatic and terrestrial biodiversity. Understanding the causes and effects of land use change helps in making public policy towards land development and planning.

The present study develops an econometric model to explain the changes in land use distribution as a function of different levels of demographic, economic and market conditions at the watershed level using time-series cross-sectional data. Impacts on land use distribution because of changes in socioeconomic variables are simulated and overall land use scenarios are predicted.

1.2 LITERATURE REVIEW AND ANALYTICAL FRAMEWORK

Generally, two types of land use change models have been seen in the literature, a Geographic Information System (GIS) based land use change models and statistics based economic analysis models. A few example of first type of models include Land Use Change Analysis System developed by University of Tennessee), Land Transportation Model (developed by Michigan State University), The SLEUTH Model (developed by University of California, Santa Barbara), UrbanSim (developed by University of Washington) and What If? (developed by Community Analysis and Planning Systems, Inc.). Each of these models support different objectives of land use change analysis, ranging from how new urban areas consume surrounding land and impact the natural environment (the SLEUTH model) to how the interactions between land use, transportation and public policy shape community's development trends and affect the natural environment (UrbanSim model). Such models that make use of multiple land cover maps created from satellite images in relatively uniform areas such as around an urban center over time. Although such models can precisely estimate the changes in particular land use over a predefined geographic area, these software-based models are often costly, data intensive and sophisticated.

The second type of models mostly deals with the economic interpretation of effects of individual policy intervention on land use changes. Such models apply different statistical tools to estimate the relationship between one or more variables can be done relatively quick and on the other variables and are more efficient in terms of costs and complexity involved in data processing and analysis. Most recent land use studies have focused on urban sprawl and its effect on agricultural land values, farmland retention and some relationship between the rural-urban interfaces (e.g., Baumol and Oates 1998; Bearlieu et al. 1998; Hsieh et al. 2000; Miller and Plantinga 1999; Onal et al. 1997; Phinn and Stanford 2001; Reynolds 2001; Wear and Bolstad 1998). Mostly these studies have used aggregate cross-sectional data at county-level for analysis. A few studies, however, have tried to explain land use conversion at micro level (e.g., Hite et al, 2003; Carrion-Flores and Irwin 2004; Hua et al. 2005). Recent studies have used complex models like survival analysis (Hite et al. 2003) and Markov-Chain techniques (Hua et al. 2005) to determine both the reasons for and timing of land use conversion. A few other studies have focused on the location and timing of development (Carrion-Flores and Irwin 2004; Irwin and Bockstael 2002). Most mainstream studies exploring the causes of land use conversion use probability based models including multinomial logit or probit models (McMillen 1989; Buldoc et al. 1997; Hardie and Parks 1997; Plantinga et al. 1999; Nagubadi and Zhang 2005).

Previous studies using multinomial logit models of land use change have mostly focused on the effect of urbanization on agricultural land values, agricultural and forest interaction, urban-rural interface and land use competition, estimating land use change as a function of particular regulation, economic activity and population growth at micro level. However, the nature of land use conversion over a wider geographic coverage with respect to population changes, economic growth, and market pressure has not been fully explained.

Population growth, urban development, and personal income from non-farm sources are expected to encourage conversion of low-return forest and agricultural land to high-return developmental use. Increased demand for developable land causes a sharp increase in the price of land in or near the city centers. Developers then search surrounding areas to find cheaper land. Thus, as the distance from the city center increases, the effect of urban expansion gradually decreases. A larger proportion of people employed in non-farm activities within the place of residence suggest a market concentration in the area. However, a higher commute time for regular work, on the other hand, indicates possible urban traffic congestion. Similarly, population structure such as average age of the people in an area also affects the demand for lands for alternative uses. People's expectation about the returns from alternative uses of land affects their decision to allocate available lands in different uses.

In this study, the allocation of fixed proportion of lands to different developed, agricultural, forest and other uses in a watershed is viewed as an optimization problem faced by a social planner (Bhattarai et al. 2006). The model has been kept to the simplest form without introducing the structural complexities of externalities. Land use is taken as a function of population density, average age, personal income, education level, employment concentration, commute time, accessibility and spatial location.

Variables such as employment concentration, commute time, and road accessibility are assumed to be indicators of urban development and market concentration. Employment concentration is measured by the ratio of people involved in non-farm employment within place of residence. Accessibility is measured by the level of transportation network and commercial infrastructure in the area. Similarly, population density, average age and education level are taken as an indicator of demographic structure. Population density is measured in terms of persons per acre of land area. Average age is the mean of all individuals' ages in each watershed. Personal income is proxies for economic development in the area, which is expressed in thousands of dollars. Education level is expressed as the ratio of people having at least bachelors level education to the education levels of total population.

Relative spatial location is expressed in terms of longitude and latitude of the watershed's centroid. If latitude and longitude have significant marginal effects on land use choice, it is expected that land use distributions are spatially related.

A modified multinomial logit model from Parks (1980) is used for the analysis. Land use in each category is expressed as the fraction of total area of land in each type in the watershed, summing to one. Since land is quantitatively fixed in a given watershed, an increase in the share of one type of land results in an equal decrease in other land use types. It is possible to estimate the total changes for each type of land proportion in the watershed using the probabilities of changes in dependent variable for a change in explanatory variable. A system of simultaneous equations, one equation for each type of land use, can solve this problem by jointly determining the model parameters.

A probability-based model takes the form of:

$$P_{ikt} = \frac{\exp(\beta'_k X_{it})}{\sum_{k=1}^{K} \exp(\beta'_k X_{it})} \tag{1.1}$$

where, p_{ikt} is the proportion of land in i^{th} watershed, in k^{th} land use at time t. X_{it} represents a vector of demographic, economic and spatial characteristics for the observed individual watershed. B_k is a vector of estimated parameters.

Normalization of equation (1) by one of the land use shares (for example, k=4; and constraining $\beta_4=0$) yields the multinomial logit model as:

$$P_{ikt} = \frac{\exp(\beta'_k X_{it})}{1 + \sum_{k=1}^{K-1} \exp(\beta'_k X_{it})} \quad \text{for k=1, 2, … K-1.} \qquad (1.2)$$

The proportion of omitted fourth category is derived from the formula:

$$P_{i4t} = \frac{1}{1 + \sum_{k=1}^{K-1} \exp(\beta'_k X_{it})} \qquad (1.3)$$

In order to simplify model estimation, equation (1) is transformed logarithmically to yield the following three (K-1) equations:

$$\ln(P_{ikt} / P_{i4t}) = \beta_k X_{it} + u_{it} \quad \text{for k = 1, …, K-1.} \qquad (1.4)$$

where u_{it} is the random error terms. However, the optimal land use proportions or P_{ikt} in the above equations are not directly observable, these values are replaced by the observed actual land use proportions for the model estimation. Thus the model to be estimated is a system of three equations which are linear in parameters.

$$\ln(y_{ikt} / y_{i4t}) = \beta_k X_{it} + u_{it} + \varepsilon_{it} \quad \text{for k = 1, …, K-1.} \quad (1.5)$$

Since the coefficients of such models are not directly interpretable in terms of coefficients from an ordinary least square estimation, marginal effects are estimated to express the probability of change in land use with respect to each independent variable measured from the mean of the variable:

$$\frac{\partial y_{ikt}}{\partial x_{ikt}} = \left(\beta_{kx} - \sum_{k=1}^{K-1} y_{ikt} . \beta_{kx} \right) . y_{ikt} \quad \text{for k=1, \ldots, K-1.} \qquad (1.6)$$

where, β_{kx} is the coefficient of X for land use k. The marginal effect on the redundant category is obvious as the sum of the marginal effects of all categories equals to zero.

1.3 DATA AND METHODS

Watersheds in five western Georgia counties, Harris, Meriwether, Muscogee, Talbot and Troup have been selected to represent different transitions of land use change in the study area. A map of study area is given in Figure 1.1.

A total of 60 watersheds are included in the analysis within the five county boundaries. Watersheds at 12-digit level hydrological unit codes are taken from the Georgia Spatial Data Clearing House website (https://gis1.state.ga.us/index.asp). The watershed areas ranged from 2,693 acres to 30,643 acres with a mean area of 16,556 acres. While most of the watersheds from this secondary source are retained for the study, two very large watersheds are divided into five smaller sub-watersheds using hydrologic modeling tools within a geographic information system application (See page 40-41 for detailed methodology of hydrological modeling in chapter 2).

Methodologically, most land use change studies compare two satellite images taken at different time periods. In recent years, formation of the Multi-Resolution Landuse Consortium (MLRC) has made it possible to use a uniform land use category developed from multiple satellite images processing taken over an annual cycle of land cover situations. The resulting digital maps show a more stable land use distribution and indicate permanent changes when they occur.

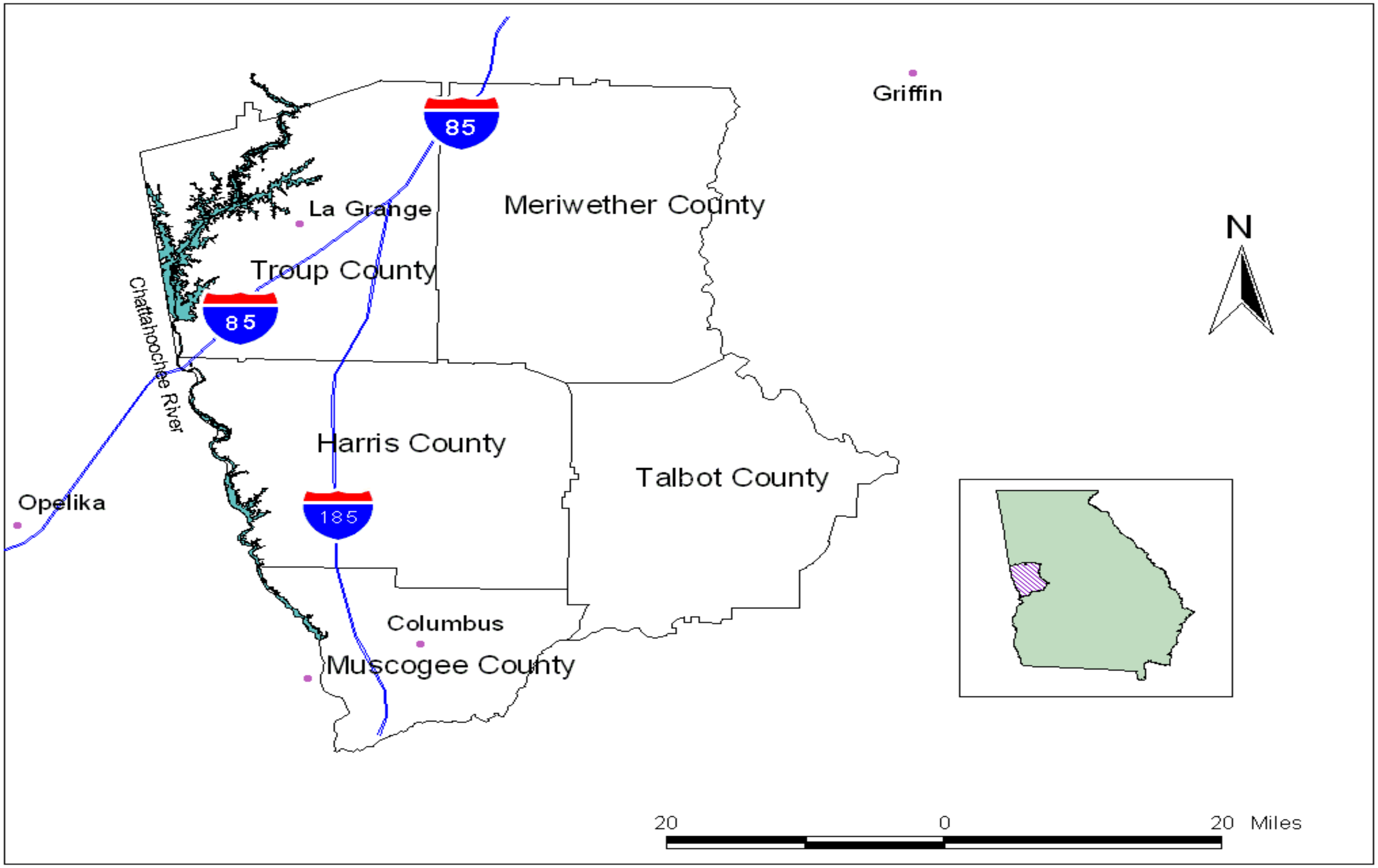

Figure 1.1 Map of study area for estimating the socioeconomic influences on land use choice using a multinomial logit model

A 21-class digital land cover map of the study area is extracted from USGS National Land Cover Dataset for 1992 (NLCD-92). This land use map is based on satellite images taken during 1992. Overall thematic accuracy level of NLCD 1992 land use data is 82% at the Anderson Level I (Stehman et. al. 2003). A similar map is obtained from the Georgia GIS Data Clearing House for the year 1998. The original source of this data is Natural Resources Spatial Analysis Laboratory (NARSAL), University of Georgia, Athens, GA. The maps are created using identical methods of NLCD database and are based on the satellite images taken during circa 1998. Overall accuracy of this land cover map at the state level is assessed to be 82% (Information from the Metadata, https://gis1.state.ga.us/data/landcov/1998landcover.html). Those maps came in a tag image file format (TIFF), which are geo-referenced for displaying and processing using GIS software. ArcView Version 3.2a is used for data processing in the GIS.

Digital land use maps are converted to standard grids to facilitate reclassification and spatial analysis. Land use grids for the five county areas are extracted using 'extract grids by polygon' feature in the 'grid analysis' extension. Existing land use grids, as indicated by the grid codes, are reclassified into four broad categories namely "Developed land", "Agricultural land", "Forestland" and "Wetlands and Others". Reclassified is done by using the 'reclassify' tool in the 'spatial analysis' extension. The land cover reclassification scheme is given in Table 1.1.

Table 1.1 Reclassified NLCD 1992 and NARSAL 1998 land cover categories

Current description of land use conditions	NLCD (1992) Grid Code	NARSAL (1998) Grid Code	Classes in multinomial logit model
Low intensity residential	21	22	Developed land
High intensity residential	22	24	Developed land
Commercial/Industrial/Transportation	23	18	Developed land
Utility swaths	-	20	Developed land
Urban/Recreational Grasses	85	73	Developed land
Pasture/Hay	81	80	Agricultural land
Row crops	82	83	Agricultural land
Transitional/Clearcut/Sparse	33	31	Forestland
Deciduous forest	41	41	Forestland
Evergreen forest	42	42	Forestland
Mixed forest	43	43	Forestland
Open Water	11	11	Wetlands & Others
Bare rock/Sand/Clay/Mud	31	07, 34	Wetlands & Others
Quarries/Strips/Mines/Gravel Pits	32	33	Wetlands & Others

The reclassified grids are then tabulated for each of the watershed polygons using 'tabulate' feature. Overall land use distribution in the five county study areas in two time periods is displayed in Figure 1.2. As we see in the figure, land cover distribution in the five county study area is 80.4% forestland, 11.3% agricultural land, 3.3% urban land and

5.0% wetlands and other uses in 1992. This land use distribution changed to 76.1% forestland, 9.5% agricultural land, 9.5% urban land and 4.8% wetlands and other land uses by the year 1998. The changes in the land use shares between two periods are weighted by area. There is an increase in developed land use by 187%, and decreases in the shares of agricultural land by 19%, forestland by 6% and wetlands and others by 4% respectively.

Census Block Group (CBG) level housing and population data (Census Bureau: STF3A Microdata) are extracted from the Interuniversity Consortium for Political and Social Research (ICPSR) database. Demographic and economic data for a total of 242 CBGs in 1992 and 226 CBGs in 2000 are extracted. ICPSR is available for free, along with the SAS or SPSS program to read data, to the participating universities. The processed data contain information related to population structure such as total counts and percentages in rural versus urban area, age structure, personal and household income, education, family structure, characteristics and counts of housing units, median house value among others. Necessary variables have been retained in the dataset and a dBase table is created with all the information at census block level. Each census block group is identified with the federal information processing standards (FIPS) code.

The processed socioeconomic data are in tabular form needed for transfer to a GIS dataset for further processing. The topographically integrated geographic encoding and referencing (TIGER) system line data for census block groups are obtained from the US Census Bureau for census years 1990 and 2000. For each year of spatial data the corresponding tabular data are matched by FIPS codes, and merged using table join feature in ArcView.

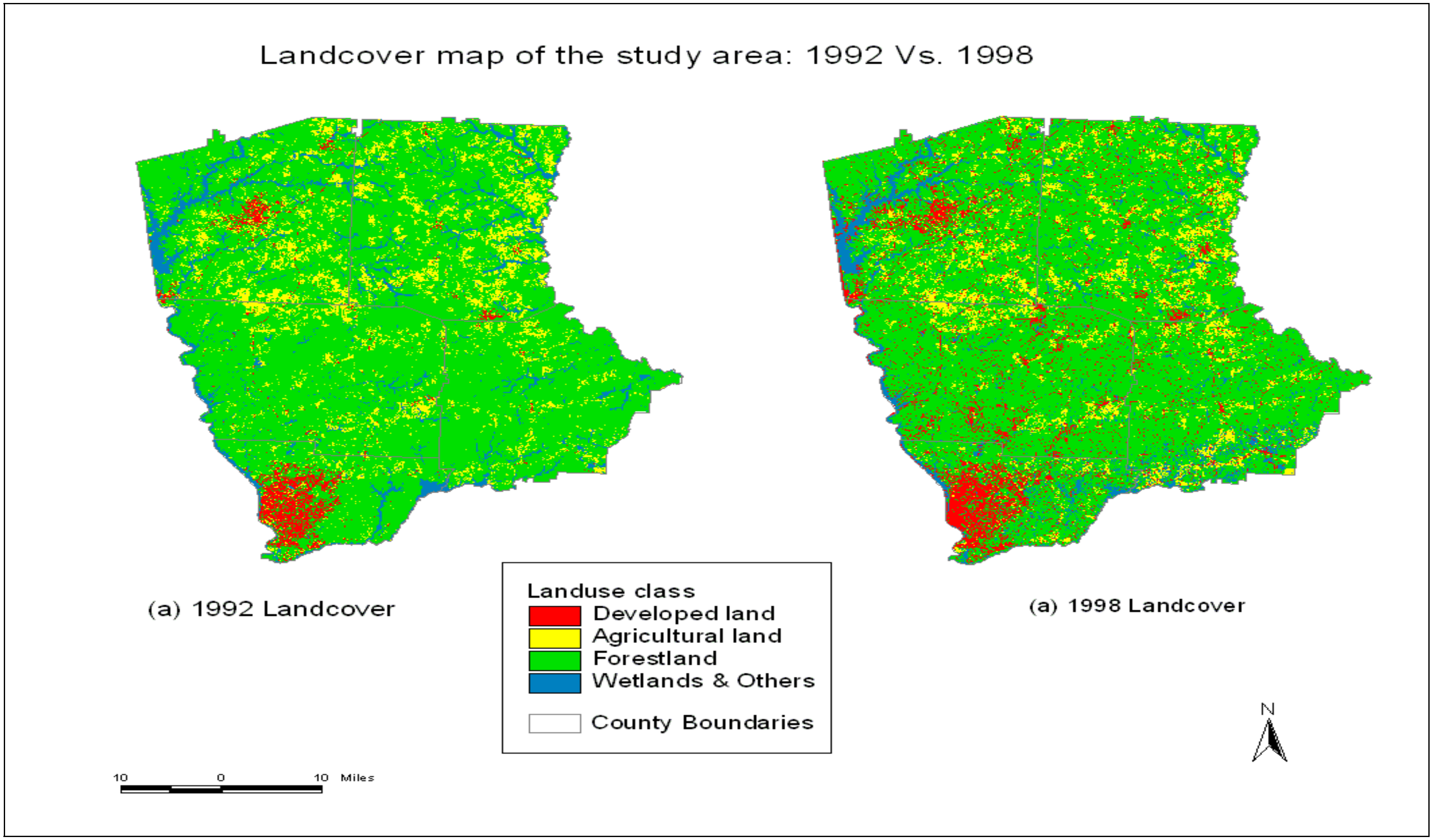

Figure 1.2 Distribution of broadly reclassified land use categories in the five county areas in Western Georgia

Once both watershed boundaries and socioeconomic data are loaded as two separate themes in the GIS project, the census block group polygons are intersected with the watershed polygons. This process resulted in hundreds of unique polygon segments along with the tabular attributes. The areas and perimeters for each unique segment are calculated using the area calculation script. The resulting attribute table is saved into a dBase file and further processing is done using SAS program.

Once in the SAS program, the ratio of each segment to the corresponding census block group is calculated. Assuming a uniform distribution of information within each census block group, this ratio is applied to calculate the weighted counts and averages for each of the watersheds that contained multiple watershed-census block group segments.

1.4 RESULTS AND DISCUSSIONS

Descriptive statistics of the study variables are given in Table 1.2. The population density and the average age of population both increased by 5% between the two census periods. In general, the number of people working at the place of residence decreased by 9% while travel time to work increased by 18%. This pattern provided evidence of urban traffic congestion and rural urban job interface.

The transportation network, defined as the total land surface area under roads and railway network, increased by 323%. Per capita income increased by 23% and proportion of population with bachelors and higher degree increased by 31%. In general, the weighted share of land use in developmental use increased by 187% while agricultural and forestland decreased by 19% and 6%, respectively.

Table 1.2 Descriptive statistics for the variables used in the multinomial logit model of land use distribution choices in West Georgia

Variables	Period I (1990)		Period II (1998)		Change
	Mean	Std.	Mean	Std.	%
Population density (persons per acre)	0.121	0.118	0.127	0.113	5%
Average age (years)	35.027	2.544	36.868	2.437	5%
Local job ratio (ratio of people working in place of residence)	0.275	0.317	0.251	0.317	-9%
Travel time to work (minutes)	23.112	4.584	27.196	6.527	18%
Transportation network (land surface area coverage)	0.020	0.042	0.084	0.080	323%
Personal income ('000)	8.790	2.824	10.853	3.279	23%
Education level (ratio of people bachelors and above)	0.148	0.078	0.193	0.095	31%
Longitude (X-Coord)	-84.823	0.167	-84.823	0.167	0%
Latitude (Y-Coord.)	32.786	0.203	32.786	0.203	0%
Land use distribution (ratio) **					
Developed land	0.077	0.182	0.145	0.191	187%
Agricultural land	0.104	0.063	0.084	0.060	-19%
Forestland	0.773	0.172	0.723	0.176	-6%
Other land	0.045	0.034	0.047	0.040	5%

** Changes in the land use distribution ratio are weighed by area

The model is estimated as a system of three equations. The equations for developed, agricultural and forestland shares are jointly determined using iterated seemingly unrelated regression (ITSUR). Both the Bruesch-Pagan and White's test showed presence of heteroskedasticity on population density and local job ratio variables in the developed land equation. Correcting for heterosckedasticity by weighting for average age resulted in non-significant test statistics at the 5% level of significance.

The parameter coefficients for such models are difficult to interpret directly. Instead the marginal effects are the only means to effectively interpret the effect of explanatory variables on the distribution of proportion of dependent variables. Marginal effects are the percentage change in the dependent variable with respect to a unit change in explanatory variable, generally measured from the mean. A positive or negative sign of marginal effects, the only reliable indicator in such models, indicates an increase or decrease in the proportion of land in that use. Table 1.3 includes the results for estimation, marginal effects and elasticity of each of the variables in each of the jointly determined models.

The marginal effect of population density in developed land is found to be non-significant. However, this effect is positive and statistically significant at 10% level of significance for both agricultural and forestland shares. The proportion of other lands such as wetland, water bodies and barren lands has reduced as a result. However, a positive effects of population density on forestland shares cannot be explained, possibly, it is contributed by the conversion of cotton land to forestland and streamside management practices in recent years.

Table 1.3 Results of multinomial logit model to estimate the land use distribution at watershed level in West Georgia

Dependent Variables →	Developed			Agricultural			Forestry		
Explanatory Variables ↓	Coeff.	M.E.	Elast.	Coeff.	M.E.	Elast.	Coeff	M.E.	Elast.
Intercept	-239.76 **			-7.421			10.425		
	(114.5)			(63.669)			(50.483)		
Population density	1.295	-0.015	-0.050	2.432 *	0.062	0.088	1.747 *	0.023	0.003
	(2.235)			(1.242)			(0.985)		
Average age	0.161 **	0.004	4.190	0.055	0.001	0.370	0.041	-0.003	-0.132
	(0.076)			(0.042)			(0.033)		
Work in place	2.98 **	0.139	1.060	-0.825	0.019	0.058	-1.285 **	-0.201	-0.063
	(1.192)			(0.662)			(0.525		
Travel time to work	0.114 **	0.005	3.810	-0.057 **	-0.002	-0.486	-0.044 **	-0.005	-0.152
	(0.045)			(0.025)			(0.02)		
Road Network	5.357	0.213	0.320	-0.506	0.027	0.016	-1.145	-0.273	-0.017
	(3.516)			(1.955)			(1.55)		
Per capita income	-0.006	0.003	0.860	-0.198 ***	-0.009	-1.027	-0.09	0.002	0.027
	(0.124)			(0.069)			(0.055)		

Table 1.3 Continued.

Variables	Developed			Agricultural			Forestry		
	Coeff.	M.E.	Elast.	Coeff.	M.E.	Elast.	Coeff	M.E.	Elast.
Education level	2.407	-0.037	-0.180	5.727 **	0.196	0.383	3.458 *	-0.017	-0.003
	(4.54)			(2.524)			(2.00)		
X-Coordinate	-2.354 *	-0.071	175.71	0.085	0.032	-31.170	-0.249	0.028	-2.810
	(1.382)			(0.768)			(0.609)		
Y-Coordinate	0.906	0.054		0.481	0.099		-0.867	-0.179	
	(1.11)			(0.617)			(0.489)		
Adjusted R^2	0.30			0.12			0.08		
Obs.	120			120			120		

***Significant at 1% level, **Significant at 5% level; *Significant at 10% level

Figure in the parenthesis indicate the Standard Errors.

Coeff. = Parameter Coefficients; M.E. = Marginal Effects; Elast. = Elasticities

Higher education level has positive influence on the share of agricultural land and negative influence on forestland share. As knowledge helps to intensify the agricultural production and increase the profit level, more people with higher level of education might be interested in intensive management of their cultivable land rather than growing trees with a low return over a longer period of time. On the other hand, per capita income is not found significant in determining the share of developed and forestland. However, higher personal income is negatively associated with the share of agricultural land.

Average commuting time has significant effects on all land use shares. It has positive relationship with developed land share and negative relationship with both agricultural and forestland shares. Similarly, the ratio of people working within the place of residence has positive relationship with the developed land share and negative relationship with forestland share. Both of these factors indicate that people move to the towns from the urban-fringes in search for jobs, that may encourages the further expansion of the urban residential areas and traffic congestion. Thus, market concentration and job availability in the area is associated with more land conversion from forest to developmental uses.

As a proxy to the relative location of the watershed with respect to the principal cities, geographic coordinates of the centriod of each watershed is included in the model. The longitude coefficient is significant and negatively influences the share of developed land while positively influencing agricultural and forestland shares. All else equal, the proportion of developed land would decrease and that of agricultural and forestland share would increase when moving from west (near the center of Columbus metropolitan area) to the east. This suggests a one directional spatial relationship between the distance and urban development. The latitude has a positive marginal effect on developed, agricultural and other land, and a negative effect on forest and other land, although, the parameter estimates are not significant for any of the equations. This is because the study area is on the southeastern U.S. costal plains. In short, the proportion of forestland use would decrease towards the north and increase towards the east direction and that the share of agricultural land would increase when moving towards north and to the east.

1.5 MODEL VALIDATION AND APPLICATION

The models are validated to assess their relative strength in predicting land use distribution. The marginal effects are used to derive the magnitude and direction of change in land use shares caused by the movement in the explanatory variables from their means. The aggregate effect on land use share in each model is obtained by adding the effects of all explanatory variables in each model. The predicted land use shares are obtained by adding this change to the original values in each watershed for both time periods. The predicted results are then compared with the observed land use ratio in each time period.

The Figure 1.3 in the following page shows the mean observed versus predicted land use shares in 1990 and 1998. In both periods predicted land use shares for developed, agricultural, forest and other lands matched with observed land use shares. Statistical significance of the means of observed and predicted land use shares in both time periods are tested using paired sample t-test. The results are insignificant at 5% level for all land use classes in both time periods. Thus the model results are suitable for using on further land use prediction in the study area.

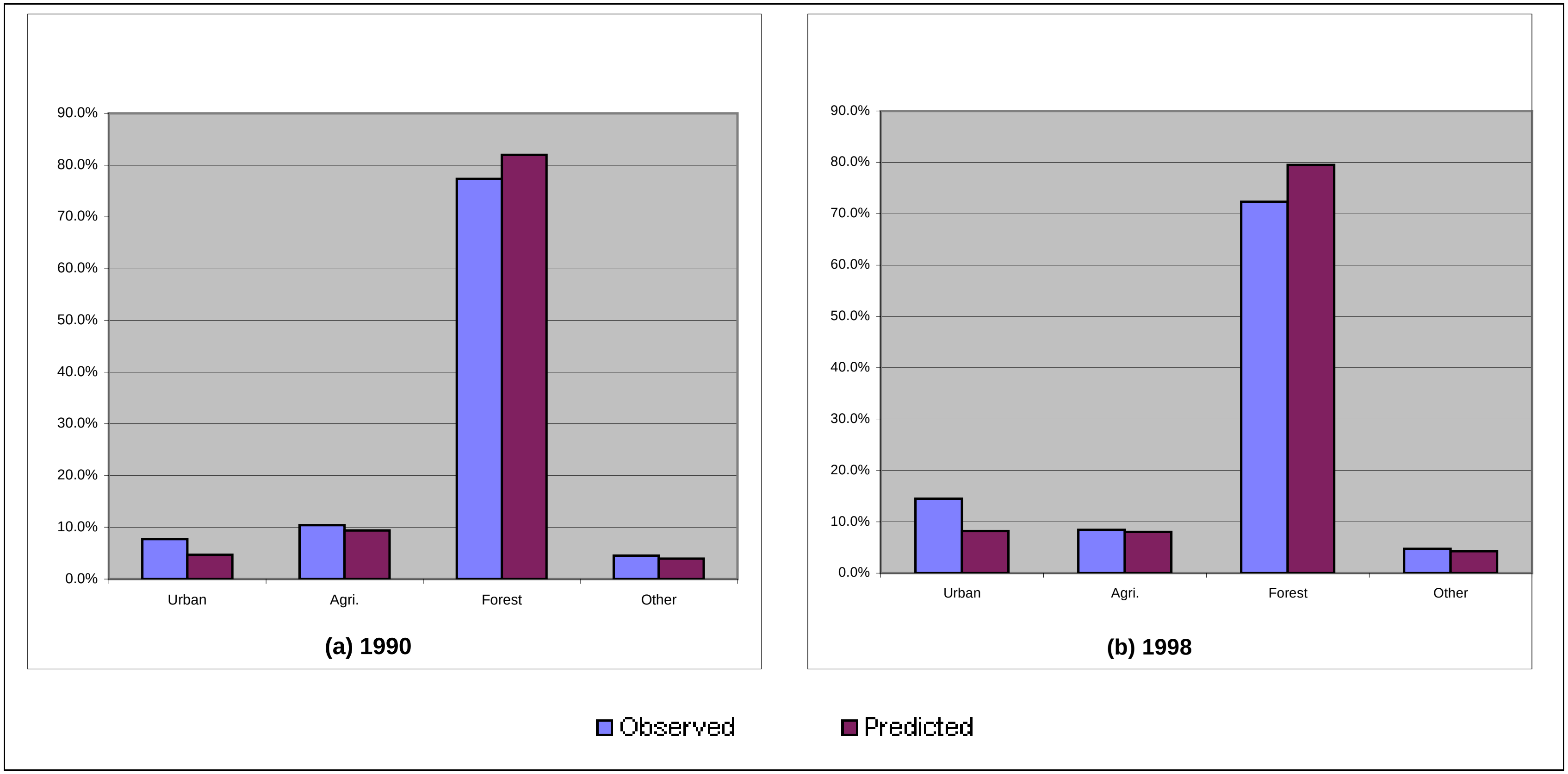

Figure 1.3 Results of validation of multinomial logit model to estimate land use distribution at the watershed level in West Georgia

Land use distribution for a year 2010 is simulated using the current rates of changes in all variables. Interestingly, the share of developed land is expected to increase exponentially beyond 2000. The prediction shows an exponential increase in the share of developed land at the cost of forestland share (Figure 1.4). Based on the relatively very small share of developed land, a large increase in developed land causes a small percentage change in the forestland or agricultural lands.

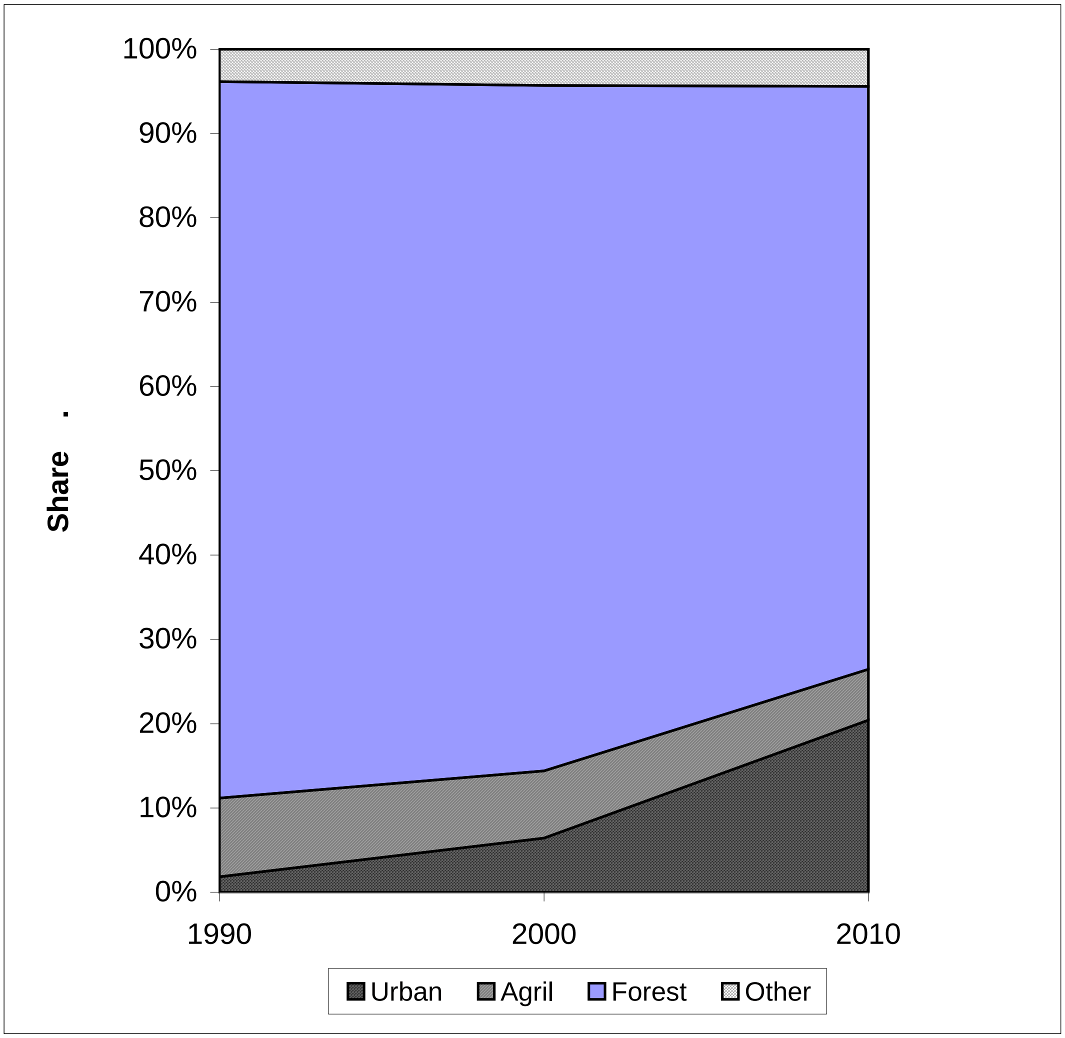

Figure 1.4 Prediction of land use distribution for current and future land use choices in West Georgia using the existing rate of change in the explanatory variables

1.6 CONCLUSIONS

This study develops an econometric model to explain the land use distribution at watershed level in five West Georgia counties. A multinomial logit model (Parks 1980) is used to explain the effect of population density, mean age, market concentration (job availability at place level), travel time to work, road accessibility, personal income, education level and longitude and latitude of watersheds.

Developed land use share is positively related to the higher market concentration and with higher average time to work, suggesting a rural-urban job interface. Personal income had only significant and negative influence in agricultural land share, which in contrast, is increased with higher proportion of people with bachelors and graduate degrees. Longitude has negative influence in developed land share and positive influence in agricultural, forest and other land use. Latitude has a positive influence in developed, agricultural and other land share while negatively influencing forestland share. These results suggest a spatial pattern of land use distribution in the study area as evidenced by the land use maps.

The model results have several applications for the land use management policy in the study area and elsewhere. The prediction of land use distribution with respect to alternative scenarios of changes in explanatory variables provides powerful insights into future land use scenarios in the study area. This will help regional planning managers to address urbanization issues. For example, the statistical results can be combined with geographic information system based analysis to determine the spatial location and nature of land use changes. This approach would also enable the researcher to develop historical land use maps in different time intervals. These maps will facilitate the visualization of spatial and temporal effects of land use changes.

The tabular results can be converted into spatial and temporal land use grids with the help of geostatistical programming, such as GEOMOD, which is beyond the scope of this dissertation. With such advanced application support, these map can be used in developing terrestrial ecosystem modeling which in turn, helps to create land productivity maps, carbon storage and sequestration maps and water quality, water stress map for historical comparison.

CHAPTER 2. ESTIMATING THE EFFECTS OF LAND USE CHANGE ON WATER QUALITY USING BASINS-SWAT MODEL

2.1 INTRODUCTION

Point source pollution has been substantially reduced since the implementation of the Clean Water Act-1972. However, non-point source pollution (NPP) that threatens majority of the water bodies in the United States remains the major environmental concern. Non-point source pollution is caused by the movement of water, over and through the ground, generally after each rainfall. The runoff picks up and carries away natural and man-made pollutants, eventually depositing them in water bodies like lakes, rivers and coastal waters. Thus the pollutants left on the surface from various sources accumulate in receiving water bodies. The Environmental Protection Agency found that over one-third of streams, lakes, rivers, and estuaries surveyed nationally in 1996 did not fully support their designated uses such as for drinking water or recreation (USEPA 1998), citing NPP as the major cause of water quality degradation.

The agricultural sector is alleged to be the largest contributor to NPP through runoff of herbicides, pesticides, sediment, and nutrients (USEPA 1998). Crop cultivation requires more use of chemicals and nutrients than natural vegetative cover like forest and grasslands. Tillage operations affect the soil structure and often make the nutrient rich topsoil fragile and cause it to lose more chemicals and soil particles during rainfall. A study by the National Assessment Synthesis Team (2000) suggests that future climate change will require higher use of chemicals, pesticides and nutrients to maintain the current level of productivity of most crops. This will further increase the rapid decline in the quality of water bodies for their intended uses.

On the other hand, lands in residential and developed uses, such as lawns and gardens are managed more intensively, which encourages the generation of even more pollutants. Urban areas have higher percentages of impervious to porous surfaces that result in lower percolation and higher runoff. During precipitation, runoff carries more nutrients and sediments from agricultural and residential lands, resulting in higher chemical levels and turbidity in the water. Thus, increasing urbanization coupled with increasing use of nutrients and chemicals in agricultural lands creates significant challenges for water quality maintenance.

Major indicators of impaired waters include higher nutrient content such as nitrogen and phosphorus, reduced dissolved oxygen, and presence of toxic substances, debris and pathogens. Higher nutrient content causes eutrophication in water bodies, especially in lakes. Nitrates and phosphates act as plant nutrients, over-stimulating the growth of algae, causing unsightly scum and unpleasant odors, and robbing the water of dissolved oxygen vital to other aquatic lives. Sediment increases cloudiness of water decreasing photosynthesis and light penetration, thereby decreasing habitat to aquatic fauna. Decomposition of plant matter causes decreased oxygen levels, increasing the mortality of aquatic plants and animals. Human sewage releases disease-causing pathogens including bacteria, viruses, and protozoa, which can cause waterborne diseases. Polluted water is unsuitable for drinking, recreation, agriculture, and industry. It diminishes the aesthetic quality of lakes and rivers. More seriously, contaminated water destroys aquatic life. Bacteria and fungi can also have human health impacts ranging from skin rashes to fungal infections. Similarly, the cost of treatment and processing of drinking water from the source whose quality is impaired with polluted runoff becomes very high.

Recent water quality studies have focused on developing and successfully applying various biophysical simulation methods to model levels of NPP and to identify critical locations from which these pollutants originate (Bhuyan et al. 2001; Marzen et al. 2000; Mankin et al. 1999). These models collect and use various geospatial data, facilitating the spatial analysis of sources and effects of point and non-point pollutants with reference to their origin and geographical locations. Calibrated biophysical models have enabled researchers to simulate the effects of different land uses and BMP combinations on surface water quality. The findings of such models help environmental policy planners to understand both the short-term and long-term effects of changes from alternative land management scenarios and simulate ways to effectively reduce through the institutionalization of best management practices.

This study aims to find the relationship between land use change and water quality by simulating levels of nitrogen, phosphorus and sediment with two contrasting land use scenarios over time. Specifically, this study demonstrates the use of geospatial technologies to gather and organize reliable and current data for inputs into the BASINS-SWAT model runs and discusses how the simulated results can be used in further economic analysis.

2.2 THE MODELING APPROACH

The modeling framework is adapted from EPA's 'Better Assessment Science Integrating Point and Non-point Sources (BASINS) model which integrates different models in a single framework. BASINS comprises a suite of interrelated components for performing the various aspects of environmental analysis including data extraction, assessment, watershed delineation, classifying digital elevation models (DEM), land use, soils and water quality observations, and watershed characterization reports. The system includes four specific watershed level biophysical models for the estimation of in-stream and watershed loading and transportation. The four models are: an in-stream water quality model, QUAL2E; two watershed loading and transportation models HSPF and SWAT; and a simplified GIS based model to estimate PLOAD, non-point loads of pollution on an annual average basis. The BASINS framework provides a centralized platform for data extraction and analysis and helps in set up of individual watershed based models and analysis at a variety of scales using different tools. BASINS can support implementation of TMDLs by state agencies using watershed-based point and nonpoint source analysis for a variety of pollutants under alternative assumptions about land management practices (BASINS Users' Manual).

Soil and Water Assessment Tool (SWAT) is a river basin or watershed scale model developed by the USDA Agricultural Research Service's Grassland, Soil and Water Research Laboratory. It is designed to assist resource managers in the long-term assessment of sediment and chemical yields in large watersheds and river basins. The model predicts the average impact of land use and management practices on water, sediment, and agricultural chemical yields in large, complex watersheds with varying soils, land uses, and management conditions over long periods of time (DiLuzio et al. 2002; Neitsch et al. 2002). In comparative studies using hydrologic and non-point source pollution models, SWAT has been shown to be among the most promising for simulating long-run NPP in agricultural watersheds (Borah and Bera 2003).

BASINS-SWAT uses an ArcView Geographic Information System interface to derive the model input parameters and simulation. Within the interface, hydrological modeling is completed using USGS National Elevation Dataset (NED). The watershed drains at the lowest elevation point of the catchment's area and contains several sequential subwatersheds with directional flow (raindrop flow) to the main channel based on the topography of land. Subwatersheds are grouped based on climate, hydrologic units (HRU), ponds, ground water, and main channels (Borah and Bera 2003). Each subwatershed is virtually divided into several hydrological response units (HRUs) which are uniquely lumped areas within the subwatershed based on weighted land cover, soil type, and management combinations at a certain threshold level (Saleh et al. 2000). SWAT model simulation requires weather parameter inputs (daily records of precipitation, wind, minimum and maximum temperatures) and management parameter inputs (irrigation, tillage, chemical and fertilizer application). These input variables are converted to standard SWAT input files within the model. A given model run will simulate runoff levels of nutrients, sediment and chemicals under a particular combination of land management scenarios. Outputs from SWAT are crop yields, sedimentation and nutrient runoff levels, which can be traced across the watersheds both for short and long period of times.

2.3 LIMITATIONS OF THE STUDY

Shares of agricultural and forestland constitute the major land use distribution in the study area. The share of developed land is relatively small. During the HRU distribution stage, the model picks up the dominant land use in each subbasin leaving out unique land use with small land coverage. This area is readjusted to the remaining land use shares, thus ignoring the effects of specific land use in a localized area.

The land use data used in this study come from 1992 and 2001 national land cover datasets. These annual land cover maps are created by overlaying multiple images taken around those years (MRLC metadata). Vegetative covers are broken down to different types of forestlands, pasture and rangeland, cropland, and different intensities of developed land. However, these maps do not contain details about which row crops and forage crops are grown in the study area. Hence, simulations are based on a dominant row crop and a dominant forage crop grown in the study area. Although forestland is included in the model as a major land cover, more effort is given to understanding the effects of cropland and pastureland management on water quality.

2.4 DATA AND METHODS

Data collection and processing

The study area is Little Double Bridge Creek (HUC #03140201230), lying within the Choctawhatchee basin in southern Alabama (HUC#03140201) which is also called Wiregrass region in the state. The Little Double Bridges Creek has 21.4 square miles of upstream drainage area and lies to the west of Enterprise city in Coffee County, Alabama. A study area map is given in Figure 2.1.

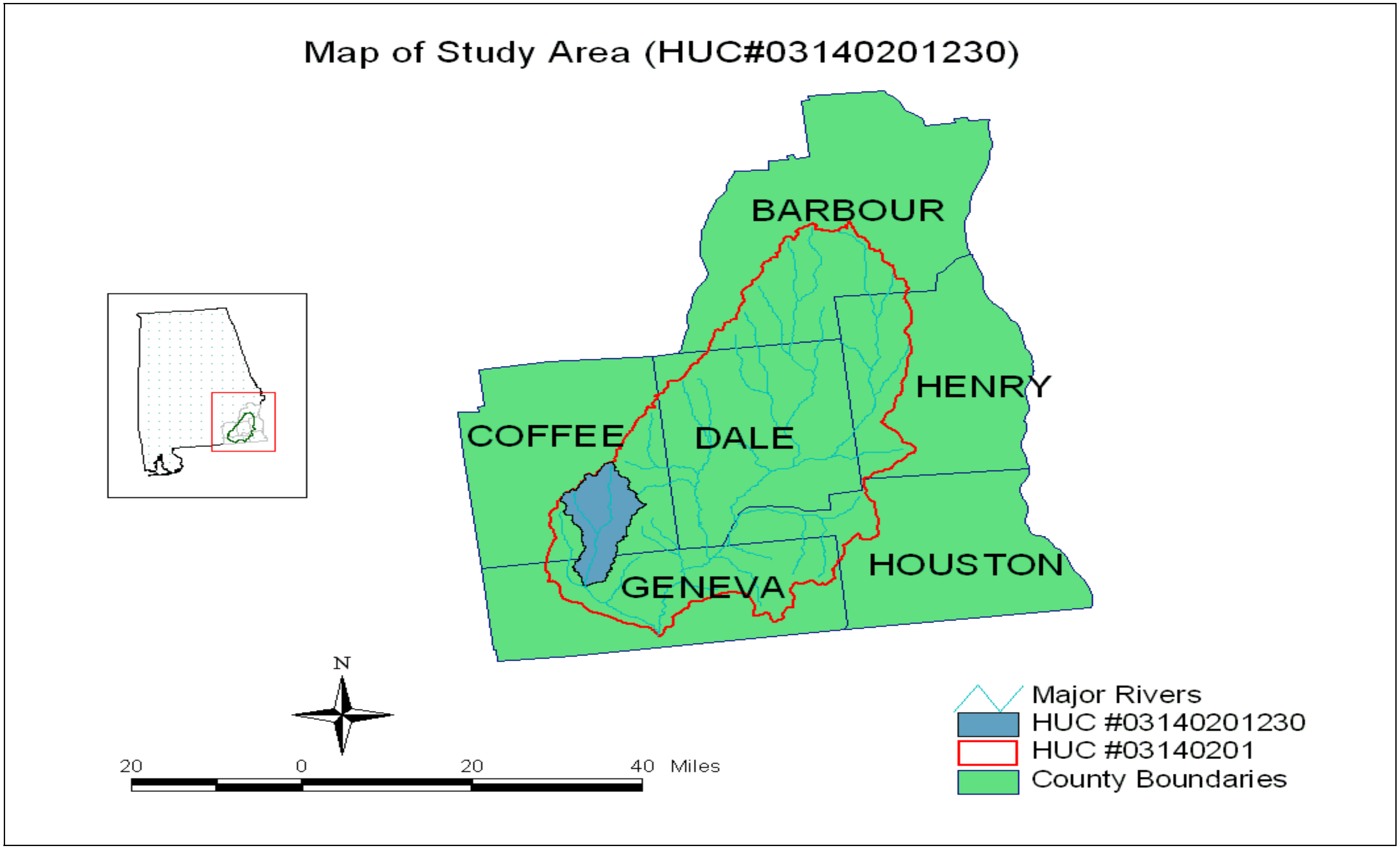

Figure 2.1 Map of the study area for estimating the effects of land use change on water quality using BASINS-SWAT model

The wiregrass region is characterized by agricultural and forestland, which are the dominant land uses in the study area. Coffee County ranks 5th in broiler production, 7th in peanut production, 9th in corn production and 14th in cotton production within the state (Alabama Agricultural Statistics 2005). On one hand, production of corn and cotton crops require higher application of nitrogen fertilizer, while on the other hand, use of poultry litter in row crop production results in elevated phosphorus levels in the soil. The study area is selected based on the importance of agricultural pollution controls and availability of required input data to run the model described in the following sections. The proposed study area covers approximately one tenth of the county and lies in a major corn belt.

The study uses secondary data from various sources. The sources and processing of individual data components are described below.

Core BASINS data: The set of core data required for analysis is obtained from the USEPA data archive using the data extraction tools within the program. This set of data includes elevation, land use, state soil survey data and watershed boundaries. All core basins data as well as elevation and land use grids are projected into a geographic map system as shown in Table 2.1.

Elevation and Land Use Data: The 1:24,000 scale 30x30m resolution national elevation model (NEM) datum for the entire area is downloaded from Seamless Data Distribution System of USGS Web Server. Two sets of National Land Cover Data (NLCD 1992 and NLCD 2001) are also obtained from the same source. The scale and resolution of these data are compatible with NED data. Overall thematic accuracy level of NLCD 1992 land use data at the Anderson Level I is 82% (Stehman et al. 2003).

Formal accuracy assessment reports are not available for NLCD 2001 land cover data for the region. However, a single-pixel accuracy assessment in three of the NLCD 2001 mapping zones suggests the accuracy range of 73 to 77 percent (Homer et al. 2004). The vertical positional accuracy for the elevation data is 2.70 RMSE (NED Press Release June 2003).

Table 2.1 Parameters used in projecting GIS data layers in BASINS-SWAT input data processing and modeling

Parameters	Unit
Map Units	Meters
Distance Units	Meters
Projection	Albers Equal-Area Conic
Spheroid	GRS 80 (Geographic Reference System)
Central Meridian	-96.0
Reference Latitude	230.0
Standard Parallel 1	29.5
Standard Parallel 2	45.5
False Easting	0
False Northing	0

Climate Data: The SWAT model uses climate information including precipitation, temperature, wind speed, solar radiation and relative humidity data. Observed daily precipitation and minimum/maximum temperature data are obtained from the National Climate Data Center (NCDC) database for four nearby climate stations between January, 1965 and December, 2005 (Source: SECC 2006). However, when no such data are available, the model has the capability to simulate these inputs based on historical observations from the nearest of more than 800 climate stations (SWAT Users' Manual).

Daily Streamflow Data: Daily streamflow data is one of the important requirements for model calibration and validation. A USGS surface water monitoring station (ID# 02362240) is located at the end of Little Double Bridge Creek. Daily streamflow data available between September 1985 and October 2003 are extracted from the USGS database as part of the core basin data download.

Farm Management Practices: The breakdown of agricultural practices at crop level, both cropland and pastureland management, is limited by the availability of digital land use map. A single major row crop (corn) and a forage crop (bermudagrass) are selected and a table of operations for these crops is derived based on the recommended cultural practices published in Alabama Cooperative Extension System reports. Typical cultural practices such as fertilizer use, tillage operations, pesticide use, harvesting and killing operations are recorded for corn and bermudagrass.

Modeling process

The BASINS process starts with automatic delineation of subbasins from the digital elevation data. The NED is processed to remove any sinks in the data. Sinks are the grids erroneously recorded as being lower than surrounding areas. Automatic watershed delineation is processed aligned with the national hydrography stream network. Digital stream networks are created with a 40-hectare headwater threshold area, which defines the minimum area required to begin a stream flowing out of the area in any part of the watershed. Digitization of stream network creates two nodes, one for each branch, at the point where two streams meet. These nodes provide the point of drainage for each of the upstream network during delineation of subbasins.

Spurious nodes are removed and intermediate nodes are marked along a larger river segments that would result in more uniform distribution of subbasins. The lowest outlet point of the stream network is selected as the drainage outlet in order to define the watershed boundary. Subbasins are created along with the calculation of their physical characteristics including area, length, width, slope, and elevation. Subbasins are physically bounded areas to which changes in management practices, yields and pollution levels can be traced during simulations. Land use grids are loaded in the program and reclassified into standard SWAT codes using the land use look up code created outside of the program (Table 2.2).

The state soil survey data (STATSGO) layer is loaded and reclassified using the standard STATSGO soils look up codes. Soils and land use layers are then spatially overlaid to facilitate the creation of hydrological response units or HRUs. An HRU is a result of interactions of land use and soils that creates a unique land area within each subbasin. Several components of the SWAT results, for example, crop yields and biomass, are later based at the HRU level. It is a statistical concept within the model which changes as the land use and soil input maps change. Selection of dominant HRUs treats each subbasin as a single HRU. This process makes the number and location of HRUs stable and facilitates the comparison of the simulation results across two time periods.

Table 2.2 Reclassification of national land cover data grids to standard BASIN-SWAT codes

NLCD 1992			NLCD 2001		
GRID	Code	NLCD Description	GRID	Code	NLCD Description
11	WATR	Open Water	11	WATR	Open Water
12	WATR	Perennial Snow/Ice	12	WATR	Perennial Snow/Ice
21	URML	Low Intensity Residential	21	URML	Developed, Open Space
22	URHD	High Intensity Residential	22	URML	Developed, Low Intensity
23	UCOM	Commercial/Transportation	23	URML	Developed, Medm Intensity
			24	URHD	Developed, High Intensity
31	RNGE	Rocks/Sand/Clay	31	RNGE	Barren Land
32	RNGE	Quarries/Strip mines/Pits	32	RNGE	Unconsolidated shores
33	RNGE	Sparse vegetation			
41	FRSD	Deciduous Forest	41	FRSD	Deciduous Forest
42	FRSE	Evergreen Forest	42	FRSE	Evergreen Forest
43	FRST	Mixed Forest	43	FRST	Mixed Forest
51	RNGB	Shrubland/Brushes	52	RNGB	Shrub/Scrub
61	ORCD	Orchards/Vineyards			
71	RNGE	Grasslands/Herbaceous	71	RNGE	Grasslands/Herbaceous
81	PAST	Pasture And Hay	81	PAST	Pasture And Hay
82	AGRR	Row Crops	82	AGRR	Cultivated Crops
83	AGRC	Small Grains	90	WETF	Forested Wetlands
84	RNGE	Fallow	95	WETN	Herbaceous Wetlands
85	URML	Recreational Grasses			
91	WETF	Woody Wetlands			
92	WETN	Herbaceous Wetlands			

Once the necessary raw data files are loaded into the program, they are converted into standard SWAT data input files. The weather station databases, which include daily accumulative precipitation and daily minimum and maximum temperature records, are uploaded. Other inputs such as solar radiation, wind speed and relative humidity information are simulated from the program.

All the necessary SWAT inputs are written using the elevation, land use, soil and weather station databases. This process builds the database files containing the information needed to generate default inputs for SWAT. Land management practices, including average nutrients and chemical uses for each type of land use are set to common practices reported in various extension service publications.

SWAT is set up to select the period of simulation, methods of rainfall, runoff and routing frequency, and potential evapotranspiration method among others. Model outputs are obtained for different land use distribution and management practices. Models are run separately with NLCD 1992 and NLCD 2001 land use maps as inputs to compare the effects. Once the effect of broad land use distribution over time is compared, further simulations are possible for crop level management practices.

2.5 RESULTS

The delineated area of Little Double Bridge Creek sub-watershed is 55.37 km^2. The mean elevation of the watershed is 97 meter above sea level (msl) with the range between 63 msl and 132 msl. The watershed is divided into 159 subbasins. The average subbasin area is 34.8 ha which ranges from 4.6 ha to 83.7 ha. Average farm size in Coffee County is 231 acres or 93.4 ha (Alabama Agricultural Statistics Bulletin 2005).

The subbasins have mean slope of 5.4% ranging from 2.9% to 8.6%. The average slope of digitized streams across flow length of subbasins is 1.8%, ranging from 0.1% to 5.7%.

Major land use distribution in the study area is given in Table 2.3. Between the years 1992 and 2001, the share of developed land increased by more than 17 times, however, its share still remains less than 5.0% of the total land. Share of agricultural land decreased by 26.0% while land in rangeland quadrupled. Pasture land increased by 13.9%. In aggregate, total forestland decreased by 10.1%; however, the structure of forestland greatly changed during the observation period from mixed and deciduous to evergreen.

Table 2.3 Comparison of land use distribution in the Little Double Bridge Creek subwatershed in Alabama using national land cover datasets of 1992 and 2001

Land use category	Area in Hectares		Change
	NLCD 1992	NLCD 2001	(%)
Developed land	14.2	261.2	1744.8%
Forestland (Deciduous)	560.5	484.5	-13.6%
Forestland (Evergreen)	642.6	931.7	45.0%
Forestland (Mixed)	1137.8	687.6	-39.6%
Rangeland / Shrubland	161.2	792.2	391.5%
Pastureland	740.0	842.7	13.9%
Agricultural row crops	1885.9	1396.3	-26.0%
Wetlands/Water	352.6	98.9	-72.0%

The structural change in land use distribution is expected to bring changes in water quality at the watershed level including surface flow, nutrient runoff and sedimentation levels. Table 2.4 shows the relative number and area coverage of dominant HRUs with two alternative land use scenarios of NLCD 1992 and NLCD 2001.

Table 2.4 Comparison of dominant hydrological response units in the hydrological modeling area using land cover conditions of 1992 and 2001

Major Land Use	Land Use by Dominant HRUs			Land Use by Area (ha)		
	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change
Row Crops	81	53	-35%	2,814	1,893	-33%
Deciduous Forest	3	4	33%	114	132	16%
Evergreen Forest	14	30	114%	525	1,180	125%
Mixed Forest	33	17	-48%	1,168	574	-51%
Pasture	18	31	72%	520	1,000	92%
Wetlands	10	0	-100%	396	0	-100%
Range/Brush	0	23	N/A	0	730	N/A
Urban	0	1	N/A	0	29	N/A
Watershed	159	159	N/A	5,537	5,537	N/A

A comparison of total 159 HRUs with two land cover scenarios indicates that number of HRUs with cropland decreased from 81 to 53, whereas evergreen forest and pastureland increased from 14 to 30 and 18 to 31 respectively. 23 new HRUs with rangeland emerged and 10 wetlands are dominated by other land uses. Figures 2.2 (a) and (b) show the dominant land cover using NLCD 1992 and 2001 land cover maps.

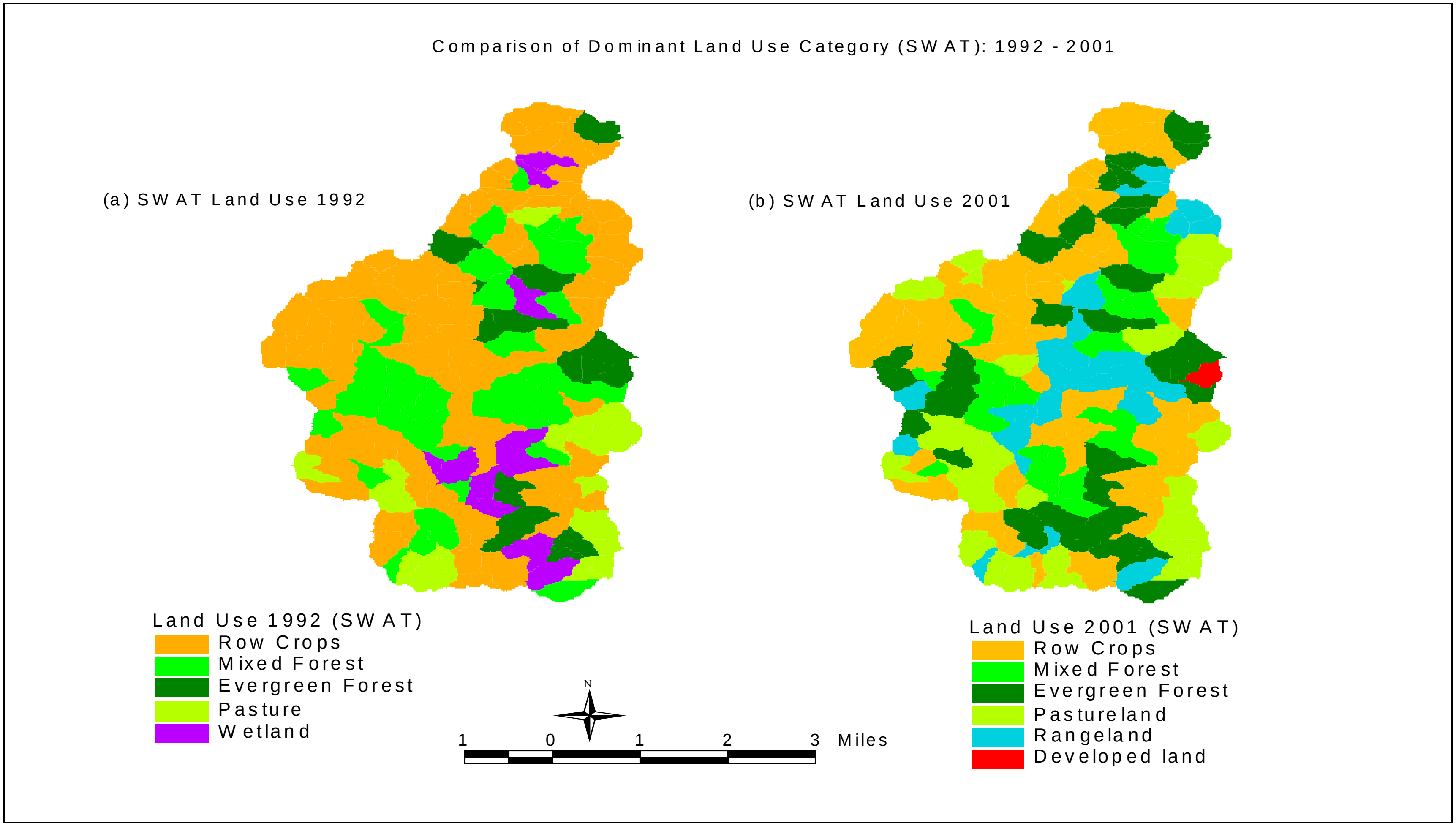

Figure 2.2 Distribution of dominant HRUs in the modeling area using the land cover conditions of 1992 and 2001

Figure 2.3 displays graphically the location in which dominant HRUs changed between two land use conditions from NLCD 1992 to NLCD 2001. In these figures, deciduous and mixed forest areas are aggregated to a single class to compare with the evergreen versus other forest types. Later, simulations are done to estimate the effects of land use change on water quality based on these changes.

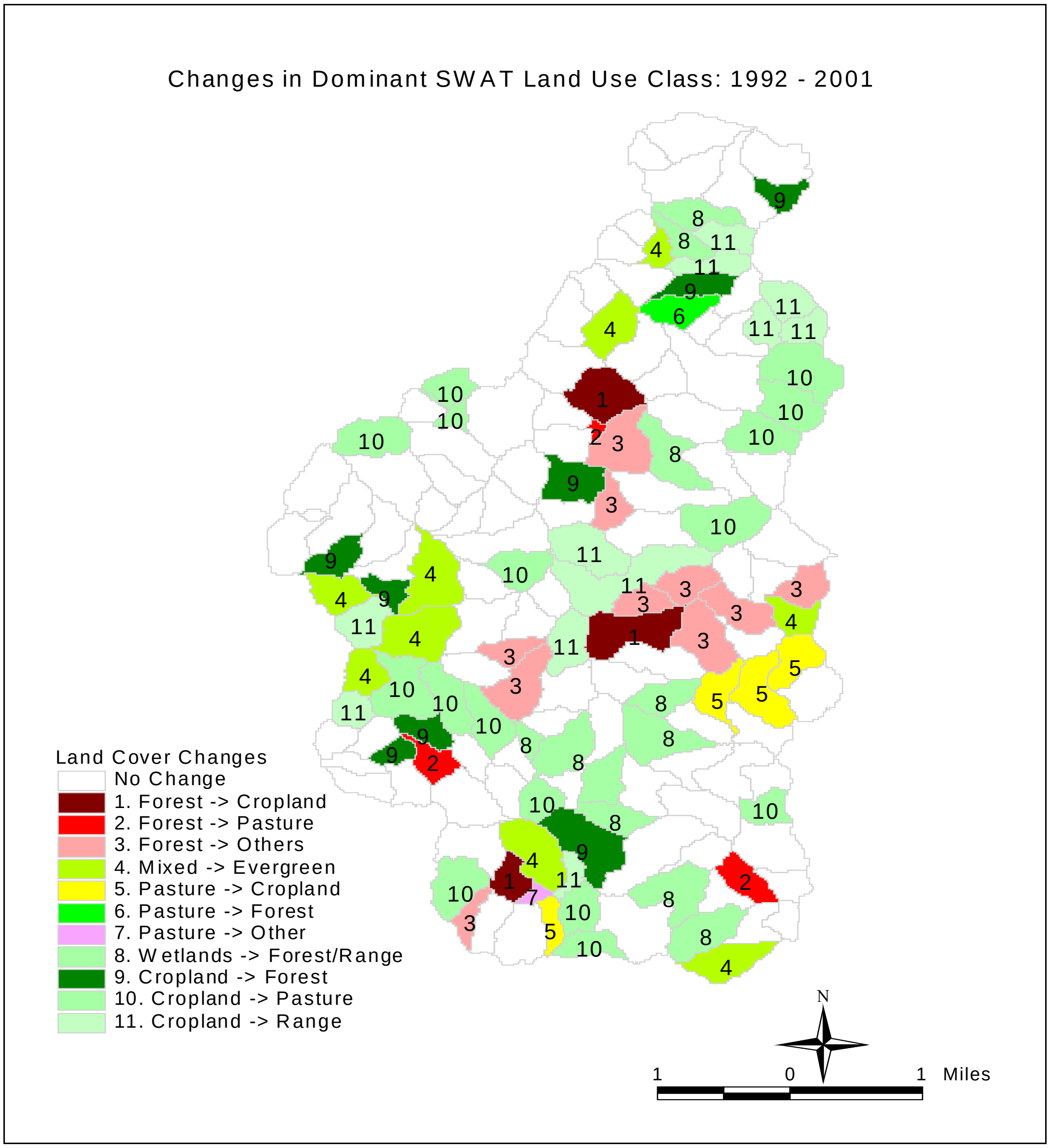

Figure 2.3 An illustration of changes in dominant land use distribution in the modeling area using the land cover conditions of 1992 and 2001

Model Calibration and Validation

Model calibration is done by comparing five years of average daily simulated versus observed streamflow between January 1991 and December 1995 using NLCD 1992 land cover map. In the beginning, model is are run between 1986 to 2003 to set aside initial five years as model warm up period and then calibrate and validate the model. The model failed to accurately predict the extreme events of March 1990 and few months afterward. Hence, model calibration is focused on the period between January 1991 and December 1995. By chosing this period, model estimation is also kept close to the land cover conditions in the current period as the land cover condition affects the amount of surface flow, infiltration, evapotranspiration and underground recharge by exposing the rainwater to different surfaces. No calibration is done with the nutrients and sediment, as there are no observed data available for these variables.

Adjustments are done in the curve number (CN2) of different land use by adjusting up to 10% of the recommended number for different hydrological group and land cover conditions. Once the flows are reasonable, adjustment are done in HRU, soil (SOL) and groundwater (GW) input parameters to adjust the surface flow and baseflow so that the Nash-Sutcliffe coefficient of efficiency (COE) and goodness of fit (R^2) are within the acceptable range of values. Although the model is set to run in a monthly time step, the model internally runs in daily time steps and averages the daily results in a monthly basis. Based on this output, simulated average daily streamflows are compared with observed daily streamflows by month. The observed and predicted streamflow during calibration period is given in Figure 2.4.

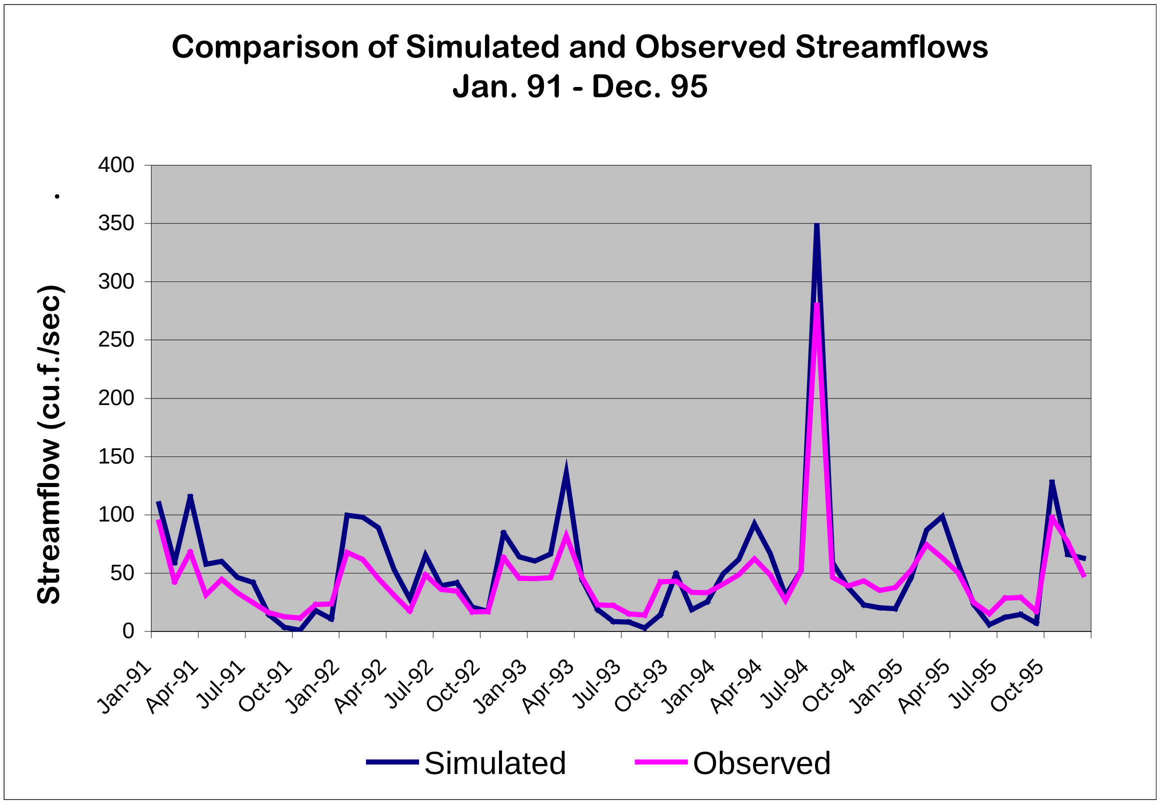

Figure 2.4 Calibration of total average daily streamflow simulated in monthly time step between January 1991 and December 1995 using prevalent crop and pastureland management practices in the study area using the land cover condition of 1992

Separate baseflow and surface flow for the monthly streamflow for the USGS monitoring data are extracted using the Web-Based Hydrograph Analysis Tool (WHAT) available from Purdue University system (http://pasture.ecn.purdue.edu/~what/). Simulated total streamflow are separated to baseflow and surface runoff by multiplying the total flow in drainage (SWAT output file: Rich) by the ratio of surface flow and groundwater flow to the total water yield obtained from the model (SWAT output file: Sub-basin). Several test statistics are derived for both separated flows and total streamflow.

The Table 2.5 summarizes the statistical results of calibration. It is shown that the calibrations for total streamflow and surface runoff are very reliable. The mean of simulated average daily streamflow (mean = 46.14 and std.dev.=48.39) lies within 3% of the observed streamflow (mean=45 and std.dev.=37.00). However, the surface runoff is slightly over predicted (18% higher) and baseflow is slightly under predicted (7% lower).

Table 2.5 Statistical Results of Model Calibration for total streamflow and separate surface runoff and baseflow scenarios between January 1991 and December 1995

Daily Streamflow (monthly average, cu.ft./sec.)	Mean		Difference	R^2	COE
	Simulated	Observed			
Total Streamflow	46.14 (48.39)	45.00 (37.00)	3%	0.88	0.75
Surface Runoff	20.90 (21.92)	17.68 (23.37)	18%	0.77	0.74
Baseflow	25.28 (26.52)	27.32 (15.40)	-7%	0.86	0.21

Note: Figures in parentheses indicate standard deviation from mean.

Table 2.5 shows that both goodness of fit (R^2=0.88) and coefficient of efficiency (COE=0.75) are within the readily acceptable range of values for total streamflow. A quite similar result for surface runoff is also obtained (R^2=0.77 and COE=0.74) except for a high goodness of fit (R^2=0.86) and very low coefficient of efficiency (COE=0.21) for baseflow calibration. These values are similar to the ones reported by Kirk et al. (2002) in their study in Rock River Basin in Wisconsin (R^2=0.74 and COE=0.61) and by Fohrer et al. (2005) in their study in (R^2=0.82 and COE=0.61). Moon et al. (2004) report a R^2 value of 0.86 and COE value of 0.78 using monthly time step comparison in Trinity

River Basin in Texas. Thus, the calibration results obtained here are within a reasonable range of values in previously published studies. When year 1990 is included in the calibration, the goodness of fit and Nash-Sutcliffe coefficient of efficiency for total flow becomes very low (R^2=0.53 and COE=0.46). A graph of linear regression result is shown in Figure 2.5.

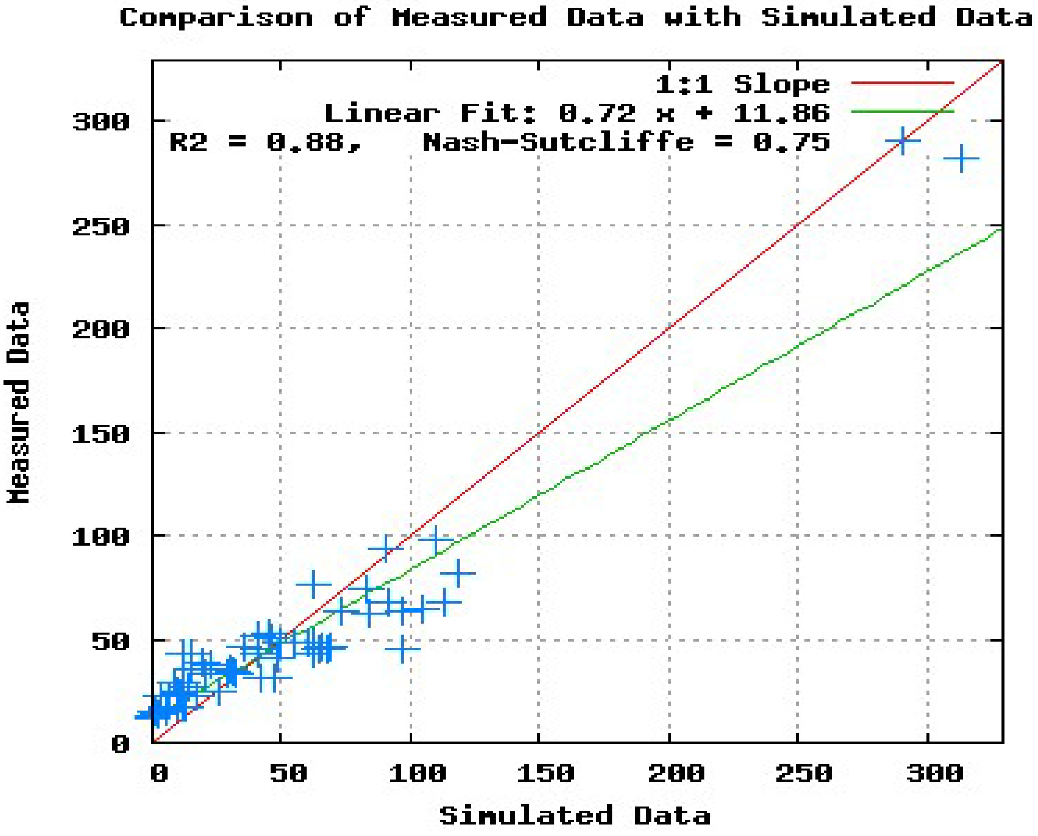

Figure 2.5 Regression results for measured (observed) versus simulated average daily total streamflow between January 1991 and December 1995.

Once the calibration is complete model is run for twenty years starting from January 1986 to December 2005 run in monthly time steps. It was important to keep 20 years of simulation because of a 10-year rotation in bermudagrass cultivation in the management file. SWAT requires the number of years of simulation in the multiple of the number of years in the crop rotation in management input file. Two sets of simulations are done using the calibrated input values, one for NLCD 1992 land cover condition and the other for NLCD 2001 land cover condition.

Impact of land use change in water quality

The area received 1448.9 mm of precipitation annually across the surface of watershed. This precipitation level results in different streamflow levels under two land use conditions. There is a total water yield of 536.35 mm with 1992 NLCD land cover as compared to 519.78 mm with the 2001 NLCD land cover condition. Total water yield here is defined as the sum of surface, lateral, and groundwater flow minus transportation loss, which will eventually pass through the main channel. For NLCD 1992 land cover condition, the predicted surface runoff and baseflow contributions to the channel are 280.05 mm and 230.37 mm respectively. In contrast, surface runoff and baseflow contributions to the channel with NLCD 2001 land cover conditions are 224.80 mm and 267.69 mm respectively. Thus, the results show that total water yield decreases by 3.1%, whereas surface flow decreases by 19.7%, and baseflow contribution increases by 16.2%. This indicates that there is less surface runoff and higher infiltration and groundwater recharge with 2001 land cover as compared to 1992 land cover condition.

The model output calculates average nitrogen and phosphorus applied in the watershed. This is more or less proportionate to the amount of agricultural land and crop management practices. On average, 127.73 kg of nitrogen and 16.92 kg of phosphorus are applied to one hectare of land with the NLCD 1992 land cover condition. With the 2001 land use distribution, the amount of nitrogen and phosphorus applied to the soil reduces to 118.00 kg/ha and 13.69 kg/ha respectively. This average includes all of watershed area.

There is change in the total nutrient runoff and sedimentation from a similar land use in two simulations. It is obvious that changes in the overall land cover conditions affects the surface runoff and baseflow and this affects how the nutrients are washed away and the soil is lost to the sedimentation. Table 2.6 compares the per unit contribution to nutrient runoff and sedimentation from each land use type for two land cover scenarios. On average, total nitrogen runoff from agricultural land decreases from 43.18 kg/ha to 32.03 kg/ha, a reduction of 26%. Similarly total phosphorus decreases by 25%, or from 16.22 kg/ha to 12.17 kg/ha. Sedimentation decreases by 44% from 67.96 tons/ha to 37.79 tons/ha. There is decrease in per unit area contribution in nutrient runoff and sedimentation in all land cover types. However, these are not compared when a land use type is completely removed from or added to the NLCD 2001 land cover conditions. At the aggregate watershed level, the nitrogen runoff, phosphorus runoff and sedimentation is reduced by 25%, 51% and 32% respectively. Nitrogen runoff is reduced from 24.12 kg/ha to 18.17 kg/ha, phosphorus runoff is reduced from 11.79 kg/ha to 5.76 kg/ha, and sedimentation decreased from 19.56 tons/ha is to 13.31 tons/ha.

Table 2.7 compares the aggregate annual values of nutrient runoff and sedimentation by each land use type for two land cover scenarios. The aggregate results at watershed level show that total nitrogen runoff decreases by 23%, total phosphorus runoff by 22% and sedimentation by 40% when land use conditions change from those of 1992 to those of 2001.

Table 2.6 Comparison of average annual nutrient runoff and sedimentation per unit of area under different land use types for land cover conditions of 1992 and 2001

Land use	Nitrogen[a] (kg/ha)			Phosphorus[b] (kg/ha)			Sediment (tons/ha)		
	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change
Row Crops	43.18	32.03	-26%	16.22	12.17	-25%	67.96	37.79	-44%
Deciduous Forest	1.77	0.33	-81%	0.20	0.01	-94%	1.13	0.03	-97%
Evergreen Forest	1.17	0.34	-71%	0.10	0.01	-88%	0.54	0.04	-93%
Mixed Forest	1.35	0.33	-75%	0.13	0.01	-92%	0.77	0.03	-96%
Pasture	4.69	3.04	-35%	0.63	0.37	-41%	1.53	0.71	-54%
Wetlands	1.80	n/a	n/a	0.20	n/a	n/a	1.08	n/a	n/a
Range/Brush	n/a	0.43	n/a	n/a	0.03	n/a	n/a	0.09	n/a
Urban	n/a	4.30	n/a	n/a	0.76	n/a	n/a	4.78	n/a
Watershed	24.12	18.17	-25%	11.79	5.76	-51%	19.56	13.31	-32%

Table 2.7 Comparison of total annual nutrient runoff and sedimentation across the watershed under different land use types for land cover conditions of 1992 and 2001

Land use	Dominant Land Use (ha)			Total Nitrogen[a] (Kg)			Total Phosphorus[b] (kg)			Total Sediment (tons)		
	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change	NLCD92	NLCD01	Change
Row Crops	2,814	1,893	-33%	1,506	1,152	-23%	567	438	-23%	2,389	1,372	-43%
Deciduous Forest	114	132	16%	66	11	-83%	7	1	-93%	41	1	-97%
Evergreen Forest	525	1,180	125%	43	13	-70%	4	1	-87%	20	1	-93%
Mixed Forest	1,168	574	-51%	47	11	-76%	5	1	-89%	27	1	-96%
Pasture	520	1,000	92%	136	98	-28%	19	12	-35%	45	23	-48%
Wetlands	396	0	-100%	73	0	-100%	8	0	-100%	45	0	-100%
Range/Brush	0	730	n/a	0	14	n/a	0	1	n/a	0	3	n/a
Urban	0	29	n/a	0	137	n/a	0	22	n/a	0	137	n/a
Watershed	5,537	5,537	0%	1,871	1,436	-23%	609	474	-22%	2,568	1,538	-40%

[a] Total Nitrogen = Organic N + NO3 in Surface Runoff + NO3 in Lateral Flow + NO3 in Groundwater

[b] Total Phosphorus = Organic P + P in Sediment + Soluble P + P in Groundwater

Bioeconomic Analysis

Comparing land use conditions between NLCD 1992 and NLCD 2001 land cover shows the relative change of dominant land use across the watershed. In Table 2.8 dominant land uses are broadly reclassified as row crops, forestland, pasture and other lands such as wetlands and range/brushlands. The agricultural land decreases by 919 hectares (33%). The pastureland increases by 480 hectares (92%) followed by 362 hectares (91%) and 79 hectares (4%) increases in other land and forestland respectively.

A simple bioeconomic analysis is done to estimate effects of land use change on farm profits and water quality at the watershed level. The Table 2.8 compares the total agricultural and forest revenues and expenses with two land use scenarios. As described earlier in the limitation of the study and the methodology, farm income has been estimated only for a single row crop 'corn', single forage crop 'bermudagrass' and single 'pine plantation' for forestland. The average yield and cost of operation for corn are taken from Alabama Cooperative Extension System bulletin AEC BUD 1-1 (January 2006). The average yield and cost of operation under recommended practices for bermudagrass are taken from AEC BUD 1-2 (May 2005). Based on these publications, returns to corn production and bermudagrass cultivation are calculated in the absence of government payments. Similarly, returns to forest plantations ($63 per hectare) are taken from the online bulletin MTN 9C, a publication of Mississippi State University Extension Service.

Table 2.8 Effects of land use change in farm returns under different land use distribution in study area

	NLCD 1992					NLCD 2001					Change	
	Area (ha)	Yield	Cost $/ha	Revenue $/ha	Total Profit	Area (ha)	Yield	Cost $/ha	Revenue $/ha	Total Profit	Area (ha)	Revenue ($)
Corn[a] (bushels)	2,814	208	770	519	-706,225	1,893	208	770	519	-475,101	-921	231,125
Forest[b]	1,808	n/a	n/a	n/a	113,004	1,886	n/a	n/a	n/a	117,912	79	4,908
Pasture[c] (tons)	520	15	1,209	1,038	-88,814	1,000	15	1,209	1,038	-170,929	481	-82,115
Other[d]	396	n/a	n/a	n/a	n/a	758	n/a	n/a	n/a	n/a	362	n/a
Total	5,537				-682,035	5,537				-528,117		

[a] Calculations are based on ACES Publication AEC BUD 1-1, January 2006

[b] Calculations are based on ACES Publication AEC BUD 1-2, May 2005

[c] Calculations are based on MSU CARES Publication MTN 9C

[d] Other lands include wetlands, wastelands, rangebrush and urbanlands.

In the absence of government payments, farms are currently operating at a loss with both the corn and bermudagrass productions, losing an average of $251 and $171 per hectares respectively. These figures are derived based on production costs using recommended inputs according to the above mentioned extension bulletin and setting the exiting output prices of corn ($2.50 per bushel) and bermudagrass ($70.00/ton). Five-year average crop yield in crop reporting district 60 is used for calculation of revenues. Based on these figures, changing land use from corn production to bermudagrass causes a large reduction in operating loss. For instance, the Table 2.8 in the previous page shows a corresponding $231.1 thousand reduction in operating loss for 921 hectares decrease of corn acreage. If equal area is converted from corn to bermudagrass, net reduction in operating loss will be 73.6 thousands dollars only. No economic returns have been imputed for wetlands and wastelands like range/brush lands.

Table 2.9 Differences in the farm profit and water pollution when land cover changes from 1992 to 2001

Land use	Area (ha.)	Net Return Per Ha.	Profit ($)	N Runoff (kg)	P Runoff (kg)	Sediment (tons)
Row Crop	-921	-251	231,031	-655	-202	-1,070
Forest	79	63	4,908	-39	-3	-21
Pasture	481	-171	-82,082	-30	0	0
Other	362	n/a	n/a	95	19	123
Watershed			153,857	-628	-186	-968

[a] Loss minimization

The Table 2.9 presents the summary of bioeconomic impacts of land use change in the study area. It shows that a large decline in corn acreage with simultaneous increase in pastureland acreage and some forest acreage causes a net reduction in operating loss of 153.8 thousand dollars at the watershed level. At the same time, the impact on water quality is desirable for all kinds of land cover. Total nitrogen and phosphorus runoff reaching the channel decrease by 434 kg and 135 kg per year respectively. Sedimentation decreases by 1030 metric tons per year across the watershed.

2.6 CONCLUSION

The water quality in a watershed is affected directly by vegetative cover and agricultural and other land management practices. The pattern of land cover changed in the study area from 1992 to 2001. There is decline in both agricultural land (26%) and overall forestland (10%). However, the structure of forestland changed with a 45% increase in evergreen forest. Developed land increased by seventeen times, however, the weighted share of developed land still remains less than 5% of total land. The share of rangeland increased by 392% followed by a 14% increase in pastureland. Wetlands decreased by 72%.

Changes in agricultural crops such as switching from corn production to cotton production or other crop rotations remain unidentified at this level of study. However, comparison of sediment and nutrient runoff across subbasins that changed from one SWAT land cover class to another class shows a great variability in the results. Changing from forest to agricultural land or from wetlands to pasture land has great impacts on water quality, including the quantity of surface flow, nutrient runoff and sediment loadings at the main channel.

The study indicates that decrease in the cropland has resulted in lower overall nutrient application in the watershed. The surface runoff reduces by 19.7% with more surface vegetation as derived from 2001 land cover maps. While farm management practices are held constant over two land use scenarios, changes in the land use have caused the decrease in the application of total nitrogen and phosphorus across the watershed. The aggregate nitrogen runoff at the channel decreases by 23%, total phosphorus runoff by 22% and sedimentation by 40% when land use condition changes from 1992 to 2001 conditions.

In the absence of government payments, farms are currently operating under loss with both the corn and bermudagrass productions, losing an average of $251 and $171 per hectares respectively. Taking away land from corn production to bermudagrass causes a large reduction in operating loss. For example, about 231.1 thousands dollors reduction in operating loss is experienced when corn acreage in the watershed is decreased by 33%. A net reduction of 73.6 thousands in operating loss is experienced when converting the same land to pastureland. Hence, a large decline in corn acreage with simultaneous increase in pastureland causes a net reduction in operating loss of 165.2 thousand dollars at the watershed level. In the same time, the impact on water quality is positive for all kinds of land cover. Total nitrogen and phosphorus runoff reaching the channel decrease by 434 kg and 135 kg per year respectively. Sedimentation decreases by 1030 metric tons per year across the watershed.

CHAPTER 3. DISAGGREGATING THE EFFECTS OF ENVIRONMENTAL QUALITY USING TWO STAGE HEDONIC MODELS

3.1 INTRODUCTION

Hedonic models have been widely used to explain the effects of public goods such as environmental quality, neighborhood safety, school quality and water quality, on the values of adjacent properties (e.g. Michael et al. 1996; Burnell 1998; Brasington, 1999; Hite et. al. 2001; Weimer and Wolkoff 2001). The characteristics of differentiated goods such as houses are bundled together and are not traded directly in the market. However, as first noted by Rosen (1974), composite goods can be viewed as a sum of the implicit expenditures on the characteristics of which they are comprised. The implicit prices embodied in this relationship can be determined by hedonic regression estimations. Rosen (1974) first recognized that characteristic demands can be estimated and a number of studies have used multiple metropolitan or city data to identify such demand models (e.g., Witte, Sumka and Erekson 1979; Palmquist 1984; Michaels and Smith 1990; Clark and Cosgrove 1990). From the first stage, marginal implicit prices of individual characteristics are obtained and used to estimate demand curves for public goods in the second stage. The demand curves then can be used to estimate nonmarginal impacts of public goods on house prices.

Methodologically, the current study follows the general trend in two-stage hedonic price models, with the estimation of marginal implicit prices in the first stage and a demand curve in the second stage. However, this paper adds more than previous papers in the literature by using a simultaneous hedonic demand model to examine the relative values of local public goods. Previous studies have applied single equation demand models to estimate the demand and price elasticity for a single variable in question. Those papers compare the elasticity of demand for schooling, for example, from one set of data to the elasticity for environmental quality from a different set of variables or an entirely different set of data. Simultaneous estimation of demands for four public services compares the demand parameters on an equal basis, as well as captures correlations in the error structure. By jointly considering four important local public goods, namely public safety, environmental, water and school quality, we are able to consider trade-offs that may be made by homebuyers when making house location choices. From cross-price relationships, we can uncover the way that valuations of different public goods may augment or detract from one another.

Witte et al. (1979) used three simultaneous equations to estimate the demand for housing characteristics and obtained better than OLS results. In this study, comparison of simultaneous equations model with multiple single equation models in the second stage did not reveal significant differences in the demand coefficients. Unfortunately, this paper predates those that recognize the inherent identification problems in single market hedonics, so the results may not be valid. Nevertheless, the use of simultaneous equation models provides good estimates for cross-price elasticites between multiple goods.

The current paper also calculates the non-marginal welfare measures for all four public goods, illustrating another benefit of a system approach. That is, the s system may be used to examine examine relative benefits of spending on alternative local public programs. Such information will be valuable to policy makers, helping to rank funding priorities.

While the paper contributes to the literature by using simultaneous equation systems in the estimation of hedonic demand models, the choice of marginal implicit price method for public safety is another important feature of this paper. Instead of indirect measures of public safety, such as using tax share to measure the price of police services (Bergstrom and Goodman 1973; Turnbull and Djoundourian 1993) or the relative wages of police (Chapman 1976; Mathis and Zech 1985) crime ratio is used as the measure of public safety. This is a directly perceivable characteristic a homebuyer would assess before buying a house in a neighborhood.

3.2 BACKGROUND

The transaction prices of houses located in different areas reflect buyers' willingness to pay for different property characteristics. Housing prices are determined by both structural housing characteristics and the social and neighborhood characteristics where a house is located. Generally, housing values are derived from the number of bedrooms, housing area, lot size, age, and other amenities associated with the house. In addition to housing characteristics, house values are affected by many other spatial characteristics such as quality of schools, reported crime rates, distance to market centers, and distance to hazardous release sites. Users value each of these characteristics, positively or negatively, based on their preferences, to derive an aggregate house value.

About half of Ohio's 88 counties are located within one of fifteen metropolitan areas. We focus on the five largest metropolitan areas, in which the mean housing prices vary from \$64,490 to \$77,043. This study expands on previous research in Ohio metropolitan areas that find house price impacts from local public goods. For example, while investigating the property-value impacts of landfill sites in Franklin County, Hite et. al. (2001) find that crime rates and a school competitiveness index are significant variables in the hedonic price model, and that presence of landfill sites significantly affects property values. Brasington (1999) provides empirical evidence that school characteristics are capitalized into housing prices in six Ohio metropolitan statistical areas.

The current study uses a two stage hedonic model to estimate house buyers' demands for four particular local public goods – environmental quality as measured by the distance to nearest hazardous site, neighborhood safety as measured by an index created by normalizing the crime ratio, school quality as measured by the amount spent per student in the school district, and water quality as measured by an index created by normalizing the total length of EPA listed impaired stream network times priority list for TMDL intervention by Ohio Natural Resources Conservation Services. To achieve model identification, the market segmentation approach is used to estimate different hedonics in multiple MSAs (Michaels and Smith 1990).

3.3 LITERATURE REVIEW

The hedonic model has been used to estimate property value impacts and to derive attribute demands for various house characteristics including environmental quality (Rosen 1974; Atkinson and Halvorsen 1984; Brasington and Hite 2005). The effect of landfills on residential properties has been widely documented in the literature (Palmquist 1984; Reichert et al. 1991; Hite et al. 2001). A few studies have also explored the effect of water quality on local house price (e.g. Michael et al. 1996; Bejranonda et al.

1999). Many studies use the hedonic model to estimate property value impacts of public goods – such as public safety and school quality – and public bads – such as proximity to environmental disamenities (e.g., Palmquist 1984; Reichert et al. 1992; Nelson et al. 1992; Hite 1998; Hite et al. 2001). Environmental features increase or decrease land and house value as they are seen as desirable or undesirable characteristics.

A study by Deller and Ottem (2001) in Wisconsin counties suggests that murder and rape, two different kinds of crime variables, have very high disamenity values with implicit prices of -$4,400 to - $3,500 in metropolitan counties. They also find that disamenity values of crime in rural areas are generally higher than metropolitan areas, which suggests that rural residents are more sensitive to crime overall than urban residents. Some types of crime, such as burglary, are attracted to high quality of life areas.

Brasington (1999) finds that residents internalize school qualities in housing values. Using data from six metropolitan areas in Ohio, he finds that the passing rates for math, science and citizenship proficiency tests for 9th grade students added a $72.3 marginal implicit value to mean house values where expenditure per student is used as an indicator for school quality.

In a study of Monroe County in New York, Weimer and Wolkoff (2001) found that housing values in the central city are elastic with respect to improvements in elementary school outputs. Jud (1985) finds evidence that public school quality, as measured by reading achievement, has a significant effect on community housing values in Los Angeles and San Francisco.

Michaels and Smith (1990) use a hedonic model to investigate the impact of hazardous waste sites on house prices in suburban Boston and find that property values increase with distance from the house to the nearest hazardous waste site. Kohlhase (1991) studies the impact of toxic sites in Houston on property values before and after the sites have been listed in the Superfund National Priorities List (NPL) and reports that toxic sites have a significant impact on house prices after being listed in National Priority List (i.e. Superfund) maintained by the US Environmental Protection Agency. A positive relationship between house price and distance to the nearest site is observed up to 6.2 miles. However, once the waste site has been cleared, the marginal price to avoid a toxic waste site disappears.

Nelson et al. (1992) examine the effect of a landfill on house sales in Minnesota. They conclude that landfill has a negative impact on house values for homes within two miles and the value of a house located on the landfill boundary could decrease by more than 12 per cent from the prevailing price of the same house located two miles asay.

3.4 ANALYTICAL FRAMEWORK

This study employs a two-stage hedonic price and demand model for housing characteristics. In the hedonic model, a mixed log-linear regression of housing price over housing and spatial characteristics is estimated for each of the five MSAs included in the analysis. A Kolmogorov-Smirnov test for goodness-of-fit of variables suggests that different variables are best transformed to linear, log or exponential distributions. Appropriate functional forms of the variables are chosen for the first stage model based on the test results. House price (LNHPRICE), house size (LNHSIZE), lot size (LNLOT), distance to nearest hazard (LNMINDIST), expenditure per student in school district

(LNEXPEND), income (LNINCOME), population (LNPOPCBG) and housing units are log distributed. Proportions of residents with graduate degree (EGRADDEG), residents below poverty level (EPOVTOT) and vacant housings in the census block groups (EPVAC) have exponential distribution. Variables such as indices of water quality (WQINDEX) and neighborhood safety (SAFETY), distance to central business district from the center of school district (DISTANCE), age of house (AGE), garage size (GARG), proportion of residents with children at home (PKIDTOT), and percentage of white population (PWHITE) are linear. See Tables 3.1 and 3.2 for a description of the variables used and their descriptive statistics. The first stage model is specified in equation 1.

$$\begin{aligned}\mathrm{LNHPRICE}_i &= \alpha_0 + \alpha_1{*}\mathrm{PATIO}_i + \alpha_2{*}\mathrm{AIR}_i + \alpha_3{*}\mathrm{BEDROOMS}_i + \alpha_4{*}\mathrm{DECK}_i + \alpha_5{*}\mathrm{FIRE}_i + \\ &\quad \alpha_6{*}\mathrm{FULLBATH}_i + \alpha_7{*}\mathrm{PARTBATH}_i + \alpha_8{*}\mathrm{GARGDUM}_i + \alpha_9{*}\mathrm{GARG}_i + \alpha_{10}{*}\mathrm{LNHSIZE}_i \\ &\quad + \alpha_{11}{*}\mathrm{LNLOT}_i + \alpha_{12}{*}\mathrm{AGE}_i + \alpha_{13}{*}\mathrm{LNMINDIST}_i + \alpha_{14}{*}\mathrm{SAFETY}_i + \alpha_{15}{*}\mathrm{LNEXPEND}_i \\ &\quad + \alpha_{16}{*}\mathrm{DISTANCE}_i + \alpha_{17}{*}\mathrm{EGRADDEG}_i + \alpha_{18}{*}\mathrm{EPOVTOT}_i + \alpha_{19}{*}\mathrm{PWHITE}_i + \\ &\quad \alpha_{20}{*}\mathrm{LNINCOME}_i + \alpha_{21}{*}\mathrm{LNPOPCBG}_i + \alpha_{22}{*}\mathrm{EPVAC}_i + \alpha_{23}{*}\mathrm{LNHUNIT}_i + \\ &\quad \alpha_{24}{*}\mathrm{PKIDTOT}_i + \alpha_{25}{*}\mathrm{WQINDEX}_i + \varepsilon_i; \qquad (2.1)\end{aligned}$$

House characteristics such as presence of patio (PATIO), deck (DECK), central air conditioning (AIR), fireplace (FIRE), number of full bathrooms (FULLBATH) and partial bathrooms (PARTBATH), presence of garage (GARGDUM) and its size (GARG), size of the house (LNHSIZE) and lot size (LNLOT) are expected to have positive effects on price of a house. Environmental quality (LNMINDIST), neighborhood safety (SAFETY), school quality (LNEXPEND) and water quality (WQINDEX) are all expected to be positive. Percent of residents in the neighborhood (as defined by a Census block group) under the poverty level is expected to have a negative influence on housing values, as is age of the house.

Marginal implicit prices are derived from the partial derivative of the predicted hedonic price function with respect to the variable of interest. A particular focus of the study is to estimate demand functions for school quality, neighborhood safety, and environmental and water qualities. Using a semi-log model with linear or log-linear variables in the first stage model helps to determine the point at which positive or negative impacts of local public goods become irrelevant to house value.

Once the models are estimated for each MSA and implicit prices are obtained, instruments for predicted prices are created by running implicit price regressions. Irwin and Bockstael (2001) suggest using instrumental variables to minimize the potential for endogeniety among variables. Predicted values from the regression are used as price instruments in the second stage demand model. Instruments are selected for the variables such that included variables have low correlation with the original variables and have higher correlation with the marginal implicit prices. Because of the close relationship among the variables cut-off points are set for correlation coefficient between variables. The cutoff point between the instrumental variables and the original variable is set at the maximum of 0.30 and correlation between the instrumental variables and marginal implicit prices is set at the lowest of 0.10 (Hite and Brasington xxxx). Growth rate in MSA (GROWTH), commute time in minutes (COMT), ease of commuting (COMMUTE) and level of recreational facilities (RECREATN) are chosen for instrumental variables.

Four demand models are obtained by regressing the indicators of environmental quality, neighborhood safety, school quality and water quality over the instrumental marginal implicit prices variables, along with the shift variables. The second stage demands are estimated by generalized least squares using the following system of equations.

$$\begin{aligned}\mathrm{MINDIST}_i = \exp(&\beta_0 + \beta_1{*}\mathrm{PHMINDIST}_i + \beta_2{*}\mathrm{PHSAFETY}_i + \beta_3{*}\mathrm{PHEXPEND}_i + \\ &\beta_4{*}\mathrm{PHWQINDEX}_i + \beta_5{*}\mathrm{PHHSIZE}_i + \beta_6{*}\mathrm{LNINCOME}_i + \beta_7{*}\mathrm{GRADDEG}_i + \\ &\beta_8{*}\mathrm{PKIDTOT}_i) + \omega_i \qquad (2.2)\end{aligned}$$

$$\begin{aligned}\mathrm{SAFETY}_i = \exp(&\gamma_0 + \gamma_1{*}\mathrm{PHMINDIST}_i + \gamma_2{*}\mathrm{PHSAFETY}_i + \gamma_3{*}\mathrm{PHEXPEND}_i + \\ &\gamma_4{*}\mathrm{PHWQINDEX}_i + \gamma_5{*}\mathrm{PHHSIZE}_i + \gamma_6{*}\mathrm{LNINCOME}_i + \gamma_7{*}\mathrm{GRADDEG}_i + \\ &\gamma_8{*}\mathrm{PKIDTOT}_i) + \nu_i \qquad (2.3)\end{aligned}$$

$$\begin{aligned}\mathrm{EXPEND}_i = \exp(&\delta_0 + \delta_1{*}\mathrm{PHMINDIST}_i + \delta_2{*}\mathrm{PHSAFETY}_i + \delta_3{*}\mathrm{PHEXPEND}_i + \\ &\delta_4{*}\mathrm{PHWQINDEX}_i + \delta_5{*}\mathrm{PHHSIZE}_i + \delta_6{*}\mathrm{LNINCOME}_i + \delta_7{*}\mathrm{GRADDEG}_i + \\ &\delta_8{*}\mathrm{PKIDTOT}_i) + \varphi_i \qquad (2.4)\end{aligned}$$

$$\begin{aligned}\mathrm{WQINDEX}_i = \exp(&\phi_0 + \phi_1{*}\mathrm{PHMINDIST}_i + \phi_2{*}\mathrm{PHSAFETY}_i + \phi_3{*}\mathrm{PHEXPEND}_i + \\ &\phi_4{*}\mathrm{PHWQINDEX}_i + \phi_5{*}\mathrm{PHHSIZE}_i + \phi_6{*}\mathrm{LNINCOME}_i + \phi_7{*}\mathrm{GRADDEG}_i + \\ &\phi_8{*}\mathrm{PKIDTOT}_i) + \psi_i \qquad (2.5)\end{aligned}$$

where MINDIST is distance to nearest hazardous site, SAFETY is the index of neighborhood safety, EXPEND is expenditure per student in school district, and WQINDEX is the index of water quality in the subwatershed where the house is located. PHMINDIST, PHHSIZE, PHSAFETY, PHEXPEND and PHWQINDEX are the predicted marginal implicit prices of distance to hazard site, house size, public safety, school quality and water quality respectively. Shift variables are income (LNINCOME), proportion of graduate degree population (GRADDEG) and proportion of household with children under 18 years age (PKIDTOT).

A measure of welfare changes resulting from moves between two points on the demand functions. These are calculated by integration of demand curve using mathematical softwares, Maple. Predicted hedonic house prices are derived for the actual mean level of characteristics and a target level of improvement in the public goods. Welfare effects resulting from a move from the mean level of characteristics to the new level (say 10 percent improvement in the characteristics of public goods) are estimated by changes in consumer surplus. Changes in consumer surpluses are calculated by integrating the demand function with respect to the predicted marginal implicit price of the characteristics at the actual mean.

3.5 DATA AND METHODS

Transaction values for 45,222 houses in Akron, Cincinnati, Cleveland, Columbus, Dayton and Toledo metropolitan areas for calendar year 1990-1991 are obtained from Amerstate, Inc. All socioeconomic and demographic data are obtained from the Census of Population 1990.

The water quality index is a normalized score, on a scale from 0 to 10. The raw score of water quality is derived by adding the total length of impaired stream network within a 14-digit HUC watershed multiplied by the intervention priority of the watershed given by USEPA. This value is assigned to all individual house which lies within the boundary of that watershed. Information on impaired water and priority listing of subwatersheds are obtained from the United States Environmental Protection Agency documents and maps. USEPA gives an intervention priority score to each watershed after assessing the quality of water in all of Ohio's 11-digit hydrological code units. Since all lower order (corresponding with more digits in the HUC code) watersheds are nested into higher order watersheds (less digits in HUC code) the priority ratings for 11-digit watersheds are assigned to their respective 14-digit subwatersheds. For example, priority point of watershed 04110002020 is assigned to subwatersheds 04110002020010 through 04110002020060.

National hydrography network information is missing for a large part of the Cincinnati MSA necessitating its exclusion from the analysis. Unique samples lying in non-contiguous subwatersheds are also dropped from the analysis. Final sample size is 36,415 after these two adjustments are made.

The index for neighborhood safety is also obtained by normalizing the crime ratio, on a scale from 0 to 10, as reported in the appropriate reporting districts by the Office of Criminal Justice Service. No adjustment is done to the school quality indicator. The amount of dollars per student spent in each school district is taken from the Ohio Office of the Department of Education – EMIS data.

After cleaning for missing values for some observations and removing outliers, the sample size is 36,313. A graphical display of the study area is given in Figure 3.1. Each transaction record includes a number of physical housing characteristics and neighborhood characteristics. A description of variables used in the study is given in Table 3.1.

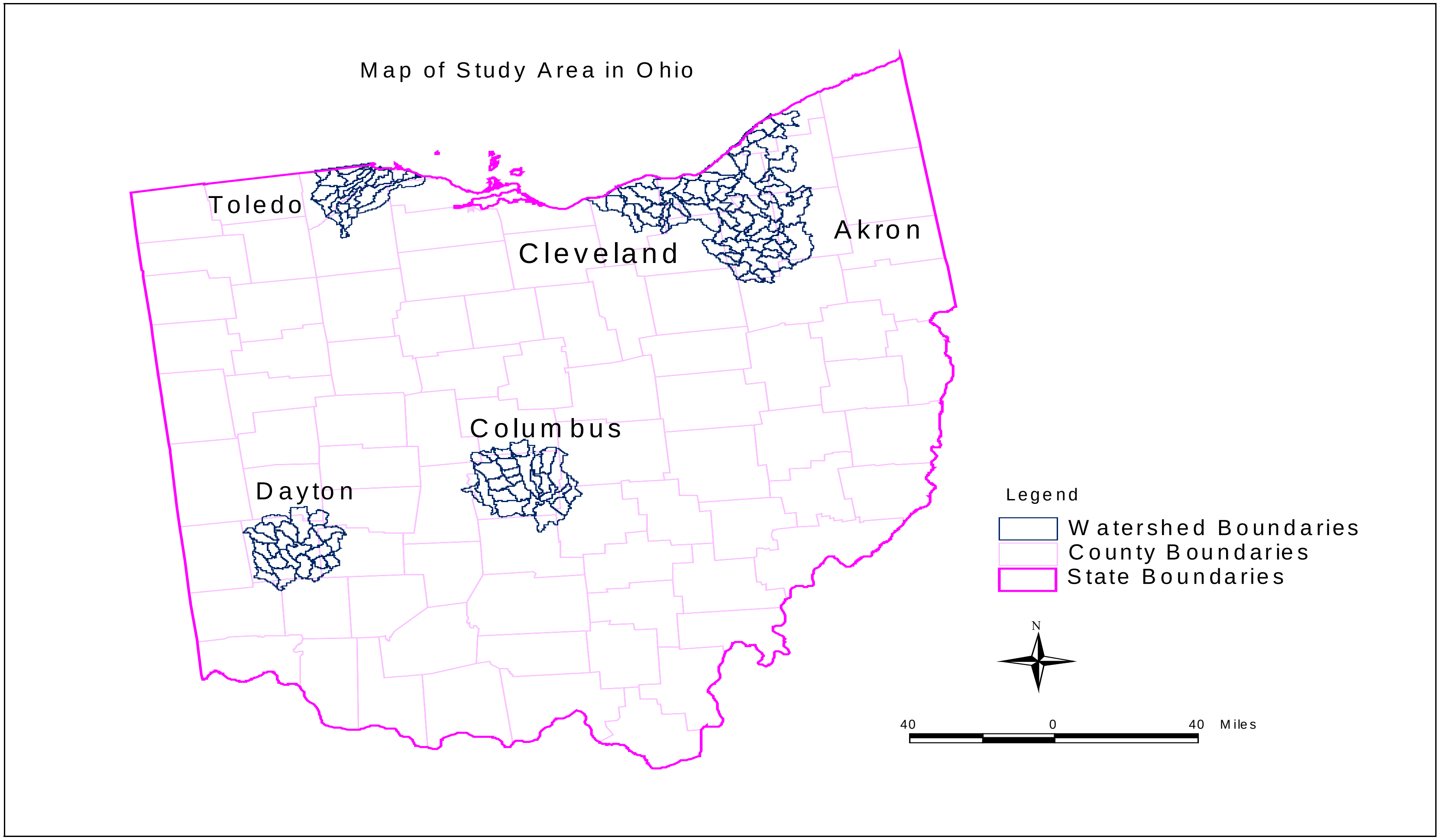

Figure 3.1 Map of study area for disaggregating the effects of environmental quality using two stage hedonic models

Table 3.1 Description of variables used in the hedonic demand model for public goods

Name	Variable Description (Functional form)
AGE	Age of house, years
AIR	Dummy for central air condition (1=Yes, 0=No)
BEDROOM	Number of bedrooms in house
COMMUTE	Accessibility or ease of commute within MSA
COMT	Average commuting distance, minutes
DECK	Dummy for deck in the house (1=Yes, 0=No)
DISTANCE	Distance from center of school district to CBD, miles
EGRADDEG	Proportion of population in CBG with graduate degree (Exponential)
EPOVTOT	Proportion of residents in CBG below poverty level (Exponential)
EPVAC	Proportion of vacant housing in the school district (Exponential)
EXPEND	School district expenditure per student, 000s of dollars
FIRE	Dummy for fireplace in the house (1=Yes, 0=No)
FULLBATH	Number of full bathrooms
GARG	Garage size, 000s of square feet
GARGDUM	Dummy for garage in the house (1=Yes, 0=No)
GROWTH	Growth of MSA population between 1980 and 1990, %
HPRICE	House transaction price for 1991 deflated by MSA, 000s of dollars
HSIZE	House size, 000s of square feet
INCOME	Average income of residents in CBG, 000s of dollars
LNEXPEND	Log of EXPEND variable (Log)
LNHPRICE	Log of HPRICE variable (Log)

Table 3.1 continued.

Name	Variable Description (Functional form)
LNHSIZE	Log of HSIZE variable (Log)
LNHUNIT	Number of housing units in CBG (Log)
LNINCOME	Log of INCOME variable (Log)
LNLOT	Lot size, 000s of square feet (Log)
LNMINDIST	Distance to nearest hazard site in miles (Log)
LNPOPCBG	Population count in CBG (Log)
MINDIST	Distance to nearest hazard site, miles
PARTBATH	Number of partial bathrooms
PATIOO	Presence of patio in house (1=Yes, 0=No)
PHEXPEND*	Price of extra 000s of expenditure in school district expenditure
PHHSIZE*	Price of extra 000s of square feet of house size
PHLOT*	Price of extra ten thousand square feet of lot size
PHMINDIST*	Price of extra mile of distance to nearest hazard
PHSAFETY*	Price of extra unit of public safety derived from hedonic regressions
PHWQINDEX*	Price of Extra unit of water quality index
PKIDTOT	Proportion of households in CBG with children <18 years of age
PWHITE	Proportion of residents in CBG who are white
RECREATN	Availability of recreation activities in the MSA
SAFETY	Index of public safety, 0 to 10 scale, continuous
WQINDEX	Water quality index, 0 to 10 scale, continuous

* Price of extra unit of variable is derived from the hedonic regression

3.6 RESULTS

The means of the variables used in the first stage hedonic model are given in Table 3.2. Aggregate mean house price is $71,847 ranging from $64,490 in Akron to $78,043 in Dayton. Aggregate means of distance of a house to the nearest hazard (environmental quality), index of neighborhood safety, school expenditure per student (school quality), and index of water quality in the subwatershed are 1.316 miles, 5.002, $4,999 and 8.401 respectively. The lowest mean distance from a hazardous site is found in Akron (0.995 miles) and the highest is found in Dayton (1.505 miles). The index of public safety is highest in Cleveland (6.325) and lowest in Toledo (3.825) making them the safest and least safe MSAs in terms of crime rates. School expenditure is highest in Columbus ($5,190 per student) and the lowest in Akron ($4,633).

The generalized least square results of the mixed log-linear model, correcting for heteroskedasticity in house size, are given in Table 3.3. General White test results suggest the presence of heteroskedasticity in the model. Bruesch-Pagan tests on a few suspected variables indicate house size as the primary variable associated with heteroskedasticity in the data.

The presence of central air conditioning, decks, fireplaces, garages, numbers of bedrooms, number of full and partial bathrooms, log of house size, log of lot size, garage dummy and garage size have mostly significant and positive results. Presence of patio has the expected relationship only in Columbus and Dayton.

Table 3.2 Mean and standard deviation of variables used in the hedonic demand model for housing prices in Ohio

Variables	Akron (n=4,797)		Cleveland (n=13,301)		Columbus (n=7,601)		Dayton (n=6,757)		Toledo (n=3,857)	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
AGE	47.393	23.550	46.183	23.863	35.352	22.625	38.564	22.628	42.138	25.943
AIR	0.228	0.420	0.192	0.394	0.504	0.500	0.474	0.499	0.349	0.477
BEDROOM	2.973	0.703	3.068	0.673	3.118	0.609	2.999	0.663	3.045	0.693
DECK	0.066	0.248	0.106	0.308	0.127	0.333	0.085	0.279	0.089	0.284
DISTANCE	4.562	4.199	12.155	7.338	6.417	4.655	6.310	4.083	5.797	3.588
EGRADDEG	1.072	0.080	1.078	0.101	1.103	0.112	1.089	0.083	1.085	0.090
EPOVTOT	1.126	0.163	1.087	0.120	1.095	0.144	1.091	0.126	1.093	0.127
EPVAC	1.048	0.046	1.041	0.045	1.047	0.045	1.043	0.046	1.048	0.048
EXPEND	4.633	0.372	5.069	0.954	5.190	0.611	4.944	0.568	4.937	0.283
FIRE	0.350	0.477	0.333	0.471	0.453	0.498	0.451	0.498	0.353	0.478
FULLBATH	1.241	0.458	1.212	0.435	1.331	0.492	1.422	0.533	1.230	0.447
GARG	3.133	2.046	3.555	1.651	2.743	2.101	3.461	1.892	3.688	1.780
GARGDUM	0.849	0.358	0.922	0.268	0.750	0.433	0.872	0.334	0.895	0.307
HPRICE	64.490	44.124	71.285	40.983	74.085	41.447	77.043	41.341	69.420	43.822
HSIZE	13.827	4.790	14.522	4.944	14.507	4.719	14.759	5.339	14.558	5.391

Table 3.2 continued.

Variables	Akron (n=4,797)		Cleveland (n=13,301)		Columbus (n=7,601)		Dayton (n=6,757)		Toledo (n=3,857)	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
INCOME	37.182	18.548	41.053	19.671	42.302	19.665	40.883	17.155	43.216	20.841
LNEXPEND	1.530	0.075	1.608	0.164	1.639	0.123	1.592	0.114	1.595	0.058
LNHPRICE	3.953	0.672	4.109	0.582	4.154	0.574	4.196	0.577	4.047	0.645
LNHSIZE	2.571	0.329	2.623	0.320	2.625	0.314	2.631	0.346	2.615	0.353
LNHUNIT	6.087	0.522	6.168	0.609	6.194	0.629	6.429	0.669	5.966	0.643
LNINCOME	3.521	0.418	3.633	0.385	3.659	0.407	3.636	0.381	3.675	0.411
LNLOT	2.183	0.674	2.102	0.618	2.069	0.442	2.216	0.542	2.032	0.553
LNMINDIST	-0.179	0.627	0.066	0.670	0.122	0.746	0.234	0.634	-0.066	0.717
LNPOPCBG	6.994	0.538	7.093	0.614	7.116	0.663	7.328	0.698	6.889	0.676
MINDIST	0.995	0.605	1.294	0.753	1.470	1.123	1.505	0.853	1.163	0.761
PARTBATH	0.332	0.503	0.352	0.499	0.400	0.499	0.287	0.470	0.391	0.516
PATIO	0.008	0.089	0.053	0.224	0.321	0.467	0.510	0.500	0.189	0.392
PKIDTOT	0.339	0.113	0.336	0.113	0.367	0.135	0.338	0.108	0.366	0.118
PWHITE	0.890	0.210	0.853	0.264	0.866	0.220	0.891	0.217	0.908	0.174
SAFETY	4.776	1.917	6.325	2.438	4.030	2.528	4.325	3.147	3.825	2.643
WQINDEX	8.685	2.244	8.696	2.170	6.995	3.839	9.286	1.230	8.253	1.916

Table 3.3 First stage hedonic regression results by metropolitan areas in Ohio

Explanatory	Akron		Cleveland		Columbus		Dayton		Toledo	
Variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
CONSTANT	0.988	0.236***	2.642	0.114***	2.027	0.170***	2.312	0.149***	1.397	0.254 ***
PATIO	-0.041	0.056	-0.030	0.013**	0.023	0.008***	0.021	0.007***	-0.009	0.013
AIR	0.100	0.014***	0.051	0.008***	0.066	0.009***	0.086	0.008***	0.051	0.012 ***
BEDROOM	0.021	0.009**	0.013	0.005**	0.042	0.008***	0.033	0.007***	0.005	0.009
DECK	0.079	0.023***	0.050	0.009***	0.044	0.012***	0.081	0.014***	0.046	0.020 **
FIRE	0.105	0.013***	0.071	0.007***	0.052	0.009***	0.058	0.008***	0.078	0.012 ***
FULLBATH	0.018	0.015	0.033	0.009***	0.022	0.010**	0.040	0.009***	0.045	0.016 ***
PARTBATH	0.066	0.013***	0.057	0.007***	0.019	0.009**	0.056	0.009***	0.033	0.012 ***
GARGDUM	0.135	0.018***	0.126	0.013***	0.014	0.012	0.117	0.014***	0.160	0.020 **
GARG	0.010	0.003***	0.003	0.002	0.009	0.003***	0.010	0.003***	0.009	0.004 ***
LNHSIZE	0.341	0.024***	0.403	0.014***	0.449	0.020***	0.397	0.017***	0.503	0.024 ***
LNLOT	0.075	0.011***	0.096	0.006***	0.091	0.011***	0.086	0.009***	0.113	0.012 ***
AGE	-0.007	0.000***	-0.005	0.000***	-0.004	0.000***	-0.004	0.000***	-0.006	0.000 ***
LNMINDIST	0.012	0.008	-0.002	0.004	0.004	0.005	0.020	0.006***	-0.001	0.006

Table 3.3 continued.

Variables	Akron		Cleveland		Columbus		Dayton		Toledo	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
SAFETY	0.030	0.004***	0.032	0.002***	0.024	0.003***	0.025	0.002***	-0.006	0.006
LNEXPEND	0.591	0.094***	0.107	0.023***	-0.045	0.050	0.202	0.044***	0.143	0.124
DISTANCE	-0.002	0.002	-0.008	0.001***	-0.008	0.002***	-0.006	0.002***	0.011	0.004 ***
EGRADDEG	1.130	0.112***	0.156	0.050***	1.011	0.061***	0.574	0.074***	0.883	0.094 ***
EPOVTOT	-0.090	0.056	-0.310	0.037***	-0.152	0.047***	-0.465	0.045***	-0.200	0.058 ***
WHITE	0.485	0.029***	0.219	0.012***	0.326	0.021***	0.369	0.018***	0.412	0.033 ***
LNINCOME	0.193	0.031***	0.356	0.018***	0.265	0.023***	0.174	0.022***	0.228	0.028 ***
LNPOPCBG	-0.271	0.051***	-0.421	0.030***	-0.662	0.040***	-0.450	0.038***	-0.280	0.048 ***
EPVAC	-1.083	0.148***	-1.079	0.079***	-0.945	0.115***	-0.765	0.101***	-1.036	0.126 ***
LNHUNIT	0.306	0.051***	0.447	0.029***	0.659	0.040***	0.459	0.038***	0.308	0.049 ***
PKIDTOT	-0.154	0.055***	-0.041	0.035	0.173	0.045***	-0.040	0.046	-0.209	0.051 ***
WQINDEX	-0.011	0.003***	-0.004	0.001***	0.002	0.001*	0.011	0.003***	0.013	0.002 ***
Adj. R^2	0.754		0.726		0.736		0.797		0.831	
# OBS	4,797		13,301		7,601		6,757		3,857	

*** significant at 1% level; ** significant at 5% level; * significant at 10% level

The coefficient for distance to hazard site is positive across MSAs, except for Cleveland and Toledo. The coefficients have mixed results in terms of statistical significance. The coefficients for public safety are significant and positive in all MSAs with the exception of a negative result in Toledo. Similarly, the coefficients for school expenditure are significant and positive Akron, Cleveland and Dayton. The water quality index is significant in all MSAs. Though, the signs are negative in Akron and Cleveland. The sign of the water quality coefficient is negative in Columbus whereas Toledo has positive but non-significant coefficient. Income has significant and positive coefficients in all MSAs.

Mean predicted marginal implicit prices of environmental quality, public safety, school quality and water quality are \$396, \$1,719, \$2,216 and \$85 respectively. These values suggest that for a unitary increase in the level of those characteristics, the marginal implicit prices increase by those amounts for the chosen characteristics. For example, a \$396 appreciation in the house price is expected if the house were to be moved to one mile further away from the nearest hazardous site. The second stage demand model also includes income, proportion of residents with a graduate college degree, and proportion of households with children under 18 years of age as shift variables. The marginal implicit prices are used to estimate demand curves for environmental quality, public safety, and school quality.

Table 3.4 shows the regression results for the demand for environmental quality, public safety, school quality, and water quality. Demand curves based on these results are illustrated in Figure 3.2 – 3.5.

Table 3.4 Second stage model regression results for demand for four public goods across the five metropolitan areas in Ohio

Explanatory	MINDIST		SAFETY		EXPEND		WQINDEX	
Variables	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
CONSTANT	-7.943	0.909 ***	31.589	0.722 ***	2.868	0.188 ***	21.802	0.459 ***
PHMINDIST	-0.186	0.081 **	2.770	0.065 ***	0.081	0.017 ***	1.712	0.040 ***
PHSAFETY	0.418	0.021 ***	-0.327	0.016 ***	-0.015	0.004 ***	-0.254	0.011 ***
PHEXPEND	0.180	0.036 ***	-1.278	0.029 ***	-0.056	0.007 ***	-0.756	0.018 ***
PHWQINDEX	-0.067	0.015 ***	-0.345	0.012 ***	0.002	0.003	-0.070	0.006 ***
PHHSIZE	2.865	0.424 ***	-15.290	0.338 ***	-0.541	0.088 ***	-9.320	0.215 ***
LNINCOME	0.439	0.013 ***	0.602	0.009 ***	-0.022	0.002 ***	0.010	0.006 *
EGRADEG	-1.785	0.065 ***	-0.900	0.040 ***	0.775	0.011 ***	0.072	0.027 ***
PKIDTOT	0.249	0.029 ***	0.521	0.020 ***	-0.187	0.006 ***	-0.011	0.014
Adj. R^2		0.100		0.336		0.255		0.090
# OBS		36,313		36,313		36,313		36,313

*** significant at 1% level; ** significant at 5% level; * significant at 10% level

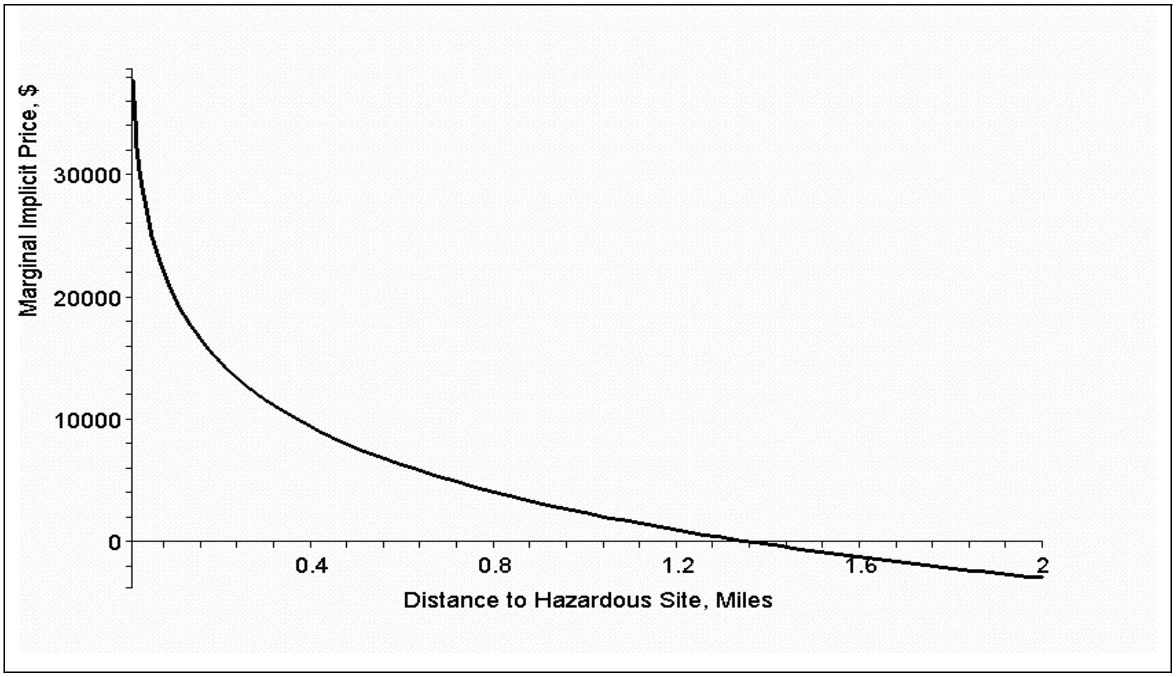

Figure 3.2 Demand for environmental quality as measured by the distance to nearest hazard in five metropolitan areas in Ohio

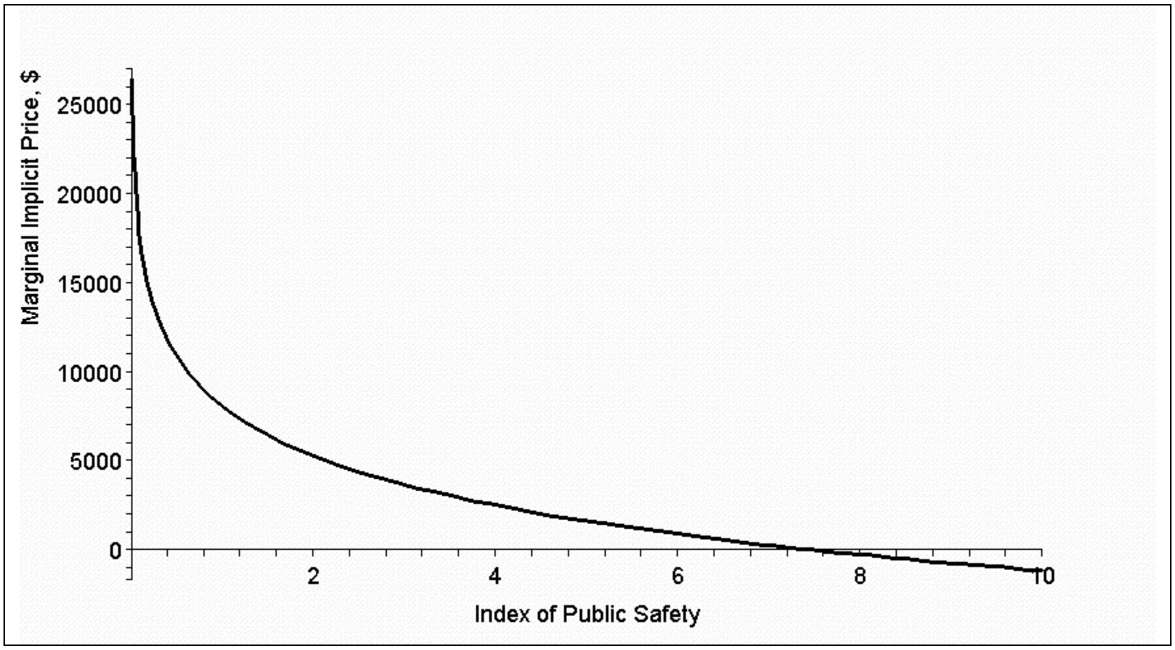

Figure 3.3 Demand for public safety as measured by the normalized index of neighborhood crime ratios in five metropolitan areas in Ohio

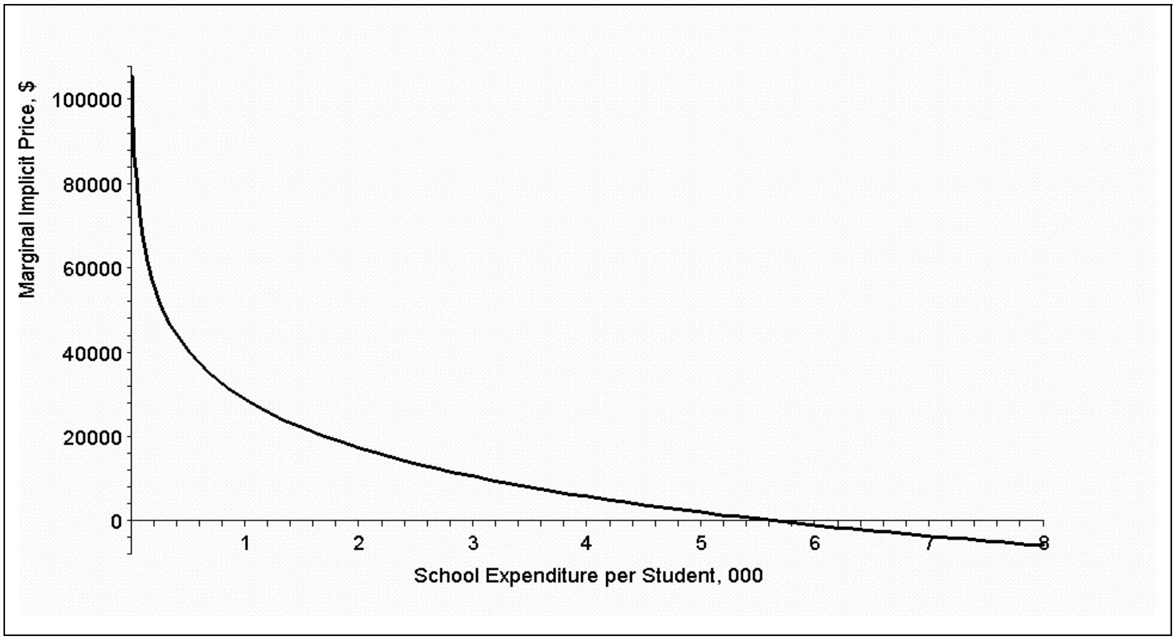

Figure 3.4 Demand for school quality as measured by the amount of expenditure per student in each school district in five metropolitan areas in Ohio

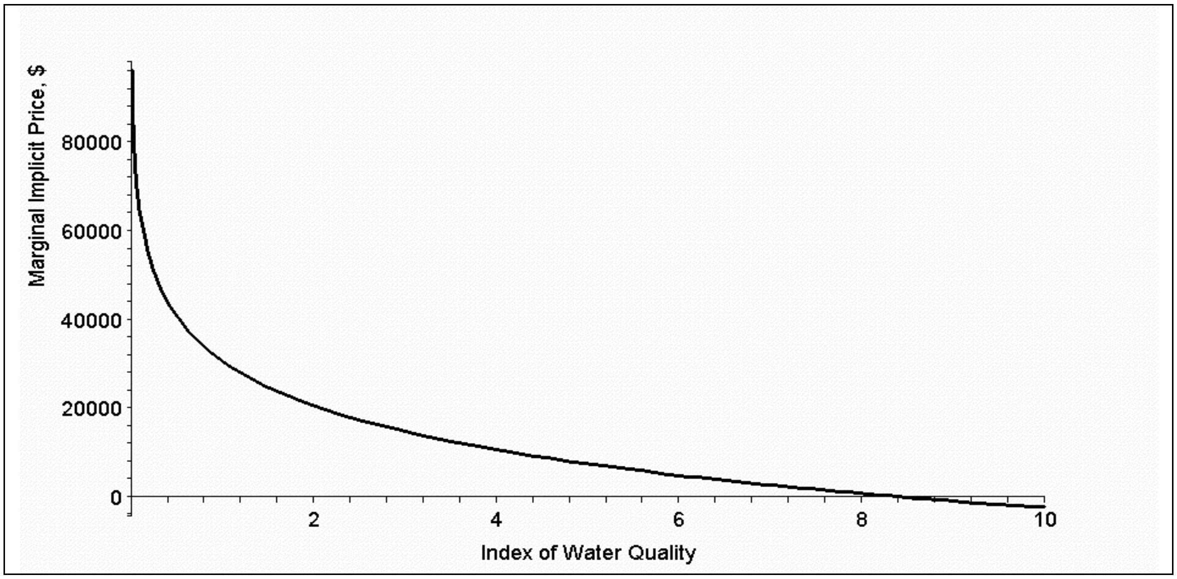

Figure 3.5 Demand for water quality as measured by the normalized index of the impaired stream networks times their intervention priority in each of the watershed in five metropolitan areas in Ohio

Table 3.5 shows that own price elasticities for all public goods, environmental quality, neighborhood safety, school quality and water quality are negative and significant. Cross price elasticities have different relationships with one another.

Table 3.5 Elasticity of demand for environmental quality, school quality, public safety and water quality across the five metropolitan areas in Ohio

Variables	Environmental Quality (MINDIST)	School Quality (EXPEND)	Public Safety (SAFETY)	Water Quality (WQINDEX)
Price of Environmental Quality	-0.074	0.032	1.098	0.679
Price of School Quality	0.398	-0.124	-2.833	-1.676
Price of Public Safety	0.719	-0.025	-0.562	-0.437
Price of Water Quality	-0.006	0.0001	-0.029	-0.006
Personal Income Per Capita	0.439	-0.022	0.603	0.010

A handful of papers have investigated the demand for environmental quality. The current study finds a price elasticity of demand for environmental quality of -0.074. Previous estimates range from -0.002 for the price elasticity of demand for visibility (Beron et al. 2001), to -0.503 for the price elasticity for air pollution reduction (Bender et al. 1980). Zabel and Kiel (2000) find a price elasticity of demand for ozone of -0.479 and -0.128 for particulates. Brasington and Hite (2005) also use distance to the nearest environmental disamenity as a dependent variable, and they find a price elasticity of -0.120. The estimated price elasticity here is well within the range of thosefound by previous studies.

Cross price elasticity of demand for environmental quality with respect to the price of school quality is found to be 0.398. The only other estimate in the literature to which this result is comparable comes from Brasington and Hite (2005), who find an estimate of -0.80. The difference in the elasticities probably stems from the measure of school quality: the current study measures school quality by expenditures, while Brasington and Hite (2005) uses levels of proficiency test passage as a school quality measure. Future research should use other measures of school quality to see to what degree the cross price elasticity depends on the measures of school quality used.

The current study also finds a cross price elasticity of demand for environmental quality with respect to price of public safety of 0.719 suggesting a complementary relationship between these two variables. All else equal, a ten percent increase in the price of public safety causes a seven percent increase in the quantity demanded of environmental quality. Similarly, the cross price elasticity between water quality and environmental quality is –0.006. This suggests that environmental quality and water quality are very weak complements and for a ten percent increase in the price of water quality causes a corresponding 0.06% decrease in quantity demanded of environmental quality. This is one of the primary contributions of the current study, as no comparison is available in the literature.

The income elasticity of demand for environmental quality is 0.439. Brasington and Hite (2005) also find an income elasticity of demand of 0.044. Both estimates suggest that, all else constant, people do not purchase much more environmental quality when their incomes rise.

Several studies have investigated the demand for public safety, but they use very different measures of demand and price. That said, the price elasticity of demand for public safety is found to be –0.562. Bergstrom and Goodman (1973) use expenditures to measure the demand for police services instead of crime data, and they use tax share to measure the price of police services instead of an implicit hedonic price, and they find a "price" elasticity of demand of -0.250. Turnbull and Djoundourian (1993) find an elasticity of police expenditures with respect to tax share of -0.330. Mathis and Zech (1985) find the elasticity of the number of police per capita with respect to maximum police salary to be -2.780, and Chapman (1976) uses similar measures to find an elasticity of -0.500. With the exception of Mathis and Zech (1985), the price elasticity of demand in this study is consistent with that of the rest of the literature.

However, this is the only study to estimate cross price elasticity of demand for public safety. The cross price elasticity between public safety and environmental quality is 1.098 suggesting a strong substitution between these two goods. This suggests that for a ten percent increase in the price of environmental quality causes an 11% increase in the quantity demanded of public safety. However, public safety and school quality are strong complements with a cross price elasticity of –2.833. This means that, all else constant, a ten percent increase in the price of public school quality is associated with a 28% decrease in the quantity demanded of public safety.

The income elasticity of demand for public safety is found to be 0.603. Previous studies find the income elasticity within very inelastic to elastic range. For example, Turnbull and Djoundourian (1993) find it 0.12, Bergstrom and Goodmand (1973) find it 0.71 and Mathis and Zech (1985) find it 1.75.

The third public good in the model is school quality. The price elasticity of demand for school quality is –0.124. Most studies find price elasticity between -0.20 and -0.40 (Reiter and Weichenrieder, 1997). Although he measures school quality with proficiency test passage rather than expenditures, Brasington (2002) finds a price elasticity of demand of -0.110, almost identical to the current estimate of -0.124. Reid (1990), who uses expenditures, finds price elasticity between -0.04 and -0.21. Rubinfeld, et al. (1987), who also use expenditures, achieve an estimate of 0.07, and Jud and Watts, who use proficiency tests, find the elasticity to be -0.413.

No published studies are found to compare the estimated cross price elasticities of demand for public school quality. The purchase of school quality is not strongly tied to the purchase of other major public services. It is found that school quality and environmental quality are weak substitutes, with a cross price elasticity of 0.032. It suggests that with all else constant, a ten percent increase in the price of public safety causes a 0.32% increase in the quantity demanded of school quality. On the other hand, school quality and public safety are complements with a cross price elasticity of –0.025 which suggests that a ten percent increase in the price of public safety causes a quarter of percent increase in the quantity demanded of school quality.

The estimate for the income elasticity of demand for public schooling is -0.022. Other studies generally also find an income inelastic demand for public schooling. Brasington (2002) finds an income elasticity of demand of 0.32; Rubinfeld, et al. (1987) find an estimate of -0.08, and Reid (1990) finds a range of estimates from 0.20 to 0.30. The most income elastic estimate is found by Jud and Watts (1981) with the income elasticity of 0.70.

The final public good included in the study is water quality. Own price elasticity of demand for water quality index is –0.006. The cross price elasticity between water quality and public safety is –0.437 suggesting a weak complementary relationship between these variables. This suggests that for a ten percent increase in the price of water quality there is a four percent decrease in the quantity demanded of public safety. Similarly, the cross price elasticity coefficient is –1.676 between water quality and school quality. This shows an elastic relationship between the two variables, one good being a strong complement of the other good. It shows that for a ten percent increase in the price of water quality there is 17% decrease in the quantity demanded of school quality. Water quality and environmental quality area substitutes with a cross price elasticity of 0.679 suggesting a seven percent decrease in the quantity demanded of environmental quality for a ten percent increase in the price of water quality.

The own price and cross price elasticities for each of the variables are average elasticities estimated for each of the observation. The magnitudes of cross price elasticities between the variables are different in each set of equations when measured for each good as a baseline. For example, cross price elasticity between the price of environmental quality and quantity demanded of public safety is 1.098. This elastic relationship becomes inelastic (0.719) when the cross price elasticity is measured using the price of public safety and quantity demanded of environmental quality. This may be particularly true when people have different preferences for what they have and what they have to forgo for it. Since the cross price elasticities are calculated at the individual observation level and it also gives the realistic sign and parameter coefficients for the variables, cross price elasticities are not imposed in this study.

An effort is made to impose equality restriction in the system of equations so that cross price elasticities between the same set of variables are equal in each equation. It is done by equating the product of parameter coefficient and the mean of the variables in each set of equations. However, when such restrictions are imposed, the own price elasticities switched changes in two of the four equations.

Consumer surplus has been calculated for each of the demand equations. True consumer surplus is calculated by the integration of demand equations for two values of predicted implicit prices at the actual mean and a 10 percent improvement in the desired characteristics. In aggregate, there is an average of $397 gain in consumer surplus if a house is moved from its current location to a location 10 percent further away. Similarly, consumers will gain an average of $653 if public safety improves by 10 percent from its current level. The gain in consumer surplus for a 10 percent increase in school quality is $7,553. The gain in consumer surplus is the highest for water quality with a $7,881 net gain for a 10 percent increase in water quality index.

3.7 CONCLUSION

The relationships between house price and characteristics for housing and neighborhood characteristics are investigated in this study. The demand for environmental quality, public safety and school quality are estimated. The first stage hedonic model used a mixed model generalized least square estimation as part of 2-stage estimation. The second stage model used a semi-log model to estimate demand equations.

The first stage hedonic price estimation suggests that house prices are affected significantly both by physical housing characteristics and neighborhood characteristics such as levels of education, income, poverty, and race; household structures and environmental disamenities, such as distance to hazard sites. The marginal implicit prices of desirable features are positive, and are negative for undesirable features.

The second stage demand model indicates that demand for environmental quality, neighborhood safety, school quality and water quality are influenced by the prices of those characteristics along with other variables that shift demand. People respond by demanding fewer characteristics when their implicit prices increase.

Environmental quality and neighborhood safety are substitutes to each other whereas school quality is a complementary public good to the latter. Similarly, buyers in neighborhoods where higher proportions of residents hold graduate degrees demand more environmental quality and neighborhood safety while those in neighborhoods with lower percentage of graduate degrees and higher percentages of households with children at home demanded higher school quality and water quality.

The cross price elasticities between two goods are found to be different depending on which of the two goods is the baseline. Future analysis should focus on imposing equality restrictions on cross price elasticities to force symmetry in a proper way. Imposing these restrictions may slightly change the substitutions or complementary relationship between variables.

CHAPTER 4. CONCLUSIONS AND RECOMMENDATIONS

4.1 CONCLUSIONS

The research presented here is divided into three different subject areas focusing on three specific statistical and modeling tools commonly used in natural resource economics. The essays are interconnected by the common theme of water quality. The study focuses on water quality as a specific environmental quality indicator to demonstrate (a) how socio-economic and demographic factors affect land use distribution, (b) how changes in land use and management practices affect water quality, and (c) how much people are willing to pay for improvement in public goods including water quality.

The first essay uses a multinomial logit model to estimate the effects of urbanization, demographic structure, personal income and spatial distribution of watersheds in the allocation of fixed proportion of land to developed, forest, agricultural and other land uses in western Georgia watersheds. The study assumes the land use distribution across competing uses as an optimization problem faced by a single user. Two time-period cross-sectional data for 60 small watersheds are analyzed to explain the effect of population density, mean age, market concentration, travel time to work, road accessibility, personal income, education level and longitude and latitude of watersheds. Developed land use share is positively related to higher market concentrations and road accessibility, but with a higher average time to work, suggesting a rural-urban job interface. Personal income has a significantly negative influence on the share of agricultural land, which increases with higher proportions of college degree holders. Longitude has a negative influence on developed land share and a positive influence on agricultural, forest and other land use. Latitude positively influences developed, agricultural and other land shares, but negatively influences the share of forestland as the study area is on U.S. coastal plains. Based on the model results, and changes in the variables over time, a prediction for future land use is made. These results constitute a foundation for spatial and ecosystem models to predict long-term environmental impacts of land use change.

In the second essay, a simple bioeconomic model is used to determine how changes in land use distribution affect water quality in a small watershed in Alabama. The BASINS-SWAT model is used to estimate environmental parameters, which can be used further in economic analysis of agricultural production under environmental quality constraints. This study applies a complex long-term watershed-modeling tool to assess the effect of land use change on water quality including the sediment loadings and nutrient loadings between 1986 and 2005. Annual and monthly sedimentation and nutrient runoff is simulated with two land cover scenarios of 1992 and 2001. Over the years, agricultural cropland decreased by 26% followed by a 10% decrease in forestland. Pasture land increased by 14%. At the same time, the structure of forestland changed from dominantly deciduous forest to dominantly evergreen. The SWAT results show that average annual sedimentation loadings decreased by 20.4% and nitrogen and phosphorus runoff decreased by 21.3% and 21.2% respectively. This paper discusses the application of the model in evaluating the effects of best management practices on nutrients runoff and sedimentation at the watershed level. Combining a biophysical model with an economic model into a bioeconomic model to optimize environmental quality constraints and economic profit at the watershed is discussed.

In the third chapter, a two-stage hedonic price and demand model is developed to estimate the willingness to pay for environmental quality, neighborhood safety, school quality and water quality in five Ohio metropolitan areas. Marginal implicit prices are estimated for different characteristics in the first stage and demands for four public goods are jointly estimated in the second stage. The own price demand elasticities for all four characteristics are inelastic, ranging from –0.006 for water quality, -0.074 for environmental quality, -0.124 for school quality and –0.562 for neighborhood safety. Cross price elasticity between environmental quality and water quality is –0.006 making them weak complements. Cross price elasticity between neighborhood safety and school quality is –2.833 making them strongly complementary to each other. Environmental quality is a substitute for both neighborhood safety and school quality with cross price elasticity of 0.719 and 0.398 respectively.

4.2 RECOMMENDATIONS FOR FUTURE RESEARCH

The results from each chapter of the dissertation are of interest to different audiences. The first chapter provides a valuable tool with which urban planners can predict land use demand for alternative uses ahead of time. The results and their applicability in the planning process can be further enhanced by combining the statistical results with geographic information systems tools that can facilitate creating geospatial maps and spatial pattern analysis. Similarly, the tabular results can be converted into spatial and temporal land use grids with the help of advanced geostatistical programming, such as GEOMOD. With such advanced application support, these map can be used to develop terrestrial ecosystem modeling which in turn, helps to create land productivity maps, carbon storage and sequestration maps and water quality/water stress maps for historical comparison. Moreover, expanding the study at a regional level using data from multiple counties will foster wider application of the model.

Increasing land productivity and agricultural production while maintaining, if not improving, environmental quality, has been a challenge recently. On one hand, increasing population and economic growth has increased the demand for food production, while on the other hand it has encouraged conversion of forest and agricultural lands to developed uses. This has resulted in rapid land use change and unprecedented input use in agriculture, in turn, causing further deterioration in water quality through nonpoint source pollution.

The results presented in the second chapter are basic to the understanding of water quality impacts on land use change. These results help regional planners and watershed management policy makers by providing estimates of changes in water quality when land use changes over time. The application of the model can be extended to include more detailed land use and soil distribution in the study area using recent satellite images to create maps depicting detailed cropping patterns will help to understand the impact alternative best management practices such as minimum or no-tillage practices and reduced use of fertilizers and pesticides. Using multiple hydrological response units to simulate best management practices will give more precise effects of those practices in water quality.

These biophysical models are extremely valuable in assessing the physical impacts of BMPs on quantity and quality of water bodies in a given watershed. They can help policy planners to assess water quality and plan for intervention through TMDLs. However, it is imperative to account for the effects that BMPs may have on farmers' profitability. Specifically, the impact that changes in yield or changes in input costs have on profitability has not been examined in this study. Profitability can greatly impact the likelihood that farmers will voluntarily adopt BMPs, thereby improving water quality. Thus, watershed and farm level economic impacts must be evaluated to understand the magnitude of gains and losses to individual farmers through use of BMPs.

Agricultural BMPs have been shown to reduce NPP by reducing runoff and/or capturing sediments, and can thus be helpful to maintain water quantity and improve water quality in streams and other water bodies. However, producers believe that they will be financially burdened if they are required to implement BMPs to meet TMDL standards (Intarapapong et al. 2002; Pease and Bosch, 1994; Lichtenberg and Lessley, 1992). For example, if agricultural producers change from conventional to no-tillage row crop cultivation they may have to invest in new equipment, and/or may experience reduced yields, both of which would negatively impact farm profits. Other practices, such as filter strips or riparian buffers require producers to reduce acreage planted in row crops and may reduce pasture land for livestock, while structural practices (e.g. slotted board risers) require investment in infrastructure. Furthermore, BMP impacts on NPP and profits are dependent on a number of weather and market conditions in the long run, creating significant uncertainty for producers.

Each parcel of land, depending on farming practices, soil type, elevation and management practices discharges runoff to the drainage differently. Efforts to increase production by applying more chemicals and nutrients on marginal land results in higher nutrient wash and greater runoff to the drainage system. Individual producers, who own land of varying quality in the watershed are concerned with their own profit maximization and ignore aggregate profit levels once they meet a uniformly set TMDL requirements. However, as demonstrated by Hite et al. (2002) it is probable that all farmers in a watershed could enjoy higher profits overall, if they are to cooperatively adopt BMPs and alter land uses. Maximization of watershed level profits, however, would most likely require producers to hold less productive land to achieve lower farm-level profits, while owners of more productive land would be better off. Thus, without a policy to compensate low productivity farmers, such cooperative behavior would not be possible to achieve. Cooperative watershed management is therefore likely to increase the net social benefits obtained by efficient allocation of production resources across the watershed that will help control overall pollution levels and increase aggregate returns to producers.

This approach extends beyond the biophysical simulations and makes use of the results from this stage in a more complex mathematical programming framework. The modeling process involves the development of bioeconomic models in which the outputs of SWAT simulations are used as inputs to an economic optimization model under imposed environmental and land use constraints. Various hypothetical TMDL targets will be considered in a mathematical programming model; for example, 10% reduction in nitrogen runoff and/or 20% reduction in sediment. The objective function of the model will be economic profits, based on revenues and costs (Forster et al. 2000; Hite et al. 2002; Intarapapong et al. 2002; Paudel et al. 2003). A mathematical programming model can be used to find optimal profits and allocation of land use. Profits can be modeled under a number of land use and management practice scenarios and compared to those of actual practices over the long run in the study area. In addition, the resulting model can be used to predict the way water quality changes with changes in management practices.

The results from the third chapters are important to the real estate manager, regional urban development planners and local and state legislators. Understanding people's willingness to pay to public goods will help to determine tax assessment policies by county and state legislatures. At the same time, this will provide a basis for a benefit cost analysis for cleaning toxic substances, improving water quality, investing in school quality improvement or strengthening public safety. Using simultaneous equation systems for multiple public goods provides information on how these public goods are related to each other and how a person decides between paying for one public good by foregoing consumption of other public goods.

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