The Dynamics of Land-Cover Change in Western Honduras: Spatial Autocorrelation and Temporal Variation

Darla Munroe, Jane Southworth, and Catherine M. Tucker

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Author Contact Information:
Center for the Study of Institutions, Population, and Environmental Change (CIPEC)
Indiana University, 408 N. Indiana Ave.
Bloomington, Indiana 47408
dmunroe@indiana.edu

Abstract

This paper presents an econometric analysis of land-cover change in western Honduras. Ground-truthed satellite image analysis indicates that between 1987 and 1996, net reforestation occurred in the 1,015.12 km^2 study region. While some reforestation can be attributed to a 1987 ban on logging, the area of reforestation greatly exceeds that of previously clear-cut areas. Further, new area was also deforested between 1987-1996. Thus, the observed land-cover changes most likely represent a complex mosaic of changing land-use patterns across time and space. We estimate a random-effects probit model to capture drivers of land-cover change that are spatial, temporal or both. We employ two techniques to correct for spatial error dependence in econometric analysis suitable to qualitative dependent variables. Lastly, we simulate the impact of anticipated changes in transportation costs on land cover. We find that market accessibility, increase in national coffee prices, and agricultural suitability are the most important determinants of recent land-cover change.
Keywords: reforestation, Geographic Information Systems (GIS), remote sensing, random-effects probit, land-use/land-cover change, Honduras

1. Introduction

Explaining and predicting land-cover and land-use change with respect to social, economic, and environmental factors represents a major goal for research into the human dimensions of global change. Analysis of land-use and land-cover change offers a means of linking socioeconomic processes associated with land development, agricultural activities, and natural resource management strategies, and the ways these changes affect the structure and function of ecosystems (Turner and Meyer 1991). The study region in western Honduras presents an interesting and currently atypical process of land-cover change relevant to a spatially explicit analysis: a significant reforestation trend has been occurring. While the demographic and socioeconomic context has similarities to those in many developing regions, the reforestation represents a reversal in the dominant deforestation trend found in most Latin American countries, including Honduras. To understand the complex processes of economic development and change, we employ a spatially explicit model of the returns to land use in order to capture some of the most important drivers of land-cover change across time. We employ a random-effects probit model to incorporate both temporal and spatial factors to explain observed land-cover changes.

The research focuses on an area of approximately 1015.12 km^2 in the mountains of western Honduras. The study region includes Celaque National Park, which contains the highest point in Honduras; it also encompasses Gracias, the capital of the Department of Lempira, and the *municipio* (similar to a county) of La Campa, which is the site of in-depth fieldwork. Fieldwork in the area shows that this region is undergoing processes of population growth. Agricultural intensification is occurring in the more remote rural areas, where recent improvements in infrastructure indicate increasing market integration. The processes of agricultural change appear in part to support the predictions of Boserup (1967), who proposed that under population pressure and in the absence of a frontier for expansion, people intensify agricultural production to meet subsistence demands. In-depth fieldwork in a community within the study region reveals that agricultural intensification is associated with increased use of chemical fertilizers and oxen-drawn plows, and a shortened (or eliminated) fallow period. At the same time, coffee production for the market has been expanding throughout western Honduras, including the study region. Interestingly, a time series analysis of remotely sensed images (1987–1996) reveals that reforestation has been occurring (Southworth and Tucker in press). The analysis indicates that a small part of this process is due to the regrowth of forest on parcels that were clear-cut in the mid-1980s. Notably, logging has been restricted under local policies; therefore deforestation due to logging is not a major factor during the study period.

Historically, people raised crops under slash-and-burn agriculture and long fallows (Tucker 1996). Today, most rural households still depend upon subsistence production of maize and beans, but most have begun to cultivate fields permanently or for extended periods with short fallows. Within La Campa, agricultural intensification appears to be related to abandonment of some marginal lands, particularly those on steeper slopes. The social processes occurring in the study region have similarities to those in a number of other rural areas in the developing world. Population growth, privatization of communal lands, and increasing inequality in land distribution have been linked to deforestation (Cernea 1989, Anderson 1990, Durham 1995, Kaimowitz and Angelsen 1998). This case provides a context in which to address several puzzles facing theories of land-cover change, specifically the circumstances in which population growth, economic development, and sociocultural transformations may, at least temporarily, promote reforestation. Moreover, the patterns of this land-cover change suggest that the complex socioeconomic and biophysical processes determining land-use change must be studied in a spatial context.

2. Conceptual Framework

There is a small but growing literature addressing the socioeconomic drivers of land-cover change (see Angelsen and Kaimowitz 1999 for a thorough review). Nearly all of these studies focus on the process of deforestation, which is unidirectional and limiting, particularly because it restricts studying the effects of economic development and change on forest cover. Much international public policy related to deforestation continues to reflect the idea that deforestation is a function of high population growth, low agricultural productivity, and poverty (Angelsen 1999). This approach is invariably shortsighted and too simplistic; for example, there are cases in which population growth is associated with improved forest conditions (Varughese 2000).

Mather (1990) defined a “forest transition” as the point at which social and economic changes allow some reforestation to occur. Rudel (1998) offers some possible explanations for this transition, including innovations in agricultural production methods. Changes in land use reflect a complicated process related to economic development, changes in political or economic institutions, and/or transformations in other sectors of the economy that lead to urbanization (Rudel 1998). This section reviews some of the important factors that influence land-use change, including the role of infrastructure, agricultural intensification, and institutional variables.[1] A common theme throughout this literature is the idea of economic development and agricultural transformation as a link to probable causes of human-induced land-cover change.

2.1. Infrastructure and Accessibility

Infrastructure development, particularly the construction of roads, has been the most well documented factor that influences land-use change. Road and railway construction are the main policy instruments for regional development in rural areas. Roads affect incentives for land-use change in two ways. First, they often provide access to previously inaccessible land, which often leads directly to increased deforestation in immediate areas, encouraging migrants to convert land (Mertens and Lambin 2000). This incentive for deforestation is particularly relevant in a frontier setting, such as the settling of the Brazilian Amazon in the 1970s and 1980s (Moran et al. 1996).

Second, road construction can improve market accessibility, which may stimulate increases in agricultural production and promote forest clearing. Transportation costs, particularly in the producer prices of food products, are a substantial part of total costs. The effect of road construction on land cover depends on the type of agricultural production dominant in the region. In subsistence or near-subsistence agriculture, improvements in market accessibility are less likely to spur increased production (van

[1] See Deacon (1995) and Andersen (1997) for a theoretical model of the effect of policy on deforestation.

Amsberg 1998). Export-oriented crops, on the other hand, face world prices that do not fall with locally increased production, and any improvements may lead to increased forest clearing.

2.2. Agricultural Intensification

Agricultural improvements, such as increased yields from improved seed varieties or improved farming practices, reduce pressures on forests only if they reduce the potential profitability of agriculture on currently forested lands. This result would occur only if the demand for the agricultural product is very inelastic (as in the case of subsistence agriculture). Therefore, the effect of agricultural intensification could be a short-term increase in forest cover.

By contrast, if the price of the agricultural product were determined in world markets (for example, in the case of an export crop such as coffee), agricultural improvements would increase the potential profitability of agriculture on currently forested lands (van Amsberg 1998). In this case, intensification could lead to increased deforestation, depending on the relative suitability of the landscape for the new crops. Carpentier et al. (2000) found substantial evidence in the Amazon of increased deforestation rates corresponding to increased intensification on previously cleared land. What is missing in the literature is a study of agricultural intensification in a non-frontier setting, where land scarcity is an issue.

3. Methodology

In order to link land-cover changes to land-use change, one approach is to estimate the relative returns to land use. We assume that, in equilibrium, land is devoted to the use that generates the highest potential profitability (reflected in land rents). Forest clearing and land conversion take place when a land user estimates that the probable returns from the converted land outweigh the costs of conversion. Each parcel of land has a certain inherent productivity, which is determined by the overall suitability of the land for agricultural production, including geophysical characteristics (soil quality, slope, elevation), and climatic conditions (precipitation and temperature). In developing countries, reliable data are often lacking on location-specific prices from which we could construct measures of opportunity costs for all possible land uses. However, cost of access to market centers are an important component of both input and output prices (Chomitz and Gray 1996, Nelson and Hellerstein 1997). Building on the insights of von Thünen (1966) and Ricardo (1981), we model observed land-cover changes are as a function of the relative profitability of all possible land uses at a particular location at a particular point in time.

3.1. Recent Land-Cover Changes

Landsat 5 TM images were obtained for March of 1987, 1991, and 1996, because this month corresponds to the end of the dry season when agricultural fields can be easily distinguished from forests. Geometric rectification was carried out using 1:50,000-scale maps and the nearest-neighbor resampling algorithm, with a root mean square (RMS) error of less than 0.5 pixels (< 15 m). Using a similar procedure, the rectified 1996 image served as the basis to rectify the 1987 and 1991 images. An overlay function verified that the images overlapped exactly across the three image dates. All the images underwent radiometric calibration, atmospheric correction, and radiometric rectification. Training sample data were used to determine the land-cover classes on the ground and then train the satellite image to recognize them. Classes for agriculture, young fallows (approximately 1–3 years), cleared areas, bare soil, water, and urban areas were aggregated to create a non-forest class. Forest was defined as having a canopy closure of 25 percent or greater, based on forest plots from fieldwork. In addition, this canopy closure threshold indicates areas that function as forest, both physically and socially, for the communities who use this landscape. Only two cover classes, forest and non-forest, were used to simplify the change analysis and modeling procedure.

Fieldwork in March 2000 verified the land-cover trajectories of 100 randomly selected locations, either based solely on visual inspection of tree size and age etc., or on a combination of visual analysis and interview data. Changes in land cover across the three dates—1987, 1991, and 1996—were detected using an image grid addition technique resulting in eight possible change classes. Results of this change detection indicated significant bi-directional change over the study period, with reforestation as the dominant process (Table 1). This change image then becomes the dependent variable for the econometric models. The unit of analysis is the pixel (900 m^2), with 4,120 observations.

Mertens and Lambin (2000) also used a three-date change grid for their analyses. With classifications of forest/non-forest over three dates, 2^3 or eight possible change classes result (Table 2).

These eight change classes represent fundamentally different land cover and reflect the different land-use patterns across time. For example, forest/non-forest/non-forest represents more permanent clearing while forest/forest/non-forest is recent deforestation. In the case of western Honduras, there are three main processes of land-cover change related to land-use change. First, since 1987 an abandonment of marginal areas, on steeper slopes and closer to roads and towns, formerly used in swidden maize and bean cultivation has occurred. Secondly, from 1991 recent clearings appeared at higher elevations, farther from roads and towns, that are smaller and more likely used for coffee (Southworth et al. in review). Lastly, there is a fallow cycle, shortened though it may be, for remaining maize and bean production. Therefore, with some confidence, we can link reforestation and permanent clearing to maize and beans, and recent deforestation to coffee.

3.2. Spatially Explicit Model

An empirical spatial model of land use, first developed by Chomitz and Gray (1996), states that land will be devoted to the activity yielding the highest rent, or return to use. Formally, we specify a latent model of land rent. The potential rent, R_{ikt}, or all future returns associated with devoting plot i to land use k is given by its net present value:

$$R_{ikT} = \int_{t=0}^{\infty} \left(P_{ikt} Q_{ikt} - C_{ikt} X_{ikt} \right) e^{-r_i t} dt \,, \tag{3.1}$$

where P_{ikt} is the price of output of k at point i ¸ C_{ikt} is a vector of input prices to k, Q_{ikt} is the potential output, and X_{ikt} is the optimal quantities of inputs for k all at time t, with the discounting function $e^{-r_i t}$ [2](Chomitz and Gray 1996, Nelson and Hellerstein 1997). The production function is given by:

$$Q_k = G_i \prod_h X^{a_h}; \quad 0 < a_h < 1; \quad 0 < \sum_h a_h \leq 1, \tag{3.2}$$

assuming for simplicity a Cobb-Douglas relationship between the inputs and outputs, with output elasticities (the vector of a coefficients) potentially summing to 1 (Beattie and Taylor 1993). The factor

[2] We are assuming an individual-specific discount rate, which do not observe. Nelson et al. (in press and 2001) motivates this individual-specific discount rate as a function of land tenure at each point. In our case, this discount rate is part of the unmodeled heterogeneity that is incorporated into the random-effects framework.

G represents a set of geophysical features that determine the location-specific suitability for a particular land use (Nelson et al. in press).

In most cases, data for P, C, and Q are not available for every plot i,[3] and thus a reduced-form model is most often used to represent a potentially endogenous relationship between P and C (Chomitz and Gray 1996; Nelson and Hellerstein 1997, Mertens and Lambin 2000). In equilibrium, spatial differentials in farm-gate prices are related to the differences in transport costs to major markets. For each commodity, functions relating output and input prices to the distance to market, D, are given by:

$$\begin{aligned} P_{ikt} &= \exp\left(g_{0kt} + g_{1kt} D_i\right) \text{ and} \\ C_{ikt} &= \exp\left(d_{0kt} + d_{1kt} D_i\right), \end{aligned} \tag{3.3}$$

where g_{0k} and d_{0k} represent fixed costs, output prices decrease with distance ($g_{1k} < 0$), and input prices increase ($d_{1kt} > 0$).

Mertens and Lambin (2000) also considered forest pattern and fragmentation as another important determinant of profitability. The value of forest/non-forest at a particular parcel is dependent on that parcel's position in a patch of forest or agricultural land. Generally, fragmented and edge areas are more likely to experience change. Agricultural economists have begun to include these landscape measures in studies of land use (Geoghegan et al. 1997, Parker 2000[4]). Landscape pattern has been show to be related to the configuration and concentration of land values and agricultural production. An obvious example of landscape pattern and agricultural productivity is the issue of scale economies. Scale economies can vary by crop type and the intensity of production. Certain parcels may be too small or fragmented to farm efficiently. Spillover effects and spatial externalities across land uses are also important determinants of land-use change by contributing to the profitability of a particular parcel.

Substituting (3.3) and (3.2) into (3.1), following Chomitz and Gray (1996) and Nelson et al. (in press), the reduced form of the model becomes:

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[3] Note: we are equating the unit of analysis, the pixel, with a plot. This assumption induces a spatial scale issue: we do not observe the decision-maker directly (Mertens et al. 2000).
[4] Parker (2000) uses landscape concentration/fragmentation indices in land use pattern as an analogy to the familiar Herfindahl index of industrial concentration.

$$\ln R_{ik} = a_{0K} + a_{1k} D_i + a_{2k} G_i \equiv b_i X_i \,, \tag{3.4}$$

where the returns to land use k at location i is a function of the transportation costs (D), geophysical features (G), and the vector of output elasticities (a).

3.3. Econometric Estimation

Modeling determinants of deforestation alone makes most sense when land is converted in a frontier setting, or as claim for property rights. Understanding the occurrence of reforestation is more complicated. Many models do not account for reforestation at all. Mertens and Lambin (2000) were the first to study trajectories of change as a dependent variable. They contend that land-use change is necessarily a complex process of biophysical and socioeconomic interaction and, thus, cannot be captured in one absolute measure of forest cover. They estimated these change trajectories in a multinomial logit formulation, assuming that each unique combination of land-cover change represents a functionally different land-cover class (Table 2).

The trajectories of change approach has intuitive appeal precisely because it incorporates the path-dependency of land-cover change for a particular pixel. Some land-cover changes are irreversible, or arguably cannot reverse at time scales that are within the scope of a particular individual's decision-making (e.g., the return to primary forest). However, the multinomial logit formulation violates the assumptions of logistic regression: namely, that each alternative is uncorrelated (Greene 1997). The path-dependency necessitates correlation. The initial land-cover, and the land-cover at each subsequent time stage, determines the structure of the trajectories. Moreover, the latent land rent model as developed by Chomitz and Gray (1996) implies that change has occurred (in some prior time period) where it is most profitable. The distance proxies for input and output costs are only valid under the assumption of a spatial equilibrium (Nelson et al. in press). In the multinomial logit approach of Mertens and Lambin (2000), all independent variables are time-invariant, so there is no formal motivation for the determinants of *change* in land use.

We replicated Mertens and Lambin's (2000) technique in a recent paper (Munroe et al. under review). We found that the multinomial logit with eight unique outcomes was outperformed by a simple, binary logit (forest/non-forest in 1996) conditioned on prior land cover from the two previous time periods. In order to explain the dynamic and bi-directional changes more explicitly, we employ a more sophisticated model in this analysis. Due to recent theoretical advances, empirical applications of panel techniques in probit models are becoming more common (Coble et al. 1996; Gould and Dong 2000). The use of panel data in the probit formulation is a way of controlling for omitted variables, particularly those relating to heterogeneity across space. The random-effects formulation allows for correlation between the individual-specific effects and the vector of independent variables.

Assume any land cover can be represented by *k*, out of a set *j* possible uses. Following Equation (3.4) we assume that land is devoted to the use with the highest rent, or point i is devoted to use *k* at time *t* if

$$R_{ikt} > R_{ijt}, \quad \forall j \neq k . \tag{3.5}$$

This formulation can be expressed as a binary variable *Y*:

$$\begin{aligned} &Y = 1 \quad \text{if } R_{i1t} > R_{i0t} \qquad \{i=1,...,N\,; t=1,...,T\} \\ &Y = 0 \quad \text{otherwise,} \end{aligned} \tag{3.6}$$

where 1 represents forest and 0 non-forest. This formulation is sufficiently flexible to represent the removal of land from production. The latent land rent equation, Equation (3.1), represents a profit function: revenue minus cost. If the cost of cultivating a particular pixel in time *t* outweighs the potential revenue, the choice of 1 would imply the fallowing of land, or passively allowing it to return to a forested state. Likewise, conversion to agriculture or continuation of agricultural production is represented by 0.

We assume that land rent is a function of location-specific characteristics specified in Equation (3.4). However, we may not have captured all possible sources of variation in land rent. Panel techniques are one way of capturing more information about a cross-sectional data set to lead to greater efficiency in estimation. Any binary choice model assumes that the error term in the latent response function is independently, identically distributed, and independent of the vector of explanatory variables, *X*. The effects of possible omitted variables can be contributed to three types of effects: spatially variant effects, period effects, and effects that vary across time and space. We denote time by t and space by i. The error can then be written as:

$$v_{it} = a_i + l_t + e_{it}\,, \tag{3.7}$$

where a_i denotes individual effects, l_t represents time-specific effects, and e_{it} denotes effects that vary with time and space (Hsiao 1996). The fixed-effects model would assume that there is no correlation between a_i and *X*. To allow for such correlation, we incorporate factors that vary across time, space, and both. We econometrically estimate Equation (3.4) as a random-effects probit model using panel data. The specification becomes a multivariate probit model:

$$Y_{it} = 1 \text{ if } \; b_i X_i + d_{it} S_{it} + l_t T_t + u_i + v_{ikt} > 0\,, \tag{3.8}$$

where *X* is a set of parcel-specific characteristics, and *ß* is the vector of parameters (Chomitz and Gray 1996), *S* represents landscape pattern variables that vary over space and time with parameters d, l is the parameter for time effects *T*, *u* represents the individual heterogeneity, and *v* is a uncorrelated disturbance term with zero mean and constant variance.

The random-effects estimator uses both the vector of time-invariant explanatory variables, *X*, and the individual-specific disturbance term, *u*, to successfully filter individual heterogeneity. We estimate one additional parameter, r, to test for the presence of random effects:

$$\begin{aligned} \operatorname{var}\left[u_i + v_{it}\right] &= \operatorname{var}\left[e_{it}\right] = s_u^2 + s_v^2, \\ \operatorname{corr}\left[e_{it}, e_{is}\right] &= r = s_u^2 \big/ \left(s_u^2 + s_v^2\right) \end{aligned} \tag{3.9}$$

This model was estimated using LIMDEP (v 7.0) software (Greene 1998).

3.4. Independent Variables

The land-cover change trajectories are a function of the factors that determine agricultural suitability and market accessibility. Table 3 contains a list of relevant variables and their definitions. We tested for partial correlations among all independent variables to identify potential multicollinearity. While nearly all of the variables were significantly correlated, this correlation was never above 0.50 (using Pearson's *C* measure of partial correlation). Other spatially explicit models of deforestation have included measures of soil quality as a determinant of agricultural suitability. The probability of conversion depends on this suitability. Prior research suggests that soil quality does not vary significantly across the study area, so we do not include it in this study (Tucker 1996, 1999b). Instead, the effects of elevation and slope are by far the most crucial for agriculture.

The variables used in this analysis are given in Table 3. Slope and elevation for the region were calculated using a Digital Elevation Model (DEM) at a scale of 1:50,000. Distance to nearby markets is an important determinant of the agricultural suitability of a particular parcel. In this region, there are many different types of roads ranging from paved roads and seasonal roads to footpaths. We weighted the distance to market destinations by road type by assigning an impedance factor. There are roads leading to two different types of destinations. One road out of the region leads to both Santa Rosa de Copán (regional center of exchange) and Tegucigalpa (the capital city). In addition, much local exchange takes place in nearby towns and villages. We assign a base impedance factor to cleared land (1) and forested land (2). Roads and paths are given impedance factors as following: two-lane (0.05), one-lane (0.10), seasonal (0.15) and paths (0.20). Because slope is a crucial component of cost of access, we multiply these base costs by a slope function: $(1+\text{slope}^2/50)$*land-cover cost (Nelson et al. in press). Using Arc/Info GRID™, we then calculated the least-cost path from every pixel to the road out of the region, and to the nearest town or distance on this base cost surface, providing a weighted measure of distance to markets.

This region has been undergoing notable land-use change: from predominantly slash-and-burn, shifting cultivation to more instances of stable, intensified staple production. In addition to the predominance of maize and beans subsistence production, there has been a recent expansion of coffee production. Large patches of stable clearings at low elevations and flatter slopes often correspond to maize and bean production, while newer, smaller clearings at higher elevations and steeper slopes generally relate to coffee (Southworth et al. under review). To capture changing land-use patterns, we included measures of landscape configuration for each time period. Distance to edge and the size of the patch of forest/non-forest to which the pixel belonged were included. The closer a particular parcel is to a different land-cover type (i.e., forest to non-forest or vice versa), the higher the probability that it will show change. It is intuitive that most forest clearing occurs at the edge of a forest: the most accessible areas are cleared first. It is less intuitive to assume that previously cleared area is more likely to return to forest cover if it borders a patch of forest. Patch size is defined as the number of spatially contiguous (orthogonal) pixels classified as forest or non-forest, multiplied by pixel size to calculate the actual area. These measures were calculated for all three time points.

Table 4 contains descriptive statistics of the geophysical and accessibility variables by change class (f = forest, n = non-forest). Stable forest occurs at higher elevations, steeper slopes, and further from local and regional centers of exchange. Areas that have experienced reforestation over the study period also tend to be on steeper slopes, at higher elevations. For areas that have experienced reforestation from 1987-1991 or from 1991-1996, weighted distance out of the region is significantly below the mean.

Table 5 contains the trends in the distance to edge and patch size measures over time. The smallest patches were of the minimum area that can be detected by Landsat 5 Thematic Mapper (30 m x 30 m or 0.0009 km^2), and the largest patches were over 400 km^2. Mean patch size over all classes increased from 1981-1997, and then decreased from 1991-1996. The mean patch sizes for stable forest and non-forest were larger than for the classes that experienced change. Areas that experienced change were also closer to an edge, as expected. We know that the expansion of coffee production in the study area has been an important factor in land-cover change beginning in the early 1990s (Tucker 1999a, 1999b). The price of coffee nearly doubled during this time (Table 6), which can be interpreted as an exogenous shock. We added a variable representing this temporal change by including a three-year moving average percentage change in the coffee price (with 1987 as the base year equal to 1).

3.4.1. Spatial Effects

Understanding spatial patterns, both absolute and relative, is crucial in any study of land-use change. Most biophysical processes, including vegetation growth and climate, exhibit spatial autocorrelation. In addition, many human activities exhibit neighborhood effects. Only a few methods of modeling spatial effects in models of land-use choice have been tested empirically. Following Nelson and Hellerstein (1997), we incorporate a spatially weighted average of slope at neighboring locations.

Prior studies assume that deforestation in one period tends to occur in areas proximate to clearing from a previous period (Mertens and Lambin 2000). Adoption of particular farming technology or cultivation patterns might also exhibit observable spatial effects. Unfortunately, spatial effects are often omitted from econometric models of land-cover change due to the difficulty of incorporating them into models with limited dependent variables, which can result in misspecification. Anselin and Bera (1998) distinguish between error (nuisance) and lag (substantive) spatial dependence, two types of specification error. In the case of spatial error dependence, ignoring spatial effects can result in inefficient, but not biased, estimators. Ignoring substantive spatial dependence is much more serious. If the spatial dependence is caused by spatial interaction, a true functional relationship among observations across space, econometric estimation will yield biased and inefficient estimators (Anselin 1988). When human activities exhibit a spatial spread, there is every reason to think that spatial dependence will be substantive in nature. There is to date no econometric technique for estimating the full structure of spatial error dependence in a probit model except Beron and Vijverberg (in press), which involves a recursive importance simulator (RIS) that does not converge easily or quickly for a data set with more than a few dozen observations. Currently, there is no model that accounts for substantive spatial interaction in a qualitative dependent variable framework and there is no test statistic for spatial interaction, either [5] (Anselin 2001).

Mertens and Lambin (2000) chose a regular sample of their data set across space to avoid spatial autocorrelation. We test statistically whether spatial sampling can effectively correct for spatial autocorrelation. One way to test for spatial autocorrelation in land cover by distance is to examine the covariance structure among observations at varying distances. Geostatistical techniques, such as semivariogram analysis, can easily detect such autocorrelation on a continuous surface. If one wishes to find a sufficient distance to sample an image without capturing spatial dependence, a semiovariogram can provide a graphical depiction of where spatial dependence is highest. In this case, it is difficult to derive a continuous variable, particularly when the land-cover classes represent discrete choices (to clear or not to clear, for example). Therefore, a binary or multinomial measure of spatial autocorrelation must be used instead.

The join count statistic was employed using SpaceStat v. 1.90 for both a forest/non-forest and a three-date change classified image. The images were sampled using the regular sampling technique of a non-overlapping moving window, with increasing window size (9 x 9[6] up to 25 x 25, 35 x 35, and 55 x 55). The center pixel, and its value (change class), was retained for each window. The statistic is defined as:

$$\begin{aligned} BB &= (1/2)\sum_i \sum_j w_{ij} x_i x_j \quad \text{and} \\ BW &= (1/2)\sum_i \sum_j w_{ij} \left(x_i - x_j\right)^2, \end{aligned} \tag{3.10}$$

where BB is defined as the number of joins where x_i and x_j take the same value. BW is defined as the number of joins where x_i and x_j take differing values. If either is significant, one can reject the null

[5] Kelejian and Prucha (in press) have developed a suite of Moran's I statistics for various logit model formulations, but these statistics can only identify residual (or nuisance) spatial autocorrelation. See also Pinkse (1999).
[6] Because of the sheer size of the image, anything below a 9 x 9 window was so computationally intensive that it would have been very difficult to derive a weights matrix for each observation. However, at this window size, everything was spatially autocorrelated, so it is evident that an ideal window must be bigger to correct for spatial dependence.

hypothesis of spatial randomness. In the first case, a significant *BB* would imply positive spatial autocorrelation, or spatial dependence. The second case, *BW*, implies negative spatial autocorrelation or spatial repulsion (Anselin 1995). No statistic for *BW* was significant in this analysis, so they are not reported. This statistic is necessarily defined as a binary one; therefore, each change class was compared to all other change classes.[7]

A weighting function that defines sequential occurrences of land-cover change classes is need to compute this statistic. For each sampling distance, a contiguity matrix was determined by "adjacent" pixels; e.g., those pixels that were east, west, north, and south of each other as defined by the sampling distance. For example, if the sampling distance is 5 pixels on a 30-meter resolution image, pixels within 150 m are defined as neighbors. For a sampling distance of 25 pixels, pixels within 750 m are defined as neighbors. The significance of the test statistic by change class by sampling distance is reported in Table 4. Because of the skewness in land-cover change composition (the predominance of stable forest and stable non-forest and the patchiness of the classes that changed), no one sampling distance would sufficiently remove spatial autocorrelation. We ultimately chose to sample the image using a 15 x 15 window, or sampling distances of 450 meters. At this distance, we had effectively filtered out much of the spatial autocorrelation in the smaller change classes, and the extent of spatial autocorrelation (as measured by sequential occurrences of like change classes) had significantly dropped for all classes.

In addition to sampling across space we chose to employ a spatial filtering technique. One commonly used method for removing residual spatial dependence from a regression is the trend surface approach (Cliff and Ord 1981, Anselin 1995). A trend surface model is defined as some function of the spatial coordinates x_{i1} and x_{i2}:

[7] No statistic currently exists for comparing multinomial spatial dependence. In SpaceStat v. 1.90, a statistic called j_{tot} can be computed that tests for spatial heterogeneity across the data set (the *BW* case only). The statistic was also significant for this data set at varying window sizes, indicating that we could reject the null hypothesis of spatial uniformity.

$$m_i = \sum_{s=0}^{p} \sum_{r=0}^{q} b_{rs} x_{i1}^{r} x_{i2}^{s}, \tag{3.11}$$

where p and q represent the order of some polynomial relationship[8] in the spatial coordinates and m_i represents the mean of the function of regressor variables (Cliff and Ord 1981):

$$m_i = m\left(x_{i1}, \ldots, x_{ik}\right). \tag{3.12}$$

We include two variables, xcoord and ycoord, representing the x and y Universal Transverse Mercator (UTM) coordinates for each pixel.

4. Results

4.1. Spatial and Temporal Complexity

We estimated four different models and compared their relative success in predicting land-cover change from 1987 to 1991, and 1991 to 1996. We assumed that changing cultivation patterns, from primarily subsistence agriculture to increasing coffee production is a major factor in recent land-cover change, beginning in the early 1990s. Unfortunately, we have no spatially explicit measure for these patterns; i.e., yields, etc. We know that there is fundamentally a different relationship between the independent variables and the choice of subsistence or coffee production. The preferred coffee cultivars require higher, moister elevations to grow well. Effective transportation costs may be different for coffee. The Honduran Coffee Institute (IHCAFE) has been an agent for promoting modern production methods and providing technical assistance (Jansen 1998); it has given support to the region's aspiring coffee producers. Decree 175-87 has devolved funds to coffee-growing counties for road improvements in proportion to their production, and the National Coffee Fund (FCN) has provided additional funds for road improvements to counties with nascent production to encourage expansion. During this time period, no significant changes took place in the road network; however, we know that much construction has taken place since the mid-1990s. Therefore, it is possible that a coffee farmer would temporarily endure extremely high transportation costs with the high confidence that new roads were coming and

[8] Generally, the higher the order of this polynomial, the more complex the underlying spatial dependence can be. However, multicollinearity is also a consequence. We assume a linear relationship only.

costs would subsequently be reduced. We simulate a change in transportation costs for areas most suitable for coffee production (within one standard deviation of mean elevation for areas experiencing recent clearings). We also compare the predictive measure of including the spatial filter (x and y UTM coordinates). Therefore, the four models are as follows: with transportation costs and spatial effects constant, with reduced transportation costs after 1991 and spatial effects constant, with transportation costs constants and spatial effects variables, and with both reduced transportation costs after 1991 and spatial effects variables.

4.2. Parameter Values and Marginal Effects

Table 8 reports the results for all four models and marginal effects evaluated at the mean for Model 1. Elevation was positively correlated with forest cover in all four models. The effect of slope was not statistically significant, but the spatially lagged slope was significant and positive in two instances. Distance to the nearest village was also positively related to forest cover indicating that local trade may be more closely related to subsistence production and therefore the abandonment of marginal fields. , The sign of effect of distance out of the region varied, depending on whether or not a spatial filter was included. If the location was specifically taken into account (Models 1 and 2), the impact was negative, meaning that distance was positively correlated with clearing. If the spatial filtering variables were left out (Models 3 and 4), the effect was negative and much stronger if transportation costs were reduced. Thus, we think that there is a fundamentally different relationship between distance to regional markets both for newer vs. older clearings, and for more suitable areas (based on elevation and slope) for coffee than for subsistence production.

One important question in this research regarded the role of pattern in explaining land-cover changes. We tested to see whether edge agricultural areas are most likely to be abandoned, or whether edge forest areas were more likely to be converted. The marginal effect of distance to edge was negative (indicating that interior areas are more stable), but was not significant. The marginal effect of patch size (as a measure of fragmentation) was also negative. This parameter was significant in two of the models. This finding indicates that fragmented areas are also more likely to be converted.

The coefficient for r, which is the coefficient for individual heterogeneity, was significant for all models. If random effects were not present, the variance estimated for u_i, in (3.9) would be insignificant, and the correlation would collapse to zero. The spatial effects variables (x and y coordinates) were strongly positive and significant. However, when included, the magnitude of the constant greatly increased, indicating that including these effects led to overfitting of the model.

4.3. Assessing Predictive Power

For each model, we computed a pseudo-R^2 statistic using Zavoina and McKelvey's measure for probit models using an Inverse Mill's ratio (Zavoina and McKelvey 1975). According to this measure, overall predictive power of each model was roughly equivalent, ranging from 0.51-0.58. The model with spatial effects and constant transportation costs had the best fit.

In this analysis, the most important objective was to see which whether spatial and/or temporal variation would more accurately predict the bi-directional change in land cover over the study period. Using the estimated parameters, we generated probability predictions by assigning a land-cover class based on the maximum probability. Predicted values for each sample point (roughly 4,000 points out of a possible 120,000) at each time point were calculated. These results are found in Table 9. Surprisingly, all models were better at predicting the occurrence of reforestation than that of deforestation. Only the two models that incorporated a spatial filter predicted any occurrences of forest/forest/non-forest. The number of recent clearings was highest in the model with both a spatial filter and reduced transportation costs. The model with constant transportation costs and no spatial effects also predicted no occurrences of old and permanent forest clearing (forest/non-forest/non-forest). Figure 1 contains graphical depictions of actual and predicted land cover for all models.

5. Discussion

Chomitz and Gray (1996) developed a powerful and useful framework for linking observed land cover to land use. In this model, one defines the relative returns to land use using spatially explicit data, informed by theories of von Thünen (1966) and Ricardo (Currie 1981). However, there are drawbacks to this approach. In particular, there are certain factors that cannot be considered in this kind of analysis.

5.1 Data Limitations

In the current model, there is no way to know which crop is planted in an individual clearing. We observe only forest/non-forest. In other studies (Nelson and Hellerstein 1997, Nelson et al. 2001, Nelson et al. in press), several land-use classes are modeled for one point in time. Comparing only two points in time, the possibility of switching from one land use to another, as a result of some exogenous event (e.g., policy changes, road construction), can be captured through a classified land-cover image. However, the higher degree of detail in the classification, the greater the chance for error. In our analysis, we can speculate on the purpose of the observed clearings by (a) the point in time in which they occurred and (b) the location of the clearing relative to geophysical (slope, elevation) and socioeconomic (distance to markets) factors. As indicated above, fieldwork in La Campa revealed that cultivation patterns are changing (Tucker 1996). We also know that new clearings are occurring in places farther removed from markets. Therefore, some of the recent clearing likely relates to expanding coffee production. Interestingly, only one of the models could predict recent clearings with much accuracy, and they all performed much better in predicting *reforestation*. Therefore, there is likely a missing component to the model as it stands. Conversion costs are currently missing from the model: there are high start-up costs to coffee production. However, a missing or understated cost would generally lead to overprediction of this class, not underprediction. Thus, we are most likely missing a factor related to the returns to coffee expansion. We are not currently capturing enough variation in the returns to land use in each point in time.

5.2. Spatial Scale and Spatial Effects

In this formulation, the unit of analysis is the pixel, and the size of this pixel has varied based on the land-cover and other spatial data used: 30 m in this analysis; 80 m in Cameroon (Mertens and Lambin 2000); 500 m Panama (Nelson et al. in press, Nelson et al. 2001); and 1 km in Belize (Chomitz and Gray 1996). Land-cover data, generally from remote sensing techniques, are used to compensate for not having parcel-level data referenced by land users. Therefore, a spatial scale effect is induced. We cannot match the pixel to the land user. Particularly in the case of western Honduras, we know that the same person or group of people may manage many different, non-contiguous areas. In order for this scale effect not to have serious implications for model accuracy, we have to make the assumption that land is managed as a portfolio. That is to say, land users manage many different potentially heterogeneous pixels each according to its highest valued use. This assumption may be too strict. One could imagine scenarios where a land manager would retain a pixel in a land use that is really not suitable because of the fixed cost of converting that one pixel, especially if it were surrounded by other, more suitable pixels. We plan to investigate this issue in fieldwork to determine how valid the assumption is for western Honduras. We do know that recent clearings, particularly for coffee production, tend to be very small, sometimes right at or just below the size that we can accurately detect with Landsat TM data, so it may not be an unreasonable assumption.

Identifying and correcting for spatial effects in econometric models is of growing concern in studies of land use (Anselin and Bera 1998). However, many underlying spatial effects cannot adequately be captured in this framework. In a limited dependent variable model formulation, change is seen as either the realization of a process or its absence. The model is thus capturing what is called a latent regression (Liao 1994): there is an unmodeled profit or utility maximization process that is leading to land-cover change (or preventing it). It is important to remember that spatial effects, if present, would be found in this underlying process, and not necessarily in the observed land-cover changes (Anselin 2001). In other words, linking pattern to observed changes may not be enough. Because of the extreme difficulty of incorporating spatial effects in models with qualitative dependent variables, much more research is needed in this area. If one examines only landscape patterns as a means for uncovering spatial pattern in land use (e.g., the realized pattern of land-cover change), it stands to reason that one might be missing the true spatial patterns in the underlying latent regression. Any regional model should be supplemented with better knowledge of what spatial interaction might be present. A growing number of land-use studies emphasize the importance of including spatial effects (LeSage 1993, Benirschka and Binkley 1994, Polsky 2001). The fact that spatial interaction cannot be modeled in this framework currently underscores the need for careful analysis at a finer scale (e.g., the household analyses undertaken by Mertens et al. (2000) and Geoghegan et al. (1999)).

5.3. Conclusion

Both socioeconomic and forest transformations are occurring in the study region. This area is developing intensified linkages to world markets, and it can serve as an arena for future comparative studies. It is often assumed that changes in agricultural systems under conditions of population growth and poverty lead to deforestation and general degradation of the landscape. We have much evidence to suggest that the situation in western Honduras is more complex. Evidently, the availability of agricultural intensification techniques has led farmers to establish more permanent agricultural fields and to reduce the use of marginal land for the production of maize and beans. The expansion of coffee production represents a novel process that is changing the landscape directly and indirectly. Those who can afford it see coffee as a good investment, and government programs for road improvements in coffee-growing areas provide an incentive for producers. The construction of new roads then alters the relative profitability of proximate land uses by changing all transportation costs within the region.

The purpose of this analysis was to combine techniques from land-cover analysis, landscape-pattern analysis, and econometric estimation to determine the likely direction and quantity of land-cover change in the near future, as well as to rank and quantify the relative factors that have caused recent land-cover change. We account for the spatial drift in both human and biophysical activities by including distance to edge, patch size, and spatially lagged dependent variables in the analysis. Fieldwork is planned to capture on-the-ground measures of agricultural intensification and coffee expansion, to add to future analyses, and perhaps to better predict future land-cover change.

Mertens and Lambin (2000) made an important contribution to the literature by suggesting that temporal and spatial complexities must be included in a study of land-cover change: aggregate measures are not enough. More important, simultaneous deforestation and reforestation over time point to a very complex pattern of land use, one that is well addressed by a study of the relative returns to land use over time. However, obtaining reliable econometric results for these temporal complexities is difficult; the relatively simple multinomial logit formulation is not appropriate when correlation among alternatives exists (whether spatial or temporal). Predicting land-cover change in a panel formulation makes better sense for linking the socioeconomic drivers of land-use change to observed land-cover changes. In our region, we have at least two simultaneous processes of change: abandonment of marginal land and new clearings for market-oriented crops. These processes are difficult to model exhaustively solely from observed land-cover changes, and it is evident that both spatial heterogeneity (at the parcel level and across the landscape) and external processes (changes in exogenous economic conditions) are important factors.

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Table 1. Recent Land-Cover Changes in Western Honduras

	1987	1991	1996
Forest	554.38	537.57	559.92
Deforestation		82.92	90.40
Reforestation		100.68	113.74
Non-Forest	460.78	480.85	455.20

Table 2. Land-Cover Change Trajectories and Their Descriptions for 1987, 1991, 1996

Category	1987	1991	1996	Land-Cover Change Classes
1	Forest	Forest	Forest	Stable primary or secondary forest
2	Forest	Non-Forest	Non-Forest	Old and permanent forest clearing
3	Forest	Non-Forest	Forest	Old forest clearing with regrowth
4	Forest	Forest	Non-Forest	Recent forest clearing
5	Non-Forest	Non-Forest	Non-Forest	Stable permanent agriculture
6	Non-Forest	Forest	Non-Forest	Forest regrowth with new clearing
7	Non-Forest	Forest	Forest	Old and permanent forest regrowth
8	Non-Forest	Non-Forest	Forest	Recent forest regrowth

Source: Mertens and Lambin (2000:474).

Table 3. Spatially Explicit Independent Variables

Variable	Definition
Geophysical Characteristics	
Slope	Slope in degrees
Elevation	Meters above mean sea level
Accessibility Measures	
Weighted distance to nearest town/village	Distance to nearest center of trade in km, weighted by road type and transport cost
Weighted distance to outside markets	Distance to road that leads to Santa Rosa de Copán and Tegucigalpa
Changes in Landscape Pattern	
Distance to edge	Distance to nearest pixel of different cover type (forest/non-forest) for each time period
Patch size	Natural log of total area of patch that contains the pixel for each time period
Spatial Effects	
UTM X-coordinates	Meters east-west
UTM Y-coordinates	Meters north-south
Spatial lag	Weighted average of slope at neighboring locations
Temporal Effects	
Scaled coffee price	Percentage change in coffee price, three-year moving average prior to each time period

Table 4. Descriptive Statistics by Change Class

Land-Cover Change Trajectories		Slope, degrees	Spatially Lagged Slope, degrees	Elevation, 100m	Weighted distance out of region	Weighted distance to nearest village
All	Mean	15.96	16.15	13.56	1956.60	286.56
n=4720	Std. Deviation	12.80	8.87	4.60	1430.48	232.72
	Minimum	0.00	0.00	5.61	6.79	3.39
	Maximum	63.43	42.70	27.98	8827.90	1313.66
f-f-f	Mean	18.33	18.47	15.80	2646.01	403.75
n=1871	Std. Deviation	13.51	9.19	5.03	1735.08	293.11
	Minimum	0.00	0.00	5.95	48.86	11.69
	Maximum	63.43	42.70	27.98	8827.90	1313.66
f-f-n	Mean	14.30	14.99	13.13	1748.69	258.64
n=214	Std. Deviation	12.45	8.44	4.04	1101.39	178.00
	Minimum	0.00	0.00	5.89	91.70	13.35
	Maximum	57.10	34.20	26.98	6138.69	987.15
n-f-f	Mean	16.59	16.94	13.97	1860.99	242.58
n=214	Std. Deviation	12.99	8.21	4.50	1081.02	152.43
	Minimum	0.00	0.28	6.38	46.96	7.43
	Maximum	53.90	35.55	23.33	4304.49	644.84
n-f-n	Mean	14.83	15.42	12.28	1485.27	235.61
n=177	Std. Deviation	13.58	8.86	4.06	1077.93	147.11
	Minimum	0.00	0.34	5.67	91.17	14.03
	Maximum	60.00	35.84	22.07	4174.33	640.33
f-n-f	Mean	13.58	14.19	12.36	1529.18	211.54
n=294	Std. Deviation	11.44	7.59	3.11	803.02	160.90
	Minimum	0.00	0.22	5.90	82.35	19.71
	Maximum	56.16	36.22	22.46	4373.71	858.05
f-n-n	Mean	13.69	13.65	11.93	1510.45	209.86
n=227	Std. Deviation	11.09	7.49	3.15	912.17	150.03
	Minimum	0.00	0.00	5.96	156.51	9.61
	Maximum	52.18	31.96	22.74	4034.81	864.88
n-n-f	Mean	14.02	14.96	11.94	1439.48	196.96
n=268	Std. Deviation	12.08	8.49	3.25	825.52	128.31
	Minimum	0.00	0.47	5.79	8.61	14.75
	Maximum	55.17	35.68	22.20	3981.48	724.90
n-n-n	Mean	14.45	14.38	11.67	1432.98	197.29
n=1488	Std. Deviation	11.97	8.41	3.45	926.53	114.38
	Minimum	0.00	0.00	5.61	6.79	3.39
	Maximum	62.71	41.04	23.20	4227.76	626.65

Table 5. Change in Landscape Pattern by Change Class, 1987-1996

		1987 Distance to Edge, m	1991 Distance to Edge, m	1996 Distance to Edge, m	1987 Patch Size, km^2	1991 Patch Size, km^2	1996 Patch Size, km^2
All	Mean	117.67	142.31	81.91	226.34	255.14	179.17
n=4720	Std. Deviation	194.93	266.02	87.96	125.08	143.36	114.44
	Minimum	0.05	0.05	0.04	0.00	0.00	0.00
	Maximum	1966.52	2603.52	774.61	352.30	401.21	300.21
f-f-f	Mean	201.28	245.38	112.06	207.38	199.07	165.15
n=1871	Std. Deviation	278.84	388.93	108.08	71.58	75.16	70.58
	Minimum	10.29	0.13	0.04	0.00	0.00	0.00
	Maximum	1966.52	2603.52	774.61	245.79	245.79	211.56
f-f-n	Mean	59.98	51.99	37.09	166.40	151.48	103.35
n=214	Std. Deviation	94.53	126.85	53.56	98.50	99.91	142.32
	Minimum	12.25	0.05	8.02	0.00	0.00	0.00
	Maximum	1191.64	1720.61	517.96	245.79	245.79	300.21
n-f-f	Mean	23.76	43.36	41.58	158.39	145.60	112.35
n=214	Std. Deviation	26.05	47.42	45.41	175.02	103.58	91.96
	Minimum	0.20	0.20	0.57	0.00	0.00	0.00
	Maximum	169.75	352.29	294.41	352.30	245.79	211.56
n-f-n	Mean	35.55	22.43	47.19	229.35	98.37	186.31
n=177	Std. Deviation	34.55	27.76	53.32	167.94	108.25	145.55
	Minimum	0.80	0.82	12.08	0.00	0.00	0.00
	Maximum	153.99	238.91	408.33	352.30	245.79	300.21
f-n-f	Mean	43.68	34.41	38.49	147.36	236.50	93.50
n=294	Std. Deviation	34.78	24.32	44.35	104.36	197.29	90.14
	Minimum	10.22	8.05	0.05	0.00	0.00	0.00
	Maximum	235.26	192.60	310.23	245.79	401.21	211.56
f-n-n	Mean	32.67	54.08	56.13	114.79	293.68	185.13
n=227	Std. Deviation	24.89	46.35	54.59	111.85	177.78	145.39
	Minimum	8.23	9.56	9.56	0.00	0.00	0.00
	Maximum	280.36	340.95	374.47	245.79	401.21	300.21
n-n-f	Mean	37.68	50.55	24.69	220.70	284.62	69.15
n=268	Std. Deviation	43.33	45.15	27.01	169.57	182.32	86.45
	Minimum	0.05	9.52	0.05	0.00	0.00	0.00
	Maximum	276.59	343.40	222.82	352.30	401.21	211.56
n-n-n	Mean	84.02	103.30	82.29	300.36	365.01	250.83
n=1488	Std. Deviation	70.80	83.05	71.09	124.11	114.65	110.92
	Minimum	0.12	10.15	8.66	0.00	0.00	0.00
	Maximum	535.22	666.68	657.26	352.30	401.21	300.21

Table 6. Trends in National Coffee Prices, 1987-1996

Years	Value, Local Currency Three-Year Moving Average	% Change
1984-1986	3474.67	
1988-1990	3734.67	7.48%
1993-1995	6765.33	81.15%

Source: FAO (2000)

Table 7. Minimum Sampling Distance for Insignificant Join Count Statistic

Change Class	Description	Window Size	Distance (m)
10	Stable Forest	>55 x 55	1,650
12	Forest/Forest/Non-Forest	19 x 19	570
13	Non-Forest/Forest/Forest	17 x 17	510
15	Non-Forest/Forest/Non-Forest	11 x 11	330
16	Forest/Non-Forest/Forest	15 x 15	450
18	Forest/Non-Forest/Non-Forest	15 x 15	450
19	Non-Forest/Non-Forest/Forest	13 x 13	390
21	Stable Non-Forest	>55 x 55	1,650
Forest 87	Initial class	>55 x 55	1,650
Non-Forest 87	Initial class	>55 x 55	1,650

Table 8. Parameter Values, Models 1-4

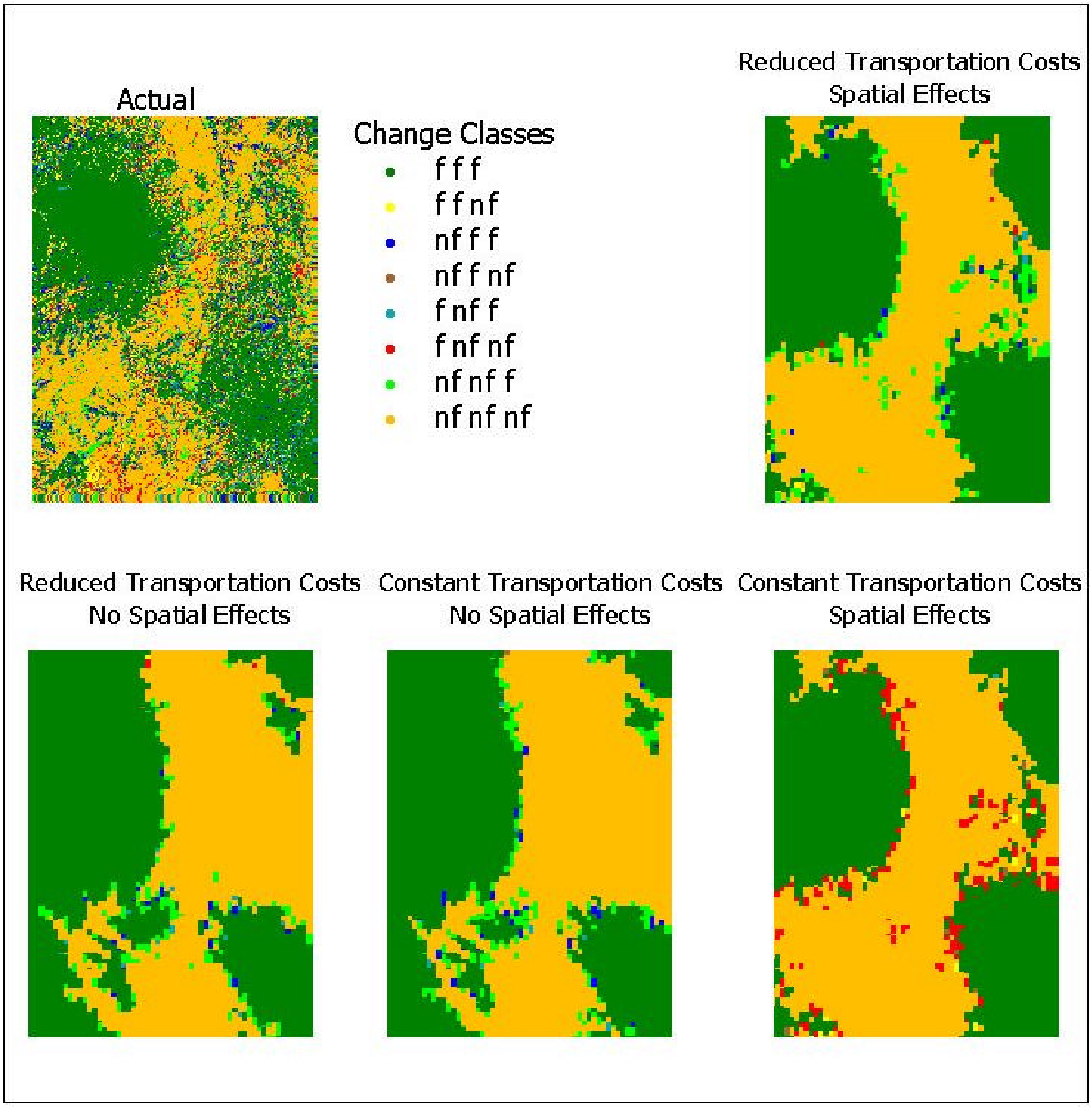
	Reduced Transportation Costs, Spatial Filter Model 1	Constant Transportation Costs, Spatial Filter Model 2	Constant Transportation Costs, No Spatial Filter Model 3	Reduced Transportation Costs, No Spatial Filter Model 4	Marginal Effects, Model 1
Constant	-97.0039***	-117.6677***	-3.2040***	-2.9187***	-20.1872***
xcoord	11.5401***	11.4569***	--	--	2.4016***
ycoord	3.3984***	4.7128***	--	--	0.7072***
Elevation	0.2815***	0.2587***	0.2092***	0.1722***	0.0586***
Slope	-0.0061	-0.0063	-0.0046	-0.0042	-0.0013
Lagged Slope	0.0239***	0.0210***	0.0062	0.0018	0.0050**
Distance to Nearest Village	0.0435***	0.0343***	0.0445***	0.0399***	0.0091***
Distance out of the Region	--	0.0003***	-0.0003***	--	
Distance out of the Region, Reduced in 1996	0.0038	--	--	-0.0064***	0.0008
Change in Coffee Price	0.1963***	0.2156***	0.1220**	0.1274***	0.0408***
Distance to Edge	-0.0004	-0.0005	0.0002	0.0002	-0.0001
Patch Size	-0.0055*	-0.0045	-0.0104	-0.0095***	-0.0011
ρ	0.7151***	0.7144***	0.7568***	0.7572***	--
Pseudo-R^2	0.57	0.58	0.51	0.52	

***indicates significance at the 99% level, ** at the 95% level, and * at the 90% level.

Table 9. Composition of Land-Cover Change Trajectories

	Actual		Model 1		Model 2		Model 3		Model 4	
forest all	1871	39.64%	2166	45.89%	2178	46.14%	2394	50.72%	2319	49.13%
f f nf	214	4.53%	8	0.17%	0	0.00%	1	0.02%	0	0.00%
nf f f	181	3.83%	25	0.53%	20	0.42%	23	0.49%	33	0.70%
nf f nf	177	3.75%	3	0.06%	1	0.02%	2	0.04%	2	0.04%
f nf f	294	6.23%	9	0.19%	10	0.21%	16	0.34%	10	0.21%
f nf nf	227	4.81%	4	0.08%	1	0.02%	3	0.06%	0	0.00%
nf nf f	268	5.68%	209	4.43%	202	4.28%	158	3.35%	195	4.13%
nonforest all	1488	31.53%	2296	48.64%	2308	48.90%	2123	44.98%	2161	45.78%

Figure 1. Actual and Predicted Values, Models 1-4



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