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# Modeling the relationships between land use and land cover on private lands in the Upper Midwest, USA

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*This paper presents an approach to modeling land-cover change as a function of land-use change. We argue that, in order to model the link between socio-economic change and changes in forest cover in a region that is experiencing residential and recreational development and agricultural abandonment, land-use and land-cover change need to be represented as separate processes. Forest-cover change is represented here using two transition probabilities that were calculated from Landsat imagery and that, taken together, describe a Markov transition matrix between forest and not-forest over a ten-year period. Using a three-date land-use data set, compiled and interpreted from digitized parcel boundaries, and scanned aerial photography for 136 sites (c. 2500 ha) sampled from the Upper Midwest, USA, we test functional relationships between forest-cover transition probabilities, standardized to represent changes over a decade, and land-use conditions and changes within sample sites. Regression models indicated that about 60 percent of the variation in the average forest-cover transition probabilities (i.e. from forest to not-forest and vice versa) can be predicted using three variables: amount of agricultural land use in a site; amount of developed land use; and the amount of area increasing in development. In further analysis, time lags were evaluated, showing that agricultural abandonment had a relatively strong time-lag effect but development did not. We demonstrate an approach to using forest-cover transition probabilities to develop spatially-constrained simulations of forest-cover change. Because the simulations are based on transition probabilities that are indexed to a particular time and place, the simulations are improved over previous applications of Markov transition models. This modeling approach can be used to predict forest-cover changes as a result of socio-economic change, by linking to models that predict land-use change on the basis of exogenous human-induced drivers.*



*Keywords*: remote sensing, Markov models, land-use change, forest fragmentation.

## Introduction

Models of land-use and land-cover change are powerful tools that can be used to understand and analyze the important linkage between socio-economic processes associated with land development, agricultural activities, and natural resource management strategies and the ways that these changes affect the structure and function of ecosystems (Turner and Meyer, 1991). We define *land use* as human activity on the land (*in sensu* Turner *et al*., 1995). Land use is influenced by economic, cultural, political, historical, and land-tenure factors at multiple scales. *Land cover*, on the other hand, is one of the many biophysical attributes of the land that affect how ecosystems function (*in sensu* Turner *et al*., 1995). In frontier regions with economies based primarily on extractive industries (e.g. developing countries), land use and land cover are often semantically equivalent. For example, the land-use activity associated with logging leads to a deforested land cover (Lambin, 1997). Therefore, satellite images can often be used to detect land-use change through observations of the biophysical characteristics of the land. However, in a post-modern and information-driven economy, like most of the contemporary United States and Europe, land use and land cover are less likely to be equivalent. Although forestry can be modeled as a land-use activity that responds to economic, social, and demographic drivers

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(e.g. Alig, 1986; Mauldin *et al*., 1999), such drivers do not provide direct predictors for understanding and modeling the amount and locations of forests and tree-cover in all parts of a landscape. Changes in the amount of carbon sequestered in forests and their soils, for example, is ambiguously related to dispersed rural residential development in a dominantly agricultural landscape. Development of second homes in a forested region may involve little clearing of trees on largely forested or reforesting lots, and agricultural abandonment or conversion into residential uses often leads to regrowth of forests (Staaland *et al*., 1998; Foster and Gross, 1999).

This paper addresses the implications of the fundamental differences between land use and land cover for modeling landscape change. Attempts to model land-cover (e.g. forest-cover) change at the landscape scale as a direct function of socio-economic change (viz., Lambin, 1997), are problematic in developed economies. Existing models rarely include the effects of land-use change on land cover explicitly. Predictive models of landscape change in a human-inhabited landscape must describe the social processes that affect land use (e.g. development, agricultural production, tourism and recreation). Because land-use change occurs parcel-by-parcel, where the parcel is the basic unit of land ownership, information should be collected, and processes modeled, with the parcel as the basic unit. To characterize the biophysical implications of land-use change, e.g. on biodiversity, water quality, and carbon sequestration, the relationships between land use and land cover must also be quantified. Land-cover change is not restricted to parcel boundaries and sub-parcel representation of land cover is preferable. Because land use and land cover are related but not equivalent, models of landscape change should include this missing link. Additionally, by coupling land-use and land-cover change models, such a link may provide modelers of land-use change with a means to use remote sensing data to help validate land-use change models.

We start by describing an approach to modeling the relationship between land-use and land-cover change as distinct, but linked, processes. We then present an empirical analysis of the linkage between rural residential development, agricultural abandonment, and changes in forest cover on private lands in the Upper Midwest USA, from the early 1970s to the early 1990s. The specific objectives of this paper are to:

- present a framework for modeling that represents land use and land cover separately and that characterizes the link using Markov transition probabilities;
- describe an approach to calculating Markov transition probabilities from multitemporal classified satellite imagery, when such imagery contains some degree of classification and positional uncertainty;
- develop functional relationships between land-cover transition probabilities and land-use change at the landscape scale; and
- present a simple illustration of the approach described for the spatial simulation of forest-cover change.

## Land-use and land-cover change modeling

Models of land-use and land-cover change have been developed to address when, where and why land-use and land-cover change occurs (for good summaries of these models see Baker, 1989; Riebsame *et al*., 1994; Lambin, 1997; Theobald and Hobbs, 1998). They usually involve empirically fitting the models to some historical pattern of change, then extending those patterns into the future for prediction. Because our ultimate goal is to understand the processes driving changes in the amount and distribution of forest in the Upper Midwest, and because the amount and distribution of forest in the Upper Midwest is largely socially and economically determined through the determination of land use, we require an approach that links the drivers of land-use change, the associated changes in land ownership and use, and the resulting changes in forest cover (Figure 1). We treat land-use change as a separate process from land-cover (i.e. forest-cover) change. The general structure shown here, i.e. using regional and global scale drivers to determine the amount of change, and geographic and landscape scale drivers to determine its pattern, is similar to that taken in the Conversion of Land Use and its Effects (CLUE) model of land-cover change in the

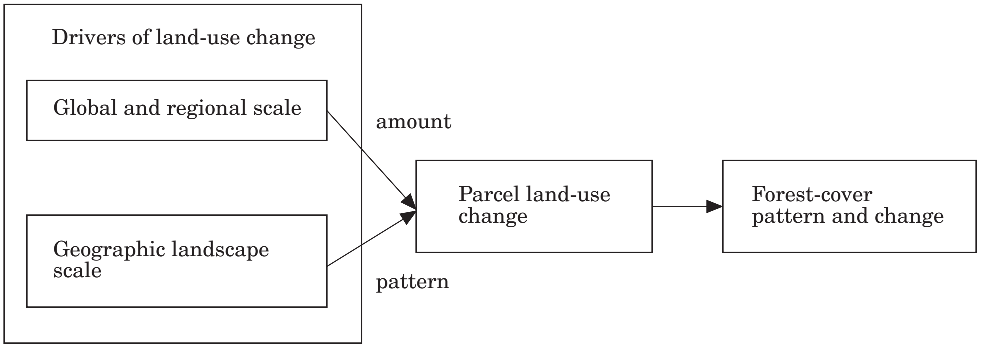


**Figure 1.** The general modeling framework used in this project. This paper focuses on the link between land use and forest-cover change.

tropical frontier (de Koning *et al.*, 1999) and the Land Transformation Model (LTM) which has been used in the Upper Midwest, USA (Pijanowski *et al.*, 2000). In this section we present background information on the forest-cover modeling approach employed.

Transition probabilities have been used extensively for analysis and modeling of land-use and land-cover change (Burnham, 1973; Bell, 1974; Turner, 1987; Muller and Middleton, 1994). The approach treats state transitions as Markovian random processes that are conditional on the initial state only. Transition models can be expressed in matrix form as:

$$n_{t+1}=Pn_t \tag{1}$$

where $n_t$ is a vector of land-area fractions in each of $m$ cover or use types at time $t$, $n_{t+1}$ is the vector of land-area fractions for the same types at $t+1$, and $P$ is an $m\times m$ matrix which expresses the probability that a site in state $i$ at time $t$ will transition to state $j$ at time $t+1$. The matrix $P$ is row-standardized, such that the sum of transition probabilities from a given state is always equal to one. The value of the approach is that the transition matrix, once specified, can be used analytically to project future landscape compositions (Jahan, 1986; Guttorp, 1995) or in simulation modeling to develop alternative landscape scenarios (Burnham, 1973; Turner, 1987). Any set of states (e.g. land-use or land-cover classes) can be used, provided their definitions do not change over time, at any scale of analysis. The change matrix is often derived from multiple temporal classifications of land use or land cover (Bell, 1974; Turner, 1987).

The primary limitations of Markov-based transition probability-based models for land-use and land-cover change analyses are: (1) the assumption of stationarity in the transition matrix, i.e. that it is constant in both time and space; (2) the assumption of spatial independence of transitions; and (3) the difficulty of ascribing causality within the model, i.e. the transition probabilities are often derived empirically from multi-temporal maps with no description of the process (Baker, 1989). This third limitation is particularly acute when land-cover changes are under investigation, for example from remotely sensed imagery, and when those changes are driven by social and economic processes (Turner, 1987). To address both limitations 1 and 3 above, Baker (1989) suggested setting state transition probabilities as a function of exogenous or endogenous variables, which vary in space and time. Equation (1) then becomes

$$n_{t-1}=P[f(t,x)]n_t \tag{2}$$

and

$$p_{ij}=f(t,x)=b_1X_1+b_2X_2+\cdots+b_sX_s \tag{3}$$

where $p_{ij}$ are the elements in the matrix of transition probabilities $P$, and the parameters (e.g. $b_s$) describe the functional relationship between some set of predictor variables (e.g. $X_s$), which can vary in both time ($t$) and space ($x$), and $p_{ij}$. Turner (1987) demonstrated an approach to conditioning the changes to initial states in adjacent sites, in addition to conditioning changes on the initial state, thereby introducing spatial dependence into the simulation (the second limitation).

Whereas Markov transition probabilities provide a convenient analytical framework for simulating land-cover change using observed transitions, e.g. from remote sensing, alternative approaches are typically used for modeling the influence of social and economic drivers on land-use change. The alternative model structures are designed to introduce a better representation of causation into the models, by relating change to either exogenous driving variables, spatial interaction processes, or both. Theobald and Hobbs (1998) summarized two primary types of causal land-use change models: regression-type models and spatial transition-based models. The former type establishes functional relationships between a set of spatial predictor variables that are used to predict the locations of change on the landscape. These include logistic regression models (Landis, 1994), hedonic price models (Alig, 1986; Geoghegan *et al*., 1997), and artificial neural networks (Pijanowski *et al*., 2000). The latter type of models is exemplified by a spatial-temporal extension of the Markov transition models referred to as cellular automata (Deadman *et al*., 1993; Clarke *et al*., 1997). Both types of models can be used to include geographic site and situation variables in modeling change. Because we view land-use change as the proximate cause of forest-cover change and the result of change in exogenous driving variables, the approach we present here bridges land-use change models based on functional relationships with human-induced exogenous driving variables and the transition probability approach to modeling land-cover change.

## Study area and data

Our study was conducted over the Upper Midwest, USA, which includes northern portions of Michigan, Minnesota, and Wisconsin (Figure 2). Secondary forests, having regenerated following nearly complete harvest of pre-European forests in the late 19th and

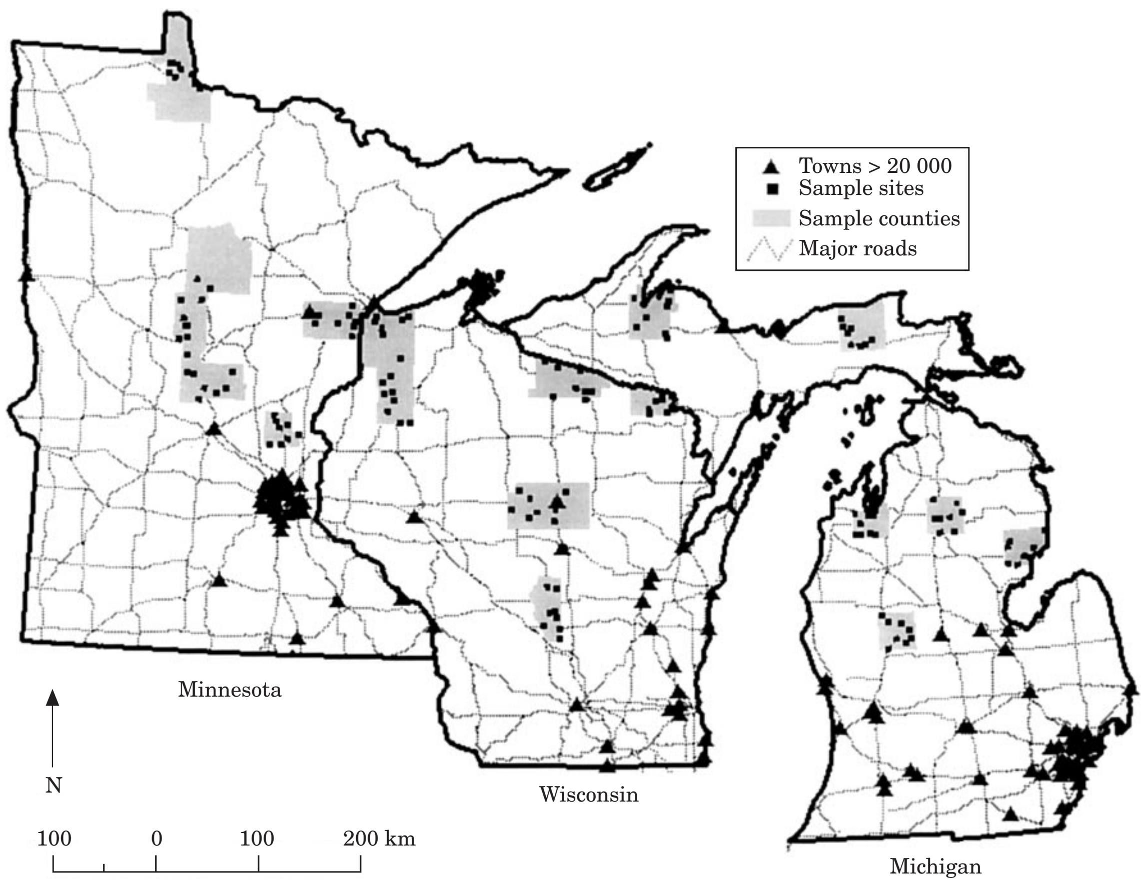


**Figure 2.** The study region, showing locations of sample counties and sample sites.

early 20th centuries (Williams, 1989), cover large portions of the region. Three major land-use trends are evident in the region. First, like many forested areas in the US and throughout the temperate mid-latitudes, forest-cover is increasing (Houghton *et al.*, 1999). Forest cover increased in the region by 3% between 1980 and 1993 (Schmidt, 1997; Miles and Chen, 1992; Leatherberry and Spencer, 1996). Second, the amount of farmland in the region declined by 5% between 1987 and 1997 (Census of Agriculture, 1997). Third, ownership became increasingly fragmented into more and smaller parcels. During the 30 years between 1960 and 1990, average private parcel sizes declined by an average of 1·2 percent per year across the region (Brown and Vasievich, 1996).

These land-use changes are related to broader demographic shifts occurring in rural areas throughout the United States, including the Upper Midwest. During the 1970s, the observed growth rate in the population of non-metropolitan areas exceeded the growth rate of metropolitan areas for virtually the first time in the 20$^{th}$ century. Widespread migration out of rural areas followed in the 1980s, due to a significant decline in the farm economy and loss of employment opportunities. Rural areas again saw significant immigration in the 1990s, because of a rebound in rural employment, a recession in the early 1990s that affected urban areas more than rural areas, and increasing integration with the national and international economies through improved transportation and communications infrastructure (Johnson, 1998; Johnson and Beale, 1998).

## *Area-frame sampling*

A stratified sampling scheme, based on a demographic/economic classification of counties and on locational differences within counties relative to urban areas, lakes, major roads and public lands, was used to select representative sample area frames. The sampling approach is summarized here, and described in more detail by Brown and Vasievich (1996). We classified county types using a cluster analysis based on variables derived from a principal-components analysis of county-level census and economic data between 1960 and 1990. All counties in the region were classified into one of four demographic/economic types, according to the dominant controls and patterns of demographic change. We selected three to six counties within each demographic/economic type, making a total of 17. The counties selected from Michigan were Baraga, Crawford, Grand Traverse, Iosco, Luce, and Mecosta; in Minnesota the counties were Carlton, Cass, Isanti, Lake of the Woods, and Morrison; and in Wisconsin they were Adams, Douglas, Florence, Marathon, Vilas, and Washburn (Figure 2).

Within each county we selected eight area frames, or sites, that were 3 by 3 survey sections, or approximately 2500 ha, in size. The sites selected within counties were stratified by proximity (near or not-near) to major roads, public lands, large lakes (greater than 4 ha), and urban areas (any that were delineated on 1:24 000 scale topographic quadrangles). Nearness was defined using a set buffer distance around each feature, ensuring that samples were taken both inside and outside the buffer. We set buffer distances, essentially working hypotheses of the influences of each feature, as follows: 8 km for roads, 5 km for public lands, 3 km for lakes, and 8 km for urban areas. Sites were positioned so that each site fell entirely within one county. Sites were not selected if they contained a substantial proportion (i.e. greater than 30 percent) of urbanized area, public land, or water. A total of 136 sample sites was identified (Figure 2).

## *Land-use data*

The land-use data we used were interpreted from parcel maps and aerial photography, and we mapped by parcel for the 136 sample sites for each of three dates (early 1970s, early–mid 1980s, and early 1990s). Parcel boundaries (Figure 3a) were digitized from plat books that are published periodically for each county at a scale of approximately 1:51 000 (e.g. Accurate Publishing, 1993 and Rockford Map Publishers, 1990). To ensure that parcel boundaries overlaid, parcels were digitized completely from the 1990s maps and edited, by deleting or adding boundary lines, to create the 1970s and 1980s maps. Aerial photography (Figure 3b) ranged in scale between approximately 1:15 000 and 1:70 000 and was scanned at the equivalent of 2 m

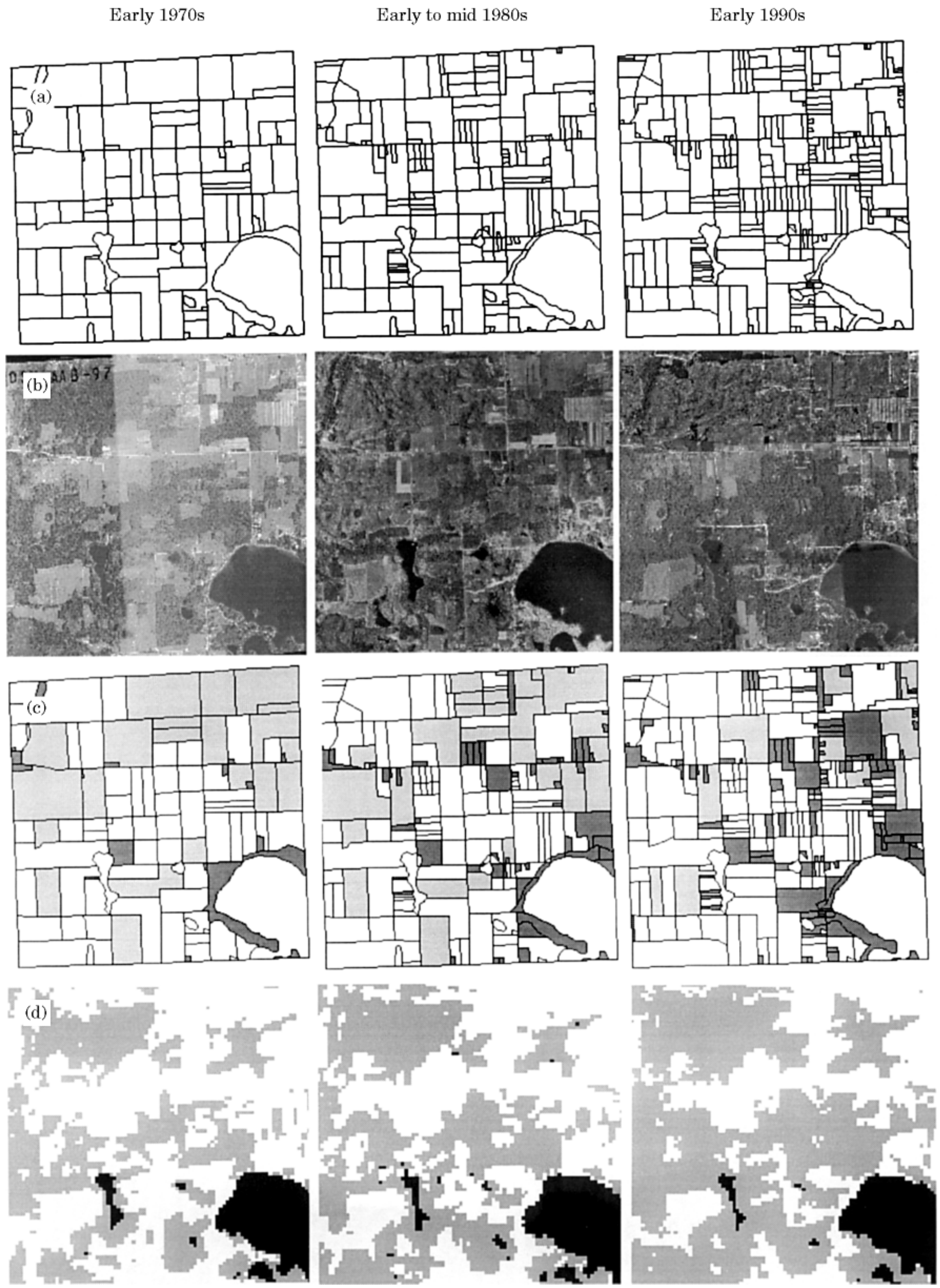


**Figure 3.** Data for one of the 136 sample sites mapped for this study. (a) Parcel boundaries digitized from published plat books. (b) Scanned and rectified aerial photograph mosaics. (c) Three major classes of interpreted land use based on the primary classification (white is undeveloped, light gray is agriculture, dark gray is developed). (d) Forest cover classified from NALC data (white is not-forest, gray is forest, black is water or cloud).

ground resolution, rectified, and mosaiced for each site at each date.

Each parcel was assigned a primary and secondary land-use code from among 27 different categories, but our analysis simplifies the categories to focus on developed, undeveloped, and agricultural uses (Figure 3c). The quality of the land-use class assignments was evaluated using three-date composites. Three different types of transitions were flagged through a database query and revisited by an interpreter to evaluate and, if needed, change the classifications at all three dates. First, several transitions were identified as unlikely in any event (e.g. transitions from most developed to undeveloped or agricultural uses). Second, overlay polygons that had a different class assignment in each of the three dates were flagged. Finally, overlay polygons were re-visited if they started the study period as one class, changed to a second class in the second time interval, then reverted to the first class in the third period. This quality control procedure was used to identify and fix the most obvious classification problems.

### *Forest-cover data*

Land cover was characterized across the entire region using the North American Landscape Characterization (NALC) data produced from Landsat Multispectral Scanner (MSS) triplicates corresponding to three time periods similar to those of the land-use data: 1972–1975, 1985–1987, and 1990–1992. Our region spans about 20 MSS scenes. The NALC data set (Lunetta *et al*., 1998) has a spatial resolution of 60 m and a target spatial uncertainty (measured as root mean squared error) of less than one pixel (i.e. 60 m). Because the actual reported spatial error in the scenes was not always less 60 m, and based on our informal assessment of image registration quality, their spatial registration posed a challenge for change analysis.

We used a combination of digital-number (DN) thresholds and unsupervised classification to assign pixels to one of four classes: forest, non-forest, water, and other (which includes clouds and cloud shadows). Brown *et al*. (2000) described the image-processing and classification procedures in detail. In the first step, thresholds were identified interactively for each image on various spectral channels and channel combinations to identify clouds, cloud shadows, and water. Areas affected by haze were also identified using DN thresholds and were adjusted according to a method described by Richter (1990) to reduce the atmospheric effect on the subsequent image classification.

Areas not classified as clouds, cloud shadows, or water were classified using the iterative self-organizing data analysis routine (ISODATA) to assign each pixel to one of between 50 and 70 spectrally homogenous clusters (Jain, 1989). Classes were labeled as forest or non-forest through on-screen comparison of spectral cluster locations with corresponding aerial photography. Forest was defined as having greater than 40% tree canopy cover, which is a reasonable threshold for the broadleaf and mixed coniferous/broadleaf forests that dominate the study region (World Wildlife Fund, 1999). We used the aerial photo-mosaics to support image classification and accuracy assessment. The accuracy of the classifications corresponding to the study sites ranged from 66·7 to 94·5%. Accuracies tended to be lower in the 1970s period and higher in the 1990s period (Brown *et al*., 2000). Forest-cover data were labeled ‘missing’ if a site was more than 50% cloud-covered.

## Methods

The empirical analysis involved developing a statistical model of the forest transition probabilities, aggregated by site, as a function of the types and magnitudes of land-use and parcel-size change within the 136 sample sites. We also calculated the change in a metric of the local spatial pattern of the forest. The transition probabilities were then used in a demonstration of an approach to simulating forest-cover change.

### *Calculating transition probabilities*

Two transition probability values were used to quantify forest change for the 136 sample sites. The values quantify the rates of transition between forest and not-forest

($p_{fnf}$) and vice versa ($p_{nff}$). Because misclassification and misregistration in the forest-cover maps can negatively affect traditional change-detection methods, we used a probabilistic change-detection approach to quantify forest change. Using a 5 by 5 moving window, we calculated the proportion of forest within the window for each pixel location to create a map of forest probability, called $p_{ft}$, from forest maps of each of the three dates. The forest and not-forest transition probabilities between two dates ($t=1$ and $t=2$) were then defined as:

$$p_{nff}=(1-p_{f1})\times p_{f2} \tag{4}$$

$$p_{fnf}=p_{f1}\times(1-p_{f2}) \tag{5}$$

where $p_{nff}$ is the probability of a pixel that changed from not-forested to forested, $p_{fnf}$ is probability of a pixel that changed from forested to not-forested, $p_{f1}$ is the proportion of forest in the 5 by 5 window of a pixel in date 1, and $p_{f2}$ is the proportion of forest in the 5 by 5 window of a pixel in date 2. If a cell was classified as either water or clouds in either time period, that cell did not contribute to the calculation of $p_{nff}$ and $p_{fnf}$.

As an example, a pixel location with $p_{f1}=1$ (100% of forest in date 1) and $p_{f2}=1$ (100% of forest in date 2), the probabilities of the pixel changing from not-forested to forested and from forested to non-forested [$p_{nff}$ and $p_{fnf}$] are both zero, while a pixel location with $p_{f1}=0{\cdot}6$ (60% of forest in date 1) and $p_{f2}=0{\cdot}3$ (30% of forest in date 2), the probabilities of the pixel being changed from not-forested to forested and from forested to not-forested ($p_{nff}$ and $p_{fnf}$) are 0·12 and 0·42, respectively. To represent the transition probabilities of each of the 136 sites, we calculated the average value of $p_{nff}$ and $p_{fnf}$ across all the pixels in each sample site.

Calculation of the transition probabilities required a pairing of NALC images for each sample site over each of the two time intervals. The pairs of NALC images represented variable time intervals ranging from 4 to 13 years in length. We decade-standardized the transition probabilities using matrix algebra (Jahan, 1986). $p_{nff}$ and $p_{fnf}$ were defined as above, such that

$$P=\begin{bmatrix}1-p_{fnf} & p_{fnf}\\ p_{nff} & 1-p_{nff}\end{bmatrix}=\begin{bmatrix}a & b\\ c & d\end{bmatrix}. \tag{6}$$

For any given time interval ($x$) that $P$ represents, the decade-standardized transition probabilities ($p^*_{nff}$ and $p^*_{fnf}$) become:

$$p^*_{fnf}=\frac{-2^{-10/x}b((a+d-R)^{10/x}-(a+d+R)^{10/x})}{R} \tag{7}$$

$$p^*_{nff}=\frac{-2^{-10/x}c((a+d-R)^{10/x}-(a+d+R)^{10/x})}{R} \tag{8}$$

where

$$R=\sqrt{a^2+4bc-2ad+d^2} \tag{9}$$

Hereafter, $p^*_{nff}$ and $p^*_{fnf}$ are referred to as NFF and FNF.

Table 1 lists the average values for these two variables across all 136 sites and for each time interval. Although there are other reasons that a place can switch from not-forest to forest (i.e. planting) and from forest to not-forest (i.e. natural disturbance such as fire), we expect that the majority of such switches are due to forest regrowth and clearing, respectively.

## *Measuring forest pattern*

In order to quantify the spatial pattern of forest cover, we use a very simple metric that describes the tendency of forested pixels to occur next to other forested pixels. The metric, called $p_{ff}$, is the site-average proportion of forested pixels among the eight neighboring pixels of any forested pixel (Riitters *et al.*, 1999). The value of $p_{ff}$ ranges from 0 to 1; where 0 indicates that all the forest pixels, if there are any, are isolated, and 1 indicates that the landscape is completely covered by a seamless cover of forest.

The change variable associated with $p_{ff}$ was DPFF (Table 1), which refers to the decade-standardized change in $p_{ff}$ values over the interval [i.e. ($p_{ff2}$–$p_{ff1}$) divided by the number of years in the interval and multiplied by ten]. Because the decadal change in $p_{ff}$ was so small (one percentage point or less, on average) we did not model DPFF as a function of land-use change. However, we did use $p_{ff}$ to constrain spatial simulations in forest cover (described below). Rather than estimate the change in $p_{ff}$ over a decade, however, we assumed that the

**Table 1.** Site variables with mean values for each of the two time-periods represented in this study

| Abbreviation | Description | 1970s mean | 1980s mean |
|---|---|---|---|
| Forest-cover variables | | | |
| FNF | Probability that a forest pixel transitioned to non-forested | 0·305 | 0·265 |
| NFF | Probability that a non-forest pixel transitioned to forest | 0·453 | 0·489 |
| DPFF | Decade-standardized change in PFF | 0·002 | 0·011 |
| Development variables | | | |
| DEV1I | Initial proportion of site area with development in primary | 0·047 | 0·070 |
| DEV | Decadal rate of development (sum of all three levels of increase | 0·310 | 0·300 |
| APSI | Initial geometric mean of parcel size ($m^2$) | 137 552 | 103 488 |
| DAPS | Decadal rate of change in mean parcel size | −0·221 | 0·090 |
| Agriculture variables | | | |
| AGI | Initial proportion of site area with agriculture in primary or secondary | 0·460 | 0·440 |
| AGDEV | Decade-standardized proportion of agriculture converting to development | 0·019 | 0·029 |
| AGUNDV | Decade-standardized proportion of agriculture abandoned | 0·099 | 0·129 |
| AGAPSI | Initial mean (geometric) agricultural parcel size | 290 928 | 226 989 |
| DAGAPS | Decadal rate of change in mean agriculture parcel size | 5·08 | 6·655 |

value remained constant in our example simulations.

## Regression model at the site scale

Because we have measured the land-use and forest-cover change at a number of sites (136) and over multiple time periods (2), the compiled data set represents a panel that can be analyzed using methods for panel data analysis developed by econometricians (Hsiao, 1989). Our basic goal in developing the model is to test for linear functional relationships at the site-scale between two response variables (NFF and FNF) and land-use change predictor variables selected to describe the processes of development and agricultural conversion and abandonment in the study region. Because the number of time periods was small (i.e. 2), and the data exhibited a significant degree of temporal dependence, we estimated conservative models using the average values between the two time periods for all variables (Hall and Cummins, 1999). The response variables NFF and FNF were transformed using the arc-sine transformation (where the transformed value of Y is $\sin^{-1} Y^{1/2}$) to address the problem of non-uniform variance common in proportion variables (Draper and Smith, 1981).

Our basic hypothesis was that land-use change, in particular development and agricultural conversion, predicts forest-cover change, and that parcel sizes and changes in parcel sizes are important covariates in those relationships. Therefore, the models were set up to evaluate change in the transformed values of forest-cover change over a ten-year period as a function of the changes in, and initial conditions of, the amounts and parcel sizes of developed and agricultural land uses over the period (Table 1). The development variables refer to the initial proportion of area coded as developed in the primary (DEV1I) classification, initial geometric mean of parcel sizes (APSI), the decadal rate of change in parcel sizes (DAPS), and the proportion of area increasing its level of development, normalized to a decade (DEV). For the latter variable, we identified two kinds of change in the land-use classification that qualified as ‘increasing level of development’: (1) parcels that initially had no development in the primary or secondary classification that added development to their primary or secondary class; and (2) parcels that initially had development in the secondary but not primary classification that added development in the primary class. The agriculture variables describe the initial proportion of the site classified (primary or secondary) as agriculture (AGI), the initial geometric mean of the area of agricultural parcels (AGAPSI), and the ten-year rate of change in the size of agricultural parcels (DAGAPS). Change in agricultural land use was characterized by the proportion of agricultural areas, defined by

AGi, that converted to development (AGDEV) or undeveloped uses (AGUNDV), normalized to a ten-year period. Because the AGDEV and AGUNDV variables were conditional on having some amount of agriculture present initially, and because the area in agriculture was small or zero in many sites, the effects of these variables were explored separately from the full model.

### *Simulating forest cover*

We demonstrate the use of the Markov transition matrix and the PFF metric of spatial pattern in forest cover through a simple simulation exercise using a single site. Given an initial map of forest cover by grid cell and a two by two transition matrix, a new map of forest cover can be created by changing the proper number of forest cells to not-forest, according to the FNF value, and the proper number of not-forest cells to forest, according to the NFF value. For example, if the map contains 100 forest cells and 200 non-forested cells and has FNF=0·25 and NFF=0·50, then a random selection of 25 forested cells can be switched to not-forest and a random selection of 100 non-forest cells can be switched to forest.

In order to constrain the selection of cells to switch, such that the resulting map pattern is more realistic, we use PFF as an objective-function to constrain the simulation of forest and non-forest transitions. We assumed that PFF remained constant over time. The spatial constraint required creation of multiple realizations of forest-cover change and retaining the realization having the closest PFF value to that of the initial forest map. To ensure that the simulation approached the objective-function efficiently, we applied heuristics to the simulation. Because switching land-cover types of grid cells that were near the edges of existing forest patches tended to increase the value of PFF, and further from patch edges tended to decrease PFF, the percentage of forest within a three by three window of each cell was used to prioritize cells for alteration. This prioritization was combined with an adjustable randomization indicator (RI). When RI was close to zero (i.e. no randomness), cells with a smaller percentage of like-classed neighbors had a higher priority of switching. The resulting simulated forest map had clustered forest patches that retained the higher PFF values of the observed landscape. When RI was large, land-cover change became random, and generated a sporadic map pattern with a lower PFF value. By altering the magnitude of RI, the simulation approached the objective-function more effectively and efficiently. However, to generate more realistic patterns when the value of NFF or FNF was large, a sequential simulation algorithm was implemented to re-evaluate the cell priority after a certain amount of cells was altered. In this case, we recalculated cell priority after one-tenth of the transitions had been made, to correspond to an annual time-step. Several equal-probable forest-cover maps, which represent the same intial forest map and identical values of NFF, FNF, and PFF, were generated by automatically fine-tuning the magnitude of RI with the sequential simulation algorithm.

## Results

According to our Landsat-based analysis, average forest cover in the sample sites remained constant between the early 1970s and early–mid 1980s (about 53%) but increased to about 57·5 percent by the early 1990s. This increasing forest cover was reflected in a higher probability of forest regrowth (NFF) than forest clearing (FNF), and was accompanied by an average increase in the spatial aggregation of forest pixels (i.e. DPFF is positive; Table 1). Table 1 also highlights the land-use trends that are evident in our sample sites. The average site-proportion in development (primary classification) increased from 4·7 percent in the early 1970s to 7·0 percent in the early-mid 1980s. On average, about 30 percent of the areas of sites experienced some from of development during each period. The proportion of site-areas used for agriculture decreased from 46 percent in the early 1970s to 44 percent in the early-mid 1980s. The rates at which agricultural land was abandoned and/or developed both accelerated between the 1970s and 1980s (Table 1), such that between the early–mid 1980s and the early 1990s, three percent of agricultural land was converted to development and 13 percent converted to undeveloped. The latter figure may be a somewhat exaggerated measure of abandonment because it does not account for new land being brought into production or the possibility that rotational fallow land might be labeled undeveloped. Overall, parcel sizes tended to decline in the 1970s, possibly due to more rapid immigration. Agricultural parcels tended to increase in average size, probably through the preferential loss of smaller farms.

## *Site-scale regression analysis*

Table 2 presents the results of the regression analysis for estimating the probabilities of conversion over a ten-year period both from forest to not-forest (FNF; Table 2a) and from not-forest to forest (NFF; Table 2b). Both models were estimated using 135 of the 136 sites, because one site was too cloud-covered in both time periods. The significant predictor variables in the two models were the same: DEV1I, DEV, and AGI ($P < 0{\cdot}04$ in all cases). The adjusted $R^2$ for the models was 0·621 for FNF (Table 2a) and 0·587 for NFF (Table 2b). The residuals for both models were not found to exhibit significant heteroskedasticity. For the FNF model LM test=0·02 ($P$=0·887) and for the NFF model LM test=0·192 ($P$=0·661).

The influence of the developed land-use variables on forest cover was fairly straightforward. Where there was more land area developed initially, or experiencing some kind of development during the period, the probability of forest clearing was greater and the probability of forest regrowth was lower. This relationship generally confirms that developed uses, defined here to include residential, retail/office, industrial/warehouse, infrastructure/transportation, institutional, outdoor recreation and mining/extractive, are negatively related to forest cover on the landscape. However, because the analysis is aggregated by site, these results do not necessarily indicate direct causation.

**Table 2.** Results of the site scale regression analysis

(a) Dependent variable: arcsine transform of FNF

| Variable | Estimated coefficient | Standard error | t-statistic (*P*-value) |
|---|---|---|---|
| DEV1I | 0·607 | 0·123 | 4·94 (0·000) |
| DEV | 0·155 | 0·065 | 2·39 (0·018) |
| APSI | −0·145E-08 | 0·419E-07 | −0·347 (0·972) |
| DAPS | 0·029 | 0·019 | 1·51 (0·134) |
| AGI | 0·454 | 0·038 | 12·05 (0·000) |
| C | 0·260 | 0·026 | 10·17 (0·000) |

(b) Dependent variable: arcsine transform of NFF

| Variable | Estimated coefficient | Standard error | t-statistic (*P*-value) |
|---|---|---|---|
| AGI | −0·361 | 0·032 | −11·25 (0·000) |
| AGAPSI | 0·680E-07 | 0·645E-07 | 1·05 (0·294) |
| DAGAPS | 0·632E-03 | 0·474E-03 | 1·33 (0·185) |
| DEV1I | −0·319 | 0·109 | −2·92 (0·004) |
| DEV | −0·113 | 0·054 | −2·11 (0·037) |
| C | 0·943 | 0·029 | 32·59 (0·000) |

The role in the models of the initial amount of agricultural land at a site was strong and somewhat complicated. Amount of initial agricultural land use was related positively to forest clearing and negatively to forest regrowth. We suspected that AGI was serving as a surrogate for other variables. To explain the effect of AGI in more detail we examined its relationship to both the proportion of the site that is underlain by prime agricultural soils, based on STATSGO soils data (National Soil Survey Center, 1994), and AGUNDV. Together, prime soils and the proportion of agricultural lands abandoned were strongly related to (both $P < 0{\cdot}000$), and predicted about one-third of the variation of, AGI (adjusted $R^2$=0·35). This suggests that sites with more agricultural activity tended to be more productive and, therefore, also less likely to be abandoned and to give way to forest regrowth.

In order to explore more directly the effects of agricultural land conversion and development on the changes in forest cover, relationships between the probability of forest regeneration (NFF) and AGUNDV and DEV were examined together for the subset of sites that had some initial level of agricultural development (i.e. AGI > 0). For this assessment, we used a fixed-effects model that treated each site-period as a separate observation, and allowed us to include time-lags in the analysis (Hall and Cummins, 1999). The results indicated a strong positive relationship between NFF and AGUNDV ($P < 0{\cdot}000$) and a strong negative relationship between NFF and DEV ($P < 0{\cdot}000$). The agricultural abandonment (AGUNDV) in the prior time period exhibited a significant positive, although less strong, relationship to forest regrowth ($P$=0·028), but development (DEV) in the prior period was not strongly related to regrowth ($P=0{\cdot}498$). The same variables were significantly related to FNF, but the signs were all reversed. This analysis shows that, on sites with some agriculture present, current development and agricultural abandonment in the previous and current ten-year periods predict the amount of forest regrowth and clearing (adjusted $R^2=0{\cdot}211$ and $0{\cdot}260$, respectively). Although the initial amount of area under agricultural management within a site (AGI) serves as a reasonable negative surrogate for agricultural marginality, abandonment, and, ultimately, the probability of forest regrowth, rates of agricultural abandonment relate strongly to the probability of regrowth. Further, there appears to be a longer time-lag for regrowth following abandonment than for clearing following development.

In all cases (Tables 2a and 2b), initial average parcel size and changes in average parcel size were not significantly correlated with forest regrowth or clearing. Although parcel sizes may indicate something about the type of land management on a parcel, if such an effect occurs it is not strong enough to appear when parcels are aggregated into spatial landscape sites.

### *Simulation example*

Figure 4 displays the results of an initial simulation example to illustrate the application of the statistical models generated here. Figure 4a is an initial forest-cover map, taken from one of our sample sites in the early 1970s time frame. If we know something about the probability of forested areas to transition to non-forested land covers (FNF) and vice versa (NFF), then we can simulate the landscape at some future time. Given the models in Table 2, we can estimate the values of NFF and FNF, using information that we may have or have estimated about the land-use change that is occurring in the site. In this case we use the observed transition probability values for illustration purposes: NFF=0·263 and FNF=0·485.

Figure 4b represents a random selection of roughly 26 percent of the non-forested areas and 48 percent of the forested areas for transition. Because the switches were selected at random, the resulting map pattern was too patchy and not very realistic. It assumes that the process of conversion occurs at random locations within the site. Constraining the simulation such that the landscape pattern that results after the simulation has the same $p_{ff}$ value as the initial landscape, resulted in Figures 4c and 4d. Although the maps in Figure 4c and 4d resulted from the same magnitude of forest and not-forest swapping as 4b, the map pattern is preserved, and is, at least visually, more realistic.

## Discussion and conclusions

### *Land-use and land-cover change in the Upper Midwest, USA*

The changes in forest cover that we observed within our sample sites are consistent with the general increase in forest cover observed in the forest inventory conducted by the USDA Forest Service (Stone, 1997) and throughout the temperate mid-latitude forests (Houghton *et al.*, 1999). At the same time, our sites experienced both an increase in the area of developed uses and a decrease in agricultural uses. These trends are consistent with changes occurring in a broad range of rural areas throughout the USA, particularly those experiencing dispersed rural recreational and residential development, including the Colorado Front Range (Theobald *et al.*, 1996) and the Southern Appalachians (Turner, 1990) among other regions.

Our results suggest that agricultural activities and development are strongly related to the forest-cover change processes that we observed through remote sensing. In our aggregated landscapes (2500 ha), much of the change in forest cover occurring between the early 1970s and the early 1990s was predicted on the basis of the amount of land used for agriculture and development, and the rate at which development was increasing on the landscape (Table 2). All of these variables were positively related to forest clearing and negatively related to forest regrowth. Because much of the study area is marginally productive as agricultural land, the areas with a lot of agricultural land use were those that tended to have the best soils and were also those that were, therefore, least likely to be abandoned. At the scale of sites, parcel

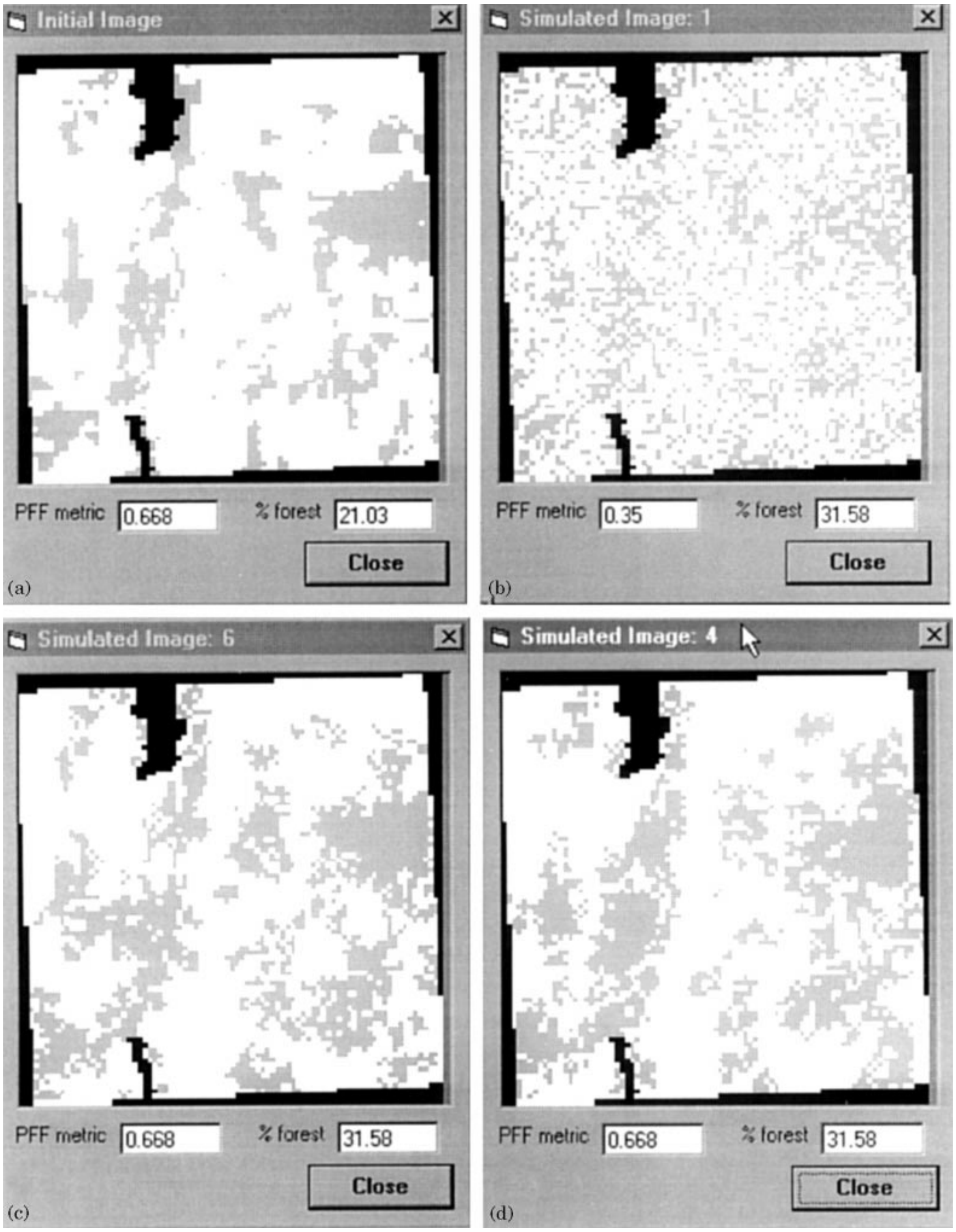


**Figure 4.** Application of transition probabilities for forest-cover simulation. Cover types are displayed using the same legend as in Figure 3. (a) Initial forest-cover map. (b) Simulation of forest-cover change without spatial constraint (NFF=0·263 and FNF=0·485). (c and d) Simulations of identical forest-cover change probabilities as (b), but with spatial pattern constrained to PFF=0·688.

sizes bear no direct relationship with changes in forest cover.

## *Value and limitations of the approach*

The strengths of the relationships between forest-cover change processes and the amounts and changes in agricultural and developed land uses in this region suggest that there is promise for the proposed modeling approach. Land use and land cover are clearly linked to one another. However, we argue that mapping and modeling them as separate processes is both more theoretically defensible and practical. As an example, consider the question of the effects of rural residential and recreational development on carbon storage in trees and their associated soils. The process is driven by demand for residential and recreational land and governed by a market, which uses the parcel as its basic unit. Trees and forests are important aesthetic and environmental components of this residential land, often enhancing its value. However, in most cases, trees do not cover entire parcels, sometimes occurring in patches that span parcel boundaries, and representing, at best, a secondary use of lands that are otherwise used for hunting cabins, permanent residences, seasonal residences, or other recreational activities. If we model the economic conditions giving rise to such development, a direct prediction of the effects on forest cover is unlikely to be obtained. Similarly, if we observe changes in tree cover, e.g. via satellite remote sensing, the relationship of such changes to the demand for land for various purposes is ambiguous. Our approach, therefore, serves as a bridge between models that predict changes in land use, e.g. development (Alig, 1986; Landis, 1994; Clarke *et al.*, 1997; Geoghegan *et al.*, 1997), and assessments of the impacts on land covers that provide environmental services, e.g. forests. The approach could be extended to look at the effects of urban sprawl on various environmentally-significant land covers.

The linear functional relationships established between land-cover change and land use, through regression analysis, confirm that land use and land-use change can be used to predict changes in the amount of forest cover at the landscape scale. The simple models developed here were based on the average land use, land-use change, and land-cover change conditions for two time-periods (1970s and 1980s). This temporal aggregation limited our ability to test for time-lags and temporal non-stationarity in the models. However, we did demonstrate the value of including time-lags in the models for exploring temporally dynamic relationships. The data used to generate the models were also spatially aggregated, which reduces their ability to directly reflect the parcel by parcel nature of land-use change.

Further development of the models is needed, based on the analysis presented here. First, the addition of more time periods, e.g. 1960s and 1990s, will facilitate analysis of the functional relationships in more detail. Specifically, more time periods will permit more formal evaluation of the influence of time-lags through estimation of fixed- and/or random-effects models of land-cover dynamics. Second, in the case of predicting NFF, the use of time-lags and information about site-quality might improve the prediction of regrowth. We observed the existence of a time-lag in the relationship between agricultural abandonment and forest regrowth, but have an insufficient number of sites to evaluate differences in regrowth lags by site. Third, analysis at the parcel scale is required to validate the relationships found at the site scale and to provide more detailed information about the processes that give rise to the relationships observed. Specifically, a statistical model of Markov transition probabilities at the parcel scale, like that presented here for the site scale, would facilitate finely detailed simulation of forest cover, given parcel-based maps of land use and land-use change. Finally, alternative modeling approaches might be more appropriate in this application. Specifically, regression trees, a decision tree-based analysis that is robust to missing values (Michaelson *et al.*, 1994), could be used to isolate specific types of sites and the change occurring on them. For example, with a regression tree it would be possible to first identify the influence of amount of agricultural land use, then, on those sites that have agricultural land use, evaluate the influence of agricultural land use conversion to development or abandonment.

Estimation of forest-cover change probabilities from land-use information provides an important conceptual link that can be used to generate forest-cover change simulations on the basis of land-use change predictions. The simulation approach demonstrated here can be linked to models that predict land-use change over large areas for estimation of the effects on forest cover. We demonstrated the use of the Markov transition probabilities in a simulation model that creates and updated forest-cover map given estimated probabilities that are specific to that time and place (Figure 4). By estimating the Markov transition probabilities as a function of land-use change variables, we relax the assumption inherent in most Markov-based models, that the transition probabilities are spatially and temporally stationary, and we improve the interpretability of the model. Because the spatial patterns of forest clearing and regrowth are not random, the simulation requires a spatial constraint. Here we have demonstrated the application of a simple spatial constraint based on the $p_{ff}$ value described above. By simulating the forest changes that adhere to the estimated transition probabilities and to the target $p_{ff}$ value, it is possible to produce multiple realizations of the possible forest landscapes that could result given land-use change.

The simulation presented here is meant only as an example and could be improved. First, we intend to work with alternative simulation algorithms for generating spatially-constrained simulations, including simulated annealing, to achieve better results. Further, the simulations could be constrained on the basis of parcel boundaries, such that individual parcel land-use changes can be used to simulate forest cover within individual parcels. If simulations are constrained by parcel boundaries, additional spatial constraints could be added. For example, any clearing of the forest that is expected with the development of a parcel could be constrained to occur along the road frontage of the property and any remaining forest could be maintained towards the back of the property to reflect real processes. Finally, more than two class transitions could be modeled to allow for the inclusion of other land-cover categories (e.g. wetlands, grassland, impervious, etc.). The trade-off with all of these suggested improvements is that they demand additional computational resources in order to produce more realistic forest-cover simulations.

## Conclusion

The amount of forest cover on the landscapes has broad-ranging implications, from amelioration of climatic extremes and decreased energy usage in local urban areas, to sequestration of carbon and potentially dampening the effects of global climate change brought on by anthropogenic greenhouse-gas emissions on the global scale. In order to understand and model forest-cover dynamics within developed countries, it is necessary to link those dynamics to the social and economic drivers of land-use change. We have argued that models of land-use change can be linked to critical land-cover outcomes (like forest cover) through the use of Markov land-cover transition probabilities, that are calculated as a function of land-use conditions and land-use change. This step in the evolution of Markov simulation models, such that transition probabilities are variable, and can be estimated in time and space, improves both their practicality and their ability to represent causal processes. A simple simulation was presented as an example. We expect that simulations like that presented could be used to predict patterns of forest cover over large areas for which estimates of land use and land-use change are available. Deriving such estimates from models of land-use change, that are driven by exogenous variables, can provide a system for the assessment of future forest-cover impacts of economic, social, and policy changes. This paper provides a key step in the development of such a system.

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## References

Accurate Publishing. (1993). *Atlas and Plat Book: Mecosta County, MI*. Battle Lake, MN: Accurate Publishing.

Alig, R. J. (1986). Econometric analysis of the factors influencing forest acreage trends in the southeast. *Forest Science* **32**, 119–134.

Baker, W. L. (1989). A review of models of landscape change. *Landscape Ecology* **2**, 111–133.

Bell, E. J. (1974). Markov analysis of land use change: Application of stochastic processes to remotely sensed data. *Socioeconomic Planning Sciences* **8**, 311–316.

Brown, D. G., Duh, J. D. and Drzyzga, S. (2000). Estimating error in an analysis of forest fragmentation change using North American Landscape Characterization (NALC) Data. *Remote Sensing of Environment* **71**, 106–117.

Brown, D. G. and Vasievich, J. M. (1996). A study of land ownership fragmentation in the upper midwest. In *Proceedings, GIS/LIS '96 Conference*, Denver, CO., pp. 1199–1209. Bethesda, MD: American Society for Photogrammetry and Remote Sensing.

Burnham, B. O. (1973). Markov intertemporal land use simulation model. *Southern Journal of Agricultural Economics* **July**, 253–258.

*Census of Agriculture* (1997). Washington, D.C.: U.S. Dept. of Agriculture, National Agricultural Statistics Service.

Clarke, K. C., Gaydos, L. and Hoppen, S. (1997). A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. *Environment and Planning B* **24**, 247–261.

Deadman, P., Brown, R. D. and Gimblett, H. R. (1993). Modelling rural residential settlement patterns with cellular automata. *Journal of Environmental Management* **37**, 147–160.

de Koning, G. H. J., Veldkamp, A. and Fresco, L. O. (1999). Exploring changes in Ecuadorian land use for food production and their effects on natural resources. *Journal of Environmental Management* **57**, 221–237, doi:10.1006/jema.1999.0305.

Draper, N. R. and Smith, H. (1981). *Applied Regression Analysis*. New York: John Wiley and Sons.

Foster, B. L. and Gross, K. L. (1999). Temporal and spatial patterns of woody plant establishment in Michigan old fields. *American Midland Naturalist* **142**, 229–243.

Geoghegan, J., Wainger, L. A. and Bockstael, N. E. (1997). Spatial landscape indices in a hedonic framework: An ecological economics analysis using GIS. *Ecological Economics* **23**, 251–264.

Guttorp, P. (1995). *Stochastic Modeling of Scientific Data*. New York: Chapman and Hall.

Hall, B. H. and Cummins, C. (1999). *Time Series Processor Version 4·5. User's Guide*. Palo Alto, CA: TSP International.

Houghton, R. A., Hackler, J. L. and Lawrence, K. T. (1999). The U.S. carbon budget: Contributions from land-use change. *Science* **285**, 574–578.

Hsaio, C. (1989). *Analysis of Panel Data*. New York: Cambridge University Press.

Jahan, S. (1986). The determination of stability and similarity of Markovian land use change processes: A theoretical and empirical analysis. *Socio-Economic Planning Science* **20**, 243–251.

Jain, A. K. (1989). *Fundamentals of Digital Image Processing*. Englewood Cliffs, NJ: Prentice Hall.

Johnson, K. M. (1998). Renewed Population Growth in Rural America. *Research in Rural Sociology and Development* **7**, 23–45.

Johnson, K. M. and Beale, C. L. (1998). The Rural Rebound. *Wilson Quarterly* **12**, 16–27.

Lambin, E. F. (1997). Modelling and monitoring land-cover change processes in tropical regions. *Progress in Physical Geography* **21**, 375–393.

Landis, J. D. (1994). The California Urban Futures Model: A new-generation of metropolitan simulation-models. *Environment and Planning B* **21**, 399–420.

Leatherberry, E. C. and Spencer, J. S. (1996). *Michigan Forest Statistics, 1993*. Resource Bull. NC-170. St. Paul, MN: USDA Forest Service, North Central Forest Experiment Station.

Lunetta, R. S., Lyon, J. G., Guindon, B. and Elvidge, C. D. (1998). North American Landscape Characterization dataset development and data fusion issues. *Photogrammetric Engineering and Remote Sensing* **64**, 821–829.

Mauldin, T. E., Plantinga, A. J. and Alig, R. J. (1999). Determinants of land use in Maine with projections to 2050. *Northern Journal of Applied Forestry* **16**, 82–88.

Michaelson, J., Schimel, D. S., Friedl, M. A., Davis, F. W. and Dubayah, R. C. (1994). Regression tree analysis of satellite and terrain data to guide vegetation sampling and surveys. *Journal of Vegetation Science* **5**, 673–686.

Miles, P. D. and Chen, C. M. (1992). *Minnesota Forest Statistics, 1990*. Resource Bull. NC-141. St. Paul, MN: USDA Forest Service, North Central Forest Experiment Station.

Muller, M. R. and Middleton, J. (1994). A Markov model of land-use change dynamics in the Niagara Region, Ontario, Canada. *Landscape Ecology* **9**, 151–157.

National Soil Survey Center (1994). *State Soil Geographic (STATSGO) Data Base*. Misc. Pub. No. 1492. Fort Worth, TX: US Dept. of Agriculture, Soil Conservation Service.

Pijanowski, B. C., Gage, S. H., Long, D. T. and W. E. Cooper. (2000). A land transformation model for the saginaw bay watershed. In *Landscape Ecology: A Top Down Approach* (J. Sanderson and L. D. Harris, eds), pp. 183–198. Boca Raton, FL: Lewis Publishers.

Richter, R. (1990). A faster atmospheric correction algorithm applied to Landsat TM images. *International Journal of Remote Sensing* **11**, 159–166.

Riebsame, W. E., Parton, W. J., Galvin, K. A., Burke, I. C., Bohren, L., Young, R. and Knop, E. (1994). Integrated modeling of land use and cover change. *Bioscience* **44**, 350–356.

Riitters, K. H., Wickham, J. D., Jones, K. B. and O'Neill, R. V. (1999). Global survey of forest fragmentation. *Abstracts, International Association for Landscape Ecology, 5th World Congress*, Snowmass Village, CO. Fort Collins, CO: IALE, p. 130.

Rockford Map Publishers (1990). *Land Atlas and Plat Book: Grand Traverse County, Michigan*. Rockford, IL: Rockford Map Publishers, Inc.

Schmidt, T. L. (1997). *Wisconsin Forest Statistics, 1996*. Resource Bull. NC-183. St. Paul, MN: USDA Forest Service, North Central Forest Experiment Station.

Staaland, H., Holand, O., Nellemann, C. and Smith, M. (1998). Time scale for forest regrowth: Abandoned grazing and agricultural areas in southern Norway. *Ambio* **27**, 456–460.

Stone, R. N. (1997). Great Lake States Forest Trends, 1952–1992. In *Lake States Regional Forest Resources Assessment: Technical Papers*. GTR NC-189. St Paul, MN: USDA Forest Service, North Central Forest Experiment Station.

Theobald, D. M., Gosnell, H. and Riebsame, W. E. (1996). Land use and landscape change in the

Colorado mountains II: A case study of the East River Valley, Colorado. *Mountain Research and Development* **16**, 407–418.

Theobald, D. M. and Hobbs, N. T. (1998). Forecasting rural land-use change: A comparison of regression- and spatial transition-based models. *Geographical and Environmental Modelling* **2**, 65–82.

Turner, B. L. and Meyer, W. B. (1991). Land use and land cover in global environmental change: Considerations for study. *International Social Sciences Journal* **130**, 669–667.

Turner, B. L., Skole, D., Sanderson, S., Fischer, G., Fresco, L. and Leemans, R. (1995). *Land-Use and Land-Cover Change Science/Research Plan*. Joint publication of the International Geosphere-Biosphere Programme (Report No. 35) and the Human Dimensions of Global Environmental Change Programme (Report No. 7). Stockholm: Royal Swedish Academy of Sciences.

Turner, M. G. (1987). Spatial simulation of landscape changes in Georgia: A comparison of three transition models. *Landscape Ecology* **1**, 29–36.

Turner, M. G. (1990). Landscape changes in nine rural counties in Georgia, USA. *Photogrammetric Engineering and Remote Sensing* **56**, 379–386.

Williams, M. (1989). *Americans and Their Forests: A Historical Geography*. Cambridge: Cambridge University Press.

World Wildlife Fund (1999). *Forests for Life Page*. 15 June, 1999 <http://www.panda.org/forests4life/whatisforest.htm>.