Spatial Logistic Regression and GIS to Model Rural-Urban Land Conversion

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Abstract: Urban expansion significantly influences land use patterns and local economy. Hence, urban and economic planners and decision-makers are keen to understand the complexity of urban growth and forecast future land use patterns. Modeling the rural-urban land conversion pattern is a prerequisite to understand the urban expansion process. This paper addresses the problem of building a land transformation model of urban growth to predict land use evolution in New Castle County, Delaware. GIS coupled with a statistics software namely Minitab, is employed to process land use data and perform spatial logistic regression analysis. Spatial logistic regression is used to obtain the development patterns in the region and to assess the prognostic capacity of the model, while GIS is used to develop the spatial, predictor drivers and perform spatial analysis on the result. The model is built using land use changes between1984-1992 and 1992-1997 and is then validated over the span of 1984-1997.

INTRODUCTION

The rapid strides made by the industrialized nations in the latter half of the past century have resulted in uncontrolled expansion, which if left unchecked, would hinder sustainable development in the long run. Urban populations are persistently increasing at alarming rates and in developing countries, the migration from rural to urban areas keeps escalating. It is high time to dedicate considerable research efforts towards achieving and maintaining a viable balance between rural and urbanized areas to preserve natural resources while catering to the needs of an ever-demanding population.

Unquestionably, population induced land use changes have influenced biogeochemical cycles to a great extent. Rapid urbanization has led to an increased consumption of food and water in several regions and these have in turn resulted in associated sewage and pollution problems. Numerous studies relate urbanization with increasing surface temperatures in and around the cities and also attribute several other local and global climate changes to urbanization. Furthermore, industrialization and associated activities may impact agricultural production since agricultural areas are being converted into residential and industrial zones. Nevertheless, urban areas contribute significantly to a nation’s economy and continue to open the doors for growth and development. Hence, it is necessary to strike a balance between the urban activities and the associate land conversion in order to attain sustained growth over a longer period of time. It is hence inevitable for governmental agencies to understand the trends in land use changes for proper planning and management of resources. Geographical Information Systems (GIS) can be employed to model urban growth with a higher level of spatial accuracy. Of late, considerable research efforts have been directed towards implementing extrapolative models into a GIS to study and project possible future development and scenarios.

From a global environmental perspective, urbanization refers to the conversion of a natural land cover to an artificial one consisting of human settlements characterized by residences and offices. Understanding the trends in rural-urban conversion is important to recognize the impacts of urbanization at global and regional levels and lately this has emerged into a hot research topic. The rapid physical and socio-economic restructuring of cities in developing countries, especially Chinese cities, have increasingly been attracting the attention of researchers throughout the world (1, 2, 3, 4). Land transformation research in these places tend to explore the various means of land use change and the social, economic, and spatial variables influencing it. Several techniques such as exploratory spatial data analysis, regression analysis, artificial neural networks (ANNs), cellular automata (CA), and genetic algorithm, etc, are employed in such land transformation research. Urbanization is not a uniform process that occurs alike in different regions on the surface of the globe. On the other hand, urbanization is a complex phenomenon characterized by varied attributes and is influenced by diverse factors in different regions. Hence, it is beneficial to examine if the rural-urban land conversion pattern observed in developing countries holds equally well for developed countries.

This study models and interprets urbanization patterns in New Castle County, Delaware, using a GIS coupled with a spatial logistic regression model. The first section elucidates the model characteristics and the underlying assumptions. The second section elaborates the data collection procedure and delineates the processes involved in building an efficient spatial database. Details of regression analysis are provided in the third part and the final section elaborates the validation technique and discusses the results of the study.

METHODOLOGY

Several frameworks have been built in the past five decades to model urban growth. However, for the most part these were broad scaled (countrywide) and highly aggregated owing to computational restrictions. Only few averaged variables were employed as parameters for prediction, hence leading to a loss of variability and model inaccuracy. Nevertheless, recently GIS has led to the development of spatial models that can process data associated with a specific location. A vast number of them have been applied on fast-developing countries, e.g. China, and have provided accurate results with a high level of detail.

Modeling Land Use Change

Several disciplines such as geography, demography, economy, real estate, and civil engineering have applied their own criteria and framework to elucidate land use and model land use change. However, these efforts were proved to futile, since no mathematical formulation worked well as every place is influenced by different sociological and political factors. Consequently, a good number of land use studies were limited to reporting, deriving, and analyzing statistics related to spatial facts.

Nevertheless, a handful of successful mathematical models have also been developed. Early in the 19th Century, John Heinrich von Thünen, an able farmer, well-acquainted with economics, developed a model employing market processes to determine land use. This model was based on the supposition that each and every type of activity has a bid function to rent a given piece of land. If the bid is a linear function of the distance to the city-centre and landowners try to maximize their profit, the tenants will finally be located according to their bidding power. From the time of Thünen's works, the refinement of the model has taken into account the smooth transitions between different land-use types and has also incorporated several parameters other than the distance from center (5).

It might well be noted that urban activities typically have higher bidding functions than rural ones that can be located everywhere. For this reason the envelope of the bid functions gives the urban rate in the form of a distance-function. It is on this observation that the most frequently used urban density model is based. Urban hypotheses employ four functions to describe the decay effects of distance, namely the inverse linear function, negative exponential function, inverse power function, and a gamma-like function combining the exponential and power (*6*). This paper adopts an exponentially decreasing density function, which is widely used in urbanization modeling.

$$f(x) = \beta \cdot e^{-\lambda x} \tag{1}$$

where x is the distance from the city centre and λ the density gradient. Even though some found inverse power function, rather than negative exponential function, to work better for western cities (*7*), it was proved to be not as effective as negative exponential function for the case study in this paper. Next, the land use ratio P is obtained from the logistic equation:

$$P = \frac{\beta \cdot e^{-\lambda x}}{1 + \beta \cdot e^{-\lambda x}} \tag{2}$$

The principal goals of modeling land use transformation are to uncover the chief determinants that influence urban land use change and to explore the relationship among the factors of development and urban spatial structure. Two basic types of spatially explicit land use transformation model are known: regression type models and models based on spatial transition. The regression model attempts to obtain the coefficients of the empirical relationships from observations. Its goal is to establish functional relationships between a set of spatial predictor variables and the probability of land use change. Typically, the variable values and actual instances of land use change are observed from historical data. The spatial transition models are an extension of the spatial Markov technique and a form of stochastic cellular automata. This model includes simple rules of the effects of spatial adjacency that govern system dynamics and produce emergent behaviors and patterns, more complex than those generated by simple equilibrium models. This paper dwells on an application of the regression model that is simple from the computational viewpoint.

Driving Forces and Constraints

In general, land use change is influenced by a number of factors. Earlier studies reveal that no single set of factors can explain the changes in different places, since each context is different. More often than not, land use studies put forward different driving forces to explain land use trends at different places.

In their case study on China, Cheng and Masser (*8*) focused on land use conversion from rural to urban. Their literature review reported factors such as investment structure, industry structure, housing commercialization, land leasing and decentralization of decision-making. However, their model included only the industry structure, the transportation networks and the existing developed areas. They also took into consideration the constraints imposed by water and other places unfit for urban development. Landis and Zhang (*9*) investigated land use change near a railway station in their small-scale example. It included only four classes of information: the transportation network, the urban structure (residential, commercial, public and industrial buildings), locations available for change and locations where no change could occur because of constraints. It also demonstrated that explanatory factors do not need to be numerous, provided they are relevant.

Typically, land use changes from rural to urban seem to be influenced by a few recurrent parameters that cannot be overlooked. It is obvious that a city will grow if its population increases (*10*). Consequently, new residential areas will emerge in close proximity to transportation facilities (roads, railways, bus lines) and commercial centers also develop concurrently. In the meantime, industrial buildings will develop in the vicinity of those existing previously. On the whole, the urban expansion will transform vacant or low rent areas into ‘developed’ places. Besides, the agglomeration of developed areas and the availability of exploitable sites will significantly influence urban growth patterns. Therefore, this study restricts the predicting factors to population migration, the proximity of residential, commercial and industrial areas, and the proportion of urban cells and rural cells in neighborhood. The land available for change is part of the agricultural land, while forests, wetlands, or barren lands are considered inappropriate for development. The latter assumption accounts for policies favoring the conservation of natural resources.

Several other assumptions were made in addition to the selection of predicting variables. Since New Castle County covers a small area on the east coast of the United States, some factors such as climate and average slope are assumed to be identical over the territory and hence are not used to explain land use differences. Factors other than climate and slope, which are not considered, include vegetation type and some socioeconomic data like the cultural background of the population or the state policy for preserving water resources.

Spatial Logistic Regression

Regression can be considered as a process to extract the coefficients of the empirical relationships from observations. Commonly used regression approaches include linear regression, log-linear regression and logistic regression. The dependent variable of logistic regression could be binary or categorical. The independent variables of logistic regression could be a mixture of continuous and categorical variables. Normality assumption is not needed for logistic regression. Hence, logistic regression is advantageous compared to linear regression and log-linear regression. It is an approach to extract the coefficients of explanatory factors from the observation of land use conversion, since urbanization does not usually follow normal assumption and its influential factors are usually a mixture of continuous and categorical variables.

The general form of logistic regression is as follows:

$$y = a + b_1x_1 + b_2x_2 + \ldots + b_mx_m \tag{3}$$

$$y = \log_e\left(\frac{P}{1-P}\right) = \log it(P) \tag{4}$$

$$P = \frac{e^y}{1+e^y} \tag{5}$$

where x_1, x_2,…, x_m are explanatory variables, y is a linear combination function of the explanatory variables representing a linear relationship. The parameters b_1, b_2, …, b_m are the regression coefficients to be estimated. If z is denoted as a binary response variable (0 or 1), value 1 (z = 1) means the occurrence of new unit such as transition from rural to urban, and value 0 (z = 0) indicates no change. *P* refers to the probability of occurrence of a new unit, i.e. z = 1. Function y is represented as logit(*P*), i.e. the log (to base e) of the odds or likelihood ratio that the dependent variable z is 1.

Probability P strictly increases when y value increases. Regression coefficients b_1-b_m imply the contribution of each explanatory variable on probability value *P*. A positive sign means that the explanatory variable helps to increase the probability of change and a negative sign implies the opposite effect. The statistical technique is a multivariate estimation method examines the relative strength and significance of the factors.

While employing logistic regression to model rural-urban land conversion, the spatial heterogeneity of spatial data should be considered. Spatial statistics like spatial dependence and spatial sampling also have to be considered in logistic regression to remove spatial auto-correlation. Otherwise, unreliable parameter estimation or inefficient estimates and false conclusions regarding hypothesis test will result. There are two fundamental approaches to consider spatial dependence: building a more complex model incorporating an autogressive structure and designing a spatial sampling scheme to expand the distance interval between sampled sites. Spatial sampling leads to a smaller sample size that loses certain information and conflicts with the large-sample of asymptotic normality of maximum likelihood method, upon which logistic regression is based. Nevertheless, it is a more sensible approach to remove spatial auto-correlation and a reasonable design of spatial sampling scheme will make a perfect balance between the two sides.

Systematic sampling and random sampling are two widely adopted sampling schemes in logistic regression. Even though systematic sampling reduces spatial dependence, important information like relatively isolated sites are lost when population is not spatially homogeneous. On the other hand, random sampling is efficient in representing population, but does not efficiently reduce spatial dependence, local spatial dependence in particular. Consequently, a sampling scheme integrating systematic and random sampling is employed to overcome the conflict of sample size and spatial dependence.

IMPLEMENTATION

Study Area

Delaware State is subdivided into three counties: from north to south, New Castle County, Sussex County and Kent County. New Castle County covers the whole area north of Clayton city (see Figure 1a). It covers about 1,100 square kilometers and may be included in a 20 km x 60 km rectangle.

With more than 60 % of the state population (505,000 out of 796,000 inhabitants in 2001), New Castle County is the urban and manufacturing core of Delaware (Figure 1b). The northern part belongs to the suburban agglomeration of Philadelphia (PA) and consists of densely populated cities such as Wilmington and Newark while the southern part is rather agricultural (Figure 2). A land use study by the University of Delaware showed that both parts tend to become more and more urbanized and this tendency is not expected to decline in the approaching years.

Data Sources

The data used in this study was obtained from multiple data sources: land use data (including sequential land use data), demographic data, and transportation data. The rural-urban land conversion model is built using 1984-1992 and 1992-1997 land use changes and is then validated over the span of 1984-1997.

Land use data were obtained from the College of Agricultural and Natural Resources at the University of Delaware. They are readily available in ESRI exchange format (.E00). These data were collected through several campaigns of aerial photography for the State of Delaware. They provide snapshots of land use and land cover in 1984, 1992 and 1997. The 1984 land use data was developed by Earthsat Corp. on contract with the Delaware Dept. of Agriculture at resolution consistent with Landsat MSS satellite imagery (79-meter pixel size), using a modified 2-digit Anderson land-use/land cover (LULC) classification scheme, with a 15-acre minimum mapping unit. The original data were in Delaware State Plane Projection, NAD 1927, in feet, based on Clarke 1866 spheroid. The 1992 and 1997 LULC series was developed by Earth Data (formerly PhotoScience) under contract with the State of Delaware. LULC polygons were digitized on 1-meter resolution digital Orthophotos using a different modification of the Anderson LULC classification scheme, with a 4-acre minimum mapping unit. The original data were in Delaware State Plane Projection, NAD 1983, in meters, based on the GRS80 spheroid. All land use files were rasterized at a resolution of 79×79 meter, which is compatible with the lowest resolution of raw data and is expected to be low enough to erase the positional errors reported between 1984 data and 1992/1997 data. Seven different types of land use classification were employed: residential, commercial, industrial, agricultural, forest, water, barren. The first three types are considered to be urban areas, agricultural land use is considered to be rural area that has potential of urbanization, and the last three types are considered to be parcels that are not suitable for development.

The demographic data were obtained from the US Census Bureau’s demographic studies in 1990 and in 2000. The corresponding GIS shapefiles of 1990 and 2000 are provided. Unlike land use data, the projection system is GCS_North_America_1983. Therefore, the layer coordinates had to be transformed. Since the population data for 1984, 1992 and 1997 are not available, the can only be obtained by extrapolating the available data. First, the population densities of 1990 and 2000 were calculated and then rasterized. For each raster cell, an exponential growth $\alpha.\exp(\beta.\text{year})$ was assumed and the 1990 and 2000 figures were utilized to derive α and β. The formula was then employed with an approximate value of the year so that the total number of people living in New Castle County matches the real figures: 408235 in 1984, 455080 in 1992 and 478744 inhabitants in 1997 (source: Delaware Demographic – Population Database). As an indication, the approximate years are 1983.87233 instead of 1984, 1992.46569 instead of 1992 and 1996.675168 instead of 1997. The second figure is larger than the year because New Castle County had a higher immigration rate during this period.

The transportation data were procured from Delaware Department of Transportation (DelDOT). Only the shapefile of 2001 road networks is provided. Since large scale construction of the US transportation network occurred around 1960s, the geographic difference of transportation network between 1984 and 1992 is negligible. Using 2001 road network to serve as 1984 and 1992 road network will definitely reduce the accuracy of rural-urban land conversion model, but the effect is not significant.

GIS-based Predictor Variables

Seven predictor variables were compiled in ArcInfo 8.3 via the spatial analyst module based on 79m×79m cell size. A summary of these seven predictors is shown in table 1.

Three classes of predictors were employed: (1) site specific characteristics; (2) proximity; and (3) neighborhoods. Since population pressure is a principal force driving global land use change, the site specific characteristic, population density, is considered to be a chief predictor. For the sake of convenience, population density is scaled into ten levels ranging from 0 to 9. Proximity is a prime cause of urban expansion. The proximity variables measure the minimum Euclidean distances to the nearest commercial site, residential area, industrial site and transportation network respectively. The proximity predictors are scaled into ten levels ranging from 0 to 9 too. The availability of usable sites significantly influences urban growth patterns. The agglomeration of developed areas is apparent in urban development. Hence the land transformation model proposed herein consists of those urban cells in neighborhood that reflect the agglomeration effect of urban cells and the proportion of rural cells in the neighborhood which reflects the capacity to be developed into urban space. The type and size of selected neighborhood reflect the distance decaying mechanism of various factors. In this study, a circular neighborhood with a 200m radius is chosen.

Figure 3 depicts land use /cover maps of 1984 and 1992. It can straightforwardly be seen that, in 1984 most of urban land uses (commercial sites, residential sites and industrial sites) were located on the northern part of the region. The southern part of the region is almost rural land use. In 1992, the urban land use in the northern part extended. Most of rural-urban conversion happened along the boundary of the original urban land uses. The proximity factors seem to be the main driven forces for these rural-urban conversions. The rural-urban conversion in the middle part is quite different from that in the northern part. Several blocks of new urban land uses were found in 1992 and the conversions are hard to be explained by proximity force. Figure 4 illustrates all the predictors in 1984 and the state of rural-urban land conversion from 1984 to 1992.

RESULT AND DISCUSSIONS

Spatial Logistic Regression Modeling

Rural-urban land conversion probability was calibrated through a spatial logistic regression. The dependent variable is binary (whether the rural land use developed into urban land use or remains in the current state) and the predictors are the seven factors discussed in the preceding section. First of all, the predictors were prepared in ArcInfo. Then, spatial sampling was implemented to reduce spatial dependence. This study employs a sampling scheme integrating systematic and random sampling. A systematic sampling with a 20th order lag (20 pixels interval in east-west and north-south directions) is implemented for the population. After that, another 10% from sample 0 was randomly selected to gain unbiased parameter estimation. Finally, a binary logistic regression was processed using MiniTab.

The rural-urban land conversion models of 1984-1992 and 1992-1997 were analyzed respectively and the regression results presented in table 2. Two models, both significant at 0.000, show some regularity in land use conversion. The logistic regression model was estimated using maximum likelihood algorithm. One efficient way to assess the goodness-of-fit of logistic regression is to cross tabulate prediction with observation and to calculate the percentage correctly predicted (PCP). The overall percentages of correctness were 80.7% and 74.0% respectively for 1984-1992 and 1992-1997. Hence, the models can be regarded as effective descriptions of the rural-urban land conversions, as only a limited number of explanatory variables are used and land use conversions are usually distributed in a complicated way.

From the results obtained, it was found that the rural-urban land conversion pattern varies with location as well as time. Hence the rural-urban land conversion model for one region obtained in a specific period might not be suited well for the same region in another time-period. In general, averaging coefficients of models in different periods should be beneficial to eliminate this effect. As logistic regression is a method of nonlinear modeling, simple averaging coefficients can not model the non-linear relationship between the probability and predictor variables. However, as seen in Figure 5, average operation can be used when trying to obtain coefficient for a whole period from the coefficients for all its sub-periods. Hence, considering the different time span of the two models, a weighted average model for 1984-1997 span can be obtained as follows:

$$\begin{aligned} \log it(P) = 0.692 + 0.142 Dens\_Pop - 0.450 Dist\_Com - 0.0341 Dist\_\mathrm{Re}s \\ - 0.0745 Dist\_Ind - 1.16 Dist\_Road + 1.57 Per\_Urb - 0.876 Per\_Agr \end{aligned} \quad (6)$$

Model Validation

The validation process of the model is performed for the span of 1984-1997. The candidate cells and their development status of 1984-1997 were first determined. For each candidate cell, the probability of change was computed with the fitted model. Subsequently, the probability of conversion was compared with a critical probability. If the probability of conversion at a cell was greater than the critical probability, land at that cell was treated as developed, otherwise the land use remained unchanged. The critical probability can be determined in various ways. One widely adopted way is based on population prediction. Assuming the land per capita to remain the same, the rate of rural-urban land conversion can be determined. In this study, a critical probability is selected, which makes the area of urban land use calculated equal to the area of urban land use in practically.

Figure 6 presents a visual comparison of the urban area generated by model prediction with the actual urban area. From Table 3, the accuracy of model can be assessed. Unfortunately, although the overall 76.15% correct prediction is relative high, we can find that the accuracy of correct prediction for developed area is lower (45.33%).

CONCLUSION

This research employed spatial land use, population and road network data to derive a static predicting model of rural-urban land conversions in New Castle County, Delaware. Built from a spatial logistic regression analysis, the model turned out to be successful in partially revealing the land use development pattern. Using GIS and spatial logistic regression, the relationship between 7 predictor variables and urbanization was examined. The model generated enabled the calculation of the conversion likelihood values for each study-area location and hence predict the possible urbanized sites. However, the model is not very efficient, owing to the lack of relevant land use change factors and a too synoptic statistical analysis. Besides, limited knowledge of the background theory and the urban context in New Castle County hindered the formulation of helpful assumptions to enhance model performance. Nonetheless, it was found that a gamut of factors, ranging from spatial parameters to socioeconomic, political or even cultural factors, could influence land use changes. Each case is different and, therefore, requires a thorough understanding of the situation. Consequently, it can be concluded that no single model appears to perform consistently well when applied to different geographical locations.

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TABLE 1 Summary of Predictor Variables for the Rural-urban Land Conversion Model

Variable name	Description
Dens_Pop	Population density of the cell
Dist_Com	Distance from the cell to the nearest commercial site
Dist_Res	Distance from the cell to the nearest residential area
Dist_Ind	Distance from the cell to the nearest industrial site
Dist_Road	Distance from the cell to the nearest road
Per_Urb	Percentage of urban land use in the surround area within 200m radius
Per_Agr	Percentage of rural land use in the surround area within 200m radius

TABLE 2 Spatial Logistic Regression Results of Land Conversion Models of 1984-1992 and 1992-1997

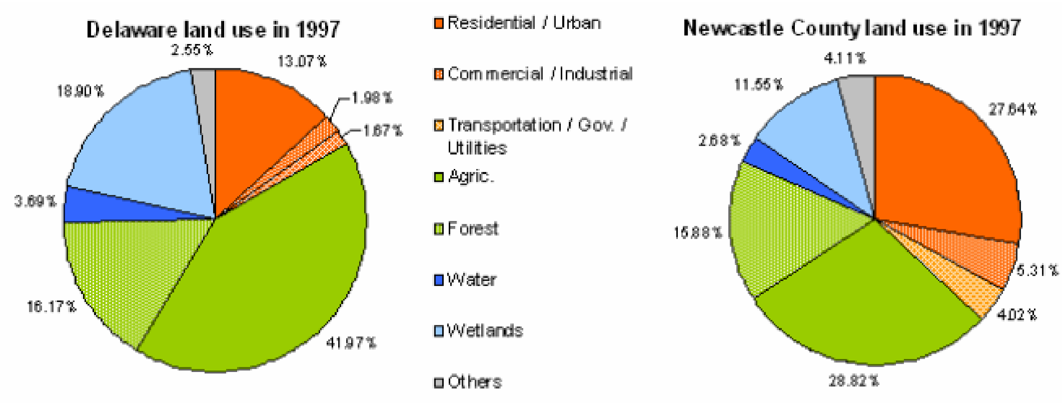
Variable	Model 1984-1992		Model 1992-1997	
	Coefficient	S.E.	Coefficient	S.E.
Dens_Pop	0.198009	0.0253911	0.0519333	0.0658720
Dist_Com	-0.523650	0.0461869	-0.332328	0.0568280
Dist_Res	-0.0903675	0.0290959	0.0559803	0.0396110
Dist_Ind	-0.0135951	0.0161105	-0.172049	0.0475877
Dist_Road	-0.902539	0.0437388	-1.57291	0.136609
Per_Urb	2.56829	0.217187	-0.0276175	0.354979
Per_Agr	-0.987741	0.138154	-0.697336	0.245149
Constant	1.23354	0.143374	-0.174733	0.267135
G.K. Gamma	0.62		0.50	
PCP	80.7%		74.0%	

Note: S.E.: standard error.
G.K. Gamma: Goodman-Kruskal Gamma
PCP: percentage correctly predicted

TABLE 3 Result of Prediction Compared with Observed Land Conversion in Number of Cells

Observed	Predicted		% correct
	Developed	Not developed	
Developed	6704	8085	45.33
Not developed	8086	44942	84.75
Overall	14790	53027	76.15

(a) Map of Delaware



(b) Land Use in New Castle County Compared to Delaware State in 1997

FIGURE 1 New Castle County Situation.

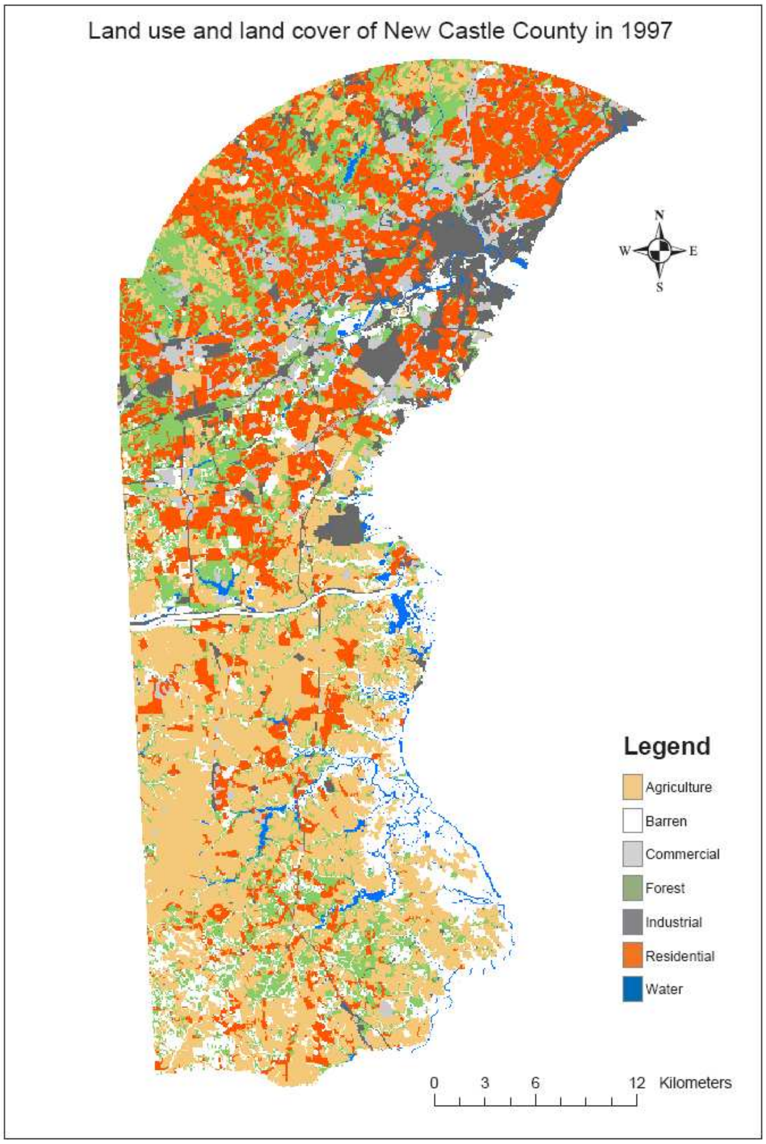
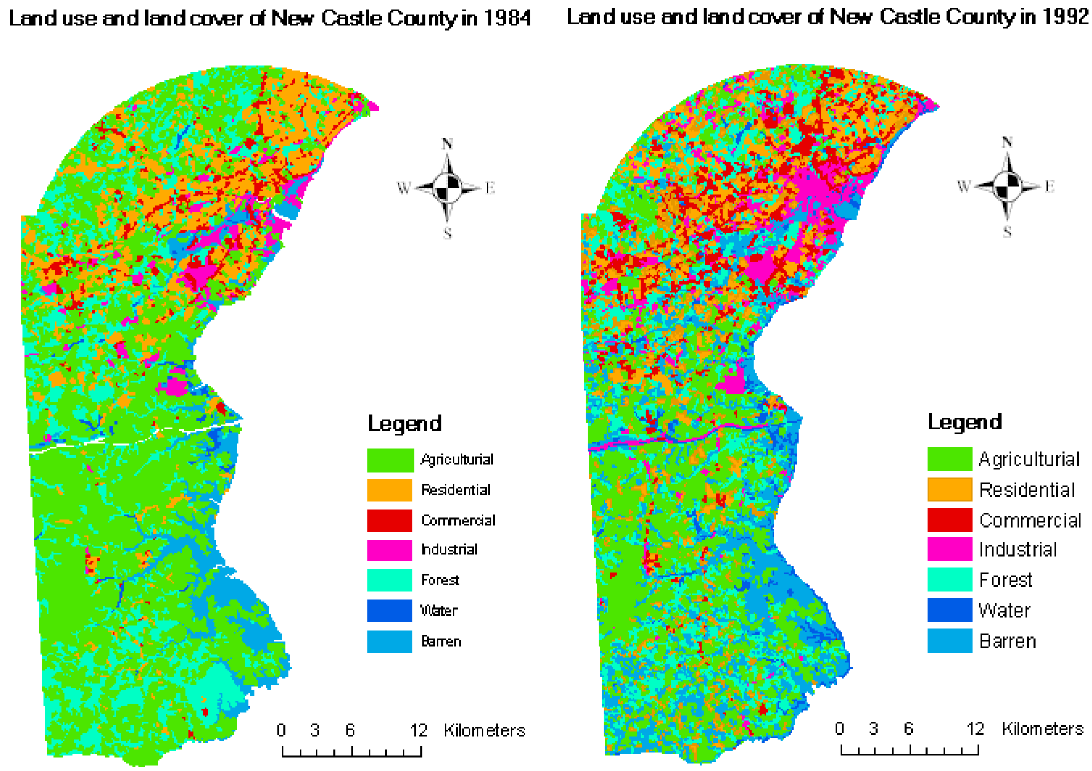
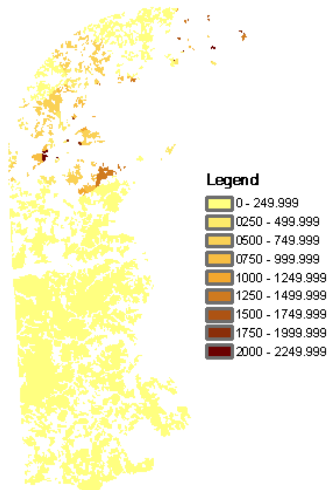


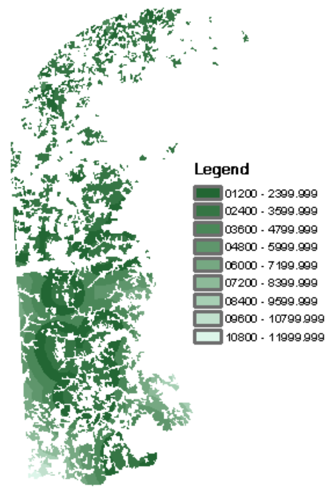
FIGURE 2 Simplified Land Use Classification of New Castle County, 1997.

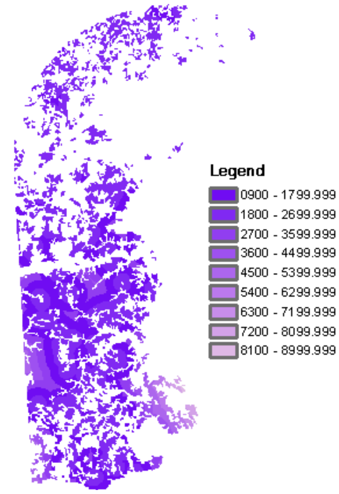


(a) Land use / cover map of 1984 (b) Land use / cover map of 1992

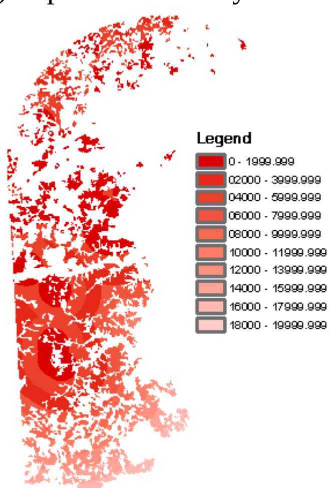
FIGURE 3 Land Use / Cover Maps of 1984 and 1992.

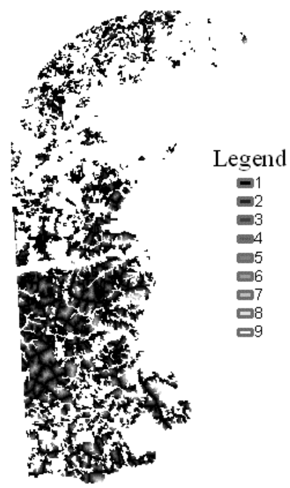


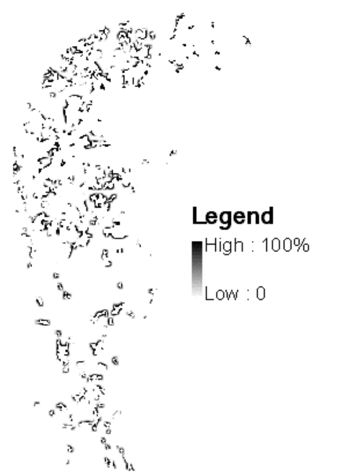




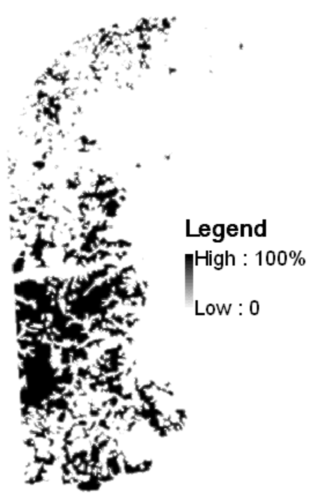
(a) Population Density (b) Distance to Commercial (c) Distance to Residential

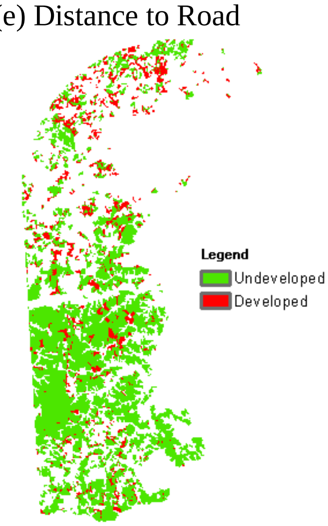


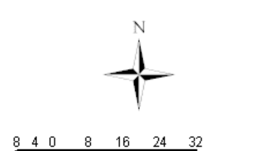




(d) Distance to Industrial (e) Distance to Road (f) Percentage of Urban LU







(g) Percentage of Rural LU (h) Development Status

FIGURE 4 Spatial Distributions of Predictors in 1984.

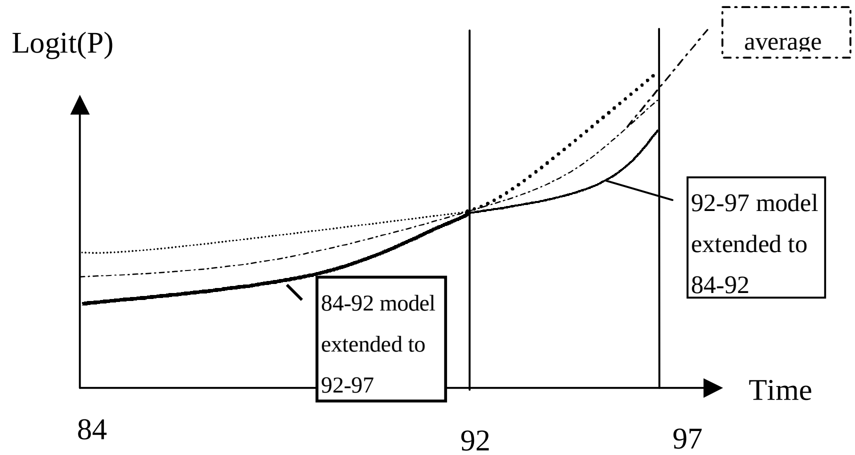
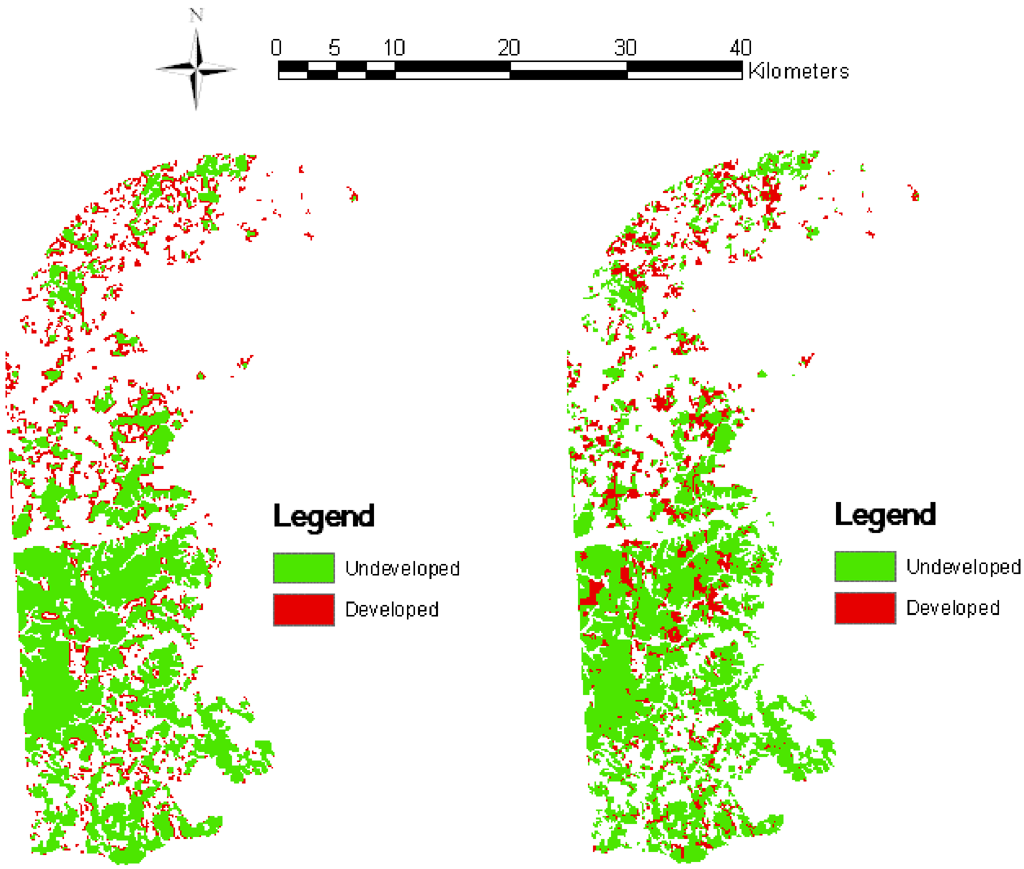


FIGURE 5 Probability of Rural-urban Land Conversion versus Time.



(a) Predicted rural-urban land conversion (b) Actual rural-urban land conversion

FIGURE 6 Rural-urban Land Conversion of 1984-1997.