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The dynamics of land-cover change in western Honduras: exploring spatial and temporal complexity

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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 forest regrowth occurred in the 1015 km^2 study region. While some forest regrowth can be attributed to a 1987 ban on logging, the area of forest regrowth greatly exceeds that of previously clear-cut areas. Further, new area was also deforested between 1987 and 1996. Thus, the observed land-cover changes most likely represent a complex mosaic of changing land-use patterns across time and space. Using satellite imagery from 1987, 1991 and 1996, we estimate a series of models, including binary probit models for each date, and a random-effects probit model using panel techniques. We also experiment with spatial sampling schemes designed to reduce residual spatial autocorrelation, and qualitatively compare the impact of spatial sampling on model accuracy. Lastly, we find that changes in relative prices, infrastructure improvement, and topography are all significantly related to changing land-cover patterns.

JEL classification: C23; O13; Q15; R220

Keywords: Forest regrowth; 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 socio-economic 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 trend of forest regrowth has been occurring. While the demographic and socio-economic context has similarities to those in many developing regions, forest regrowth and regeneration represent a reversal

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in the dominant deforestation trend found in most Latin American countries, including Honduras. To understand the complex processes of economic development and change, we develop 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 use both time-series satellite image analysis and the results of detailed household surveys in a representative portion of the study area to link observed land-cover change to likely underlying land-use changes in an econometric model.

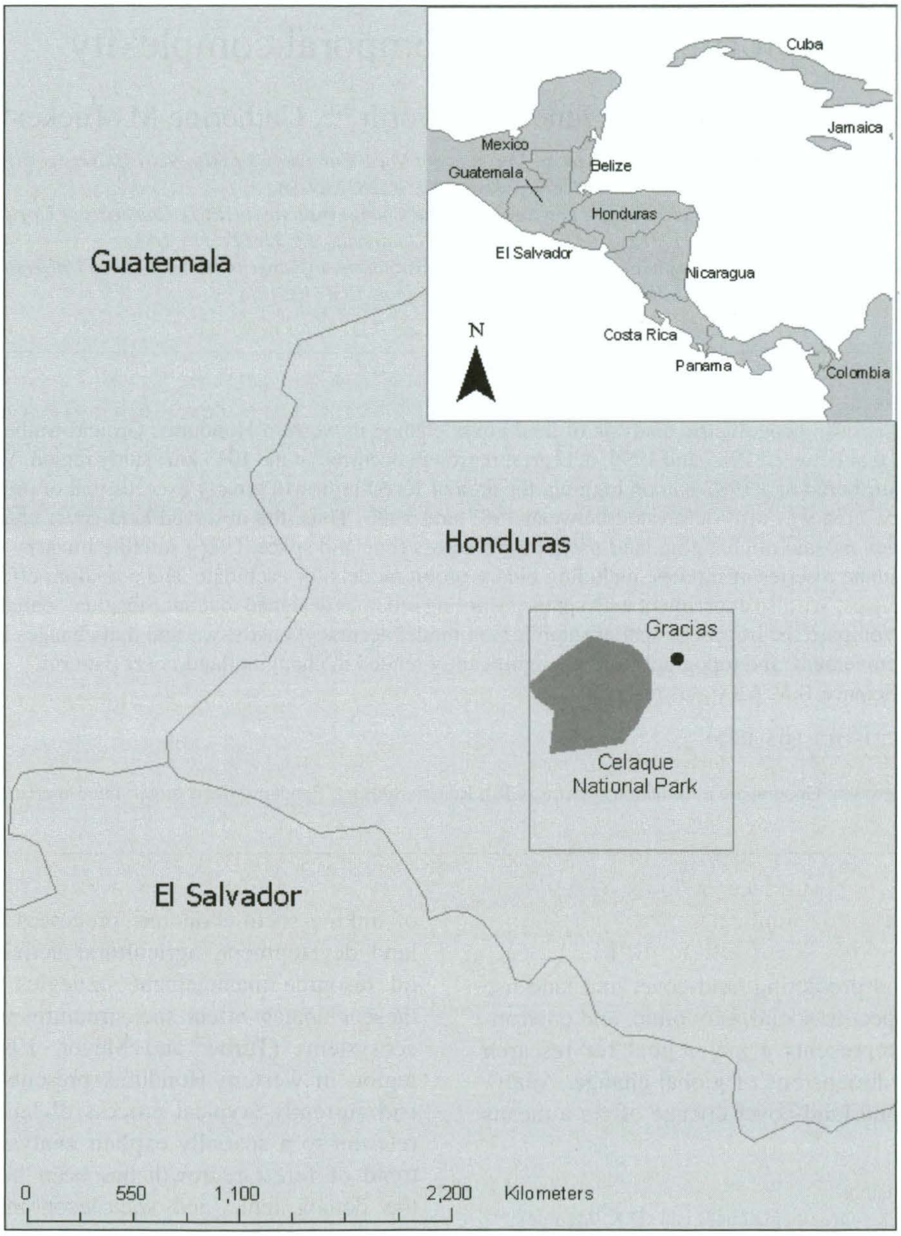

Fig. 1. Study area.

The research focuses on an area of approximately $1015\,km^2$ in the mountains of western Honduras (Fig. 1). 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. Agricultural intensification is occurring in the more remote rural areas, where recent improvements in infrastructure relate to increasing market integration. In-depth fieldwork in a community within the study region reveals that agricultural intensification is associated with increased use of chemical fertilisers 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, 1991 and 1996) reveals that forest regrowth has been occurring (Southworth and Tucker, 2001). 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. However, the area of regrowth greatly exceeds the area of prior clear-cut areas. Notably, logging has recently been restricted under local policies; therefore deforestation due to logging is not a major factor during the study period. The patterns of this land-cover change suggest that the complex socio-economic and biophysical processes determining land-use change must be studied in a spatial context.

Land-cover change is often a dynamic, multidirectional process. Modelling 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 forest regrowth or regeneration is more complicated. Many models do not account for forest regrowth 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 socio-economic interaction and, thus, cannot be captured in one absolute measure of forest cover. In order to explain the dynamic and bi-directional changes more explicitly, we estimate a binary model of forest versus cleared land for each individual time period, and in a panel formulation. We test and, when possible, correct for both spatial and temporal dependence in our data set to try and uncover some of the interrelationships between human-induced land-cover change through time and space.

The next section provides background information for the study region, with particular regard to land-use transformations. In an area with an established population, yet evolving land tenure regime, we present the assumptions that allow us to link land-cover changes to the underlying land-use patterns. Then, a review of relevant literature and the theoretical model are presented. Next, the empirical analysis follows, with special attention to accounting for both spatial and temporal complexity in our land-use models. The last section contains discussion and conclusions.

2. Site description

Extensive fieldwork conducted in the study region provides the context for the analyses. Researchers have collected data in the municipio of La Campa in 1993–1995, 1997, 1998 and 2000, representing over 14 months of work in the area. Data collection methods have included semi-structured and structured interviews, household surveys, land-cover/land-use observations (training samples), forest mensuration, archival research and participant observation. Interviews with community elders, farmers, housewives, local officials and representatives of governmental and non-governmental organisations have provided critical information on trends in agricultural practices and forest uses, and processes of economic development and social change.

The population of La Campa has been growing steadily since the early part of the 20th century. Between 1926 and 1988, the date of the last Honduran census, the population grew from 1606 to 5545 residents (República de Honduras, 1981; SECPLAN, 1990). Through the 1990s, fieldwork observations indicate continuing population growth. Population growth is associated with the decline in swidden agriculture. Elders reported that in their youth, they cleared fields by slash-and-burn methods, and abandoned them to fallow after one to three years of planting. They noted that a decline in available land, and the introduction of fertiliser in the late 1960s, encouraged extended cultivation and plowing.

Research in the municipal archives confirmed the historical dominance of shifting cultivation; permits to clear fields for slash-and-burn agriculture under temporary usufruct rights outnumbered grants for permanent usufruct rights (usually for houselots or pasture). In 1994, 68.4% of the surveyed households reported that they did not have any slash-and-burn fields, and 27.4% responded that they had used slash-and-burn methods only to augment an existing field, clear a fallow, or open an area for permanent cultivation. Over half of the households reported fallow fields, which they anticipated clearing again to plant in the future (Tucker, 1996). This suggests that farmers are rotating fields under short fallow. The data, however, did not include remote villages and less populated areas where households may continue to prefer shifting cultivation.

Economic development programs in the region through the 1980s and 1990s, supported by governmental and non-governmental organisations as well as local initiatives, have accomplished many potable water projects in rural villages, encouraged export coffee production, and supported road construction. Improved roads and transportation have eased travel to cities and permitted frequent visits by travelling merchants who vend staples, tools and household goods. Bus service through La Campa to Gracias has increased from one bus to three since 1994. Two of the buses originate their routes in neighbouring municipios, where improved roads now permit regular vehicular access. In 1994, the road from Gracias to Santa Rosa de Copan, the largest city in western Honduras, was paved and the construction of new bridges was completed. This development facilitated a notable growth in the variety of market products available in Gracias and a marked increase in bus traffic and tourism to Celaque National Park. Agricultural outreach programs have presented seminars on soil conservation methods, correct use of fertilisers and herbicides, and techniques for growing high-yield coffee plants.

Farmers in the study region have responded favourably to national initiatives to expand export coffee production. Credit for coffee farmers has become more readily available even for those who do not have private land titles, such as those in La Campa. Municipal governments have welcomed the national law, Decree 175-87, which provides a subsidy for road improvements to municipios in accordance with their coffee production. In La Campa, the expansion of coffee production has led to improved economic conditions among the minority who planted coffee in the late 1980s and early 1990s; they benefited from a period of high coffee prices. The situation has increased socio-economic heterogeneity, with deepening land scarcity and inequity as the better-off coffee growers have laid claim to the best land (Tucker, 1999a). The research has yet to reveal whether the changing circumstances will encourage permanent outmigration, increased clearing of marginal forestland for agriculture, or changes in economic strategies such as greater emphases on education and off-farm employment.

3. Conceptual framework

3.1. Modelling land-use change

There is a growing literature of models focusing on tropical land-use change. Many early models focused on deforestation, particularly in a frontier setting (such as the impact of settlement programs in the Brazilian Amazon) (Moran et al., 1996; Pfaff, 1999; Walker et al., 2000; Weinhold and Reis, 2001). 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 short sighted and too simplistic; for example, there are cases in which population growth is associated with improved forest conditions (Tiffen et al., 1994; Varughese, 2000).

More recently, scholars have begun to document changes in forest cover that relate to agricultural transformation patterns, and tried to relate these patterns to spatially explicit returns to land use in settings with an established population (Mertens and Lambin, 2000; Mertens et al., 2000). Mather (1990) defined a "forest transition" as the point at which social and economic changes allow some forest regrowth 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

(Rudel, 1998), and/or transitions from subsistence- to market-oriented production systems as input and output market linkages expand and develop (Vance and Geoghegan, 2002).

Templeton and Scherr (1999) provide a comprehensive review of nearly 70 empirical studies, and they conclude that the missing link is the land-labour relationship. To understand the impact of population on the surrounding environment, one must account for changes in the marginal physical product of labour (equal to the effective wage) relative to the cost of land. They propose a U-shaped relationship between land productivity and relative land/labour costs. Initially, as population grows and land becomes scarcer relative to labour, land productivity declines. As population growth continues, farmers may adopt land-saving technologies, which may lead to greater land productivity, which may in turn reduce pressure on more marginal areas. This story is consistent with Boserup's (1967) prediction of agricultural intensification in the face of land scarcity and population growth. Angelsen and Kaimowitz (1999) provide further empirical support for an inverse relationship between rural wages and deforestation rates.

3.2. The empirical 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. This model is sufficiently flexible to be applied in an established, non-frontier setting. For example, sufficient changes in input or output prices may spur land conversion, but this conversion may play out differentially across space.

The returns to land use are determined by two factors. First the inherent productivity, or Ricardian land rent (Currie, 1981) is a function of biogeophysical factors such as topography, soil fertility, and climatic conditions (e.g. temperature and precipitation). The second important factor is market accessibility, drawing on Thünian notions of the crucial importance of transportation costs in the overall spatial pattern of land use (von Thünen, 1966). Therefore, market infrastructure, particularly the existence of roads and road quality, are an important factor influencing the spatially explicit returns to land use (Chomitz and Gray, 1996; Nelson and Hellerstein, 1997; Pfaff, 1999).

Formally, we specify a latent model of land rent. The potential rent, R_{hlT} or all future returns associated with devoting plot l to land use h at time T is given by:

$$R_{hlT} = \int_{t=0}^{\infty} (P_{hlT+t} Q_{hlT+t} - C_{hlT+t} X_{hlT+t}) e^{-i_l t} \, \mathrm{d}t \tag{3.1}$$

where P_{hlT} is the price of the output of use h at point l, C_{hlT} a vector of input prices to use h, Q_{hlT} the potential output of use h, and X_{hlT} is the optimal quantities of inputs for use h all at time t, with the discounting function $e^{i_l t}$, which can be used to account for variations in land tenure (Nelson et al., 2001).[1] The production function is given by

$$Q_{jt} = G_i \sum_{ht} X^{\alpha_{ht}}; \qquad 0 < \alpha_h < 1;$$
$$0 < \sum_{h} \alpha_h \leq 1 \tag{3.2}$$

assuming for simplicity a Cobb–Douglas relationship between each input (h) and output (j) at time t, with output elasticities (the vector of α coefficients) potentially summing to 1 (Beattie and Taylor, 1993). The factor G represents a set of geophysical features that determine the location-specific suitability for a particular land use (Nelson et al., 2001).

3.3. Implementation

In most cases, data for Q are not available for every plot l,[2] and thus a reduced-form model is most often used to represent a potentially endogenous relationship between P and C (Chomitz and Gray, 1996; Mertens and Lambin, 2000; Nelson and Hellerstein, 1997). In equilibrium, spatial differentials in prices are related to

[1] Nelson et al. (2001) used this location-specific discount rate to account for variations in land tenure within a national park, where protected areas were managed by a distinct group of users, indexed by a dummy variable in the econometric analysis. In our study area, land tenure transformations are related to land-use transformations; thus, we do not separate this effect with a dummy variable, but it is implicit in the modeled land-use trajectories.

[2] One notable exception is Geoghegan et al., 1997, 2001. Because of the *ejido* system in the Yucatan, the area managed by a particular user did not change over time, and they were able to match time-series satellite imagery to household surveys. This project is one of the most successful to date at linking the household to the landscape.

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

$$\begin{aligned} P_{lht} &= \exp(\gamma_{0ht} + \gamma_{1ht} D_l) \quad \text{and} \\ C_{lht} &= \exp(\delta_{0ht} + \delta_{1ht} D_l) \end{aligned} \tag{3.3}$$

where γ_{0ht} and δ_{0ht} represent fixed costs, output prices decrease with distance ($\gamma_{1ht} < 0$), and input prices increase ($\delta_{1ht} > 0$). To represent two land uses (subsistence agriculture and coffee), we calibrated P and C with the actual producer prices for coffee (national), and maize (local). The effect of transportation cost should vary by product, and though the market price does not vary across space, its combined spatial-temporal impact may vary.[3] Thus, though the component of the farm-gate price should be small relative to total transportation costs, we will still have relative differences, and these relative differences will change through time.

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] These studies demonstrated that landscape pattern is related to the configuration and concentration of land values and agricultural production. An obvious example of the relationship between 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. Spill-over effects and spatial externalities across land uses are also important determinants of land-use change by contributing to the profitability of a particular parcel (Irwin and Bockstael, 2001).

Formally, we assume that land is devoted to the use with the highest rent, or point l is devoted to use h at time t if

$$R_{hlt} - w > R_{jlt}, \qquad \forall j \neq h \tag{3.4}$$

where w represents some fixed conversion cost. We assume that this conversion cost is orthogonal to the other explanatory variables,[5] but may be prohibitive in some cases. For example, the start-up costs for coffee production may be beyond the means of certain households in the study region, such that even if they had access to suitable land, they would not be able to proceed to clear for coffee.

Substituting (3.3) and (3.2) into (3.1), the reduced form of the model becomes:

$$\begin{aligned} \ln R_{hlT} &= \eta_{0ht} + \sum_h (\eta_{1ht} + \eta_{1h} D_l) \\ &\quad + \eta_{2ht} S_{lt} + \eta_{3h} G_l \equiv \beta_{lt} X_{ht} \end{aligned} \tag{3.5}$$

where the returns to land use h at location l is a function of the set of spatially- and temporally-variant input and output costs (η_1), the effective transportation costs (D), landscape pattern variables (S), geophysical features (G), and the vector of parameters (η). This model can either be represented in a binary probit formulation:

$$\begin{aligned} Y &= 1 \quad \text{if } R_{i1} > R_{i0} \\ Y &= 0 \quad \text{otherwise} \end{aligned} \tag{3.6}$$

where 1 represents cleared land and 0 forest. This formulation is sufficiently flexible to represent the removal of land from production.

4. Analysis

4.1. Satellite image analysis

Landsat 5 TM images were obtained for March of 1987, 1991, and 1996, because this month corresponds

[3] Many thanks to Alex DePinto for the interesting and creative suggestion to include temporally-varying prices in the spatial differential.

[4] Parker (2000) uses landscape concentration/fragmentation indices in land-use pattern as an analogy to the familiar Herfindahl index of industrial concentration.

[5] We give thanks to an anonymous reviewer for pointing out the relevance of conversion costs. We also note that timing may be a crucial factor in land conversion, but do not model the time decision here (Irwin and Bockstael, 2001). The assumption of orthogonality of conversion costs may be limiting, but this assumption conforms well to our choice of land-use trajectories, and given the lack of better available data, is a good starting point.

Table 1
Mean values of independent variables across land-use classes

	Stable forest	Deforestation	Fallow	Forest regrowth	Stable agriculture	All classes	Units
Area	401.40	97.13	93.95	102.72	319.91	1015.12	km^2
Elevation	15.89	12.46	12.83	12.53	11.67	13.59	100 m
Slope	18.43	15.30	14.51	16.95	14.54	16.39	Degrees
Spatially lagged slope	18.28	15.02	14.76	16.40	14.49	16.25	Degrees
Distance to the nearest town	11.71	7.59	6.57	6.21	5.21	8.20	Scaled, weighted cost of access
Distance out of region	19.99	16.81	16.97	16.28	16.60	17.94	Scaled, weighted cost of access
Patch size	1.79	1.33	1.33	1.01	2.83	2.17	km^2

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-neighbour resampling algorithm, with a root mean square (RMS) error of <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 (observations of land cover at discrete, random points) were used to determine the land-cover classes on the ground and then train the satellite image to recognise 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. The areas of water and urban were very small, so the non-forest class is almost entirely land cleared for agricultural uses. Forest cover included existing forest and forest regrowth due to natural regeneration, and was defined as having a canopy closure of 25% 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.

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 trajectories. Results of this change detection indicated significant bi-directional change over the study period, with forest regrowth as the dominant process (Table 1). The minimum mapping unit from the satellite image, the 900 m^2 pixel, becomes the econometric unit of analysis, which roughly conforms to the size of the smallest plots.

Mertens and Lambin (2000) developed a schematic to link a three-date land-cover change grid to underlying land uses. In the case of western Honduras, there are three main processes of 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., 2002). Lastly, there is a fallow cycle, shortened though it may be, for remaining staple crop production. Therefore, with some confidence, we can link forest regrowth and permanent clearing to subsistence production, and recent deforestation to coffee. We associate forest across all three dates with stable forest, non-forest across all three dates with stable agriculture, and cyclical changes from forest to non-forest with a fallow cycle.

4.2. Econometric estimation

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 in particular allows for unmeasured or unmodelled variation across counties is due to exogenous, random shocks (such as climate, business cycle fluctuations, etc.) (Greene, 2001). There is a risk of unmodelled or uncorrected time dependence in panel approaches, which can bias estimators. However, tests for serial autocorrelation (such as the Durbin–Watson statistic) for previous analyses were insignificant. Moreover, the 4 year time step between observations greatly reduces the risk of serial autocorrelation. Lastly, with only three time periods, we would not be able to identify the correct autoregressive procedure.

In this analysis, we account for varying spatial and temporal complexity in the pattern of land-cover change in western Honduras. We employ an iterative procedure to correct for spatial autocorrelation and examine its effect on model accuracy for a binary probit model of forest/non-forest across three dates. Then, we estimate a random-effects probit including all three time periods.

4.2.1. Independent variables

The land-cover change trajectories are a function of the factors that determine agricultural suitability and market accessibility. 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 centre of exchange) and Tegucigalpa (the capital city). In addition, much local exchange takes place in nearby towns and villages, so we include these population centres as additional local market destinations. We initially assigned a base impedance factor to cleared land (2) and forested land (1). Prior analyses (Nelson and Hellerstein, 1997) have assumed that cleared land is more easily traversed than forested land. Given that the forest cover in our study region is dry tropical, and cleared land is likely privately managed, we actually assume forestland (which is more often commonly managed) is in effect easier to traverse. 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., 2001). Using Arc/Info GRID^{TM}, we then calculated the least-cost path from every pixel to the road out of the region, and to the nearest town or village on this base cost surface, providing a weighted measure of distance to markets. Patch size was also calculated using Arc/Info as the total area in which each sample pixel was found, in km^2. Table 1 contains mean values for these explanatory variables.

For the single-period probit models, we used simply these weighted distances to local and regional markets. For the panel probit model, variations in relative prices were incorporated (following (3.5)). Assuming that land users may not instantly respond to changes in price, we used a 3 years moving average smoothed price for the following crops: maize, beans, and coffee. Assuming that maize and beans are traded locally, these prices were combined with the weighted distances to local markets, while the coffee price was combined with the weighted distance to regional markets.

4.2.2. Spatial complexity

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 neighbourhood effects (see Anselin, 2002). 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-use change due to the difficulty of incorporating them into models with limited dependent variables, which can result in mis-specification (Anselin, 2002).

Following Mertens and Lambin (2000), we employ spatial sampling to filter residual spatial autocorrelation. We are now also able to check the validity of this approach, using a new Moran's I-test statistic suitable for a wide range of discrete choice models which has been developed by Kelejian and Prucha (2001). Traditionally, Moran's I is defined as:

$$I = \frac{e'We}{e'e} \tag{4.1}$$

where e represents a vector of estimated regression residuals, and W represents the chosen spatial weighting function (see Cliff and Ord (1981) for a discussion of spatial weighting functions). In order to test a probit model for spatial autocorrelation, one must first estimate regression residuals. The probit model is based on the standard normal distribution. The probabilities that y (the observed outcome) will take the values forest (0) or non-forest (1), are given by

$$\begin{aligned} \Pr(y_i = 1) &= \Phi(x_i\beta) \\ \Pr(y_i = 0) &= 1 - \Phi(x_i\beta) \end{aligned} \tag{4.2}$$

Therefore, estimated residuals are given by

$$y_i = \Phi(x_i\beta) + \varepsilon_i \tag{4.3}$$

where $E(\varepsilon_i) = 0$ and $E(\varepsilon_i^2) = \Phi(x_i\beta)[1 - \Phi(x_i\beta)]$. We let $\hat{\varepsilon}_i = y_i - \Phi(x_i\hat{\beta})$, and $\hat{\sigma}_{i,n}^2 = \Phi(x_i\hat{\beta})[1 - \Phi(x_i\hat{\beta})]$ (Kelejian and Prucha, 2001). The new Moran's I statistic is then defined as:

$$I_n = \frac{Q_n^*}{\tilde{\sigma}_{Q_n^*}} \xrightarrow{D} N(0,1), \quad \text{where} \quad Q_n^* = \hat{\boldsymbol{\varepsilon}}' \boldsymbol{W} \hat{\boldsymbol{\varepsilon}} \tag{4.4}$$

The numerator Q_n^* looks like the familiar Moran's I-test, while the denominator consists of a scaling factor $\tilde{\sigma}_{Q_n^*}$ to account for the limited dependent variable y:

$$\begin{aligned} \tilde{\sigma}_{Q_n^*} &= \frac{1}{2}\sum_{i=1}^{n}\sum_{k=1}^{n}(w_{ik,n} + w_{ki,n})^2 \hat{\sigma}_{i,n}^2 \hat{\sigma}_{k,n}^2 \\ &= \mathrm{Tr}(W_n \hat{\Sigma}_n W_n \hat{\Sigma}_n + W'_n \hat{\Sigma}_n W_n \hat{\Sigma}_n) \end{aligned} \tag{4.5}$$

where $\hat{\Sigma}_n = \mathrm{diag}(\hat{\sigma}_{i,n}^2)$, with the variance estimator defined above (see Kelejian and Prucha, 2001 for proof of consistency). This test is unfortunately susceptible to heteroskedasticity, but it is useful as one useful diagnostic tool in distinguishing and quantifying spatial effects.

We explored the impact of spatial sampling (e.g. creating distance between observations) on both diagnostics for spatial autocorrelation, and the overall accuracy of econometric predictions. We iteratively sampled the data set, beginning with a distance of 627 m (19 Landsat TM pixels), and ending with a distance of 1815 m (55 Landsat TM pixels). There is a practical trade-off between the reduction in spatial autocorrelation, and in the number of observations caused by spatial sampling.[6] In the study area, there was a total number of 1,127,910 pixels, so the greater the sampling distance, the fewer the observations. A sampling distance of 627 m led to 5040 observations, whereas a sampling distance of 1815 m left only 1071 observations. From a probit model for the first-time period, we calculated regression residuals for five different sampling distances, and calculated the difference in the Kelejian–Prucha Moran's I statistic. The significance of that statistic is given by a t-test, since the statistic is asymptotically normally distributed. The value of the statistic ranged from 17.99 (at 627 m) to 5.02 (at 1815 m), so according to this statistic, sampling our data set spatially reduced the extent or magnitude of spatial autocorrelation, but did not eliminate it completely.

In order to quantify the impact of spatial sampling on overall model accuracy, we used techniques from the remote sensing literature to evaluate the number of correct predictions at each sampling distance (Table 2). This matrix shows the number of total and predicted occurrences in each category for each model. Values on the diagonal are observations correctly predicted according to the observed value. The overall accuracy is the ratio of the sum of total correct predictions to the overall number of observations. A last helpful measure of accuracy is the Kappa statistic. The Kappa statistic ranges between 0 (completely inaccurate) and 1 (completely accurate) and measures the observed agreement between the classification and the reference data and the agreement that might be attained solely by chance matching (Jensen, 1996).

What is most interesting about the effect of sampling on prediction accuracy is the change in the Kappa statistic with increased sampling distance. Fig. 2 presents the change in both the Kelejian–Prucha

[6] One could, of course, expand the size of the study area to obtain more observations for spatial sampling at greater distances. We did not have field data for any greater area than this region, and the cost or effort of generating reliable independent variables would thus greatly increase.

Table 2
Error matrix for a probit model of forest/non-forest, 1987

Actual	Non-forest	Forest	Total
Sampling distance = 627 m			
Non-forest	2699	1194	3893
Forest	1762	2901	4663
Total	4461	4095	8556
Overall	65.45%		
Kappa	0.74		
Sampling distance = 825 m			
Non-forest	1549	765	2314
Forest	1075	1651	2726
Total	2624	2416	5040
Overall	63.49%		
Kappa	0.78		
Sampling distance = 1089			
Non-forest	844	444	1288
Forest	570	1058	1628
Total	1414	1502	2916
Overall	65.23%		
Kappa	0.30		
Sampling distance = 1485 m			
Non-forest	509	210	719
Forest	353	488	841
Total	862	698	1560
Overall	63.91%		
Kappa	0.28		
Sampling distance = 1815 m			
Non-forest	368	137	505
Forest	233	333	566
Total	601	470	1071
Overall	65.45%		
Kappa	0.31		

Moran's I and the Kappa statistic as sampling distance increases. Overall prediction accuracy does not change or only slightly declines as sampling distance increases, but after the sampling distance increases beyond 825 m, the Kappa statistic decreases from 0.78 to 0.30. This finding was confirmed by comparing the ratios of the log likelihood and restricted log likelihood values across models; the ratio was the greatest at this sampling distance, indicating that the model had the most explanatory power in terms of the variation captured by the parameter estimates for independent variables. Therefore, the reduction in observations (and thus information in the independent variables) caused by spatial sampling greatly reduces the overall predictive power of the regressions. Thus, we decided to use the sampling distance of 825 m in the final analysis.

4.2.3. Temporal complexity

Satellite imagery analysis is a useful tool for the production of maps at greater spatial extents or over more frequent time steps than in situ field studies. Too often, however, the distinction between land use and land cover is not well understood. Mertens and Lambin (2000) were the first to propose a link between land-cover change trajectories and land use. They contended that a three-date change image exhaustively describe a set of land-use practices in their study region (Mertens and Lambin, 2000).

In this empirical example, we have a complicated mosaic of changing land-cover patterns over time. Prior analysis has indicated that the relationship between market distance, topography and land-cover change is substantially different in the period 1991–1996 than in 1987–1991 (Southworth and Tucker, 2001). Therefore, we wished to test for changing temporal effects in this analysis. To test whether the estimated coefficients were actually different across the three time periods, a likelihood ratio test was used. We ran a probit model on the time invariant variables: slope, spatially lagged slope, and elevation for each time period separately, then pooled the data from all time periods. The test statistic, Lrtest, was calculated as follows:

$$\text{Lrtest} = 2(L1 + L2 + L3 - L) \tag{4.6}$$

where $L1$ is the likelihood ratio from the probit model for time period 1, $L2$ and $L3$ the likelihood ratios for time periods 2 and 3, and L is the likelihood ratio for the pooled regression. This test statistic is subject to a χ^2 distribution (Greene, 2001). We rejected the null hypothesis (that the relationships between the dependent variable and the time-invariant independent variables were the same across all time periods) at a level of significance >95%, which indicates that a panel model is preferable to a pooled approach.[7]

[7] As one reviewer correctly pointed out, the panel approach is still subject to unknown heteroskedasticity, which can bias parameter estimates. Currently, there is no correction available for heteroskedasticity in random-effects probit models. For a thoughtful discussion of the impact of uncorrected heteroskedasticity in probit models see Lechner (1995).

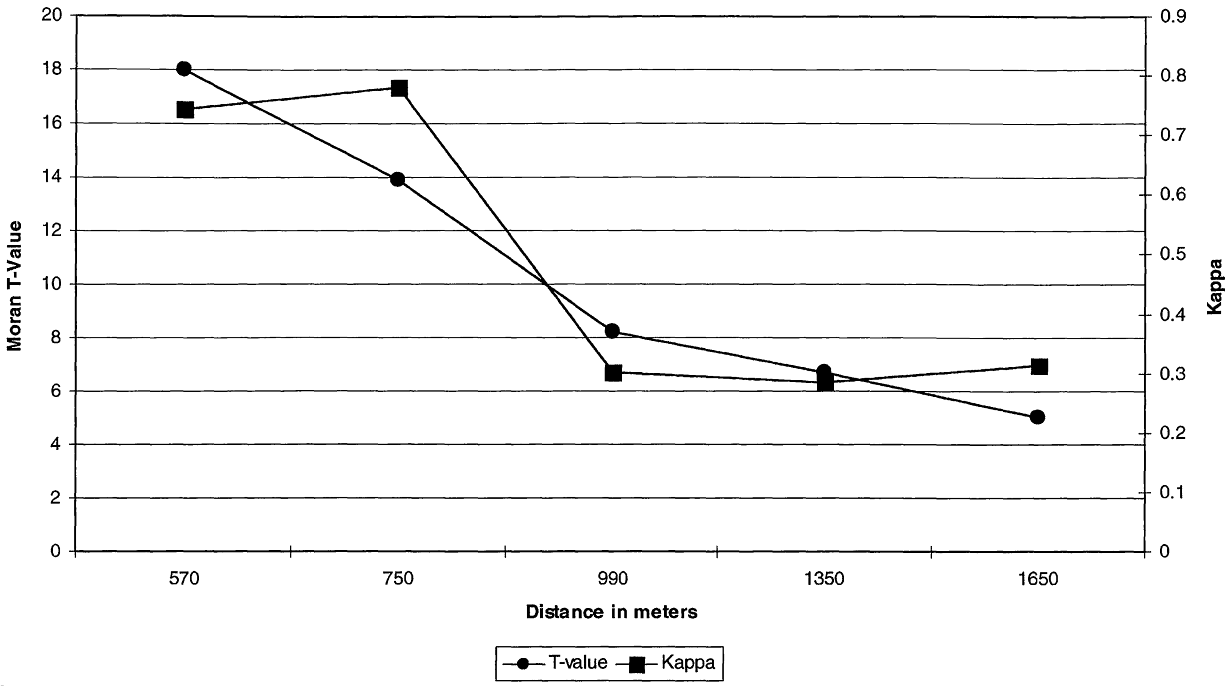

Fig. 2. Significance of the Kelejian–Prucha Moran's I statistic and the estimated Kappa statistic at different sampling distances.

5. Results and prediction accuracy

Table 3 contains estimated marginal effects for each independent variable on the probability of cleared land. We tabulated these effects by five land-use classes. The probability of non-forest is inversely related to elevation, and this impact is stronger in the first period (1987–1991) than the second (1991–1996). The probability of non-forest is positively related to the coffee price plus weighted cost of access out of the region, and inversely related to the maize price plus weighted cost of access to local markets.

Overall, the random-effects probit model explained roughly 60% of total variation in land-cover change from 1987 to 1996, according to the pseudo-R^2 measures calculated by LIMDEP. An additional means for evaluating model accuracy is to generate predictions of land cover for each observation. A predicted

Table 3
Marginal effects (probability of deforestation) by land-use category, random-effects probit model

Variable	Stable forest	Deforestation (1987–1991)	Deforestation (1991–1996)	Fallow cycle	Stable agriculture	All obs.
Constant	0.1973	0.2299	0.2258	0.2280	0.2088	0.2285
Elevation	−0.0367	−0.0427	−0.0420	−0.0424	−0.0388	−0.0425
Slope	−0.0012	−0.0014	−0.0014	−0.0014	−0.0013	−0.0014
Maize price + distance to nearest village	−0.0132	−0.0154	−0.0151	−0.0153	−0.0140	−0.0153
Coffee price + distance out of region	0.0055	0.0064	0.0062	0.0063	0.0058	0.0063
Patch size	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

Table 4
Predicted versus actual cross-tabulation, random-effects probit

Land cover 87–96	Random-effects probit								Total	Percent correct (%)
	f–f–f	f–f–n	n–f–f	n–f–n	f–n–f	f–n–n	n–n–f	n–n–n		
f–f–f	453	1	115	29	0	0	4	55	657	68.95
f–f–n	30	11	23	11	0	0	5	9	89	12.36
n–f–f	43	3	20	4	0	4	2	4	80	25.00
n–f–n	22	1	10	24	1	0	1	5	64	37.50
f–n–f	28	0	16	2	22	1	10	16	95	23.16
f–n–n	14	0	14	0	2	10	5	14	59	16.95
n–n–f	31	4	5	3	8	1	31	21	104	29.81
n–n–n	59	3	29	4	3	13	17	404	532	75.94
Total	680	23	232	77	36	29	75	528	1680	
Overall accuracy	0.58									
Kappa	0.42									

value was assigned to each observation (with probability >0.50) for each time period. Overall prediction accuracy was 0.58, but the Kappa statistic was only 0.42 (Table 4). We were able to separate out stable forest and stable non-forest at >60% accuracy. User's accuracy (percent of correct predictions) for reforestation ranged from 8.62 to 61.11%, whereas accuracy of deforestation ranged from 31.17 to 47.83%. Therefore, this simple model is capturing some of the complex changes occurring in the landscape.

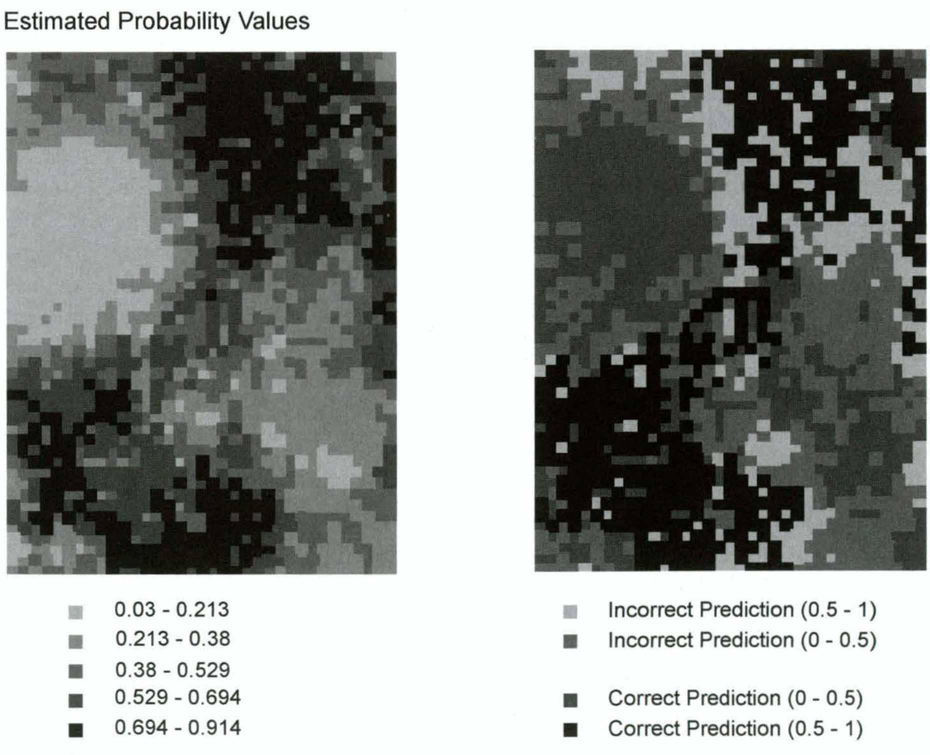

Fig. 3. Random-effects probit estimated probabilities.

Overall, the spatial distribution of this change conforms quite well to actual land cover. However, the assignment of forest or non-forest based on probability values only provides some information on predictive power. Another important measure is the actual probability values themselves. Fig. 3 contains estimated probabilities of non-forest (i.e. prob = 1 implies non-forest). A graphical depiction of predicted versus actual land-cover change can be found at http://www.cipec.org/publications/munroe_southworth_tucker_figures.html. As expected, the estimated probability of non-forest is the lowest at high elevations, far from roads, and highest at low elevations, close to roads, but there is a lot of variation among the edges. In particular, the estimated probabilities of non-forest are closest to 0.5 (implying roughly equal probability of forest or non-forest) at edge areas. Incorrect predictions were more likely to occur in smaller patches around the edges of more stable forest or non-forest. These estimated probabilities can also serve as a tool for further analysis. For instance, one could investigate with fieldwork areas where predicted probabilities were lower to determine what other significant variables might be missing from the analysis, and could be incorporated in future.

6. Discussion and conclusion

This analysis has demonstrated the necessity of a spatial approach in studying land-use/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 forest regrowth over time point to a very complex pattern of land-use transformations. 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. Our analysis shows that additional information is gained by employing panel approaches that specifically account for individual heterogeneity across time.

Both socio-economic 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. In addition, extended cultivation and coffee planting have led to a decline in communal tenure and increasing de factor private tenure. The change in tenure also relates to population growth relative to land availability and the resulting change from shifting cultivation to short fallow fields.

The expansion of coffee production represents a novel process that is changing the landscape directly and indirectly. Many farmers see coffee as a good investment despite substantial start-up costs, and government programs for road improvements in coffee-growing areas provide a further 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 most significant finding in this analysis is that the probability of stable agricultural production is significantly greater at lower elevations, flatter slopes, and in larger patches than areas of forest cover in the region. Stable agriculture also tends to be found in areas that are relatively more accessible to local markets, but less accessible to regional markets. Accessibility to regional markets is relatively more important for the probability of deforestation than for stable agriculture during the study period, again, underscoring the increasing market orientation of the region. Overall, stable forest and stable agriculture were predicted with much higher accuracies, followed by the prediction of forest regrowth. The number of accurate predictions of deforestation was the lowest across all models, indicating that the conceptual model, as it stands, is missing an important incentive, and that topography and market infrastructure are not the only relevant drivers of land-use conversion in western Honduras. However, given the simplicity of the model, we were able to explain much of the complexity in land-cover transformations in the region.

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. Much attention has been paid to "slash-and-burn" cultivators and their role in deforestation (Myers, 1994). Swidden or shifting cultivation often results in further encroachment into primary forest, and the cyclical abandonment of land, sometimes leading to secondary forest regrowth. Shifting cultivation is found under conditions of land abundance and labour scarcity (Netting, 1982), but also relates to the social and institutional context of production, and the relative undervaluing of forestland as a means of production. The true social value of forestland should reflect also its role in habitat provision, species preservation, carbon sequestration, and other functions less likely to be considered by an individual land user. The immediate value of forestland in the user's perspective may consider only its relative scarcity and the cost of land conversion (Pearce and Brown, 1994). In the study region, transformations of agricultural production systems are closely related to transformations of property rights regimes, from common property to de facto and de jure private property (Tucker, 1999a,b). We do not have records for these changes, but because they are closely associated with the level or extent of intensification, we can with some confidence use land-cover changes not only as an indicator of land-use transformations, but of continued institutional changes and development.

The purpose of this analysis was to combine techniques from land-cover change 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 explicitly correcting and testing for spatial autocorrelation. 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.

Recent developments in spatial statistical techniques have facilitated a rigorous, quantitative test of the efficacy of spatial sampling in reducing spatial autocorrelation. Interestingly, we found a trade-off between spatial sampling and model accuracy. There is likely an underlying base level of correct predictions that will occur by chance, and though spatial sampling reduces spatial autocorrelation, it also reduces the total information in the dataset (particularly if the size of the study region remains constant). More research is needed on the interplay between traditional information criteria evaluation approaches, spatial accuracy and the explanatory power of econometric models (see Pontius (2000) for some promising suggestions).

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