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Population Growth and Land Use Dynamics along Urban–Rural Gradient

Maksym Polyakov and Daowei Zhang

In this study we apply a spatial conditional logit model to determine factors influencing land cover change in three contiguous counties in West Georgia between 1992 and 2001 using point (pixel) based observations of land characteristics. We found that accessibility to population and population growth affect not only development of rural lands and transition between agricultural and forestry uses, but also influence changes between forest types. The model could be used to project land use–land cover change at watershed or subwatershed level and thus serve as a valuable tool for county and city planners.

Key Words: conditional logit, land use change, population gravity index, spatial lag

JEL Classifications: Q15, Q23, R14

Driven by landowners seeking maximization of economic benefits, change in land use patterns affects both human and natural systems, and is recognized as the key factor of environmental change (Bockstael). Land use change often produces negative externalities such as congestion, air and water pollution, loss of biodiversity, wildlife habitat fragmentation, and increased flooding. When the majority of a land base is privately owned, as in the U.S. South, it is important to understand how socioeconomic and environmental factors affect private landowners' decisions concerning land use.

There is a considerable demand for small scale, spatially explicit land use change models that could be integrated into multidisciplinary studies of ecological and social implications of urbanization to predict changes in ecosystem services such as water quality and plant biodiversity (Lockaby et al.). Furthermore, because the dynamics of rural land use is influenced by human activity and urbanization, and is an important determinant of ecosystem services, it is important to model not only patterns of urban land use development, but also changes between rural land use–land cover types at the watershed level. The objective of this study is to build a spatially explicit econometric model of changes between an exhaustive set of land cover–land use and forest management types using remotely sensed data and to use this model for predicting dynamics of land use–land cover and forest type change at watershed and subwatershed level.

The paper is organized as follows. In the next section we present an overview of the

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relevant literature on economics of land use change. In the following section we describe the study area. Then we lay out a discrete choice model of land use change and the corresponding econometric model, followed by description of data. The remaining sections present the results of spatial conditional logit estimation of the model of land cover–land use change, validation of the model, prediction of land cover–land use change for the next two decades, and conclusions.

Literature Review

Following the classic land use theory developed by David Ricardo and Johann von Thünen, the vast majority of the econometric studies of land use model land use patterns in terms of relative rent to alternative land uses, which depends on land quality and location. There is a broad variation in approaches to model land use with respect to data aggregation, dynamics, scale, and scope.

Depending on the data availability, land use–land cover could be modeled at the individual or aggregate level. Aggregate data describe areas or proportions of certain land use categories within a well defined geographic area, such as a county, as a function of socioeconomic variables and land characteristics aggregated at the level of the geographic unit of observation (Alig and Healy; Parks and Murray; Stavins and Jaffe; Zhang and Nagubadi). Models based on individual level or disaggregate data use parcels (Carrión-Flores and Irwin; Irwin and Bokstael), sample plots (Kline, Moses, and Alig; Lubowski, Plantinga, and Stavins), or remotely sensed (Chomitz and Gray; Turner, Wear, and Flamm) data.

A distinction should be made between studies that model *allocation* of land among different uses and studies that model land use *change*. The models of land use allocation that utilize aggregate data estimate proportions of land shares (Miller and Plantinga), while those utilizing disaggregate data estimate the probability of allocating a particular parcel or plot to one of the alternative land uses (Nelson et al.). Comparing pooled, fixed effects, and random effects specifications of the cross-sectional time-series model of allocation of land use shares, Ahn, Plantinga and Alig conclude that pooled specification does not adequately control for cross-sectional variation in dependent variables. As a result, the models' parameters measure a combination of spatial and temporal effects and cannot be used for making inferences regarding land use change or land use change predictions. They suggest that a specification with cross-sectional fixed effects provides a better measure of temporal relationship. However, the use of cross-sectional fixed effects requires a relatively long time series and prevents the use of explanatory variables that do not have temporal variation (like land quality). In contrast, models of land use change use plot- or parcel-based observation of land characteristics over several periods to directly measure land use transitions. These transitions are modeled using either the discrete choice approach (Bockstael; Kline; Lubowski, Plantinga, and Stavins; Polyakov and Zhang) or survival analysis (Irwin and Bockstael).

The scale of land use models affects the choice of explanatory variables. In the small scale models, the relative rents to alternative land uses (which determine land use and drive land use change) are assumed to be a function of site characteristics (e.g., land quality) and location (e.g., distance to the central business district). In the large scale models, spatial variability of prices, economic and climatic conditions allows us, in addition to site characteristics and location, also to include variables such as observable returns to agriculture, forestry, and residential uses (Lubowski, Plantinga, and Stavins; Miller and Plantinga) or property taxes (Polyakov and Zhang).

Finally, econometric land use models vary broadly by scope. While large scale models usually model exhaustive sets of land uses (Lubowski, Plantinga, and Stavins), most of the small scale, spatially explicit econometric models of land use change are restricted to the analysis of conversion from rural to developed land uses (Bockstael; Carrión–Flores and Irwin; Irwin and Bockstael). One of the few exceptions is the work by Turner, Wear, and Flamm who model changes between forest, grass, and

Table 1. Population and Land Use Statistics in Harris, Meriwether, and Muscogee Counties

Characteristics	County			Total
	Harris	Meriwether	Muscogee	
Population:				
Person, 2000	23,695	22,534	186,291	232,520
Person/km^2, 2000	19	17	325	75
Annual % change, 1990–2000	3.3	0.1	0.4	0.6
Agricultural lands:				
% of land base, 1997	6.3	10.2	5.5	7.8
Annual % change, 1992–1997	−0.3	−3.1	−4.7	−2.5
Forest lands:				
% of land base, 1997	78.3	80.5	24.8	69.3
Annual % change, 1992–1997	−0.4	0.8	−2.1	0.0
Developed lands:				
% of land base, 1997	6.9	5.9	29.8	10.7
Annual % change, 1992–1997	4.6	4.1	3.8	4.1

unvegetated land covers. Furthermore, to our knowledge, no small scale, spatially explicit econometric model of land use change has been used to quantify and predict changes between both land uses and forest types.[1]

Study Area

Our study area is in the Georgia Piedmont, a region that displays rapid development and ranks highest among the regions in terms of percentage increase in developed land area in the 1990s. Within this region we study land use change in three contiguous counties: Muscogee, Harris, and Meriwether. Despite being contiguous, these counties exhibit a broad range of population pressures and patterns of land uses and land use change from urban (Muscogee County) to rural (Meriwether County). Columbus, located in Muscogee County, is the third largest city in Georgia. Muscogee County accounts for 80% of the population of the three-county region. However, during the 1990s it had a moderate population growth. The population of Harris County, which is located north of Muscogee County and is becoming its bedroom community, increased by one third during the same period, while the population of Meriwether County remained almost unchanged (Table 1).

Figure 1 shows the population density in 2000 and change of population density between 1990 and 2000. It reveals that population increases around populated places and, at the same time, declines in the immediate proximity to centers of the most populated places, especially Columbus. Furthermore, land is being converted to developed use at a greater rate than the population increase. According to data collected by the National Resources Inventory (NRI), during the period 1992–1997 the average annual increase of the area of developed land in these three counties was 4.1%, while the average annual increase of population in the 1990s was 0.6% (Table 1). Thus, the "elasticity" of land development with respect to population growth was nearly seven. Most of the developed land was converted from forest. However, due to simultaneous conversion of agricultural land to forest land, the proportion of forest land did not change much, while agricultural lands declined by one third between 1987 and 1997. These patterns of population growth and land

[1] However, Nagubadi and Zhang model land use and forest type allocation using aggregate (county level) data, and Majumdar, Polyakov, and Teeter model changes between nonforest land uses and forest types using Forest Inventory Analysis sample plot data for Alabama.

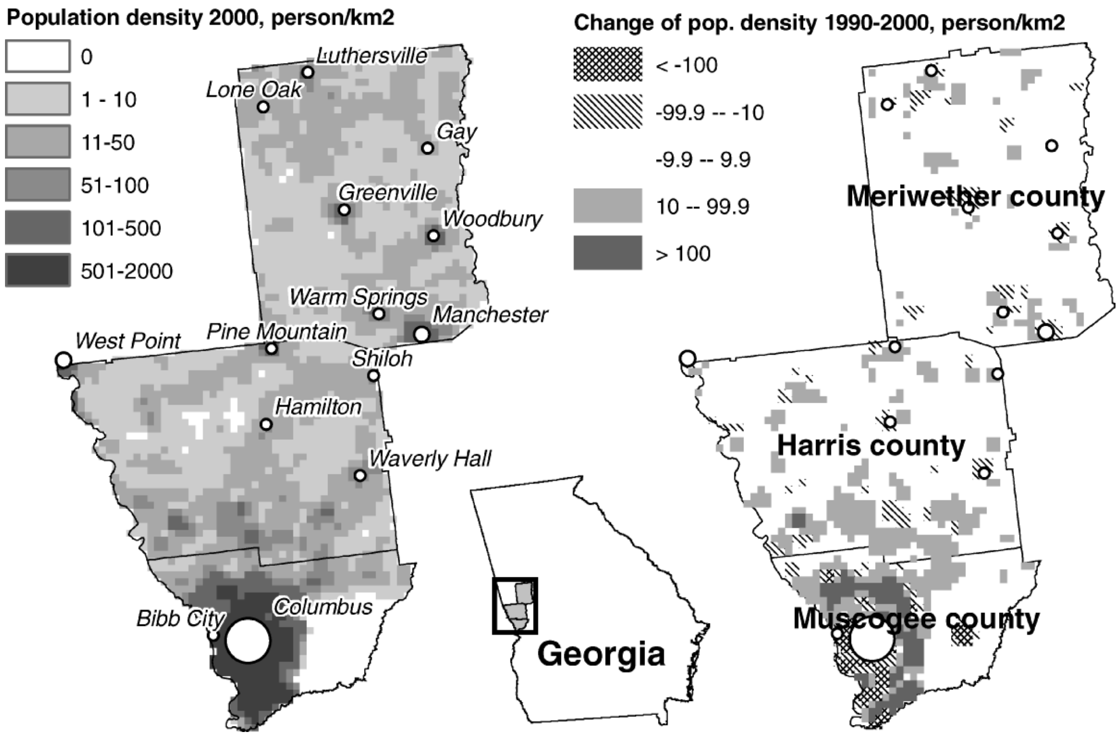

Figure 1. Spatial Patterns of Level and Change of Population Density in Three West Georgia Counties

use change are a reflection of discontinuous low density development that is often cited as urban sprawl (Bogue).

The Theoretical Model

Our modeling approach is based on the assumption that land use and land cover spatial patterns and their changes are results of decisions of the owners of individual land parcels or cells in the landscape. A landowner chooses to allocate a parcel of land of uniform quality to one of J possible alternative uses. We assume that the landowner's decision is based on the maximization of net present value of future returns generated from the land. The landowner's expectations concerning future returns generated by different land uses are drawn from the characteristics of the parcel and historical returns.

Let W_{ni} be the return or net present value of parcel n in use i, which depends on characteristics of a parcel such as land quality and location, as well as economic conditions. Converting a parcel from use i to alternative use j involves a one time conversion cost C_{nij}, which depends on the land uses that a parcel is being converted from and to, the characteristics of the parcel, as well as institutional settings such as zoning regulations. Let $U_{nj|i} = W_{nj} - W_{ni} - C_{nij}$ be the landowner's utility of converting a parcel to new land use j conditional on current land use i. The parcel could be converted to land use j if $U_{nj|i}$ is positive. Furthermore, the parcel will be converted to a land use, for which the utility of conversion is the greatest. The parcel will remain in current land use ($C_{nii} = 0$; $U_{ni|i} = 0$) if $U_{nj|i} < 0 \; \forall \, j \neq i$.

Neither return for each of the land uses nor conversion costs are directly observable for individual parcels. However, there are observable attributes of plots $\mathbf{x}_n$ that are related to either returns or conversion costs. Furthermore, there might be spatial dependencies Z_{nj} because some of the spatially related factors affecting decisions are not observable directly. Utility of land use change can be expressed as $U_{nj|i} = V_{nj|i} + \varepsilon_{nj}$, where $V_{nj|i} = V(\mathbf{x}_n, Z_{ni})$ is the representative utility and ε_{nj} captures the factors that are affecting utility, but not included into representative utility, and are assumed to be random. The probability of converting parcel n to land use j is

$$(1)\quad \begin{aligned} P_{nj|i} &= \text{Prob}\left(U_{nj|i} > U_{nk|i} \forall k \neq j\right) \\ &= \text{Prob}\left(V_{nj|i} + \varepsilon_{nj} > V_{nk|i} + \varepsilon_{nk} \forall k \neq j\right) \end{aligned}$$

Depending on assumptions about the density distribution of random components of utility, several different discrete choice models could be derived from this specification (Train). Assuming random components are independent and identically distributed (iid) with a type I extreme value distribution, we obtain a conditional logit model (McFadden):

$$(2)\quad P_{nj|i} = \frac{\exp\left(V_{nj|i}\right)}{\sum_{k=1}^{J} \exp\left(V_{nk|i}\right)}$$

The representative utility of converting parcel n from land use i to land use j could be expressed as a linear combination of observable attributes of plots ($\mathbf{x}_n$), land use specific parameters ($\boldsymbol{\beta}_j$), transition specific parameter (α_{nij}), and spatial dependencies across decision makers ($Z_{nj} = \sum_{s=1}^{S} \rho_{ns} y_{sj,t-1}$):

$$(3)\quad \begin{aligned} V_{nj|i} = V(\boldsymbol{x}_n) &= \alpha_{nij} + \boldsymbol{\beta}_j' \boldsymbol{x}_n - \boldsymbol{\beta}_i' \boldsymbol{x}_n \\ &\quad + \sum_{s=1}^{S} \rho_{ns} y_{sj,t-1} \end{aligned}$$

where ρ_{ns} is a coefficient representing the influence parcel s has on parcel n and $y_{sj,t-1}$ is equal to 1 if parcel s was in land use j, and 0 otherwise. In spatial statistics, ρ usually takes a form of a negative exponential function of the distance (D_{ns}) separating two units of observation:

$$(4)\quad \rho_{ns} = \lambda \exp\left(-\frac{D_{ns}}{\gamma}\right),$$

where λ and γ are parameters, and

$$(5)\quad \begin{aligned} Z_{nj} &= \sum_{s=1}^{S} \lambda_j \exp\left(-\frac{D_{ns}}{\gamma}\right) y_{sj,t-1} \\ &= \lambda_j \sum_{s=1}^{S} \exp\left(-\frac{D_{ns}}{\gamma}\right) y_{sj,t-1}. \end{aligned}$$

Substituting (3) and (5) into (2), we obtain:

$$(6)\quad \begin{aligned} &P_{nj,t|i,t-1} \\ &= \left[\exp\left(\alpha_{ij} + \boldsymbol{\beta}_j' \boldsymbol{x}_{n,t-1} - \boldsymbol{\beta}_i' \boldsymbol{x}_{n,t-1} + \sum_{s=1}^{S} \rho_{ns} y_{sj,t-1}\right)\right] \\ &\div \left[\sum_{k=1}^{J} \exp\left(\alpha_{ij} + \boldsymbol{\beta}_k' \boldsymbol{x}_{n,t-1} - \boldsymbol{\beta}_i' \boldsymbol{x}_{n,t-1} + \sum_{s=1}^{S} \rho_{ns} y_{sk,t-1}\right)\right] \\ &= \left\{\exp\left[\alpha_{ij} + \boldsymbol{\beta}_j' \boldsymbol{x}_{n,t-1} + \lambda_j \sum_{s=1}^{S} \exp\left(-\frac{D_{ns}}{\lambda}\right) y_{sj,t-1}\right]\right\} \\ &\div \left\{\sum_{k=1}^{J} \exp\left[\alpha_{ij} + \boldsymbol{\beta}_j' \boldsymbol{x}_{n,t-1} + \lambda_j \sum_{s=1}^{S} \exp\left(-\frac{D_{ns}}{\lambda}\right) y_{sk,t-1}\right]\right\} \end{aligned}$$

To remove an indeterminacy in the model we restrict $\alpha_{ij} = 0\ \forall i = j$ and $\boldsymbol{\beta}_j = \mathbf{0}$, where J is the reference outcome (land use). The estimation of spatial dependency ρ requires estimation of parameters λ_j and γ. One of the ways to do this is through the search procedure over a range of numbers by trying out different values of γ while estimating the value of λ_j as standard parameters in the conditional logit model (Mohammadian and Kanaroglu).

Because land use change is modeled in a relatively small region, we assume that prices and costs are constant across the study area and do not affect relative rents and land use choice behavior (Bockstael; Turner, Wear, and Flamm). The factors that are variable within the study area and influence relative rents to alternative land uses are (i) location of sample point relative to employment and market centers, populated places, and transportation networks; (ii) restriction of land use through protected areas on public or private lands; and (iii) physical site characteristics.

Location is a factor that has been widely used in land use modeling literature to explain allocation of land to alternative uses. Following Alonso's adaptation of von Thünen's location rent model, urban rent that drives conversion of land from rural to urban use is commonly explained by such measures of location as distance to central business district (Bockstael) or population density (Alig and Healy; Hardie and Parks). Allocation of land between agricultural and forestry uses is also affected by the location. In particular, accessibility to markets and accessibility to populated places determine costs of transporting labor and other inputs to the site and commodities to the markets. Because agriculture is a more labor and capital intensive land use than forestry and usually yields higher returns, accessibility to markets and populated places has greater impact on agricultural rent than on forestry rent. As a result, the slope of the location rent function for agricultural land use is steeper than the slope of the location rent function for forestry land use. Therefore, rural lands with relatively greater accessibility to markets and population are more likely to be converted to or retained in agricultural land use, and rural lands in remote locations are more likely to be converted to or retained in forestry use. A number of empirical studies of tropical deforestation model the effect of accessibility to markets on conversion of undisturbed forests to agriculture (Chomitz and Gray; Parks, Barbier, and Burgess). However, to our knowledge, there were no attempts to model impact of accessibility to markets and population on land use change between agriculture and forestry in a region with intensive forest management, such as the U.S. South.

Within forestry use, intensity of forest management is also affected by location. On the one hand, a forest is managed more intensively when it is closer to the mill (Ledyard and Moses). On the other hand, intensity of forest management is adversely affected by population pressure or proximity to populated places (Munn et al.; Polyakov, Majumdar, and Teeter; Wear et al.). We assume that location (accessibility to population and wood processing facilities) affects changes between forest management types because these changes are driven by differences in intensity of forest management.

Following the previous arguments, we hypothesize that by affecting relative rents to alternative land uses, location (accessibility to jobs, markets, and population) influences changes both between rural and developed land uses, between agricultural and forestry uses, and between forest cover types (forest management types).

It is a challenge to quantify the effect of location when multiple employment, market, and population centers influence each parcel of land simultaneously. Regional scientists traditionally evaluate and compare their influences using gravity potential, which is proportional to the size (usually population) of the center and inversely proportional to the squared distance between the center and the parcel of interest. Because the influences of multiple centers on a given parcel are additive, Hoover suggests aggregating gravity potentials into a single index. This approach has been used by a number of land use change studies (Kline, Azuma, and Moses; Kline, Moses, and Alig; Majumdar, Polyakov, and Teeter; Polyakov and Zhang). Because the data about sizes of employment centers (e.g., number of jobs) and market centers are not available at the resolution sufficient for our analysis,[2] we use population to characterize the size of population centers, as well as the size of employment and market centers. To quantify accessibility to jobs, markets, and population, we calculate the population gravity index (PGI) using

[2] The data about location of pulp mills and sawmills are available for the study region. We have experimented with distance to pulp mill, distance to sawmill, and the mills' gravity indices. However, none of these variables was significant in our model. Apparently, high concentrations of sawmills and pulp mills and a developed transportation network create competition for raw materials and may annihilate local differences in rent attributable to the proximity to wood processing facilities.

the traditional specification[3] suggested by Hoover:

$$\text{(7)} \quad \mathrm{PGI}_i = \sum_k \frac{P_k}{D_{ki}^2} \quad \forall\, k : D_{ki} \leq 80 \text{ km},$$

where PGI_i is the population gravity index for parcel i, P_k is the population of census block k within 80 km (~50 mi.) from each parcel, and D_{ki} is the distance between parcel i and census block k in kilometers.[4] Because the distribution of PGI is heavily skewed toward zero, in our model we use the natural logarithm of PGI. The 1990 and 2000 census block data for the PGI calculation are obtained from ESRI Data and Maps (ESRI 1999, 2005).

The other factor that affects accessibility of a parcel is the proximity to a transportation network. We hypothesize that proximity to roads and highways may have a different effect on relative rents to different land uses and forest types. In particular, proximity to highway may be irrelevant for the rural land uses, and have both a positive effect and negative externality effect for the developed (residential) use. Distances from each sample plot to the nearest road and to the nearest highway are calculated using TIGER/Line spatial data from the U.S. Census Bureau.

The restrictions of land use change are taken into account using "Conservation Lands" dummy variable, which takes a value of 1 if a parcel of land is located on conservation easements managed by the U.S. Fish and Wildlife Service and the U.S. Army Corps of Engineers, military reservations, state parks, state wildlife management areas, or private conservation lands. The information about conservation lands is obtained from the Georgia Spatial Data Clearinghouse (GSDI). We assume that parcels located on the conservation lands are less likely to be converted to developed or agricultural uses, and more likely to be converted to less intensively managed forest types (e.g., hardwoods or mixed).

Among observable physical characteristics of the site, we use slope.[5] We hypothesize that the site on a steeper slope is less likely to be converted to agricultural or developed land uses. The value for the slope attribute is derived from the Digital Elevation Model (DEM) obtained from the Georgia Spatial Data Clearinghouse (GSDI).

Land Use and Land Cover Data

To develop a model of land use–land cover transitions, we need information about land cover characteristics for a set of sample points in at least two points in time. We use two National Land Cover Datasets (NLCD): NLCD 1992 and NLCD 2001 based on satellite images taken around 1992, and 2001,

[3] Other specifications of either numerator or denominator of gravity in Equation (7) are possible. For example, Kline, Moses, and Alig use square root of population. We believe that nonlinear transformation of the numerator is inappropriate because it results in the value of the gravity index being dependent on the way populated places are defined, and in case of census blocks would lead to inconsistency between censuses because census block boundaries are often redefined. Other specifications have also been used for the denominator in Equation (7). For an overview, see Song. By testing several specifications with different exponents on distance, we have found that that specification with squared distance performed best in terms of log likelihood ratio.

[4] Other studies that employ a gravity index to model land values or land use change use the three largest cities in the region (Shi, Phipps, and Coyler) or three nearest cities with a population greater than 5,000 persons (Kline, Moses, and Alig) to calculate gravity index.

[5] Soil quality is a physical characteristic of the site that affects transitions between agricultural and forestry uses and is most widely used in econometric models of land use change (Hardie and Parks). We do not use soil quality in our model because the Soil Survey Geographic (SSURGO) Database, which contains soil quality data (prime farmland) at sufficient resolution, is available for only part of the study area. We estimated our model with the soil prime farmland explanatory variable for the area where SSURGO data are available. In the standard conditional logit model, the coefficients for the land quality variable are significant and have expected signs (prime farmland is more likely to be converted to agricultural use and less likely to be converted to forestry use). However, in the spatial conditional logit model, the presence of spatial lag variable for agricultural lands makes the land quality variable insignificant. This indicates that the spatial lag variable captures land quality characteristics of the site.

Table 2. Land Use–Land Cover Transitions, 1992–2001 (Number of Sample Points)

Land Cover–Land Use 1992	Land Cover–Land Use 2001											
	DV	TR	FC	FH	FS	FM	AG	WW	WL	WB	O	Total
Developed (DV)	336											336
Transportation (TR)		224										224
Forest, clear-cut (FC)	1			7	233	3	1				2	247
Forest, hardwood (FH)	25	1	62	1,127	18	26	7			3	7	1,276
Forest, softwood (FS)	28	2	186	2	1,088	34	9				6	1,355
Forest, mixed (FM)	39	3	64	169	131	502	5			3	2	918
Agriculture (AG)	9			2	32		491				7	541
Woody wetland (WW)			1					238		2		241
Wetland (WL)									5	1		6
Water body (WB)									1	106		107
Other (O)	2			1	3						56	62
Total	440	230	313	1308	1,505	565	513	238	6	115	80	5,313

respectively. The resolution of NLCD data sets is 30 m; the study area is covered by over 2 million 30×30 m pixels. However, these data sets cannot be used directly to model land cover transition on a point (pixel) basis. First, the classification schemes of these two data sets are slightly different; some land cover types of NLCD 1992 cannot be matched with land cover types of NLCD 2001 and vice versa. Second, the accuracy is not good enough to model land cover transition on a pixel basis. Finally, NLCD land cover classifications do not differentiate between developed land use and a transportation network, and do not identify clear–cuts and young plantations among other (nonforest) barren, grasses, and shrub land cover types. Transportation infrastructure has distinctively different patterns of transition than the rest of developed uses. Similarly, clear-cuts and young plantations are land cover types that belong to forestry land use; they have different land cover change patterns than nonforestry barren land, grasses, or shrubs.

Correction of these problems required manual reclassification and validation of initial data sets. Because manual validation would be not feasible for every pixel of NLCD data sets, we have performed a systematic sampling by placing a 750-m rectangular grid over the study area, yielding 5,313 30×30 m sample points. The values of land cover types from NLCD 1992 and NLCD 2001 data sets were assigned to sample points. A GIS layer with sample point polygons was overlaid with black and white aerial orthophotos with 1-m resolution dated 1992 and with color aerial orthophotos with 0.8-m resolution dated 2003. The land cover values of the sample points were then visually validated and corrected or reclassified, if necessary, according to the NLCD 2001 classification scheme with additional differentiation of transportation, clear-cut, and young plantation land cover types (21 types total). Based on the analysis of occurrence of different land use–land cover types in a data set, we have collapsed the number of land use–land cover types to 11: developed, transportation, forestry–clear-cut, forestry–hardwood, forestry–softwood, forestry–mixed, woody wetland, agriculture, wetland, water body, and other. The transition matrix of land use–land cover types is shown in Table 2.

Estimation and Results

We model transition between land uses–land cover types over a 9-year interval (1992–2001). Because there is virtually no transition to and from such land use–land cover types as woody wetlands, wetlands, and water bodies (see Table 2), we excluded them from the consideration. As the transition to developed and transportation land uses are practically irreversible, they were excluded from the list of initial land use–land cover types. Finally, there is no theoretical explanation of conversion to and from "other" land use–land cover types. Therefore this type was excluded from the model as well. As a result, in our model we consider seven final (j) land use–land cover types (developed, transportation, clear-cut, deciduous forest, coniferous forest, mixed forest, and agricultural), and five initial (i) land use–land cover types or alternatives (all the preceding except for developed and transportation).

The spatial CL model of land use–land cover change was estimated using SAS 9.1 (SAS Institute, Inc.) over a range of values of parameter γ subject to maximization of log–likelihood function. The maximum of log–likelihood function ($-2{,}221$) was reached at $\gamma = 3.5$. The McFadden pseudo-$R^2 = 0.733$ indicates a good of fit of the model. The results of the spatial CL model estimation are presented in Table 3.

The coefficients for plot attribute variable indicate the effects a particular attribute has on probabilities of transitions to each of the final land uses relative to the probability of transition to the reference land use (agricultural). For example, a significant and positive coefficient of developed land use for the Log PGI variable indicates that the higher the value of Log PGI is, the greater is the probability of development relative to the probability of conversion to agricultural use. Because the values of coefficients and their errors depend on the choice of reference outcome (land use–land cover), we tested joint significance of all coefficients for each of the variables using the log likelihood ratio test. Log likelihood ratio values and their significance are presented in the last column of Table 3. The coefficients for each variable are jointly significant at 1% level.

It is difficult to interpret the coefficients in a conditional logit model because the effect of the variable on a particular transition probability is jointly determined by all the coefficients for this variable. In Table 4 we presented marginal effects of the explanatory variables on the transition probabilities and their errors estimated at the sample mean.[6] Marginal effects of the explanatory variables, calculated separately for each initial land use (see Table 5), while being consistent with marginal effects calculated at the mean of the full sample, provide some additional insights about the factors affecting land use–land cover changes.

The marginal effects for conservation lands dummy indicate that on conservation lands the most likely transition is to mixed forest, while development or transition to agricultural use are the least likely (Table 4). Further analyzing the marginal effect of initial land use–cover types (Table 5), we observe that the probability of hardwood or mixed forest being harvested (converted to clear-cut) is adversely affected by the conservation lands status. Also, on conservation land, mixed forest is less likely to be converted to softwood forest; mixed or hardwood forest is more likely to remain mixed or hardwood forest, and agricultural land is more likely to be converted to softwood forest.

Accessibility to population (as indicated by PGI) and population growth (as indicated by PGI rate of change) significantly influence conversion between land uses and the forest land cover types. First of all, conversion to developed land use is more likely with higher accessibility to population and population growth.[7] This is consistent for development of agricultural lands as well as all forest cover types (Table 5). Second, higher accessibility of population increases the probability of conversion to agricultural land and adversely affects the probability of conversion of agricultural lands to softwood forest (conversion of agricultural lands to forest in most of the

[6] The marginal effect of attribute m of a sample plot on the probability of transition to land use–land cover type j is $\partial P_j / \partial x_m = P_j \left(\beta_{jm} - \sum_{k=1}^{J} \beta_{km} P_k \right)$. The standard errors of marginal effects are calculated using the delta method (Greene).

[7] The elasticity of the probability of development with respect to PGI rate of change calculated at the mean of the sample is equal to 6.7, indicating that a 1% increase in PGI (population density) leads to a 6.7% increase of probability of development. This corresponds with 0.6% annual population growth and 4.1% annual increase of developed lands shown in Table 1.

Table 3. Conditional Logit Model of Land Use Change in West Georgia

Explanatory Variables	Regression Coefficients for Alternative *j*							LLR
	Development	Transportation	Clear-cut	Hardwood	Softwood	Mixed	Agricultural	
Conversion specific constants (α_{ij}):								
Initial clear-cut				**4.326*** (3.236)	**11.384***** (2.686)	**5.753**** (3.053)		
Initial hardwoods	−**6.254**** (3.147)	2.638 (32.102)	−0.778 (2.537)		−0.135 (2.431)	−2.547 (2.544)	−**7.018**** (3.225)	
Initial softwoods	−**10.181***** (2.579)	−1.001 (36.027)	−**3.296**** (1.731)	−**8.136***** (2.459)		−**6.117***** (1.853)	−**10.459***** (2.627)	
Initial mixed	−**8.009***** (2.892)	1.390 (37.125)	−2.520 (2.126)	−**5.595**** (2.568)	−1.026 (1.835)		−**9.302***** (2.951)	
Initial agricultural	−0.871 (3.230)				**6.691***** (2.579)		3.747 (3.269)	
Coefficients for attributes of plots ($\boldsymbol{\beta}_j$):								
Conservation lands			**2.138**** (0.964)	**2.846***** (0.975)	**2.636***** (0.883)	**3.483***** (0.954)		**44.1*****
Log PGI	**0.805***** (0.252)	−0.443 (7.031)	−**0.729**** (0.354)	−0.274 (0.359)	−**0.634**** (0.318)	−0.443 (0.357)		70.8***
Change in log PGI	**6.957***** (2.065)	8.544 (12.385)	0.449 (2.075)	1.343 (2.070)	−0.564 (1.927)	1.133 (2.063)		44.6***
Slope	0.060 (0.098)	−0.044 (1.474)	**0.197**** (0.087)	**0.204**** (0.088)	**0.203**** (0.083)	**0.258***** (0.093)		18.7***
Log distance to highway	−**0.567***** (0.185)	−**0.896*** (0.670)	−0.111 (0.185)	−0.202 (0.191)	−0.202 (0.175)	−0.216 (0.194)		33.5***
Log distance to road	−0.164 (0.167)	−0.337 (2.385)	**0.313**** (0.154)	0.194 (0.158)	0.099 (0.144)	−0.129 (0.165)		28.1***
Spatial lags (λ_j)	−2.338 (2.671)	−0.547 (338.929)	**7.562***** (2.869)	**2.556*** (1.618)	1.200 (0.994)	**5.228***** (1.680)	**8.023***** (2.249)	40.4***
Number of observations	4,274							
McFadden's pseudo-R^2	0.733							
Log Likelihood	−2,221							

Note: Standard errors in parentheses.
* Significant at 20%. ** Significant at 10%. *** Significant at 1%.

Table 4. Marginal Effects of Explanatory Variables on Transition Probabilities in Spatial Conditional Logit Model of Land Use–Land Cover Change in West Georgia

	Final Land Use–Land Cover Type (Alternative *j*)						
Explanatory Variables	Development	Transportation	Clear-cut	Hardwood	Softwood	Mixed	Agricultural
Initial land use–land cover types							
Clear-cut	**−0.276***** (0.096)	−0.003 (0.018)	**−0.847***** (0.299)	**−0.725*** (0.457)	**2.122***** (0.404)	−0.058 (0.064)	**−0.214**** (0.092)
Hardwoods	**−0.199**** (0.092)	0.001 (0.004)	−0.014 (0.163)	0.136 (0.384)	0.304 (0.405)	−0.054 (0.061)	**−0.175**** (0.086)
Softwoods	**−0.259***** (0.099)	0.001 (0.008)	−0.045 (0.170)	**−1.099***** (0.423)	**1.702***** (0.427)	**−0.093*** (0.070)	**−0.208**** (0.092)
Mixed	**−0.192**** (0.092)	0.001 (0.004)	0.007 (0.159)	**−0.629*** (0.397)	**0.922**** (0.431)	**0.074**** (0.038)	**−0.184**** (0.088)
Agricultural	**−0.173**** (0.092)	−0.001 (0.009)	**−0.437***** (0.159)	**−0.841**** (0.392)	**1.576***** (0.519)	**−0.115***** (0.044)	−0.008 (0.068)
Attributes of plots							
Conservation lands	**−0.088***** (0.028)	−0.001 (0.006)	−0.037 (0.040)	0.076 (0.075)	0.090 (0.087)	**0.029**** (0.013)	**−0.068***** (0.023)
Log PGI	**0.046***** (0.014)	0.000 (0.002)	**−0.025**** (0.013)	0.046 (0.037)	**−0.082**** (0.046)	0.001 (0.005)	**0.014*** (0.010)
Log PGI rate of change	**0.237***** (0.052)	0.003 (0.020)	0.018 (0.082)	**0.223*** (0.157)	**−0.497***** (0.181)	0.024 (0.026)	−0.008 (0.051)
Slope	**−0.005**** (0.002)	0.000 (0.001)	0.000 (0.003)	0.002 (0.006)	0.006 (0.008)	**0.002*** (0.001)	**−0.005**** (0.002)
Log distance to highway	**−0.013***** (0.003)	0.000 (0.002)	0.010 (0.008)	0.000 (0.015)	−0.001 (0.016)	0.000 (0.003)	0.005 (0.005)
Log distance to road	**−0.010***** (0.004)	0.000 (0.001)	**0.021**** (0.010)	0.015 (0.017)	−0.014 (0.017)	**−0.007**** (0.003)	−0.003 (0.004)
Spatial lag (λ_j)	−0.080 (0.092)	0.000 (0.113)	**0.733**** (0.412)	**0.423*** (0.271)	0.290 (0.241)	**0.146**** (0.066)	**0.214***** (0.073)

Note: Standard errors in parentheses;
* Significant at 20%. ** Significant at 10%. *** Significant at 1%.

Table 5. Marginal Effects of Explanatory Variables on Transition Probabilities Calculated Separately for Each Initial Land Use/Land Cover Type

		Final Land Use–Cover Type (Alternative J)						
Explanatory Variables	Initial Land Use	Development	Transportation	Clear-Cut	Hardwood	Softwood	Mixed	Agricultural
Conservation lands	Forest, clear-cut							
	Forest, hardwood	−0.019***		−0.028*	0.054**		0.003*	−0.006**
	Forest, softwood	−0.018***				0.075*	0.004**	−0.010**
	Forest, mixed	−0.057***		−0.068***		−0.050**	0.198***	−0.007**
	Agriculture	−0.001**				0.119***		−0.124***
Log PGI	Forest, clear-cut				0.010*	−0.015**		
	Forest, hardwood	0.007**		−0.019**		−0.007*		
	Forest, softwood	0.010***			0.003*			0.003*
	Forest, mixed	0.022**		−0.017*				
	Agriculture	0.006**				−0.029**		0.024*
Log PGI rate of change	Forest, clear-cut				0.052*	−0.079**		
	Forest, hardwood	0.038***				−0.038**		
	Forest, softwood	0.052***			0.015**	−0.179**	0.006*	
	Forest, mixed	0.103***				−0.136**		
	Agriculture	0.046**						
Slope	Forest, clear–cut							
	Forest, hardwood	−0.001**						0.000**
	Forest, softwood	−0.001**						−0.001**
	Forest, mixed	−0.003**					0.012**	−0.001*
	Agriculture					0.009**		−0.010**
Log distance to highway	Forest, clear-cut							
	Forest, hardwood	−0.002**						
	Forest, softwood	−0.003***		0.010*				
	Forest, mixed	−0.006**						
	Agriculture	−0.004**						0.013*
Log distance to road	Forest, clear-cut							
	Forest, hardwood	−0.002**					−0.001**	
	Forest, softwood	−0.002**		0.024***		−0.021**	−0.001**	
	Forest, mixed			0.024***	0.010**	0.014**	−0.046***	
	Agriculture							

Note: Marginal effects are not shown if the significance level is less than 20%.
* Significant at 20%. ** Significant at 10%. *** Significant at 1%.

cases is conversion to softwood forest). Finally, PGI and/or PGI rate of change affect the probabilities of important transitions between forest cover types. Both PGI and PGI rate of change affect conversion of clear-cuts to either hardwood or softwood forest with accessibility to population and population growth adversely affecting the probability of conversion to softwood forest (a more intensively managed forest management type, usually pine plantations). High values of PGI decrease the probability of clear-cuts of hardwood and mixed forests. Higher PGI rate of change negatively affects conversion of all forest types to softwoods and increases the probability of converting softwood forest to hardwood or mixed forest (less intensively managed forest types). The effects of PGI and PGI rate of change on transition between forest types indicate that landowners are not willing to manage forest intensively, and, in particular, invest in plantations in a proximity to locations with growing population because of the higher chance of development in the near future. Furthermore, forests located near populated places are more likely to be managed for amenity values. This corresponds with findings of Munn et al.; Polyakov, Majumdar, and Teeter; and Wear et al.

The slope of the site negatively affects the probability of development and transition to agricultural land use because steeper slopes increase development costs and impede agricultural operations. At the same time, slope positively affects the probability of conversion to mixed forest and conversion of agricultural lands to softwood forest. Development is more likely closer to highways and roads. Proximity to roads decreases the probability of clear-cuts and increases the probability of conversion to mixed forest.

Positive and significant values of marginal effects for spatial lags are shown for clear-cut, hardwood and mixed forest, and agriculture. Conversion to and retention of these land uses are more likely in proximity to the concentration of these land uses in a previous period.

None of the explanatory variables explains transition to transportation land use. The possible reason for this is that there are very few instances of conversion to transportation land use in our data set. However, on the positive side, this means that roads do not pose an endogeneity problem in our model.

Validation and Projections

The challenge of using the results of land use–land cover change model for simulation stems from the fact that discrete choice models yield probabilities of conversions (Bockstael). For example, in our sample during the study period an average parcel of softwood forest has a 0.849 chance to remain softwood forest, a 0.007 chance to be developed, a 0.127 chance to be clear-cut, a 0.009 chance to be converted to hardwood, and a 0.004 chance to be converted to mixed forest or agricultural use. Direct evaluation of the forecasting performance of the model is not possible. Simply assuming that the parcel will be converted to the land use–land cover type according to the highest probability of conversion would yield no change for most of the parcels because retention of the current land use–land cover type often has the highest probability.

We evaluated the forecasting performance of the spatial conditional logit model using information indices and statistics developed for evaluating the performance of discrete choice models by Hauser.[8] He suggests using information index $I(\mathbf{A};\ \mathbf{X})$ to quantify information provided by the explanatory variables:

$$(8) \qquad I(\mathbf{A};\mathbf{X}) = \frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{J}\delta_{mj}\ln\left(\frac{p(a_j|\mathbf{x}_n)}{p(a_j)}\right),$$

where $p(a_j)$ is the prior (without the model) likelihood of land use–land cover type j, $p(a_j \mid \mathbf{x}_n)$ is land use–land cover type j predicted by the model, and δ_{mj} is the binary variable indicating land use–land cover type j observed at sample plot m. The information measure is compared with the expected information

[8] For evaluating performance of land use change models these indices were used by Kline, Azuma, and Moses, and Wear and Bolstad.

Table 6. Information Indices and Statistics Computed for the Forecasting Model Applied to Validation Data Sets

	n	H(A; X)	I(A; X)	EI(A; X)	V(A; X)	t-Statistic	U^2	LLR
Within sample	4,274	1.5248	1.0050*	1.0052	0.6642	0.0002	0.6591	8,591*
Out of sample:								
Random 10%	439	1.5213	0.9491*	1.0130	0.6848	0.0772	0.6239	833*
Harris county	1,766	1.5418	0.9469*	0.9441	0.6393	0.0035	0.6141	3,344*
Meriwether county	1,906	1.5278	1.0547*	1.1290	0.5793	0.0976	0.6904	4,021*
Muscogee county	602	1.4805	1.1870*	1.3515	1.0583	0.1599	0.8018	1,429*

* Significant at 1%.

provided by the model:

$$(9)\qquad EI(\mathbf{A};\mathbf{X}) = \frac{1}{N}\sum_{n=1}^{N}\sum_{j=1}^{J} p(a_j|\mathbf{x}_n)\ln\left(\frac{p(a_j|\mathbf{x}_n)}{p(a_j)}\right)$$

The information index I(**A**; **X**) is normally distributed with a mean of EI(**A**; **X**) and a variance of V(**A**; **X**):

$$(10)\qquad V(A;X) = \frac{1}{N}\sum_{n=1}^{N}\left\{\sum_{j=1}^{J} p(a_j|x_n)\left[\ln\left(\frac{p(a_j|x_n)}{p(a_j)}\right)\right]^2 - \left[\sum_{j=1}^{J} p(a_j|x_n)\ln \times \left(\frac{p(a_j|x_n)}{p(a_j)}\right)\right]^2\right\},$$

which allows testing the accuracy of the model.

The index of prior (before observing **X**) entropy:

$$(11)\qquad H(\mathbf{A}) = -\sum_{j=1}^{J} p(a_j)\ln p(a_j|\mathbf{x}_n)$$

is a benchmark of uncertainty in the system and allows measuring the proportion of uncertainty explained by the model:

$$(12)\qquad U^2 = I(\mathbf{A};\mathbf{X})/H(\mathbf{A}).$$

Furthermore, the log-likelihood ratio LLR = $2n \times I(\mathbf{A};\mathbf{X})$ is χ^2 distributed with degrees of freedom equal to the number of coefficients in the model and allows testing the significance of the empirical model.

To evaluate the forecasting performance of our model, we have conducted within-sample and out-of-sample predictions of land use–land cover change probabilities for the study period. We used two approaches for out-of-sample predictions. First, we randomly selected 10% of sample plots as a validation data set, estimated the model using the remaining 90% of sample plots, and applied model coefficients to predict transition probabilities for the validation data set. Second, we reserved sample plots of one county as a validation data set, estimated the model using sample plots of the two remaining counties, and predicted transition probabilities for the validation data sets. This was repeated for each county. Information indices and statistics calculated for within-sample and out-of-sample predictions are presented in Table 6. The U^2 values suggest that the proportion of uncertainty explained by the empirical model is relatively high and are comparable with McFadden pseudo-R^2 (Table 3). The t-statistics computed based on the projected land use–land cover transition probabilities suggest that the empirical model is accurate, while the log-likelihood ratios (LLR) indicate that model is statistically significant.

To predict land cover change for the 20-year period, we applied coefficients of the spatial CL model of land use–land cover change to the full NLCD 2001 dataset covering three counties. Before applying the model, we used color aerial orthophotos with 0.8-m resolution to reclassify developed land use into transportation and developed, and to separate clear-cuts and young plantations from ''shrub–scrub,'' ''grassland–herbaceous,'' and ''barren land'' land covers.

For the period of projection, we assumed that population changes with the same rate it was changing during 1990–2000 period. For

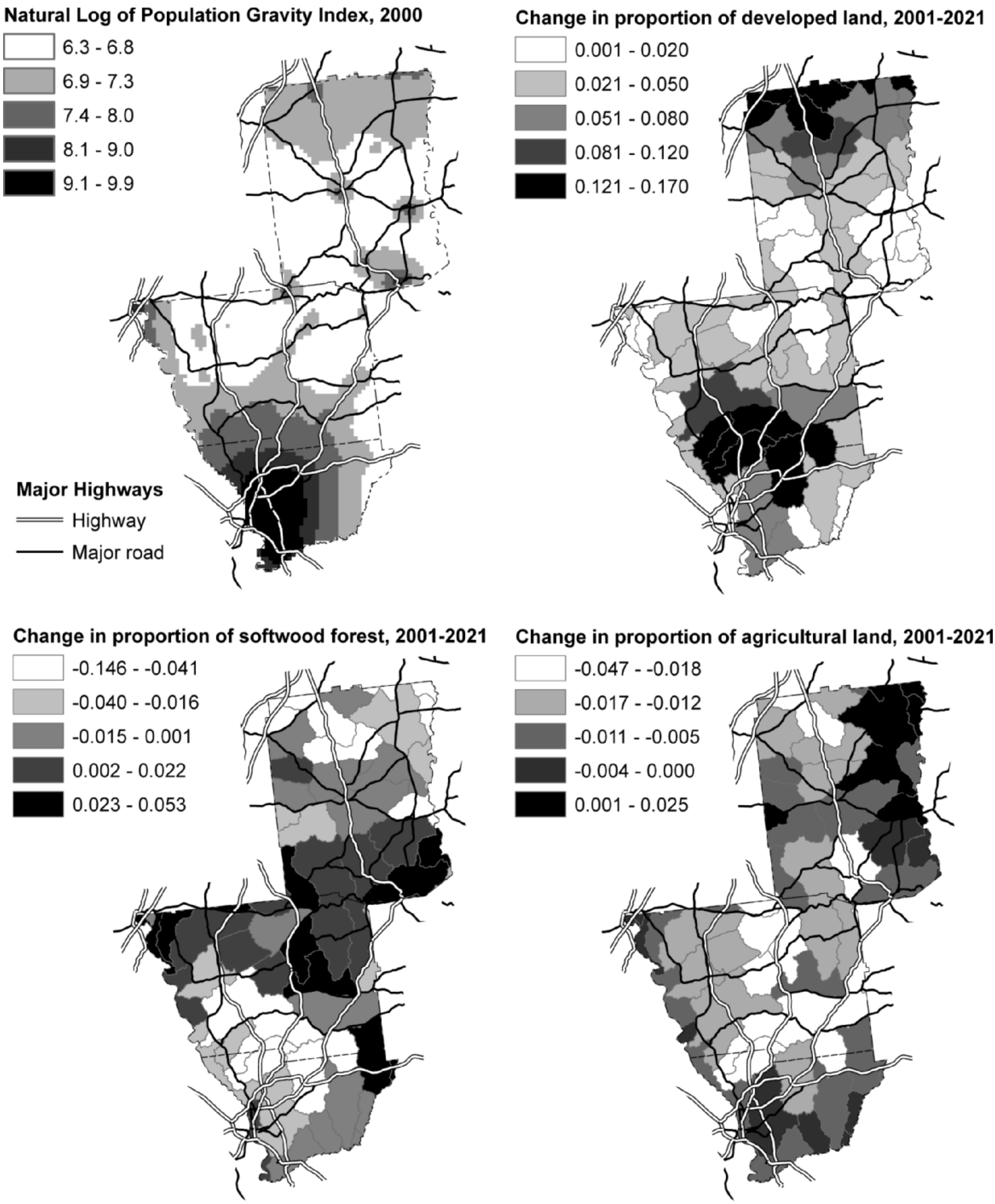

Figure 2. Distribution of Population Gravity Index and Prediction of Change in Developed and Agricultural Land Uses and Softwood Forests at Watershed Level

example, if the population of some census block increased by 20% during 1990–2000, we assumed that it will increase with the same rate during the next two decades. The estimated spatial CL model coefficients were combined with projected PGI to calculate the probabilities of land cover type changes for each at 10-year intervals. Following Bockstael (1996), predicted probabilities were translated into percentages. This approach does not allow for predicting the exact land use–land cover type for each individual pixel.[9] However, aggregation of land use–land cover shares to particular geographic areas allows projecting land use–land cover dynamics for these areas. For illustration, we aggregated our projections to 12-digit hydrologic units.[10] The dynamics of developed and agricultural land uses and softwood forest type are presented in Figure 2. The greatest increase of the proportion of developed lands is predicted for the outskirts of the city of Columbus in the north of Muscogee County and the south of Harris County. Another location with predicted significant increase in proportion of developed lands is the northern part of Meriwether County, where development is caused by proximity to the Atlanta metropolitan area and the I-85 corridor. An increase in the proportion of softwood forests is predicted for the northern part of Harris County and southern part of Meriwether County, while some increase in the proportion of agricultural land use is predicted for the eastern part of Meriwether County. For the purposes of the WestGA Project (Lockaby et al.) similar aggregations were obtained for 26 smaller watersheds (300 to 2700 ha) selected across three counties that are used to address the effects of urbanization on water quality, biodiversity, and ecosystem processes.

Conclusions

This article presents a spatial conditional logit model of land cover–land use change in three West Georgia counties during the period 1992–2001. The use of spatial lag allows spatial correlation between observations of the same sample plot to account for the panel data. The results show that both the level and change of PGI (a measure of accessibility to population) are important factors affecting allocation of land between rural and developed uses, between agricultural and forestry uses, and between forest management types.

The contribution of this study lies in the following areas. First, we implement a spatially explicit econometric model of land use–land cover change that models changes between rural and urban uses, between agricultural and forestry uses, and between forest cover types. This model can be used to forecast land use change at a small (subwatershed and watershed) scale and serve as a useful tool for ecologists, hydrologists, and city and county planners. Second, our model simultaneously describes land use changes occurring among several different land use classes, as opposed to modeling changes for each initial land use separately. This allows better utilization of land use change data where probabilities of changes are relatively low and probabilities of retention are relatively high. Third, we find that accessibility to population drives not only the transition of rural land uses to developed land and allocation between forestry and agricultural uses, but also transition between forest cover types (forest management types).

There are several limitations and shortcomings of this study, however, that we hope to correct in the future. First, the conditional logit model assumes that the independence of the irrelevant alternatives (IIA) property holds. This is a very strong assumption. It can be relaxed by applying nested or random parameter logit models. Second, we do not take into account zoning, which determines, among other things, possibility and maximum density of development. Finally, alternative scenarios of population growth could be explored. For example, the opening in 2008 of the new automotive plant in West Point, GA, which is adjacent to the study area, could have a large impact on population growth and thus land use in the neighboring watersheds.

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[9] Another way of converting predicted probabilities of land use change into discrete outcomes is to apply Monte Carlo simulation (Lewis and Plantinga).

[10] A hydrologic unit is a topographically defined area of land, the boundaries of which are ridge tops. A 12-digit hydrologic unit is a level 6 subwatershed. The sizes of the 12-digit hydrologic units within the study area range between 3,000 to 12,000 ha.

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