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SPRAWL DYNAMICS AND THE DEVELOPMENT OF EFFECTIVE SMART GROWTH POLICIES

A Thesis in

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by

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Abstract

Sprawling urban development is a major driving force of global environmental change. Its impact on Earth system functions is likely to increase in the future when the proportion of the world's population living in urban areas is expected to grow dramatically. Thus, many policymakers are starting to look for ways to control sprawl through smart growth policies before it becomes unmanageable. However, the mechanisms by which sprawl takes place and the likely impact of smart growth on sprawl and on various stakeholders are not yet fully understood. Therefore, there is a need to develop a comprehensive methodology for sprawl analysis and its containment.

Consequently, the goal of this dissertation was to provide a research framework and methodologies that contribute to the understanding of sprawl dynamics and its containment. It arrives at this goal through three analyses. The first analysis addresses sprawl and landscape fragmentation in Centre County, Pennsylvania through cross-tabulation, identifying the dominant and systematic land use transitions in the area and subsequently, the explanatory drivers of urban land use location through logistic regression. The second analysis projects future urban land use location in Centre County through simulation modeling using the CLUE-S modeling framework and includes validation and uncertainty analyses of the simulated products. By assessing the price elasticity of residential land demand and housing supply, the third analysis evaluates the feasibility of remedying sprawl by implementing smart growth policy through land price increases without compromising affordability of housing in Centre County.

The results of these analyses demonstrate that land use transitions are predominantly from agriculture to urban land. The primary explanatory drivers of urban land use location in Centre County are soil and topographic factors. The validation of the simulation of near future urban land use location is encouraging, although sprawl projections show significant temporal decay. The output of the sprawl simulation is sensitive to decision rules on the ease of conversion to urban of other land use categories and to weights of input parameters. Price elasticity of residential land demand is relatively high, thus implying that smart growth policies that increase land price are likely to contain sprawl without increasing housing price. In sum, the analyses suggest that effective sprawl containment not only calls for a comprehensive analysis of local land use dynamics to confirm that sprawl is a problem, but also requires that policy makers are aware of the uncertainty inherent in sprawl model projections for informed and realistic application of model output in their planning policies. To avoid failure of sprawl amelioration measures, stakeholders who are liable to feel the effects of these measures and are likely to resist their implementation should be identified and incorporated in the policy process from its inception.

Key words: urban sprawl, smart growth, affordable housing, explanatory drivers, simulation uncertainty, land demand

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

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CHAPTER ONE

General introduction

1.1. Background

The phenomenon of sprawling urban development is one of the major forces driving land use/land cover change in the world. Urban sprawl has been characterized as a distinct form of dispersed and inefficient urban growth, haphazard in configuration, and highly reliant on the automobile (Hasse and Lathrop, 2003). The United Nations Human Settlement Programme (2004) notes that urban development is proceeding at a rapid rate around the world and most metropolitan and urban areas are adding land at a much faster rate than they are adding population, resulting in large amounts of natural and agricultural lands consumed for urban growth while accommodating comparatively small numbers of people considering the amount of land consumed per person (Fulton et al., 2001; Hasse, 2004; Lathrop et al., 2006).

Sprawl refers to a type of spreading suburban development with negative outcomes, such as increased commuting time. The Florida Growth Management Plan (1993) defines sprawl as an unplanned suburban development allowing land use patterns that inflate facility costs and that fail to protect natural resources and agricultural lands. Burchell and Shad (1999) specifically define it as the intrusion of low-density residential and nonresidential development into rural and undeveloped areas. The costs and negative externalities of urban sprawl have been widely documented (e.g., Kahn, 2000; Freeman, 2001) and include loss of prime farmlands and ecosystems fragmentation. The challenge to planners and environmental managers, therefore, is to balance urban development with the preservation of natural resources (Daniels, 1997). *Smart growth* is one growth management policy that has gained popularity as a viable solution to contain sprawl through its advocacy for compact development among other things (Danielsen et al., 1999; Hasse, 2004; Smart Growth Network, 2006).

The term *smart growth* has been widely adopted to characterize compact patterns of development that do not embody the negative characteristics of sprawl (Danielsen et al., 1999; Hasse, 2004; Smart Growth Network, 2006). Such programs often involve a package of tools such as zoning, comprehensive plans, subdivision regulations, development fees, exactions, and infrastructure investments, applied together with high density development (Nelson et al., 2002). Hasse (2004) points out that urban growth following the principles of smart growth – e.g., pedestrian-friendly development, multi-nodal transportation coordination, and urban redevelopment – holds the potential to lessen the environmental impacts and social costs of sprawling development. Staley and Gilroy (2004) emphasize increase in housing affordability and diversity as the core principle of most smart growth policies, stressing that low-density residential and commercial development reduces the overall quality of urban life through reliance on the automobile, whereas compact, higher density land use patterns improve the quality of life through a pedestrian lifestyle and provide a wide range of housing choice.

In contrast, others have argued that urban sprawl generates private benefits and that an important cost of smart growth is an increase in the price of housing (Segal and Srinivasan, 1985; Conte, 2000; Gordon and Richardson, 2000). Private benefits from sprawl can arise from the satisfaction of consumer preferences for more socioeconomically segregated communities that are less densely settled and may be able to offer lower housing prices (Wassmer and Baass, 2006). Further supporting sprawl, Glaesar and Kahn (2004) point to cheaper and larger homes as a benefit. Burchell et al. (2000) note that land further from the center of a metropolitan area is less expensive, resulting in cheaper housing. In their response to critics of sprawling land use patterns in the United States, Gordon and Richard (2000) emphasize that Americans' desires for larger houses and lot sizes are more likely to be met in outlying areas. Kahn (2001) notes that sprawl increases housing affordability in central cities and suburbs, leading to a reduction of the Black-White housing consumption gap. Levine (1999) shows that growth management measures in California have accelerated the movement of minorities and the poor from central cities. An assessment of the impact of smart growth on housing affordability by 11 scholars states that it is possible for smart growth to coexist with affordable housing, but concludes that further empirical study is necessary before any definitive cause and effect statements are possible about the impact of smart growth on housing prices (Nelson et al., 2002).

These diverging views on the disadvantages and benefits of sprawl and of smart growth call for a detailed sprawl analysis in an area of interest to determine if sprawl is problem and also determine its underlying processes. A trade off analysis of the likely impact of smart growth on various stakeholders is essential for effective adoption and implementation of smart growth policy. Downs (2005) states that successful implementation of smart growth policies requires adopting policies that contradict long-established traditions such as low density living patterns. Therefore, effective implementation of smart growth policy requires a better understanding of the dominant land use conversions in the landscape in order to help identify the likely impact of sprawl on landscape fragmentation and the stakeholders who will be affected by implementation of smart growth policies. Smart growth implementation results in different opportunities and negative externalities for various stakeholders. For instance, real estate owners in the periphery of urban areas would likely be disadvantaged by smart growth implementation as the value of their property would probably be reduced when development is confined to the city boundary while brown fields owners' property values would be expected to gain. Effective smart growth implementation requires that all affected stakeholders be on board, hence to avoid low rates of adoption, there is a need to conduct a feasibility analysis of the likely impact of smart growth policy on stakeholders prior to its implementation to avoid low rates of adoption.

Gyourko and Voith (1999) indicate that the impact and desirability of any smart growth policy depends on the nature of the elasticity of residential land demand. If households have strong preferences for residential land and change their land consumption very little in response to a large increase in land price, then smart growth policies raising the price of land would have little impact on patterns of land use (Pryce, 1999). Furthermore, attempts to change land use patterns would make house ownership costly. However, if consumers readily adjust the quantity of land they consume in response to changes in price, then smart growth policies that moderately change the price of land could have a large impact on land use patterns

(Voith, 2001). Another important market parameter that could be used to evaluate the likely impact of smart growth policies is the elasticity of housing supply. Glaeser et al. (2006) find that the elasticity of housing supply determines whether increases in economic productivity will create bigger sprawling cities or compact cities with expensive housing.

Consequently, the goal of this dissertation is to provide a research framework and methodologies that contribute to understanding sprawl and its effective management at a local level. The dissertation also aims to evaluate the feasibility of developing affordable housing while pursuing a smart growth policy aimed at containing sprawl. The specific objectives of the dissertation are to determine (1) major land use transitions at the county scale and (2) sprawl dynamics and its underlying processes. Furthermore, the dissertation seeks to evaluate (3) the sensitivity of the agreement between the simulated urban location map and the reference map to input parameter variation and uncertainty of sprawl modeling output and (4) the feasibility of developing affordable housing policy that is consistent with smart growth as a move to contain sprawl.

1.2. Case study area

Centre County, Pennsylvania (Figure 1.1) typifies a growing debate regarding the tradeoffs between socioeconomic growth and development and their impacts on the landscape. Although it is the fifth largest county in Pennsylvania, two thirds of its land area (2887.837 km^2) is protected conservation area while, at the same time, the land available for development is located in prime agricultural land in the valleys. Furthermore, the county has one of the highest median housing values in

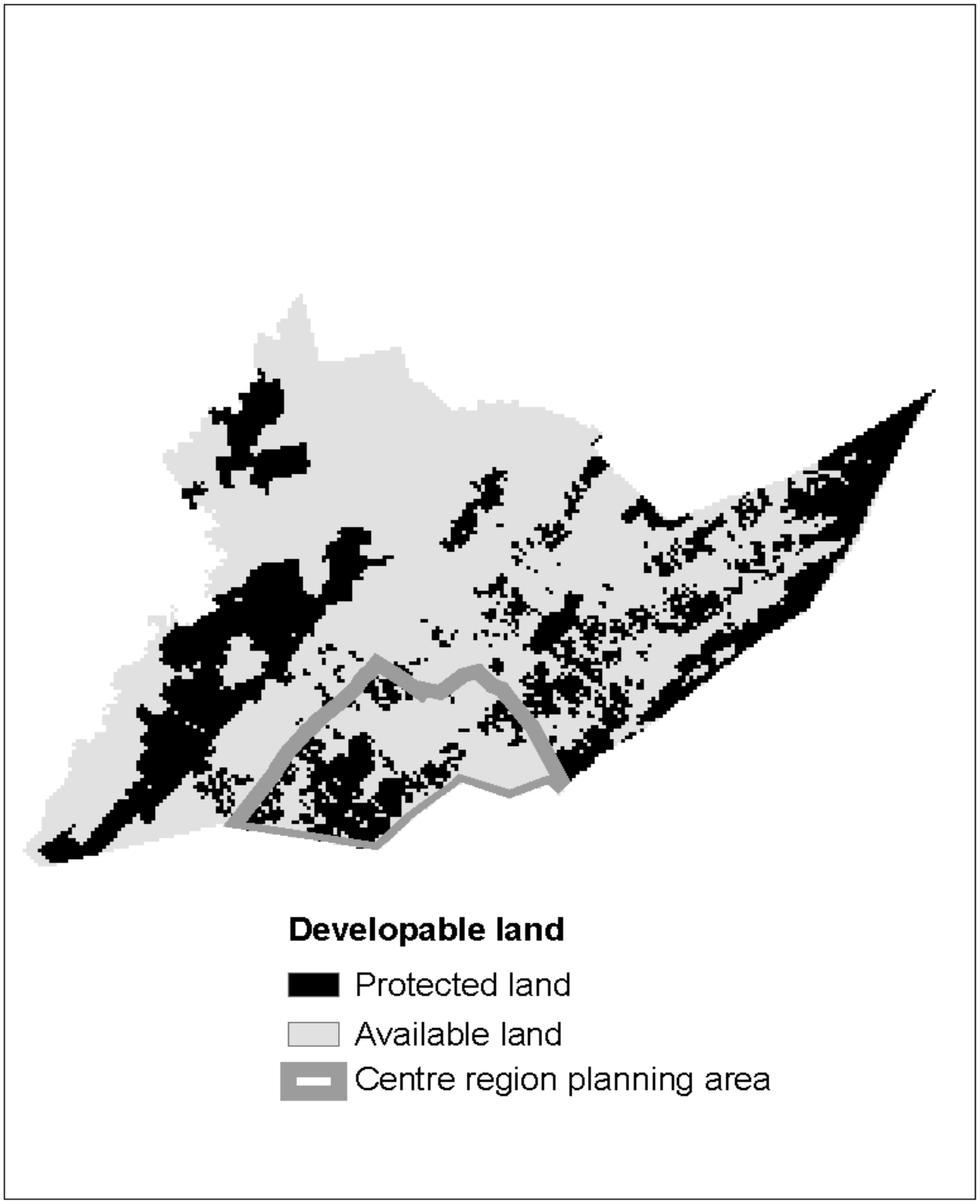

Figure 1.1. The location of Centre County in Pennsylvania

Pennsylvania with a single family housing median price of $156,000 in 2005 and has high rating as a retirement destination (Centre County 2005).

A wide range of land uses and land covers coexist within Centre County, with forests and agricultural lands being important components of the landscape. Forests are mainly concentrated where topography is steep and land is marginal for agricultural purposes, whereas agriculture is concentrated mainly in the fertile limestone and shale soils of the valleys (Centre County 2005). Over the years the number and size of farms have decreased as the number of rural non-farm residents has increased, leading to a loss of 1,618 hectares of prime farmland between 1977 and 2005 (Goetz et al., 2004). The county is divided into seven planning regions. The Centre Region Council of Governments is the planning region that is the most urbanized and home to The Pennsylvania State University. The Centre Region includes the State College Borough and College, Ferguson, Halfmoon, Harris, and Patton townships. This work uses the Centre Region to represent the *sub-county level* or *sub-county extent* for comparison with the *county level* or *county extent*.

The Mid-State and University Park airports service the county and the Keystone Shortway (Interstate 80) runs east-west across the county. This highway has greatly facilitated accessibility to major markets for the county's products by the eight motor freight carriers that serve the area. The imminent completion of Interstate 99 is likely to increase the accessibility of the county's products to markets in other parts of Pennsylvania and beyond. In addition to these commercial benefits brought by the highways to the county, increased ease of commuting by workers to commercial centers such as State College is likely to result in increased conversion of agricultural and forest lands to residential use (Centre County 2005).

Therefore, the competition for land between residential and agricultural uses in the valleys and the anticipated housing demand increase makes Centre County a good place to study sprawl and its amelioration. Land use decisions in the United States, especially in Pennsylvania, are based on jurisdiction, so it is imperative that studies on sprawl are carried out at local level where land use decisions are made.

1.3. Structure of the dissertation

This dissertation is essentially a collection of interconnected papers that will be submitted to international peer-reviewed journals for publication. As a consequence, the three body chapters (i.e., Chapters 2-4) have individual introductions and objectives based on key objectives identified in section 1.1. The chapters contain some inevitable overlaps, especially with respect to the data sets. It is also worthwhile to note that sprawl dynamics and land use transitions, as well as their impact on landscape fragmentation, are analyzed at county and sub-county levels in Chapter 2 to evaluate the effect of spatial resolution on patterns and processes of sprawl reported in previous studies. Subsequent chapters are analyzed at the county level only. Chapter 2 further determines explanatory variables of urban land use location through logistic regression. The explanatory variables of urban land use location are used in simulation modeling to project urban land use location into the near future. Although Chapter 3 deals with sensitivity and uncertainty of sprawl simulation output, it relies on validation results from Chapter 2 to determine the uncertainty of that output.

Chapter 3 determines the uncertainty of sprawl modeling output and its sensitivity to variations in input parameters in an attempt to sensitize planners and policy makers to the errors inherent in sprawl simulation products. Chapter 4 carries out a feasibility analysis of developing affordable housing policy that is consistent with smart growth as a measure to contain sprawl in the county. Chapter 5 concludes the dissertation with remarks on the implications of the results for sprawl management with possible directions for future research.

CHAPTER TWO

Urban Expansion in Centre County, Pennsylvania: Spatial Dynamics and Landscape Transformations

2.1. Introduction

The 1990 Census showed that for the first time more Americans were living in suburbs than in central cities. About one-fifth of the nation's prime farmland was located within metropolitan counties and, when nonmetropolitan counties adjacent to metropolitan counties are included, these greater metropolitan areas contain over one-third of the nation's prime farmland (Mieskowski and Mills, 1991; Daniels, 1997). Farmland and natural lands contribute to flood control, air cleansing, and water filtering; those amenities, as well as the inherent societal value of open space, are lost when these lands are developed (Nelson, 1992). Therefore, one challenge to land resource management in areas where urban development is taking place in prime agricultural lands is to achieve compact development that does not degrade these natural resources (Couch and Karecha, 2006). Although urban areas make up 14 percent of the Earth's land surface area (Grubler, 1994), urban sprawl can cause larger changes in environmental conditions than other land uses (Folke et al., 1997; Lambin et al., 2001; Fang et al., 2005). Urban development and associated changes in landscape composition and pattern set off a cascade of environmental impacts that are of growing concern (Alberti, 1999; Bartlett et al., 2000; McKinney, 2002; Nilsson et al., 2003). Urban growth can lead to landscape fragmentation resulting in loss of habitat and of migration routes for many animal species. These environmental impacts are likely to increase in the 21^{st} century when more than one half of the world's population is expected to be living in urban areas (The United Nations Human Settlement Programme, 2004).

The rapid pace and broad scope of urban growth is stressing the ability of land use planners and environmental resource managers to address the cumulative degradation of ecosystems (Lathrop et al., 2006). Fang et al., (2005) note that in order to keep ecosystems functioning well, it is necessary for environmental researchers, managers, and decision makers to understand the spatial dynamics of sprawl. Complementing this idea, Gaurs and van Wee (2006) stress that a comprehensive exploration of the consequences of urban growth is needed for informed decisions on sprawl patterns and its costs. Ichikawa et al. (2006) conclude that an examination of future implications of urban development on ecosystems functioning is critical for an informed land use planning process to avoid ill-advised and irreversible land use decisions.

Nevertheless, the mechanisms through which sprawl occurs are not well understood (Galster et al., 2001; Cutsinger et al., 2005; Wolman et al., 2005; Zeng et al., 2005). Hasse (2004) highlights that while substantial research and academic discourse have addressed many of the socioeconomic issues related to sprawl, far less research has focused on developing concrete methodologies able to identify and characterize sprawl. Lopez and Hynes (2003) further point out that lack of a coherent methodology to measure sprawl has been a major cause for contention among various groups concerned with sprawl because of differences in the definition of sprawl . This lack of progress in understanding patterns and processes of urban growth within a landscape is due to lack of consistency in measuring urban land use patterns (Cutsinger et al., 2005; Tsai, 2005). A first step toward gaining insight into patterns and processes of urban sprawl, therefore, should be an empirical analysis that quantifies urban land use patterns and processes through land use change modeling (Batty et al., 1999; Wu, 2002; Fang et al., 2005).

This chapter presents such a step. Specifically, the chapter seeks to determine systematic land use transitions at sub-county and county levels with a view of determining whether sprawl is a problem in a county. The chapter further seeks to determine the explanatory variables of urban land use location within the county and project urban land use location to the year 2012.

2.2. Data and Methods

2.2.1. Data

Land use/land cover data classified at Anderson level 1 from Landsat TM images of the county for 1993 and 2000 were available and used to calibrate and validate the simulation model respectively and were obtained from the Centre for Integrated Regional Assessment (CIRA), The Pennsylvania State University. Land use maps had six land use categories: Urban, Forest, Agriculture, Water, Rangeland and Abandoned Mining Sites. These classifications were performed by an experienced analyst from the United States Geological Survey for 1993 and 2000, were ground truthed extensively, and are considered to be highly reliable. The Water, Rangeland and Abandoned categories were aggregated into a single land use category called Others for analysis because none of these categories was expected to convert to urban. GIS layers of potential drivers of urban land use location used in the simulation were obtained from the Land Analysis Lab, The Pennsylvania State University. The soil layer was obtained from the Soil Survey Geographic (SSURGO) database of The Natural Resources Conservation Service (NRCS). The SSURGO database is at a scale of 1:24,000 resulting in 30, 000 polygons for Centre County. Each polygon has three components, with the dominant component accounting for 90 percent of the variance in the polygon (NRCS, 2001). The 30m resolution land use maps were aggregated to 100m and 250m for sub-county and county levels, respectively, and the same was done to the potential drivers' layers. Kok et al. (2001) emphasize the importance of modeling and validating land use change at multiple spatial resolutions.

2.2.2. Objectives and analysis

The objectives of the research presented in this chapter were (1) to identify systematic, non-random land use transitions in Centre County and (2) to determine explanatory variables of urban land use location resulting from these transitions through logistic regression. Furthermore, the study sought (3) to use the determined explanatory variables of urban land use location to project future urban land use patterns based on linear extrapolation of current urban land demand in the county based on the assumptions that land transitions to urban is continuous and quantitative and (4) to determine the accuracy of the simulated urban land use patterns. From these four analyses, the work aimed (5) to determine the effect of scale on explanatory variables of urban land use location and on predictive model performance.

2.2.2.1. Land use transitions analysis

A cross-tabulation matrix was used to assess land use transitions among the categories of Urban, Agriculture, Forest, and Others between 1993 and 2000 at sub-county and county levels according to two pairs of components: net change and swap, and gross gains and losses. In Table 2.1, the rows display the categories of time 1 (1993) and columns display the categories of time 2 (2000). The notation P_{ij} denotes the proportion of the landscape that experiences a transition from category i to category j, where the number of categories is J (J = 4). Entries on the diagonal indicate persistence, so P_{jj} denotes the proportion of the landscape that shows persistence of category j. Entries off the diagonal indicate a transition from category i to a different

Table 2.1. Cross-tabulation matrix for determining land use transitions

Time 1	Time 2				Total time 1	Loss
	Category 1	Category 2	Category 3	Category 4		
Category 1	P_{11}	P_{12}	P_{13}	P_{14}	P_{1+}	$P_{1+} – P_{11}$
Category 2	P_{21}	P_{22}	P_{23}	P_{24}	P_{2+}	$P_{2+} – P_{22}$
Category 3	P_{31}	P_{32}	P_{33}	P_{34}	P_{3+}	$P_{3+} – P_{33}$
Category 4	P_{41}	P_{42}	P_{43}	P_{44}	P_{4+}	$P_{4+} – P_{44}$
Total time 2	P_{+1}	P_{+2}	P_{+3}	P_{+4}	1	
Gain	$P_{+1} – P_{11}$	$P_{+2} –P_{22}$	$P_{+3} – P_{33}$	$P_{+4} – P_{44}$		
Total change	Loss + Gain					
Swap	2 x Min($P_{j+} –P_{jj}$, $P_{+j} – P_{jj}$)					
Net change	Total change – swap					

category j. In the Total column, the notation P_{i+} denotes the proportion of the landscape in the category i in time 1, which is the sum over all j of P_{ij}. In the Total row, the notation P_{+j} denotes the proportion of the landscape in category j in time 2, which is the sum over all i of $P_{ij.}$ The gains are the differences between the column totals and persistence, whereas the losses are the differences between row totals and persistence. Total change is the sum of gains and losses. The amount of swap is two times the minimum of the gain and loss, and each grid cell that gains is paired with a grid cell that loses to create a pair of grid cells that swap. (Pontius et al., 2004).

The matrix is analyzed using the chi-square statistic, which compares the matrix of observed values to a matrix of expected values. The chi-square computes the expected values by assuming that each total, P_{i+} and P_{+j}, is given a priori. The expected proportion of the landscape that experiences a transition from category i to category j due to chance is P_{i+} times P_{+j}. The expected proportion of the landscape that experiences persistence of category j due to chance is P_{j+} times P_{+j}. Equation (2.1) gives the formula for the chi-square statistic, where N is the number of grid cells in the map.

$$X^2 = \sum_{i=1}^{J}\sum_{j=1}^{J}\left\{N \times \frac{[P_{ij} - (P_{i+} \times P_{+j})]^2}{(P_{i+} \times P_{+j})}\right\}$$

2.2.2.2. Explanatory variables of urban land use location

Land use is defined by the purposes for which humans exploit the land cover governed by the variability in time and space in biophysical environments, socioeconomic activities, and cultural contexts that are associated with land use change. Therefore, identifying the causes of land use change requires an understanding of how people make land use decisions and how various factors interact in specific contexts to influence decision making on land use. Decision making is influenced by factors at the local, regional, or global scale. Proximate (or direct) causes of land use change constitute human activities or immediate actions that originate from intended land use and directly affect land cover (Ojima et al., 1994). They involve a physical action on land cover. Underlying (or indirect or root) causes are fundamental forces that underpin the more proximate causes of land cover change. They operate more diffusely (i.e., from a distance), often by altering one or more proximate causes (Lambin et al., 2003). Underlying causes are formed by a complex of social, political, economic, demographic, technological, cultural, and biophysical variables that constitute initial conditions in the human-environment relations and are structural (or systemic) in nature (Geist and Lambin, 2002).

Proximate causes generally operate at the local level (individual farms, households, or communities). By contrast, underlying causes may originate from the regional (districts, provinces, or country) or even global levels, with complex interplays between levels of organization. Underlying causes are often exogenous to the local communities managing land and are thus uncontrollable by these communities. Only some local-scale factors are under the control of local decision makers. An important system property associated with changes in land use is feedback that can either accentuate or amplify the speed, intensity, or mode of land use change, or constitute human mitigating forces; for example, via institutional actions that dampen, impede, or counteract factors or their impacts. Examples include the direct regulation of access to land resources, market adjustments, or informal social regulations (e.g., shared norms and values that give rise to shared land management practices) (Lambin et al., 2003).

Place-based research followed by systematic comparative analyses of case studies of land use dynamics have helped to improve understanding of the causes of land use change (Kates and Haarmann, 1992; Wiggins, 1995). These syntheses produced general insights on the sectoral causes of land use change and on the mode of interaction between various causes. Insights from these sectoral analyses have led a unifying theory on drivers of land use change in the form of:

Multiple Causes. Land use change is always caused by multiple interacting factors originating from different levels of organization of the coupled human-environment systems. The mix of driving forces of land use change varies in time and space, according to specific human-environment conditions. Driving forces can be slow variables, with long turnover times, which determine the boundaries of sustainability and collectively govern the land use trajectory (such as the spread of salinity in irrigation schemes or declining infant mortality), or fast variables with short turnover times (such as food aid or climatic variability associated with El Nino). Biophysical drivers may be as important as human drivers. The former define the natural capacity or predisposing conditions for land use changes. The set of abiotic and biotic factors that determine this natural capacity varies among localities and regions. Trigger events, whether these are biophysical (drought or hurricane) or socioeconomic (war or economic crisis), also drive land use change. Changes are generally driven by a combination of factors that work gradually and factors that happen intermittently (Lambin et al., 2001).

Natural Variability. Natural environmental change and variability interact with human causes of land use change. Highly variable ecosystem conditions driven by climatic variations amplify the pressures arising from high demands on land resources, especially under dry to sub-humid climatic conditions. Natural and socioeconomic changes may operate as synchronous but independent events. Natural variability may also lead to socioeconomic unsustainability, for example when unusually wet conditions alter the perception of drought risk and generate overstocking on rangelands. When drier conditions return, the livestock management practices are ill adapted and cause land degradation (Puigdefagas, 1998).

Economic and Technological Factors. At the time scale of a decade or less, land use changes mostly result from individual and social responses to changing economic conditions, which are mediated by institutional factors. Opportunities and constraints for new land uses are created by markets and policies (Lambin et al., 2001).

Demographic Factors. At longer timescales, both increases and decreases of a given population also have a large impact on land use (Turner, 1999). *Institutional Factors*: To explain land use changes, it is also important to understand institutions (political, legal, economic, and traditional) and their interactions with individual decision making (Ostrom et al., 1999).

Cultural Factors. Numerous cultural factors also influence decision making on land use. Land managers have various motivations, collective memories, and personal histories. Their attitudes, values, beliefs, and individual perceptions influence land use decisions; for instance through their perception and attitude toward risk (Lambin et al., 2003). The above insights on drivers of land use change and discussion with Centre County planners formed the basis for selection of the potential drivers of urban location evaluated in this dissertation.

The land use map for 1993 was reclassified by assigning urban land use a value of 1, while other land uses were assigned a value of 0. The reclassified map was then used as the dependent variable and the potential drivers as independent variables (Table 2.2) in stepwise regression. The variables *distance to water networks* and *distance to roads* are euclidean distances of the dependent variable (a 100 meter squared land parcel at sub-county level and 250 meter squared land parcel at county level) to the nearest water line and road. *Distance to various townships* is the euclidean distance of the dependent variable to the center of each of these townships. The variables *slope* and *elevation*

Table 2.2. Explanatory variables of urban land use location

Variables	**Explanation (units)**
Population density	Inhabitants (km^2)
Elevation	Digital elevation model (m)
Slope	Derived from DEM (%)
Distance from roads	(m)
Distance from water networks	(m)
Distance from sewer networks	(m)
Distances from urban centers	(m)
Soils suitable for agriculture	*
Soils suitable for septic works	*
Zoning	*

*categorical variables

are slope and elevation values within each land parcel and the variables *soils suitable for agriculture* and *soils suitable for septic works* are the suitability ranking of soils within each land parcel for agricultural production and septic works based on the USDA soil capability classification system. Distances were log transformed before analysis to increase normality.

The problem of using conventional statistical methods, like linear and logistic regression, in spatial land use analysis is that these methods assume the observations to be statistically independent and identically distributed (Cliff and Ord 1981). However, land use data have the tendency to be spatially dependent, a phenomenon known as spatial autocorrelation. Spatial autocorrelation may be defined as the property of random variables to take values over distance that, due to geographic proximity, are more similar or less similar than expected for randomly associated pairs of observations (Legendre and Legendre, 1998).

On the one hand, spatial dependency could be seen as a methodological disadvantage because conventional statistics may lead to the wrong conclusions. On the other hand, such spatial relations actually provide information on spatial pattern, structure, and processes. Thus, spatial dependency contains useful information, but appropriate methods must be used to deal with it statistically. The effects of spatial dependence on conventional statistical methods are various, including for example biased estimation of error variance and overestimation of R^2 (Anselin and Griffith 1988). All the usual statistical tests have the same behaviour, however: in the presence of positive autocorrelation, computed test statistics are often declared significant under the null hypothesis: negative autocorrelation may produce the opposite effect (Legendre and Legendre, 1998). This error results from the fact that a spatially autocorrelated observation carries less information than an independent observation because it is partly predictable from its neighbors so a new sample point does not bring with it one full degree of freedom (Cliff and Ord, 1981; Legendre and Legendre, 1998). Several methods exist that minimize the effect of autocorrelation in statistical analysis (Kaluzny et al. 1997; Long, 1998; LeSage, 1999; Anselin, 2002; Nelson and Geoghegan, 2002; Polsky, 2004). To reduce the potential effects of spatial autocorrelation in this analysis, a random sample of 25 percent of the observations (all pixels) was used in the logistic regression (Wassenaar, et al., 2006).

Model variables were selected by entry testing based on the significance of the score statistic, and removal testing was based on the probability of the Wald statistic. Probability for entry and removal were respectively set to 0.05 and 0.10. Collinearity was accounted for by eliminating the variable with the least significant Wald statistic. contribution to the model. (Wassenaar, et al., 2006). The performance of logistic regression models was evaluated by the relative operating characteristic (ROC) (Pontius and Schneider, 2001). In ordinal least squares regression, the coefficient of determination (R^2) gives a measure of model fit, but there is no equivalent for logistic regression. Instead, the goodness of fit can be evaluated with the ROC method, which evaluates the predicted probabilities of certain urban pixels to be located in the same location as explanatory variables by comparing them with the observed values over the whole domain of predicted probabilities instead of only evaluating the percentage of correctly classified observations at a fixed cut-off value. Only variables significant at the 1and 5 percent levels of signifance are reported in the results.

2.2.2.3. Simulation of urban land use location

Many research groups have developed models to simulate and explore land- use changes (Sklar and Constanza, 1991; Lambin, 1997; Kaimowitz and Angelsen, 1998; Bockstael and Irwin, 2000; Briassoulis, 2000). Differences in modeling techniques relate to differences in the purpose and the scale of the study. Explorative models (Stoorvogel, 1995) were developed to design alternatives for present land use. Derived land use patterns from explorative models represent optimizations of land use based on biophysical potentials, sometimes including socioeconomic estimates of inputs and goals.

Land use change models using cellular automata (Engelen et al., 1995) deal with scale dependency of the drivers of land use patterns in a deterministic way by prescribing the influence of drivers of land use change over a specified distance. The relations describing these impacts of neighborhood conditions (i.e., scale dependencies) on land use are most often based on expert knowledge. Cellular automata models attempt to mimic certain scale aspects, but fail to unravel the system properties that cause scale dependencies (Verburg et al., 1999). Another group of land use change models (Hall et al., 1995) explore possible changes in land use as a function of driving forces. These models provide information about the scope and impact of land use change, and are useful to resource planners for identifying areas that require priority attention. The CLUE modeling framework (the Conversion of Land Use and its Effects; Veldkamp and Fresco, 1996) and its finer scale version, CLUE-S, (Verburg et al., 2002), is such a model.

The approach used in the CLUE modeling framework to allocate land use changes attempts to account for the entire system of complex interactions among historic and present land use, socioeconomic conditions, and biophysical constraints. The CLUE framework explicitly addresses interactions between land use patterns and the scale dependency of spatial drivers of land use change (Verburg et al., 1999). The CLUE model is different from models solely based on an empirical analysis of land use change (Mertens and Lambin, 1997; Pijanowski et al., 2000) because of its explicit attention to the holistic functioning of the land use system, of its capability to simulate different land use types at the same time, and of the possibility of simulating different scenarios. Kaimowitz and Angelsen (1998), Irwin and Geoghegan (2001), and Lambin et al. (2000) note that models that relying heavily upon statistical relations between land use and driving factors are frequently criticized for their lack of causality. The CLUE model addresses this criticism by selecting spatial drivers of land use change based on the theoretical relationships between these spatial drivers and land use (e.g., Turner II et al., 1995).

The main limitation of the model is its inability to simulate land use change dynamics in an area without a compiled land use change history. CLUE uses existing land use patterns to allocate land use change. The only possible way around this limitation is the use of empirical relations derived in an area with very similar characteristics.

CLUE-S differs from CLUE in that it analysis land use change at finer spatial resolution such as watersheds or local planning areas while CLUE analysis at courser resolutions like country or continental level. CLUE-S is especially suitable for scenario analysis and the simulation of trajectories of local land use change. The model can identify critical areas of land use change (hot spots) for different scenarios. Scenarios also can be used to evaluate the impact of macro-level changes, such as changes in demographic characteristics. Other scenarios can be used to evaluate the effects of local level conditions, such as the protection of nature reserves and agricultural areas (Verburg et al., 2002). Apart from scenarios, Schneider and Pontious (2001) draw attention to the ability of the CLUE-S model to link the quantity of change to the location of change as its advantage over other spatially explicit models of land use change.

Therefore, prediction of urban land use location was conducted within the CLUE-S modeling framework (Verburg et al., 2002). CLUE-S has two distinct modules–a non-spatial demand module and a spatially explicit land use location module (Figure 2.1). The non-spatial demand module calculates the area change for all land use types in the aggregate (i.e., the sub-county and county levels in this chapter). The results from the demand module specify, for each year between 1992 and 2001, the area covered by the different land use types, which is a direct input for the land use location module. Within the land use location module (Figure 2.2), these land use demands are translated into land use

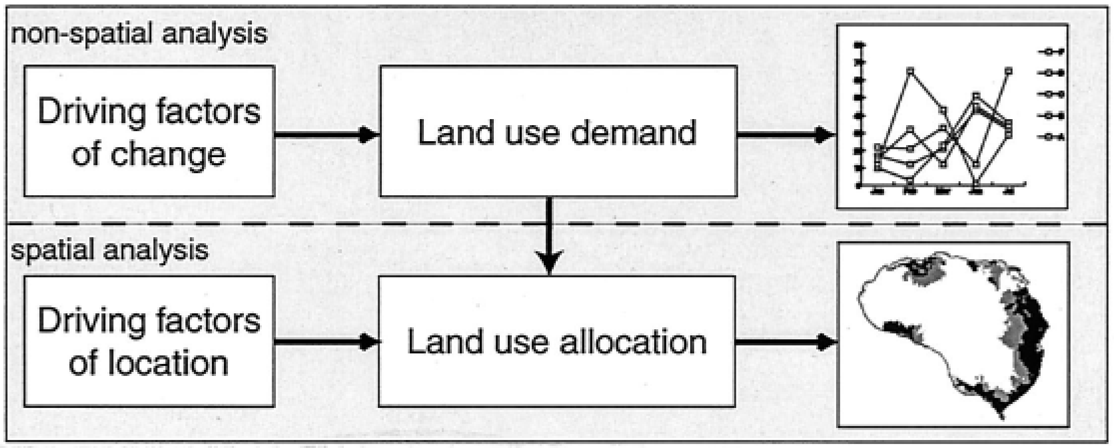

Figure 2.1. Modules within the CLUE-S model (Verburg et al., 2002).

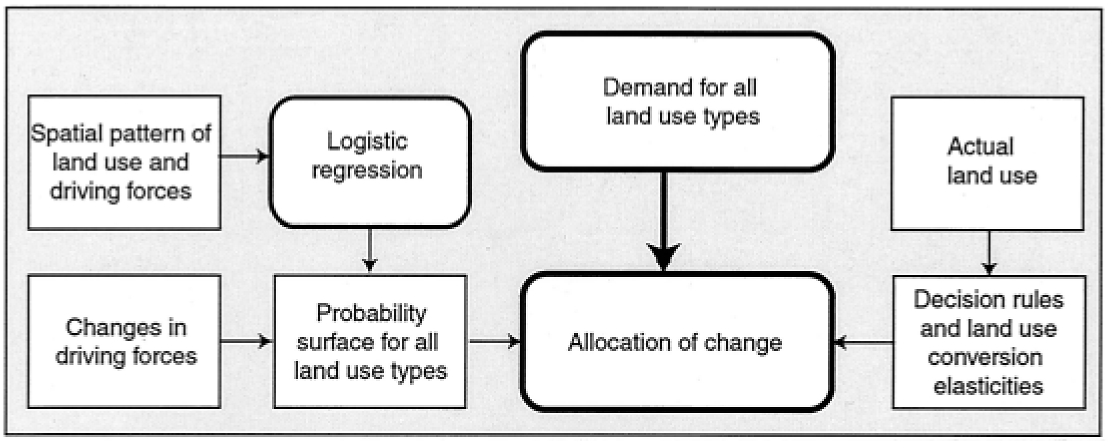

Figure 2.2. Allocation of land use change in the CLUE-S model (Verburg et al., 2002).

changes at different locations within the study area using a raster-based land use change allocation system. Determination of land use location is based upon a combination of regression analysis and a set of decision rules regarding the ease of land use conversion of different land use categories (Verburg et al., 2002). A sample of urban land use location simulations is presented in the results.

2.2.2.4. Validation of urban land use location simulations

Validation techniques (Pontius, 2000, 2002; Pontius et al. 2004) were used to determine the agreement between the 2000 urban land use reference map and the 2000 simulated urban land use location map. Furthermore, the techniques were used to compare the agreement between the 2000 reference map and the 2000 simulated map with the *null model* (i.e., agreement between the 1993 reference map and the 2000 reference map). Specifically, the validation technique (a) budgets sources of agreement and disagreement between the simulated map and the reference map and among location, quantity, and chance, (b) compares the predictive model to a null model that predicts pure persistence, and (c) evaluates the goodness of fit at multiple resolutions to see how scale influences the assessment.

Simulation models of land use and land cover change (LUCC) typically examine a landscape at initial points in time t_0 and t_1 and then predict the change from t_1 to some subsequent point in time t_2 in order to evaluate the performance of the simulation model. If the predicted map of t_2 appears similar to the reference map of t_2, it is concluded that the simulation model performed well. However, a strong agreement between the predicted map of t_2 and the reference map of t_2 does not indicate that the simulation model provides additional information beyond what would be predicted without the model. If there is no simulation model, then the best prediction of t_2 would probably be the map of t_1. Therefore, a null model would predict pure persistence (i.e., no change) between t_1 and t_2 (Pontius et al., 2004). Validation of urban land use location was based on the Kappa index, which is used to compare the reference map with the simulated map or compares two reference maps. Several measures of agreement between two or more maps have been introduced into the applied statistics literature. The collection known as Kappa coefficients comes from the notion initiated by Scott (1955) that the observed cases of agreement between two maps include some cases for which the agreement was by chance alone. The Kappa statistic is a measure of accuracy that ranges between 0 (completely inaccurate) and 1 (completely accurate) and measures the observed agreement between the classification (or simulation) and the reference map and the agreement between maps that might be attained solely by chance (Munroe et al. 2002). The original form of the definition of a Kappa coefficient is

$$\text{kappa} = \frac{P_o - P_e}{1 - P_e} \tag{2.2}$$

where P_o is the probability that a pixel will be placed in the same land use category in two different maps, while P_e is the probability that a pixel will be placed in the same land use category in two different maps by chance. Therefore, Kappa should be the fraction of all pixels not classified the same in two maps by chance (Aickin, 1990). If the agreement between two maps is perfect, then Kappa = 1; if the observed proportion of pixels in agreement between two maps is greater than expected proportion correct due to chance, then Kappa > 0; if the observed proportion of pixels in agreement is equal to the expected proportion agreement due to chance, then Kappa = 0; and if the observed proportion in correct agreement is less than the expected proportion due to chance, then Kappa < 0. A variation of the Kappa statistic (Pontius 2002) is

$$K = \frac{P_o - P_c}{P_p - P_c} \tag{2.3}$$

where P_o is the observed proportion correct, P_c is the expected proportion correct due to chance, and P_p is the proportion correct with perfect match between two maps. In addition to the standard Kappa index of agreement, Pontius (2000, 2002) defines three variations: Kappa for no information (K_{no}), Kappa for location (K_{loc}), and Kappa for quantity (K_{quan}). K_{no} is an overall index of agreement, K_{loc} is an index that measures the agreement in terms of location only and K_{quan} measures the agreement in terms of quantity. According to Pontius (2000), a Kappa value higher than 0.5 can be considered “satisfactory” for land use change modeling. Similarly, Landis and Koch (1977) characterize agreement as follows: values > 0.75 are very good to excellent, values between 0.4 and 0.75 are fair to good, and values of 0.4 or less indicate poor agreement.

2.3. Results

Tables 2.3 and 2.4 show land use transitions as proportions of the landscape at sub-county and county levels while Tables 2.5 and 2.6 show area transitions between different land use categories at sub-county and county levels for the period 1993-2000. In Tables 2.3 and 2.4, cells at the intersection of 1993 land covers (columns) and 2000 land covers (rows) represent either the percentage of the landscape converted from one land cover category in 1993 to another in 2000 or the percentage of a category that persisted between 1993 and 2000. The bold numbers in the diagonals represent the percentage of the landscape that remained in the same category between 1993 and 2000; a bold number elsewhere is the percentage of the landscape that converted from one category in 1993 to another in 2000. The numbers in italics are the proportion of the landscape in each land use transition that would have been obtained if land use change in Centre County was random. The numbers in parentheses are the difference between observed land use transitions and those that would be expected in a random process. The numbers in brackets are the numbers in parentheses divided by the numbers in italics. Therefore, the numbers in parentheses and brackets are proxy measures for systematic land use transitions. Row totals are the proportions of the landscape occupied by each land use category in 1993, whereas column totals are the proportion of the landscape occupied by each land use category in 2000. Land gain of each land cover category between 1993 and 2000 as a percentage of the landscape is the difference between column total and persistence; land loss is the difference between row total and persistence. Total change in area occupied by each category is the sum of loss and gain. Swap is

Table 2.3. Land use transitions at the sub-county level (percent of landscape)

1993 land cover	2000 land cover: Urban	2000 land cover: Agriculture	2000 land cover: Forest	2000 land cover: Others	Total 1993	Loss
Urban	**15.39** *15.39* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**15.39** *15.39* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]
Agriculture	**1.54*** *0.39* (1.15) [2.90]	**32.39** *32.39* (0.00) [0.00]	**0.00** *1.13* (-1.13) [-1.00]	**0.00** *0.02* (-0.02) [-1.00]	**33.93** *33.93* (0.00) [0.00]	**1.54*** *0.44* (1.10) [2.50]
Forest	**0.29** *0.16* (0.13) [0.81]	**0.00** *0.31* (-0.31) [-1.00]	**49.41** *49.41* (0.00) [0.00]	**0.18*** *0.01* (0.17) [17.00]	**49.89** *49.89* (0.00) [0.00]	**0.48** *0.48* (0.00) [0.00]
Others	**0.00** *0.03* (-0.03) [-1.00]	**0.00** *0.06* (-0.06) [-1.00]	**0.17*** *0.08* (0.09) [1.13]	**0.62** *0.01* (0.62) [620.00]	**0.79** *0.17* (0.62) [3.60]	**0.17** *0.17* (0.00) [0.00]
Total 2000	**17.22** *15.97* (1.25) [0.08]	**32.39** *32.76* (-0.37) [-0.01]	**49.58** *50.62* (-1.04) [-0.02]	**0.81** *0.03* (0.78) [26.00]	**100.00** *100.00* (0.00) [0.00]	**2.19** *2.19* (0.00) [0.00]
Gain	**1.83*** *0.58* (1.25) [2.20]	**0.00** *0.37* (-0.37) [-1.00]	**0.17** *1.21* (-1.04) [-0.86]	**0.19*** *0.03* (0.16) [5.33]	**2.19** *2.19* (0.00) [0.00]	

*significant at $\rho < 0.01$

Table 2.4. Land use transitions at the county level (percent of landscape)

1993 land cover	2000 land cover				Total 1993	Loss
	Urban	Agriculture	Forest	Others		
Urban	**4.61** *4.61* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]	**4.61** *4.61* (0.00) [0.00]	**0.00** *0.00* (0.00) [0.00]
Agriculture	**0.32*** *0.02* (0.30) [15.00]	**19.09** *19.09* (0.00) [0.00]	**0.00** *0.29* (-0.29) [-1.00]	**0.00** *0.01* (-0.01) [-1.00]	**19.41** *19.41* (0.00) [0.00]	**0.32*** *0.41* (-0.09) [-0.22]
Forest	**0.06** *0.06* (0.00) [0.00]	**0.00** *0.24* (-0.24) [-1.00]	**72.56** *72.56* (0.00) [0.00]	**0.28*** *0.04* (0.24) [6.00]	**72.89** *72.89* (0.00) [0.00]	**0.34** *0.34* (0.00) [0.00]
Others	**0.00** *0.03* (-0.03) [-1.00]	**0.00** *0.12* (-0.12) [-1.00]	**0.59*** *0.45* (0.14) [0.31]	**2.49** *2.49* (0.00) [0.00]	**3.09** *3.09* (0.00) [0.00]	**0.60** *0.60* (0.00) [0.00]
Total 2000	**4.99** *4.72* (0.27) [0.06]	**19.09** *19.45* (-0.36) [-0.02]	**73.15** *73.30* (-0.15) [-0.002]	**2.77** *2.54* (0.23) [0.09]	**100.00** *100.00* (0.00) [0.00]	**1.26** *1.26* (0.00) [0.00]
Gain	**0.38*** *0.11* (0.27) [2.45]	**0.00** *0.36* (-0.36) [-1.00]	**0.60** *0.74* (-0.14) [-0.19]	**0.28*** *0.05* (0.23) [4.60]	**1.26** *1.26* (0.00) [0.00]	

*significant at $\rho < 0.01$

Table 2.5. Land use transitions at the sub-county level (hectares)

1993 land cover	2000 land cover				Total 1993	Loss
	Urban	Agriculture	Forest	Others		
Urban	5983.2	0	0	0	5983.2	0
Agriculture	600.57	12594.06	0	0	13194.63	600.57
Forest	114.66	0	19215.45	70.65	19400.76	185.31
Others	0	0	66.78	243.00	309.78	66.78
Total 2000	6698.43	12594.06	19282.23	313.65	38888.37	
Gain	715.23	0	66.78	70.65		
Total change	715.23	600.57	252.09	137.43		
Swap	0	0	133.56	133.56		
Net change	715	600.57	118.53	3.87		

Table 2.6. Land use transitions at the county level (hectares)

1993 land cover	2000 land cover				Total 1993	Loss
	Urban	Agriculture	Forest	Others		
Urban	13379.31	0	0	0	13379.31	0
Agriculture	931.95	55440.63	10.8	0	56383.38	942.75
Forest	170.37	7.65	210748.05	799.83	211725.9	977.85
Others	1.08	0	1728.14	7244.55	8973.77	1729.22
Total 2000	14482.71	55448.28	212487	8044.38	290462.4	
Gain	1103.4	7.65	1738.94	799.83		
Total change	1103.4	950.4	2716.79	2529.05		
Swap	0	15.3	1955.5	1599.66		
Net change	1103.4	935.1	761.29	929.39		

obtained by multiplying by 2 the minimum value of either loss or gain. Net change is the difference between total change and swap.

Ninety-eight percent of the landscape in Centre County persisted between 1993 and 2000 (Table 2.4) and all land use transitions are systematic except Forest to Urban at the county level (Tables 2.3 and 2.4). The proportion of the landscape under urban land use increased from 15.39 to 17.22 percent, an area increase of 715 hectares at the sub-county level mainly from agricultural land use loss (Tables 2.3 and 2.5). In contrast, increase in urban land use at the county level was only 0.5 percent of the landscape, an area increase of 1103.4 hectares (Tables 2.4 and 2.6). Area under forest land use increased by 118.53 and 761.29 hectares at sub-county and county levels, respectively, from the Others land use category. Forest land use experienced positional swap with the Others land use category of 133.56 and 1955.2 hectares at sub-county and county levels, respectively (Tables 2.5 and 2.6).

Table 2.7 shows explanatory variables of urban land use location in Centre County. Beta values are logistic regression standardized coefficients of the independent variables. Slope has a negative effect on urban land use at the sub-county level but not at the county level. In contrast, soil suitability for agricultural production is a positive determinant of urban land use location at sub-county and county levels, while soil suitability for septic works is a determinant of urban land use location at the sub-county level.

Table 2.7. Beta values of the explanatory variables of urban land use location

Explanatory variable	Sub-county			County		
	Beta	Constant	ROC	Beta	Constant	ROC
		1.510	0.88		1.21	0.90
Distance to water networks	-0.001					
Slope	-0.045					
Elevation	-0.006					
Distance to roads				-0.001		
Distance to State College borough	-0.001					
Distance to Bellefonte township				-0.002		
Distance from Milesburg township				0.001		
Distance to PortiMatilda township				0.001		
Soils suitable for agriculture	0.080			0.152		
Soils suitable for septic works	0.397					

All variables significant at ρ < 0.01

The simulated 2000 urban land use location is similar to the 2000 reference map of urban land use location. Nevertheless, the future urban land use location increase in Centre County is identifiable (Figures 2.3 and 2.4). Therefore, the explanatory variables of urban location explain urban land use location in the county satisfactorily. The null model performs better than the simulation model in all aspects but $K_{quantity}$ at the sub-county level, while in contrast the simulation model performs better than the null model at the county level (Tables 2.8 and 2.9) with 39 percent of the landscape showing location agreement between the 2000 reference map and the simulated map of 2000 land use location and 42 percent of the landscape showing location agreement between the 1993 and the 2000 reference maps at the sub-county level (Figures 2.5 and 2.6). Thirty percent of the landscape shows location agreement between the 2000 reference map and the simulated map of 2000 land use location (Figure 2.7); 20 percent of the landscape shows location agreement between the 1993 and the 2000 reference maps at the county level (Figure 2.8). Therefore, for the study period, the 1993 reference map would have been a good proxy of 2000 urban land use patterns at the sub-county level, whereas the 2000 simulated urban land use location at the county level would have been a better representation of 2000 urban land use location.

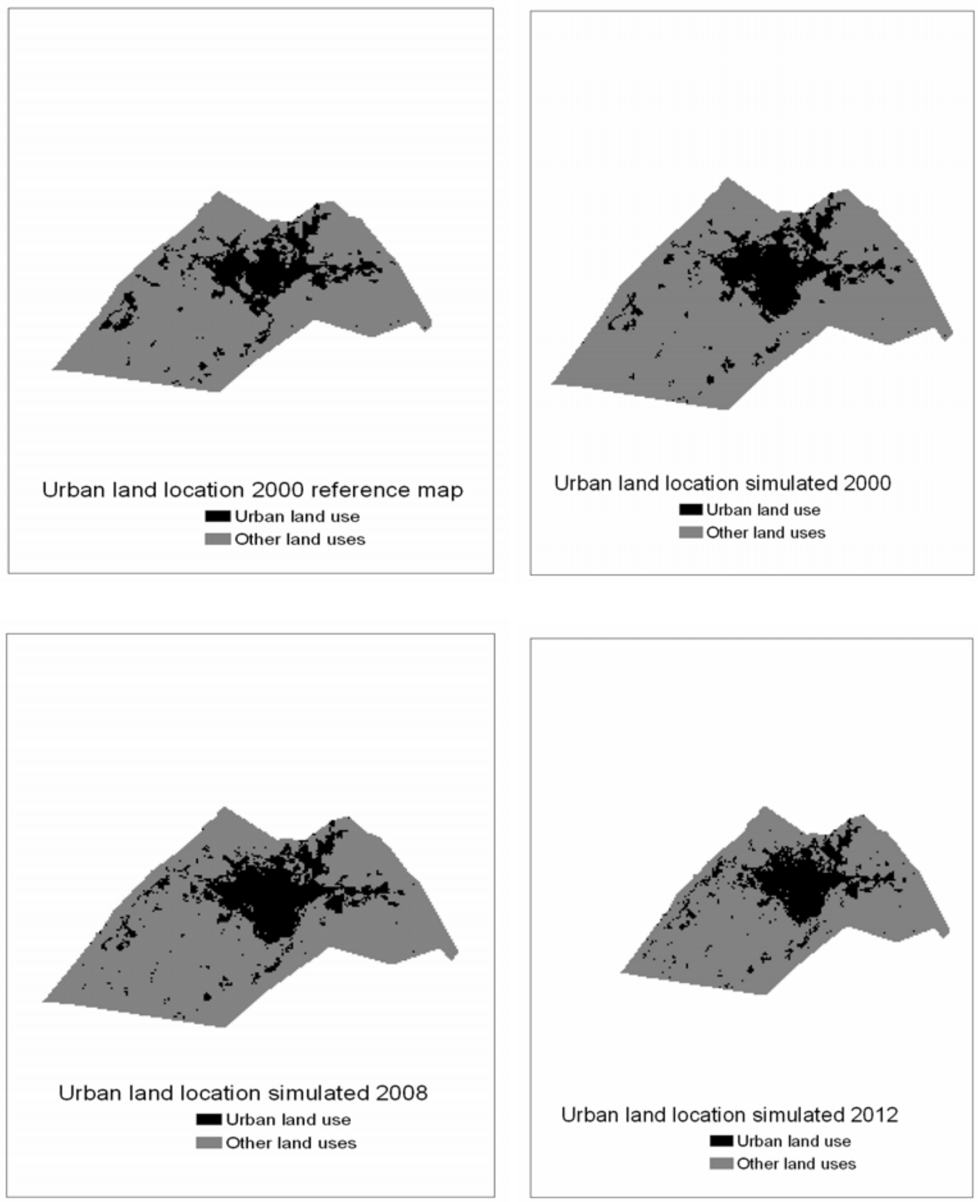

Figure 2.3. Urban land use location simulation results at the sub-county level

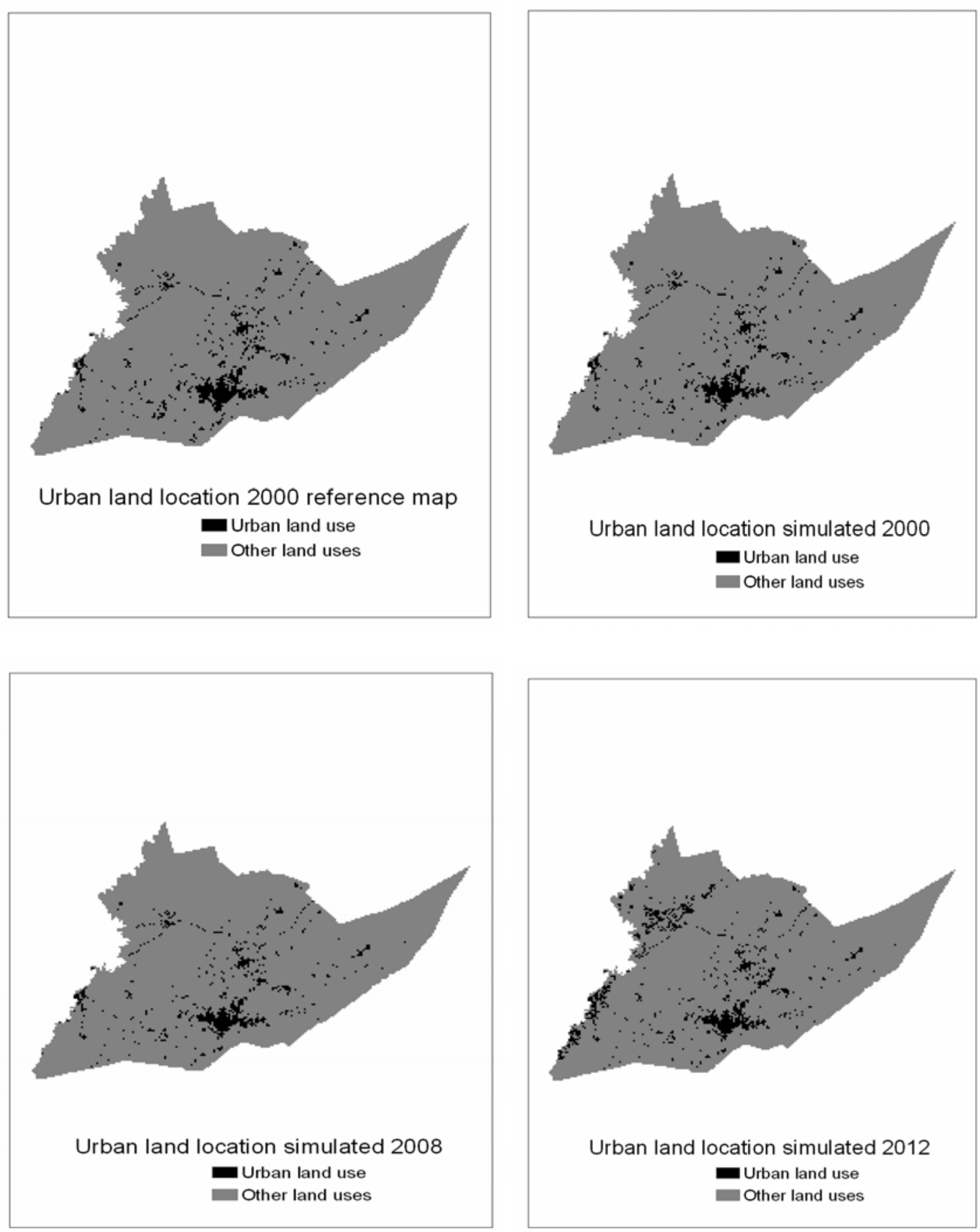

Figure 2.4. Urban land use location simulation results at the county level

Table 2.8. CLUE-S and null model validations at the sub-county level

Index	2000 reference map and 2000 simulated map	2000 reference map and 1993 reference map
K_{no}	0.94	0.97
$K_{location}$	0.93	0.99
$K_{quantity}$	0.99	0.94
$K_{standard}$	0.93	0.96

Table 2.9. CLUE-S and null model validations at the county level

Index	2000 reference map and 2000 simulated map	2000 reference map and 1993 reference map
K_{no}	0.72	0.61
$K_{location}$	0.76	0.49
$K_{quantity}$	0.76	0.88
$K_{standard}$	0.58	0.44

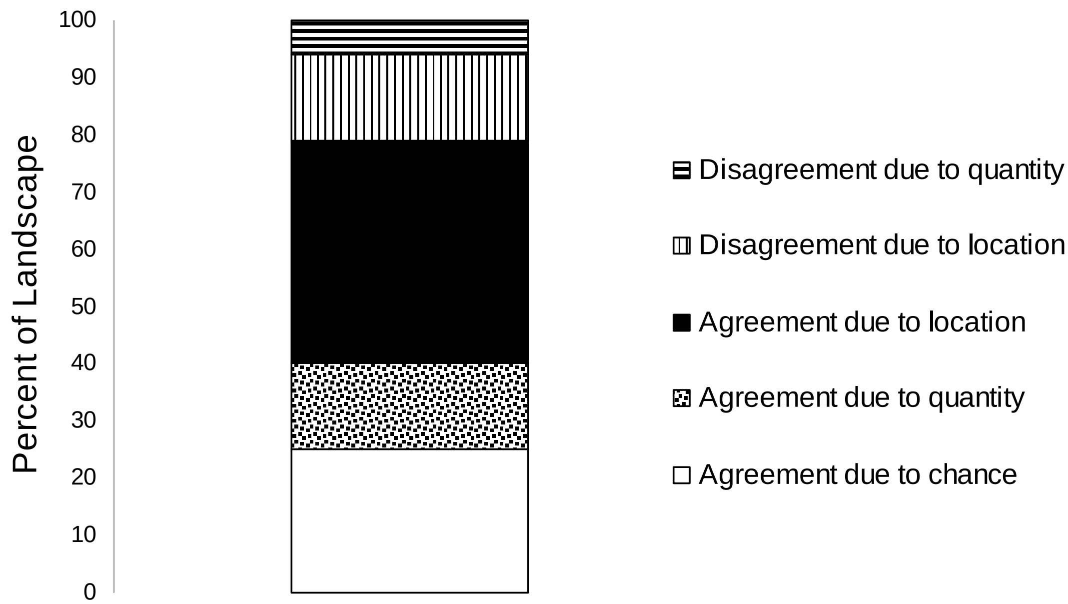

Figure 2.5. Agreement and disagreement between the 2000 reference map and the 2000 simulated map at the sub-county level.

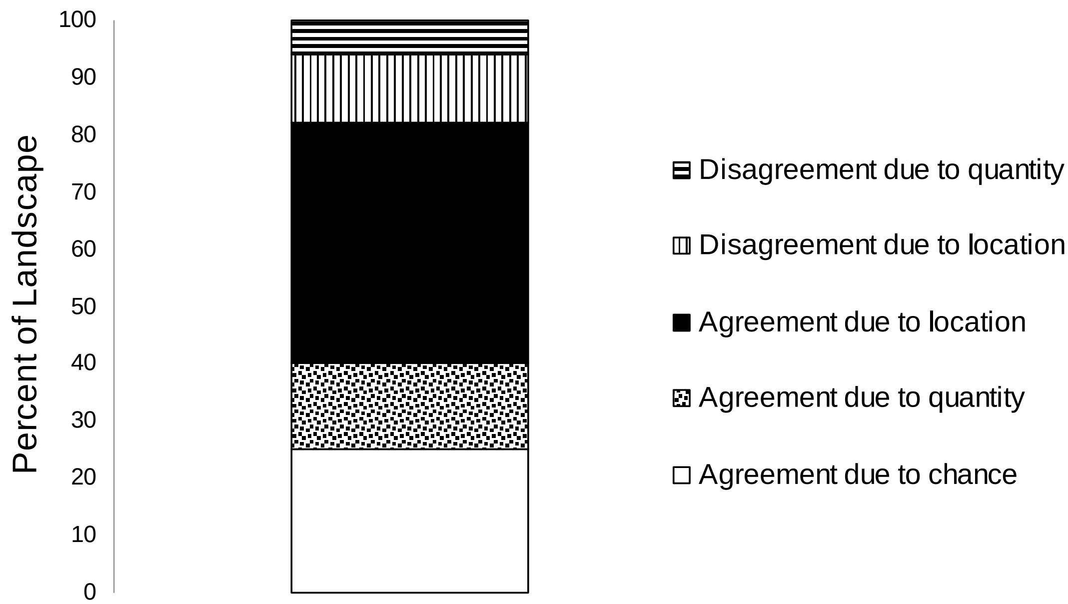

Figure 2.6. Agreement and disagreement between the 2000 and 1993 reference maps at the sub-county level

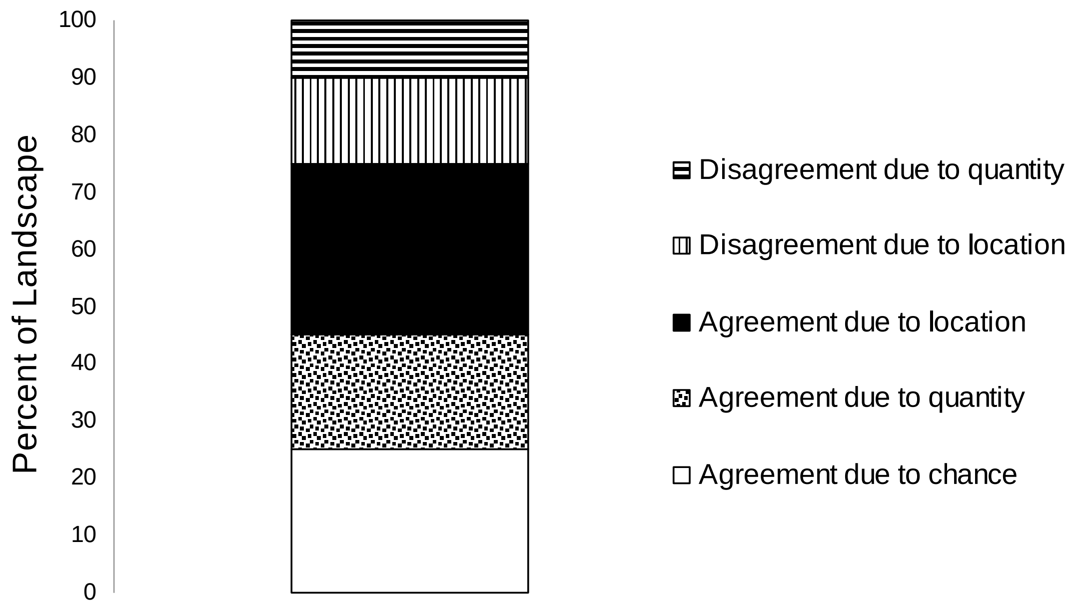

Figure 2.7. Agreement and disagreement between the 2000 reference map and the 2000 simulated map at the county level

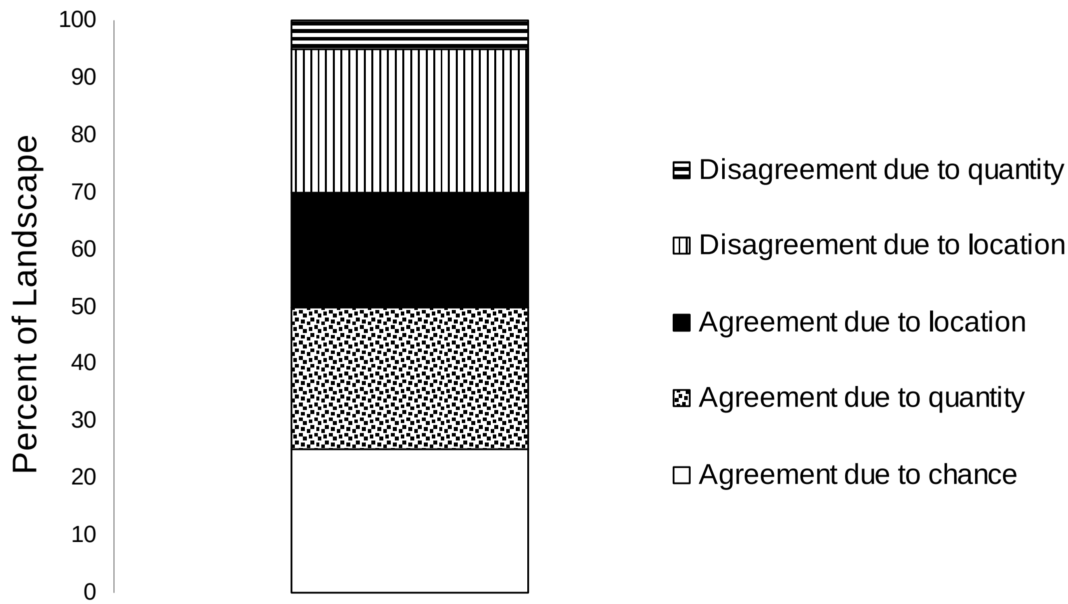

Figure 2.8. Agreement and disagreement between the 2000 and 1993 reference maps at the county level

2.4. Discussion

Land change, predominantly agriculture to urban, was only 2 percent of the Centre County landscape for the period 1993-2000, involving 1864.33 hectares. This result is consistent with findings by Mertens and Lambin (2000), Geoghegan et al. (2001), Schneider and Pontius (2001), and Chen et al. (2002) who reported high persistence and limited change in land cover/land use change studies. The result further supports the assertions by Yang (2002), Yang and Lo (2002), and Pontius et al. (2004) that even fast-growing urbanizing areas, such as the Atlanta Metropolitan Area of the United States, have experienced only 25 percent of land change to urban over the last decades although most of the change was located in prime agricultural areas. Urban land gain from agriculture was one of the dominant land use transitions in Centre County, which is consistent with findings by Hill (1986), United Nations (1995), and Verburg et al. (1999), among others. Doos (2002) notes that urban expansion is an ongoing threat to farmland because urban areas tend to have been founded in agricultural areas.

Although land change in Centre County involves a small proportion of the landscape, it can lead to irreparable ecological damage depending on the fragility of the locations of such changes. During the period 1993-2000, forest land use underwent positional swap of 1955.2 hectares with the Other land use category likely due to logging and reforestation (e.g., new forest plantation appears as grassland when the trees are seedlings). While positional swap does not necessarily involve permanent loss of forest land cover, it may have ecological significance. On the one hand, if mature trees used by birds for nesting or by other animals for shelter are logged and replanted, it may be difficult to restore the former ecological balance even when the forest regrows. On the other hand, if the logged mature trees are not in ecological sensitive areas, then their replacement by regeneration or afforestation in other parts of Centre County could be beneficial for carbon sequestration, especially if the logged wood is to be used for long term carbon storage such as housing construction or furniture because young trees sequester carbon at a faster rate than mature trees.

Most of the land use changes in Centre County take place in the valleys where prime agricultural land is located. Apart from the inevitable loss of agricultural output and loss of employment in agricultural related industries, replacement of agricultural lands by the built environment leads to an increase in runoff due to the increase in impervious surfaces, which in turn results in a reduction of aquifer recharge and an increase in flood risk. Agricultural land cover is a longstanding part of the Centre County landscape, therefore, its replacement is likely to have an impact on the organisms that have adapted to this environment over the centuries. Furthermore, agricultural land cover is an integral part of the county's rural landscape, which is a tourist attraction. In these and in other ways, loss of agricultural land to urbanization has an impact on the socioeconomic and natural fabrics of Centre County.

The results demonstrate that biophysical factors such as topography, soil suitable for agricultural production and septic works, and proximity to population are the major explanatory variables of urban land use location in the county. This finding agrees with the assertion by Pontius and Spencer (2005) that whatever the variation in economic, social, and legal explanatory variables across time, topography and geologic characteristics are supreme in determining land use location. Lambin et al. (2003) observe that biophysical explanatory variables define the natural capacity or predisposing conditions for land use change in a given locality.

Smith and Reynolds (2002) also note that, for any given human-environment system, a limited number of explanatory variables are required for predicting the general trend in land use. Here, soil constraints emerged as one of the main explanatory variables of urban land use location, which agrees with reviews by Wood and Porro (2002) and Rudel (2005). Platt (1985), Nelson (1992) and Levia (1998) found that much of the land lost to urbanization is in prime agricultural land located on coastal plains and river valleys. In Centre County, however, there were differences in explanatory variables of urban land use location at sub-county and county levels: topography had a negative effect on urban land use location at the sub-county level, but had no effect at the county level. The differential effect of topography on urban land location at sub-county and county levels might be due to apparent differences in demand for developable land at these scales. For example, the sub-county level might appear to have higher apparent demand for developable land such that construction takes place at higher elevation. In contrast, at the county level, the course resolution might make it appear that no construction takes place at higher elevation because of low developable land demand.

Simulated patterns of urban land location in Centre County for 2000 are visually similar to the 2000 urban land use reference map. This similarity is further supported by validation results that show high Kappa indexes between the reference maps and the simulated maps, although the null model is better than the simulation model at the sub-county level. Better performance of the null model when compared to the simulation model at the sub-county level is consistent with findings by Geoghegan et al. (2001), Schneider and Pontius (2001), Brown et al. (2002), Chen et al. (2002) and Lo and Yang (2002), all of whom reported greater agreement between the reference map of t_1 and reference map of t_2 than the agreement between the predicted map of t_2 and the reference map of t_2.

The relationship between urban development and agricultural land use in Centre County is evident, with soil suitability for agricultural use emerging as one of the strong explanatory variables of urban land use location, thereby implying that developable land in Centre County is mainly located within agricultural land. Therefore, a policy that intends to contain sprawl in Centre County should include agricultural land owners in the planning for successful implementation. Although agricultural easements have been used to protect agricultural land from urbanization in Centre County with some success, agricultural land owners are likely to be averse to other policies that seek to protect agricultural land through designating their lands as no development zones because of the likely negative effect on their lands' value.

The null model outperforms the simulation model at the sub-county level, where a significant proportion of the landscape underwent change when compared to the county level. While the inability of the simulation model to capture land change at this spatial extent could be excused because land change was a small proportion of the landscape over the study period, the simulation model's failure to capture landscape persistence that is well represented by the null model is unfortunate because land planning would benefit from accurate sprawl simulation models – especially in areas undergoing complex land use transitions. Therefore, this failure of the simulation model at a finer scale is a drawback in the quest for applying sprawl simulation to land use planning. However, the simulation model could be used at coarser resolution to identify areas likely to experience sprawl in the near future, to be followed by detailed empirical analysis of the identified areas.

2.5. Conclusions

The purpose of this chapter was to determine major land use transitions within Centre County through cross-tabulation in an attempt to determine whether urban development is the cause of land use change. The chapter further sought to determine explanatory variables of urban land use location through logistic regression and subsequent projection of urban land use patterns into the near future through simulation modeling using the CLUE-S modeling framework.

The results showed that land use change and landscape fragmentation in Centre County are dominated by transitions from agricultural land use to urban use and by swaps between Forest and Others land use categories. Biophysical factors, such as soil suitability for agricultural production and topography, are key determinants of urban land use location in Centre County. The CLUE-S model was able to simulate urban land use location satisfactorily at the county level, although simulations at the sub-county level were less satisfactory.

Although land use transitions involved only 2 percent of the Centre County landscape, their ecological consequences are likely to be significant as they are dominated by urbanization. Land transitions in the county involve agricultural to urban land, therefore, the involvement of agricultural land owners in land use planning policy formulation for sprawl containment is crucial. Furthermore, multi-use zoning, which encompasses green belts within residential and industrial areas, may be a suitable land planning measure to ameliorate sprawl in Centre County as it addresses, in one geographical location, interests of those intending to convert their agricultural lands to residential use and those opting to remain in farming.

CHAPTER THREE

Uncertainty Evaluation in Sprawl Simulations: Towards Policy Relevant Land Change Modeling

3.1. Introduction

Over the last decade, land use planning has drawn increased attention because of the growing negative impacts of urban sprawl, such as consumption of prime agricultural land and open space (Hanink and Cromley, 2005). Although urban areas make up 14 percent of the Earth's land surface area (Grubler, 1994), the loss of land to sprawl cannot be ignored, for urban sprawl causes greater environmental impacts than other land uses such as increase in flood occurrence, and changes in energy balances of the earth surface (Heilig, 1994; Folke et al., 1997; Lambin et al., 2001). The focus on urban sprawl in land use planning comes also from its complex driving forces and their interactions (Gimblett et al., 2001; Ligtenberg et al., 2001; Cheng and Masser, 2003; Weber, 2003). Thus, there is great need to understand sprawl and its driving factors.

There is also a need to improve models of land use change. Veldkamp and Lambin (2001) highlight the importance of land use change modeling as a planning tool for projecting alternative land use pathways into the future, whereas Fang et al. (2005) note that the first step in finding solutions to ecological and human dimensions problems of urban sprawl is through dynamic land use change modeling and simulation. The importance of modeling and simulation in sprawl studies is further emphasized by Clarke and Gaydos (1998), Batty et al. (1999) and Wu (2002). Klostermann (1999) underscores the importance of dynamic spatial urban models in assessing future growth and creating planning scenarios. Crosetto et al. (2002) agree and point out that politically and environmentally sensitive decisions on land use are increasingly based on information derived from spatial models.

Land use and land cover change models can only be as accurate as the knowledge and data from which they are produced (Fang et al., 2005). Lunetta et al. (1991) conclude that remotely sensed data, which are increasingly employed in land use change modeling, contain uncertainty and error related to the sensor systems and image processing software. Errors in spatial modeling and simulation may also occur during initial tracing of boundaries (Thappa and Bossler, 1992; Youcai and Wenbao, 1997; Burrough and McDonnell, 1998). Secondary error and uncertainty can enter during subsequent data processing when changing between vector and raster formats (Congalton, 1997). Conversion quality and boundary representational accuracy depends highly on the cell size of the resulting digital raster map. Rae et al. (2006) note that large cell size used during geoprocessing and subsequent modeling can lead to some features being “lost.” Morris (2003) underscores the problems inherent in querying features that exhibit partial membership such as land cover categories. Other processing errors occur during geoprocessing to create secondary layers and in buffering features (Veregin, 1989; Congalton, 1997; Morris, 2003). The influence of uncertainty in spatial inputs on spatial modeling predictions is therefore a cause for concern (Hansen et al., 1999; Elith et al., 2002).

Lanter and Veregin (1992) find that while the visual output of GIS and simulation models is compelling to the audience, it does not always include information on reliability and uncertainty. This shortcoming can be critical because most land use planners are unaware of the uncertainty inherent in land use change model products (Stoms et al., 1992; Hunter et al., 1995; Heuvelink, 2002). Consequently, land planning decisions based on misinterpreted or erroneous land use change model output can be costly due to their irreversibility (Norton and Williams, 1992). Ultimately, uncertainty and error in model output lead to inappropriately high or low confidence in the results, which can harm the land use planning decision making process (Foody and Atkinson, 2002; Rae et al., 2006). Pontius and Spencer (2005) further argue that land use change modeling can either facilitate or hinder the decision making process depending on how scientists present the results.

Based on this background, the purpose of this chapter is to evaluate uncertainty in sprawl simulation output. Specifically, the chapter seeks to determine the accuracy of the CLUE-S model in simulating urban land use location and the temporal decay of these simulations. Furthermore, the chapter seeks to determine the sensitivity of urban land use location simulation output to variation in input parameters within the CLUE-S modeling framework.

3.2. Data and Analysis

3.2.1. Data

As in Chapter 2, the land use maps for 1993 and 2000 used for simulation model calibration and validation, respectively, were obtained from CIRA. Again, the land use maps had six land use categories (Urban, Forest, Agriculture, Water, Rangeland and Abandoned mining sites) and the Water, Rangeland and Abandoned mines categories were aggregated into a single land use category called Others for analyzing land use transitions. GIS layers of potential drivers of urban land use location used in the simulation were obtained from the Land Analysis Lab. The 30m resolution land use maps were aggregated to 250m and the same was done to the potential drivers' layers.

3.2.2. Objectives and Analysis

There were three objectives of the research presented in this chapter. The first was to determine the accuracy of simulated urban land use location maps; the second was to estimate the temporal uncertainty in urban land use location simulations. The third objective was to determine simulation output sensitivity to variations in model input parameters. Some of the information given in the following subsections appeared in Chapter 2, but is reproduced here to clarify the presentation.

3.2.2.1. Simulation and validation of urban land use location

Simulations of urban land use location were carried out using the CLUE-S model (Verburg et al., 2002). Explanatory variables for urban land use location were determined through logistic regression, with urban land use as the dependent variable and potential drivers of urban location as independent variables (see Table 2.2, p.13). To address the stability inherent in most land use systems, each land use type was given a weight (elasticity for change) depending on its likelihood of conversion to urban use; this likelihood was based on information from county planners and literature (Verburg et al., 2002) . The relative elasticity ranges between 0 (easy to convert) and 1 (difficult to convert). The higher the defined elasticity, the more difficult to convert the concerned land use type to urban use. Demand for urban land use was based on linear extrapolation of the 1993-2000 trends.

Validation techniques (Pontius, 2000, 2002) were used to determine the agreement between the 2000 reference map and the 2000 simulated map. The agreement between the 2000 reference map and the 2000 simulated map was then compared with the agreement between the 1993 reference map and 2000 reference map to determine if CLUE-S is better than using the current urban land use map in predicting future urban land use location (Pontius et al., 2004).

3.2.2.2. Uncertainty analysis

The method of Pontius and Spencer (2005) was used to determine the decrease in simulation certainty with time based on simulation run for each year (i.e., 2000, 2001 2012) as follows:

$$F_{tm} = A + \{[1-A] \exp [B_m (t-T_m)]\} \qquad (3.1)$$

where F_{tm} is the agreement between the reference map and a prediction map that has zero disagreement due to location. A is the horizontal asymptote as time approaches infinity for agreement between the reference map and a prediction map that has zero disagreement due to location.

$$B_m = \left[\ln \frac{V_m - A}{1 - A} \right] \Big/ \Delta_m \tag{3.2}$$

Equation (3.2) defines B_m as a negative number such that F_{tm} equals V_m at time $T_m + \Delta_m$. V_m is the interpolation value for time $T_m + \Delta_m$ for run m, where m > 1. V_m is set equal to the agreement observed in run m-1 between the reference map and a prediction map that has zero disagreement due to location, given the disagreement due to quantity for run m-1 at the validation time of run m-1. V_m is in the interval [0, 1] and equation (3.2) requires that $A<V_m$; therefore, $B_m < 0$. Consequently, the factor in curvy brackets of equation (3.1) approaches zero as time progresses from T_m to infinity, thus F_{tm} approaches A as time progresses. If $V_m \leq A$, F_{tm} should be set to A for all t.

$$D_{gtm}=C_{gm}+\{(Y_{gm}-C_{gm}) \exp [B_m (t - T_m)]\} \tag{3.3}$$

where D_{gtm} is the agreement between the reference map and a prediction map that distributes the quantities of the predicted categories uniformly in space at resolution g for time t from run m; C_{gm} is the expected agreement between the reference map for time T_m and a simulated map due to chance in terms of quantity and location; and Y_{gm} is the interpolation value for time T_m at resolution g for run m, where m > 1. C_{gm} does not change with time, but grows larger as the temporal resolution becomes coarser. D_{gtm} decays to C_{gm} according to equation (3.3).

$$K_{gtm}=\exp\left(\frac{t-T_m}{m}\ln H_{gm}\right) \tag{3.4}$$

where K_{gtm} is the Kappa statistic that indicates agreement in terms of location between the reference map and the prediction map at resolution g for time t from run m; and H_{gm} is the interpolation value for expected Kappa of location statistic at resolution g for run m at time $T_m + \Delta_m$.

$$E_{gtm}=D_{gtm}+[(F_{tm}-D_{gtm})_{Kgtm}] \tag{3.5}$$

where E_{gtm} is the agreement between the reference map and the prediction map at resolution g for time t from run m. The Kappa statistic for run m decays from one to zero as time progresses from T_m to infinity, according to equation (3.4). H_{gm} is the interpolation value for time $T_m + \Delta_m$ at resolution g of run m. H_{gm} is set equal to the observed Kappa statistic in the comparison between the reference map and the prediction map for the validation at the resolution g of run m-1. Equation (3.4) requires that $H_{gm} > 0$. If $H_{gm} \leq 0$, then K_{gtm} should be set at 0 for all time t.

3.2.2.3. Sensitivity analysis

Sensitivity of the urban land use location simulation to input parameters and decision rules was analyzed by varying the regression coefficients of the explanatory variables of urban land use location one at a time. Sensitivity of simulation output to decision rules was analyzed by varying elasticity values of the different land uses that convert to urban use. Those values were obtained through discussion with the Centre County

Office of Planning and Community Development. Only the effect of agricultural land elasticity on sprawl simulation output is given in the results because the conversion of agricultural to urban land is the dominant and systematic land use transition in the county.

3.3. Results

The simulated 2000 urban land use location map shows considerable similarity to the 2000 urban land use location reference map (Figure 3.1); because of the low proportion of the landscape that experienced urbanization over the period, there is minimal visual difference between the 1993 and the 2000 reference maps and the 2000 simulated map. Nevertheless, validation results show higher agreement between the 2000 reference map and the 2000 simulated map than between the 1993 and the 2000 reference maps (Table 3.1). This result is further supported by a 30 percent location agreement between the 2000 reference map and the 2000 simulated map of land use location as compared to a 20 percent location agreement between the 1993 and the 2000 reference maps (Figures 3.2 and 3.3). Although the differences in agreement between the reference maps and between the 2000 reference map and the simulated map may not be significant, they can have profound effects on ecosystem functioning depending on the fragility of the areas involved.

The certainty of urban land use location projected into the near future decreased from 45 percent of the landscape in 2000 to 16 percent in 2012 because error in location simulation increased (Figure 3.4). The agreement between the 2000 simulated urban land use location map and the 2000 reference map increased as the

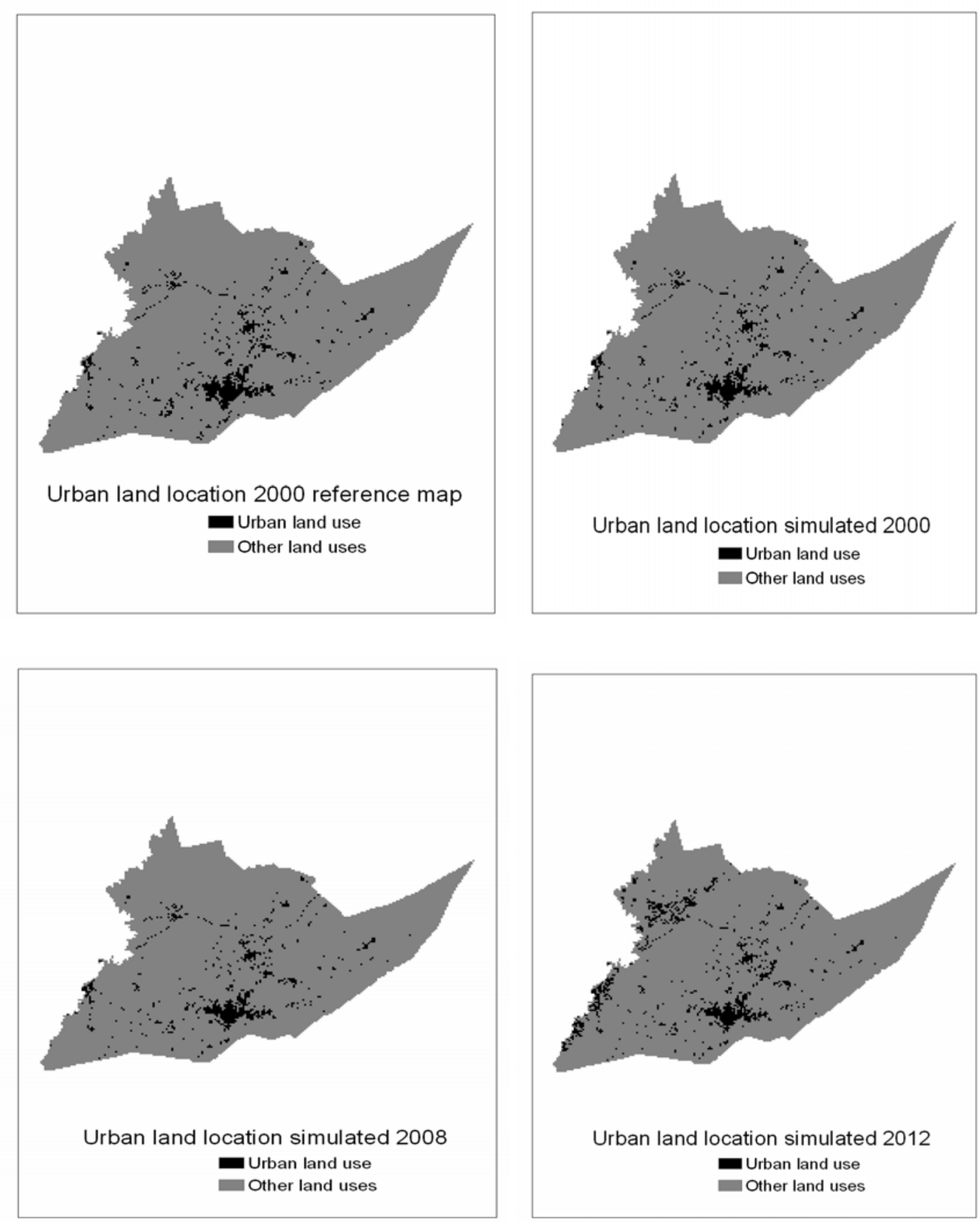

Figure 3.1. Urban land use location simulation results

Table 3.1. CLUE-S simulation and reference map validations

Index	2000 reference map and 2000 simulated map	2000 reference map and 1993 reference map
K_{no}	0.72	0.61
$K_{location}$	0.76	0.49
$K_{quantity}$	0.76	0.88
$K_{standard}$	0.58	0.44

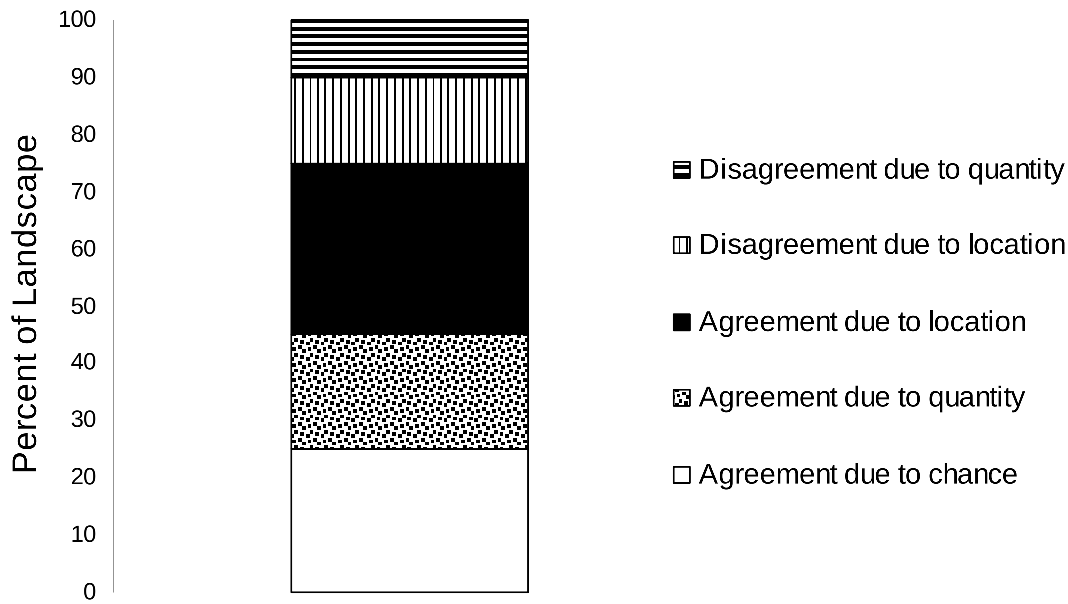

Figure 3.2. Agreement and disagreement between the 2000 reference map and the 2000 simulated map

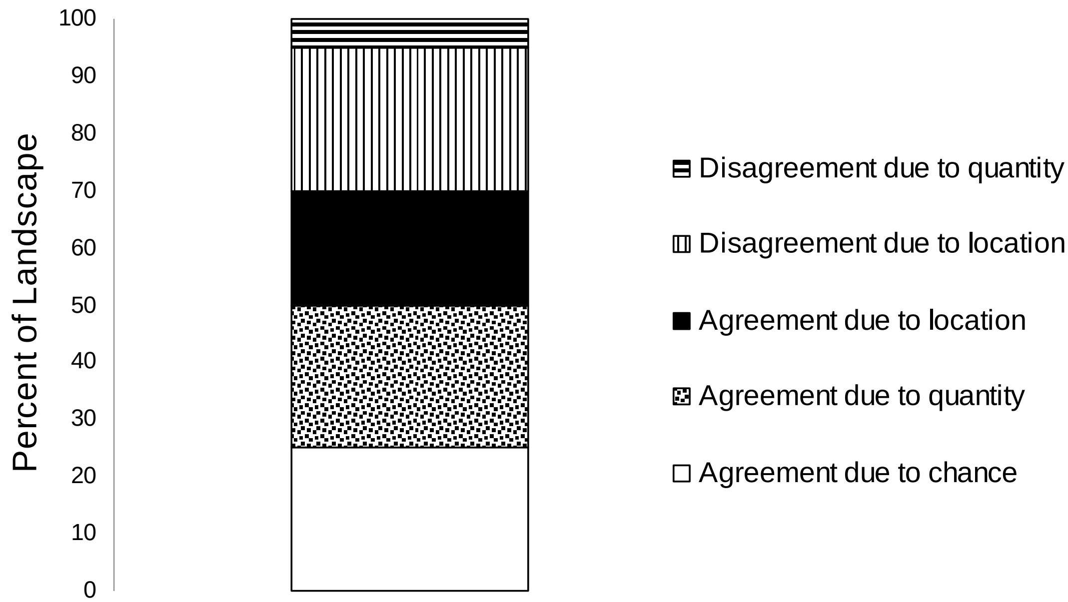

Figure 3.3. Agreement and disagreement between the 1993 and 2000 reference maps

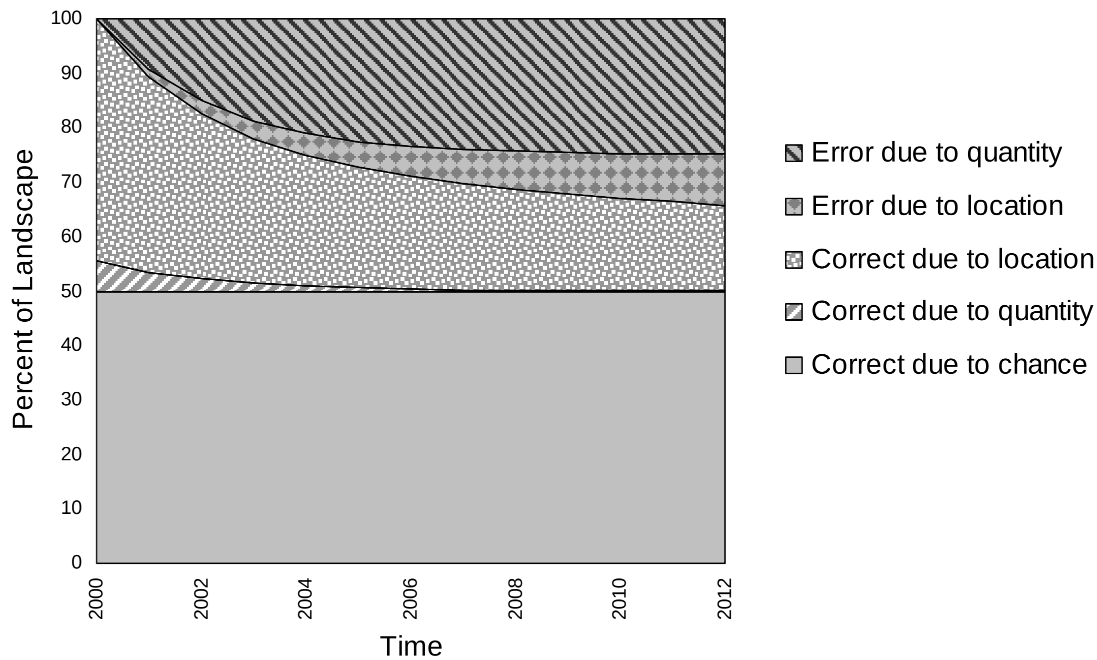

Figure 3.4. Temporal decay in the simulation certainty of urban location

ease of converting other land use categories to urban use decreased and reaches a maximum elasticity of 0.6. The response in the agreement between the two maps to variation in agricultural land elasticity is highest between 0.5 and 0.6 (Figure 3.5), implying that the ease of agricultural land conversion to urban is about 0.6. Agreement in location between the 2000 simulated map and

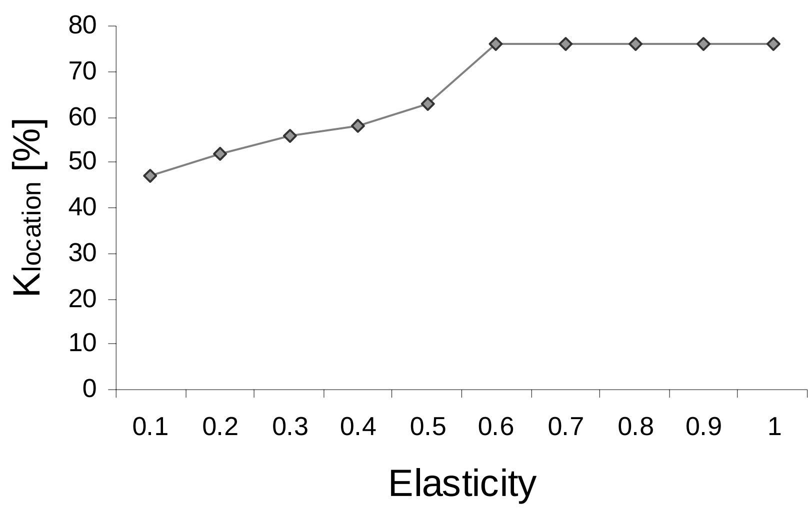

Figure 3.5. $K_{location}$ response to variations in the elasticity of land uses

the 2000 reference map showed greater sensitivity to variation in weights of slope, of soils suitability for agricultural, and of septic works. Elevation and slope variables had greater effect on location agreement between the 2000 simulated map and the 2000 reference map at low weights but less effect at high weights, whereas the effect of soils suitable for agriculture and soils suitable for septic works on location agreement between the two maps increased with increase in their weights. Variation in weights of distance to State College and distance to water networks had no effect on location agreement between the 2000 simulated map and the 2000 reference map (Figure 3.6).

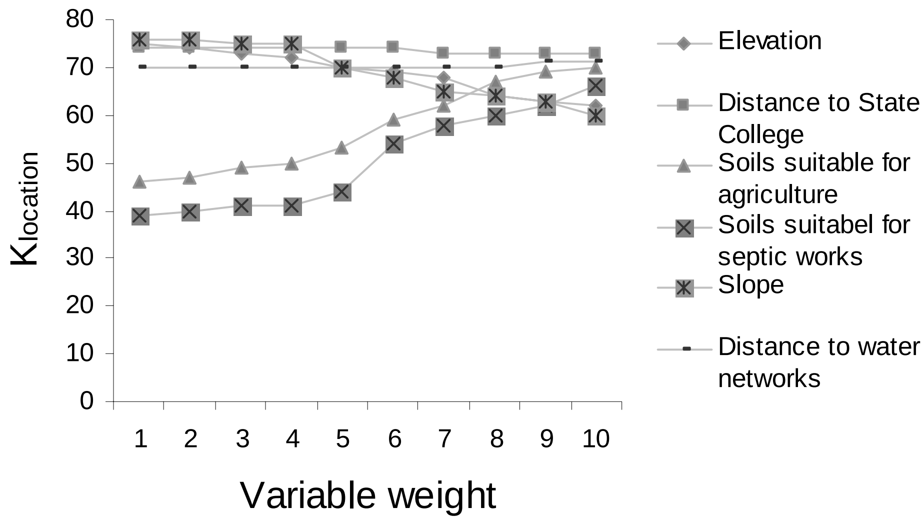

Figure 3.6. $K_{location}$ response to variations in the explanatory variables weights

3.4. Discussion

The simulation model (CLUE-S) simulated urban land use location with a Kappa location value of 0.76, which is consistent with findings by Kok et al., (2001) and Pontius et al. (2007). The certainty of the urban land use location projection decreased with time from 45 of the landscape percent in 2000 to 16 percent in 2012; this result is consistent with findings by Paladino and Pontius (2004) who reported temporal decay in simulation certainty of 21 percent over a 26 year period. The result further supports the obvious assertions by Pontius and Batchu (2003), Pontius et al. (2003), and Pontius and Spencer (2005) that prediction accuracy of land use change location degrades as one predicts farther into the future. The model output is sensitive to elasticity settings and weights of explanatory variables of urban land use location, which is consistent with findings by Verburg et al. (2002) and Wassenaar et al. (2006).

The ability of the simulation model to project future urban land use location at the county level is encouraging. However, the 29 percent temporal decay in the projection certainty of land use location over the 11 year period makes the usefulness of simulation modeling as a useful tool in land use planning questionable. Most land use planning decisions are irreversible once implemented; therefore, a margin of error of such magnitude is unacceptable because it can have serious environmental and social consequences. This conclusion suggests the need to report error margin in sprawl simulation output so that planners and decision makers are well informed in their application of simulation products to real world problems. Effective implementation of sprawl amelioration measures requires that future land use be projected well into the future, e.g., 10 years for tactical planning where the objective is to understand sprawl in areas already facing the problem, and 20 years for strategic planning where the aim is to identify the future locations of sprawl. CLUE-S is not suitable for application in either of these land use planning objectives in Centre County because its projection certainty for urban land use location in 10 years is only 16 percent and likely to be even worse for a 20 year projection.

Simulated land use location simulation is sensitive to variation in the elasticity of agricultural land, particularly between 0.5 and 0.6. County planners estimated the elasticity of agricultural land to be between 0.6 and 0.7, which is in agreement with the result, thereby suggesting that improper calibration of the land use system for a given area could lead to inappropriate conclusions from the sprawl simulation exercise. Inappropriate calibration of the ease with which the other land use categories convert to urban use could lead to higher sprawl projections in the case of low elasticity values or low sprawl projections with the use of high elasticity values. This finding implies that input from local planners and other stakeholders is indispensable in any sprawl modeling exercise.

Simulation output shows sensitivity to variability in the weights of explanatory variables of urban land use location, with greater impact on urban location of such variables as soils and slope. This finding underscores the need to allocate more resources to collecting and processing data for those variables with higher impact on urban land use location. Preparation of the explanatory variables involves some geoprocessing procedures, which are notorious for error propagation. This result suggests that the sensitivity of the modeling output to the variability in weights of the various explanatory variables might be a proxy measure of the model sensitivity to input error. To understand the contribution of input error to overall simulation output error, error generated during the geoprocessing of each explanatory variable should be stated.

3.5. Conclusions

The purpose of this chapter was to determine simulation accuracy and uncertainty in a model of sprawl for Centre County generated by the CLUE-S modeling framework. CLUE-S was able to simulate sprawl location in the county, but the certainty of sprawl location projections decreases with time significantly. Sprawl simulation has inherent uncertainty that can be attributed to error in the input parameters and to limitations in our understanding of land use systems. Uncertainty in sprawl simulation suggests that modelers should report levels of uncertainty with their simulation output because, on the one hand, if land use planners and decision makers have too much confidence in sprawl simulation, output that shows greater sprawl could lead to the adoption of unjustified extensive and expensive urban growth management policies. On the other hand, if decision makers have too little confidence in sprawl models showing greater future sprawl, they are likely to engage in weaker policies to curb future sprawl, which could have severe socioeconomic and environmental consequences. Reporting uncertainty with other simulation output provides decision makers with a platform on which to make more informed land use decisions.

CHAPTER FOUR

An Evaluation of Land and Housing Markets in Pennsylvania: A Prerequisite for Developing Effective Smart Growth Policies

4.1. Introduction

There is a growing concern that current development patterns dominated by sprawl are not in the best long-term interest of cities, suburbs, small towns, rural communities, and the wilderness (Hasse, 2004; Wassmer and Baass, 2006). Though supportive of growth, many communities question the practice of abandoning infrastructure in the central city, only to rebuild it in the suburbs. Furthermore, the social costs of the mismatch between new employment locations in the suburbs and the available workforce in the central city are an issue of contention within these communities. The wisdom of leaving behind brownfields in older communities and then converting prime agricultural lands and open space at the suburban fringe into the built environment has also come under scrutiny by many communities (Ewing, 1997; Brueckner, 2000).

Planning authorities across the United States have advanced growth management policies such as smart growth to address sprawling urban development. These growth management policies are mostly driven by theoretical concepts of urban planning and practice and therefore lack a rigorous assessment of their possible impacts and unintended consequences (Staley and Gilroy, 2004). Nevertheless, the negative impacts of growth management policies on households' quality of life, including housing affordability are likely to be significant. Smart growth policy adopts housing affordability as its principle goal, arguing that compact high density land use patterns result in a range of housing choices at affordable prices (Burchell et al., 2000). There is a limited comprehensive analysis of the real-world impacts of growth management policies that exists although some studies have shown that growth management policies can reduce housing affordability through housing price increase that limit the supply of new housing units (Conte, 2000; Gordon and Richardson, 2000).

Consequently, the purpose of this chapter is to determine land and housing market dynamics in Centre County. Specifically, the chapter seeks to determine elasticity of residential land demand and housing supply with a view to forming an opinion on the likely impact on housing affordability of smart growth policies that aim at increasing residential land price.

4.2. Data and Methods

4.2.1. Data

Economic and demographic time series data from 1990 to 2004 formed the basis of land and market dynamics analysis. These data include inflation adjusted house price appraisal from the Office of Federal Housing Enterprise Oversight (OFHEO) and interest rates from the Federal Reserve Board. Median household income and population are from the U.S. Census Bureau. Annual potential household size was derived by dividing the population by 2.4, which is the median household size in the county (Centre County Planning Commission, 2005). The Bureau of Economic Analysis provided gross domestic product (GDP) as a percentage change from the preceding year. New house building permits and property values for both single and multifamily housing came from the U.S. Census Bureau. Annual residential land supply for single family housing was calculated by multiplying the number of buildings obtained from building permits for new construction by 4,046.9 m^2, which is the median lot size for single family housing in the county. Land supply for multifamily housing was obtained by multiplying the number of new buildings by 16,187.5m^2, which is the median lot size for multifamily housing in the county (Centre County Planning Commission, 2005). Due to lack of data, land value for new construction was assumed to be 10% of the property value (Jonathan and Davis, 2004), although this assumption probably underestimates the price of land in the most urbanized areas and overestimates it in the most rural areas.

4.2.2. Analysis

Two objectives of this chapter were (1) to determine the *drivers of residential land demand and supply* in Centre County through multiple linear regression and (2) to estimate the *elasticities of land demand and supply* through regression coefficients that compare land price and land sales. Furthermore, the study sought (3) to determine the *drivers of housing demand and supply* in the county through multiple linear regression and (4) to estimate the *elasticity of housing supply* through regression coefficients that compare construction of new housing units and house price. Table 4.1 shows dependent and independent variables used in the regression

Table 4.1. Variables for estimating residential land and housing market dynamics

	Dependent variables			
	Land price (demand)	Land sales (supply)	House price (demand)	House construction (supply)
Independent variables	Interest rate	Interest rate	Interest rate	Interest rate
	GDP	GDP	GDP	GDP
	House price	House price	Income	House price
	Income	Income	Land sales	Income
	Land sales	Land price	House construction	Land sales
	House construction	House construction	Household number	Land price
	Household number	Household number	Land price	Household number

analyses. Only variables significant at the 1 and 5 percent levels of significance are reported in Tables 4.2-4.5. Time-series graphs were used to explore the correlations between land price and land sales and between land sales and new housing construction. All regressions were estimated using SPSS software version 13.0.

4.3. Results

Land prices (Figure 4.1) showed considerable growth over the study period, doubling during the fifteen years. Prices fell in four years (1991, 1996, 1997, and 2001) but rose in all others. Price rises were particularly strong in 1995 and 2004. Land sales, in contrast, displayed more variation, with sales falling in five years during the period and the 2002 peak value being more than double the 1994 low (Figure 4.2). Exceedingly strong growth in sales took place from 1999 to 2002, but was followed by sharp declines in 2003 and 2004. Although land sales in 2004 were roughly 30 percent greater than sales in 1990, the volatility of the market does not necessarily suggest overall sales growth over the 15 years. Construction of new housing units (Figure 4.3) displayed a similar trend to land sales, with construction falling in five years during the period and the 2002 peak value being more than double the 1994 low. Strong construction took place from 1999 to 2002, but was followed by steep declines in 2003 and 2004. Like sales, construction in 2004 was about 30 percent greater than in 1990, although there is no evidence of an overall increase in construction of new housing units over the 15 years. House sales more than doubled for the period 2000-2002 and remained high until 2004, after which there is a slight decline (Figure 4.4).

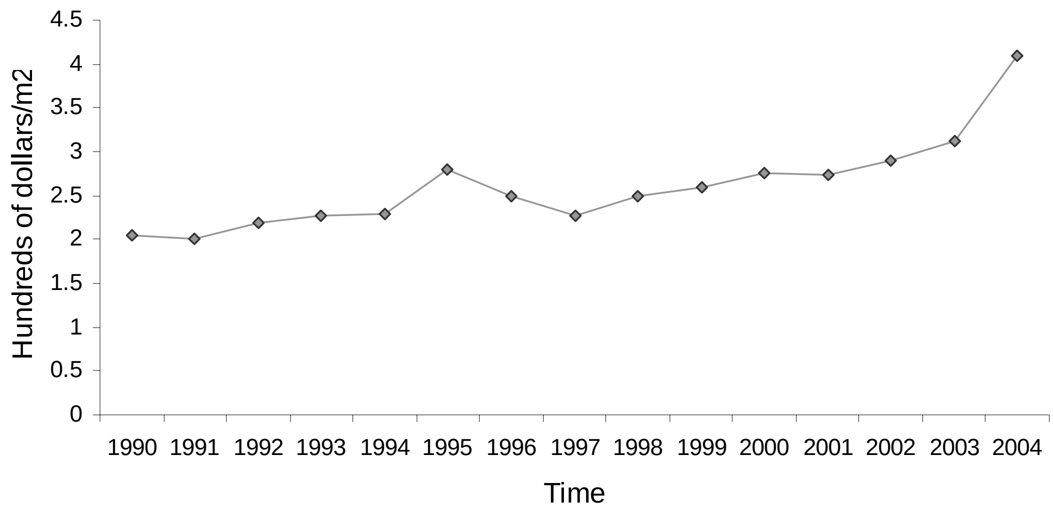

Figure 4.1. Land price for single family housing construction

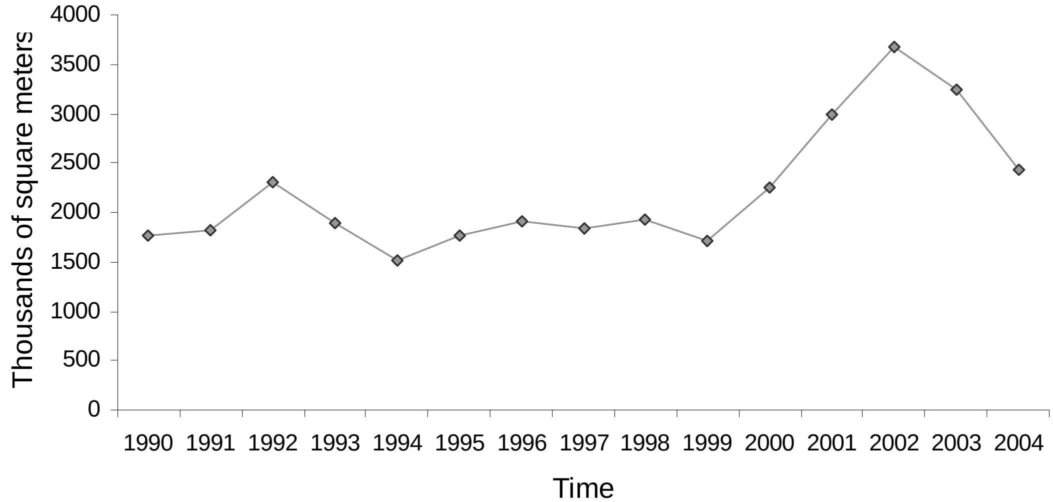

Figure 4.2. Land sales for single family housing construction

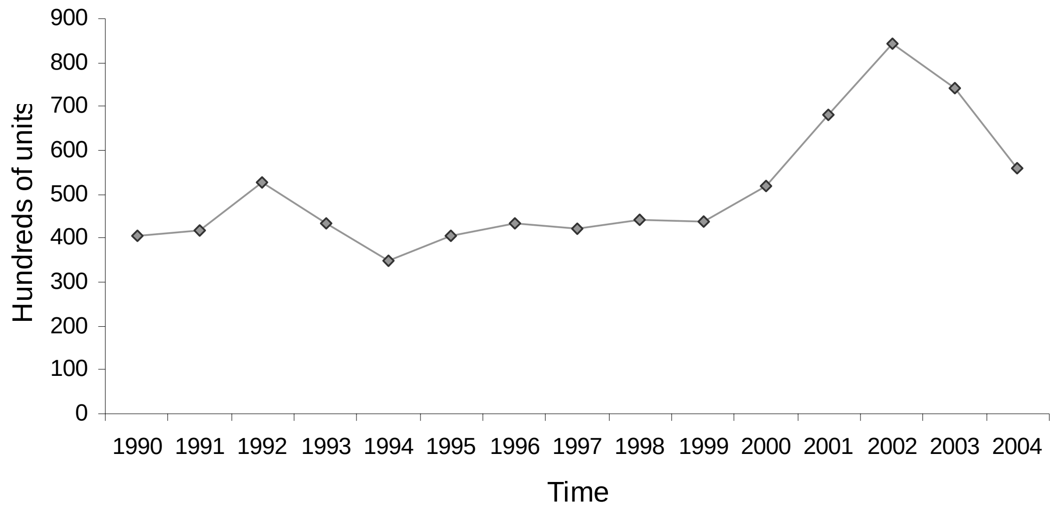

Figure 4.3. Single family housing supply dynamics

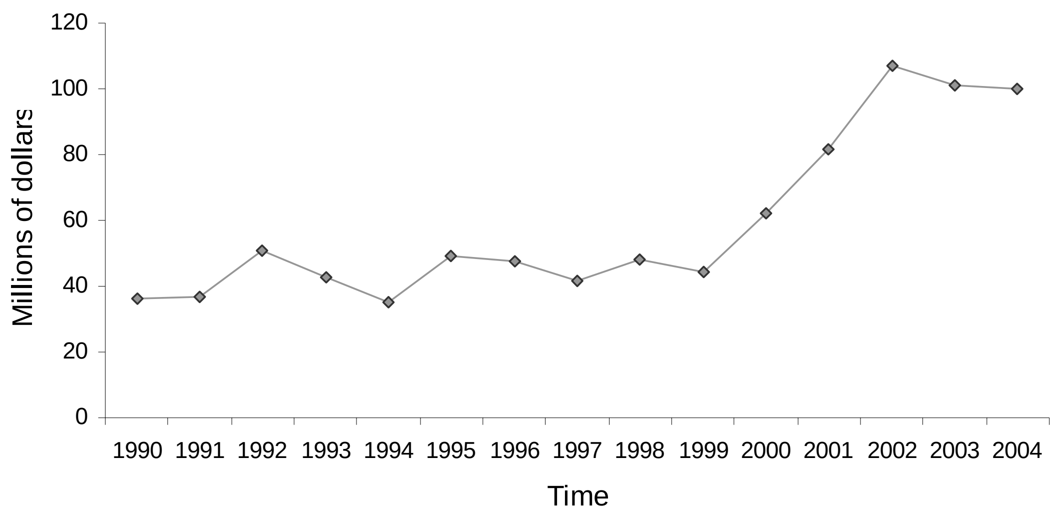

Figure 4.4. Single family housing price fluctuations

Explanatory variables for land demand (Table 4.2) were land sales and house price, with land sales having a negative effect on land demand and house price having

Table 4.2. Explanatory variables for residential land demand

Explanatory variable	Single family housing			Multifamily housing		
	Beta	Constant	R^2	Beta	Constant	R^2
		2.355*	0.980		3.132**	0.839
Land sales	-1.504**			-1.424*		
House price	2.113**			0.927*		

**significant at $p < 0.01$, *significant at $p < 0.05$

a positive effect. Price elasticities of residential land demand for single and multifamily housing were 1.504 and 1.424, with a model fit of 0.98 and 0.83, respectively. Comparatively, explanatory variables for residential land supply (Table 4.3) were house price, land price, house construction and interest rate. Land price and interest rate had a negative effect on land supply, but house price and house construction had a positive effect. The model fit for the explanatory variables of single and multifamily residential land supply was nearly 1.00 and 0.95, respectively. House demand (Table 4.4) was explained by land sales and price, with both having a positive effect on it; model fit approached 1.00 and 0.94 for single and multifamily

Table 4.3. Explanatory variables for residential land supply

Explanatory variable	Single family housing			Multiple family housing		
	Beta	Constant	R^2	Beta	Constant	R^2
		1.052**	0.995		0.235**	0.947
House price	0.767**					
Land price	-0.351**			-0.468*		
House construction	0.488**			0.876**		
Interest rate				-0.153*		

**significant at $p < 0.01$, *significant at $p < 0.05$

Table 4.4. Explanatory variables for housing demand

Explanatory variable	Single family housing			Multiple family housing		
	Beta	Constant	R^2	Beta	Constant	R^2
		0.007	0.996		0.003	0.939
Land sales	0.685					
Land price	0.464			0.305		

All variables significant at $p < 0.01$

housing, respectively. Explanatory variables for house construction (Table 4.5) were house price and land sales with a positive effect and land price with a negative effect. Price elasticities of new housing unit supply were 1.425 and 0.559 for single and multifamily housing, respectively, while model fit for single family housing was 0.99 and 0.96 for multifamily housing.

Table 4.5. Explanatory variables for housing supply

Explanatory variable	Single family housing			Multi family housing		
	Beta	Constant	R^2	Beta	Constant	R^2
House price	1.425	4.445	0.987	0.559	1.371	0.961
Land price	-0.667					
Land sales				0.464		

All variables significant at $p < 0.01$

4.4 Discussion

The findings of this study tend to be consistent with some of the results reported in the literature, but not with others. Price elasticity of residential land demand is 1.504 and 1.424 for single and multifamily housing, respectively, indicating that a 10 percent increase in land price would reduce land consumption by 15 and 14 percent in these two housing sectors. The result is consistent with findings by Voith (2001), but higher than older findings by Muth (1964), McDonald (1981), and Thorsnes (1997). Explanatory variables of residential land demand in the county are land sales and house price. Although the impact of proximity to utilities, such as water and sewer networks on land demand was not evaluated, lots closer to utilities are likely to be more expensive when compared to those outside the networks. The same applies to service centers, such as schools and health facilities. For example, schools within State College Area School District are regarded as some of the best in the country, thus land prices are likely to be high within its school district boundaries because of the desire by buyers to be located in the district. Nevertheless, there are likely to be spatial land price differences within the district, with lots in high density neighborhoods having lower demand as compared to those with low density housing. The impact of these spatial variables on land demand, at least in Centre County, is likely to apply in a similar way to housing demand because housing and land are interconnected.

The price elasticity of residential land supply is 0.351 and 0.468 for single and multifamily housing, respectively, implying that a 10 percent increase in price of land leads to increases of 4 and 5 percent in residential land supply. These elasticities are consistent with findings by Pryce (1999). However, price elasticity of residential land supply does not always reflect the true situation of the land and housing market dynamics in a given location because developers play a major role in land supply through, among other mechanisms, holding undeveloped land without construction until they deem that housing prices will increase more, thus creating artificial land shortage.

The analysis also finds that house prices exhibit a positive relationship with land sales, supporting findings by Jonathan and Davis, (2004) who observe that land price accounts for most of the variation in house price because land prices are more volatile than the price of construction materials. Land price has a negative effect on housing construction, supporting the assertion by Muth (1971) that land should be treated as an input in house production, but contradicts the argument by Alonso (1964) that households value residential land for reasons other than as input to housing production. Price elasticity of house supply is 1.425 and 0.559 for single and multifamily housing, respectively. These elasticities mean that a 10 percent increase in the price of a new housing unit results in 14 and 6 percent increase in construction of new housing units. The result for multifamily housing is consistent with those reported by de Leeuw and Ekanem (1971), Bramley (1993), and Pryce (1999), while the result for single family housing is consistent with work reported by DisPaquale and Wheaton (1994), Peng and Wheaton (1994), and Blackley (1999).

Although elasticities are not strictly comparable across studies, they provide an informative reference for understanding how the land and housing market in Centre County compares to other local markets and therefore, contributes to the development of theories of residential land markets at local level. Variations in land and housing elasticities between places are attributable mainly to differences in urban form and land use regulation (Green et al., 2005). Saks (2005) and Glaeser et al. (2005) note that in some places housing supply has become inelastic because of restrictive zoning and other land use regulations. Generally, places with stringent land use policies have low supply elasticities of housing, while those with relaxed regulatory environments have high elasticities. However, places with slow growth tend to have low supply elasticities of housing, but they might have less stringent land use and development regulations (Green et al., 2005). The price elasticity for single family housing in Centre County is relatively high, implying that housing supply is not constrained in the county.

4.5 Conclusions

The purpose of this chapter was to determine the price elasticity of residential land demand and housing supply in order to evaluate the likely impact of smart growth policies on housing affordability in Centre County. Price elasticity of land demand was determined through multiple linear regression with house price as the dependent variable and land sales as one of the independent variables. For price elasticity of housing supply, new house construction was the dependent variable and house price was among the independent variables.

House price had a positive effect on land demand while land sales had a positive effect on housing supply, emphasizing the interconnectivity of land and housing in Centre County. However, the price elasticity of residential land demand is comparatively high, implying that smart growth policies that aim to control sprawl through an increase in land price could achieve lot size reduction with a moderate price increase. High price elasticity of land demand means that potential homeowners respond to a small increase in land price by significantly decreasing their desire for large lot size. Land price is a component of the overall house price, so smart growth in Centre County is unlikely to lead to an increase in house price. It is possible, therefore, for smart growth policies to coexist with affordable housing in Centre County. When land price increases, it appears that consumers would respond by substituting large lot sizes for other goods and services. Therefore, the increase in land price would not lead to hardship because consumers in the county do not appear to have a strong attachment to large lots.

CHAPTER FIVE

Conclusions

5.1. Summary and Conclusions

The goal of this dissertation was to provide a research framework and methodologies that contribute to the understanding of sprawl dynamics and its containment. In the preceding chapters, an analysis of sprawl and landscape fragmentation in Centre County was presented, thereby allowing the identification of the dominant land use transitions in the area. The analysis further identified future urban land use location through simulation modeling, followed by validation and uncertainty analysis of the simulated products. Finally, the feasibility of remedying sprawl without compromising affordability of housing in Centre County was evaluated.

No projections of the amount of land lost to sprawl in the near future was performed here because rates of land use change are often driven by macroeconomic factors that are remote in space and time (Lambin et al., 2001). Instead, new insights into future sprawl were provided by relating urban land use location variability with its drivers. Because the presence of sprawl suggests that urban areas consume land at a faster rate than they are adding population, population increase alone is not a sufficient condition for explaining the spatio-temporal dynamics of sprawl. Chapter 2 presented the spatial variability of urban land location and its explanatory variables in Centre County, underscoring the fact that sprawl forecasting that does not consider the natural capacity of the landscape is inappropriate for reliable assessment of the likely impact of sprawl on local ecological integrity. The resulting simulation maps provided a means to provoke stakeholder awareness of sprawl severity in Centre County because information on sprawl is often nonspatial. Consequently, this dissertation adds a spatial component that makes it possible to evaluate the gravity of sprawl in terms of hectares lost to urban development, but also with regard to the fragility and importance of the ecosystems in which it takes place. Therefore, the analysis provides a tool to help in the environmental impact assessment of sprawl.

Evaluation of the uncertainty in sprawl simulation output and of the sensitivity of the output to variation in weights of the explanatory variables of urban land use location was presented in Chapter 3. The results caution against overreliance and overconfidence in sprawl simulation output. Model performance decreased as sprawl projections moved forward in time, suggesting a limit on the temporal resolution from which sprawl prediction can practically be determined. Simulation output showed differential sensitivity to weights of explanatory variables and sensitivity to decision rules regarding the ease of conversion to urban of the various land uses, implying that more effort and resources should be allocated to collecting and processing those input parameters that have greater impact on the output. The inherent error propagation in geoprocessing, which was a major component of preparing GIS layers used in this analysis, calls for careful interpretation of sprawl simulation output and avoidance of causal statements. Thus, products of sprawl simulation should not be used lightly when applied to land use planning; instead, they should be used cautiously because their production involves substantial uncertainties and assumptions. However, sprawl simulation is an indispensable tool for reconnaissance surveys where the objective is to identify sprawl locations within a planning area.

The feasibility for the development of affordable housing policy that is consistent with smart growth policy to curb sprawl was addressed in Chapter 4. The analysis adds to the literature that argues that smart growth and affordable housing policies are compatible. The empirical analysis indicated that potential homeowners will respond significantly to an increase in residential land price by decreasing plot size, which results in no significant change in house price. Therefore, smart growth implementation is not likely to counteract affordable housing in Centre County and, therefore, have a chance to succeed.

In sum, the three analyses that comprise this dissertation suggest two important conclusions. First, effective sprawl containment not only calls for a comprehensive analysis of local land use dynamics to confirm that sprawl is a problem, but also requires that policy makers are aware of the uncertainty inherent in sprawl model projections for informed and realistic application of model output in their planning policies. Second, to avoid failure of sprawl amelioration measures, stakeholders who are liable to feel the effects of these measures and are likely to resist their implementation should be identified and incorporated in the policy process from its inception.

5.2. Limitations

This study, like previous ones, indicates that land change is a small proportion of the landscape, and therefore a full understanding of its dynamics requires analysis over many years. However, suitable land cover layers were available only for a seven year period, which limits the scope of the results. Land use/land cover classification based on satellite images is notorious for high rates of classification errors, so metadata for these maps should report information on classification methods and accuracy. In this dissertation, metadata associated with the land cover maps did not report this information, thus increasing the uncertainty of the simulation outputs. Although the choice of potential drivers of urban land use location was based on literature and consultation with planners in the county, some socioeconomic drivers such as income could not be obtained at the spatial resolution of analysis due to privacy issues. Moreover, the simulation model could not handle spatial data layers at their original resolution of 30 meters, thus necessitating aggregation of these layers to 100 and 250 meters to capture sub-county and county levels, respectively. This aggregation led to the loss of some layers, such as minor roads. In addition, econometric analysis for the feasibility of affordable housing consistent with smart growth was not possible at the sub-county level because county planners were not able to share the required data, citing privacy issues.

Land use decisions in Pennsylvania are made at local level, but often made at the county level throughout much of the United States. Consequently, the county analytical scale used in this thesis is not as representative of land planning authorities in Centre County as it would be in other parts of the country because in Pennsylvania land planning takes place at scales finer than the county level.

5.3. Possible future work

This study highlighted the impact of sprawl on landscape fragmentation, which ultimately affects ecosystem functioning. Therefore, future research could focus on the impact of sprawl on ecosystem functioning. For instance, landscape changes can alter freshwater aquatic ecosystems by changing lateral fluxes of water and materials, in turn leading to feedbacks from these freshwater systems. Different ecosystems may respond to sprawl in different ways, however, so that ecosystem-specific analyses are essential. While natural feedbacks to Earth system result from relatively slow, directional changes in ecosystem physiology, anthropogenic land cover changes such as sprawl can exceed natural thresholds and lead to irreversible changes to ecosystem functions. With sufficient progress in land change modeling, sprawl impacts on ecosystems at local scales could be up-scaled to the regional level and ultimately applied in Earth system models to simulate global-scale impacts of sprawl.

The results of this research signify the importance of understanding patterns and processes of land use change as a prerequisite for the formulation of measures to ameliorate sprawl. Furthermore, the results suggest the desirability of carrying out a feasibility analysis to investigate the likely impact of smart growth policies on various stakeholders through land and housing market dynamics analysis, in this case potential homeowners, to minimize implementation stagnation. The analysis could benefit from an evaluation of the impacts that spatial variables such as proximity to service centers and utility networks have on land and housing demand. This dissertation falls short of evaluating the likely impact of smart growth policies on the value of homes, and the value of peripheral lands, such as those used for agriculture.

Homeowners and land owners are likely to resist any policy they perceive as harmful to current and future values of their property. Developers play a crucial role in residential land and housing demand and supply dynamics by “sitting” on land without construction until housing prices are favorable. As a result, the land and housing market is not self-regulating, but is greatly influenced by developers, thus necessitating their involvement in any policy process aimed at containing sprawl without increasing housing prices. Therefore, future research could include an all-encompassing trade-off analysis to evaluate benefits and disadvantages of smart growth policies to potential homeowners, current homeowners, developers, and land owners at local scales.

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