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Farm-level models of spatial patterns of land use and land cover dynamics in the Ecuadorian Amazon

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Abstract

Longitudinal studies examining socio-demographic and other contextual factors are vital to understanding landscape change. Landscape structure, function, and change are assessed for the northern Ecuadorian Amazon by examining the composition and spatial organization of deforestation, agricultural extensification, and secondary plant succession at the farm level in 1990 and 1999 through the integration of data from a satellite time-series, a longitudinal household survey, and GIS coverages. Pattern metrics were calculated at the farm level through the generation of a hybrid land use and land cover (LULC) digital classification of Landsat Thematic Mapper (TM) data. Population, labor, and other household variables were generated from a scientific sample of survey farms or *fincas* interviewed in 1990 and resurveyed in 1999. Topography, soils, and distance and geographic accessibility measures were derived for sample farms through a GIS as well as qualitative assessments from household surveys. Generalized linear mixed models (GLMMs) were generated for 155 and 157 *fincas* in 1990 and 1999, respectively, using pattern metrics at the landscape level as dependent variables, and biophysical, geographical, and socio-economic/demographic variables as independent variables. The models were derived to explore the changing nature of LULC at the *finca* level by assessing the variation in the spatial structure or organization of farm landscapes in 1990 and 1999, and the extent to which this variation could be explained by the available data. Results indicate rapid population growth causing substantial subdivision of plots, which in turn has created a more complex and fragmented landscape in 1999 than in 1990. Key factors predicting landscape complexity are population size and composition, plot fragmentation through subdivision, expansion of the road and electrical networks, age of the plot (1990 only), and topography. The research demonstrates that the process of combining data from household surveys, satellite time-series images, and GIS coverages provide an ideal framework to examine population–environment interactions and that the statistical models presented are powerful tools to combine such data in an integrated way.

Keywords: Pattern metrics; Satellite time-series; GIS coverages; Empirical models; Deforestation; Agricultural extensification; Northeastern Ecuador

1. Introduction

A growing literature on population–environment relationships reveals that the effects of LULC (land

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use/land cover) dynamics in frontier environments can be considered as occurring through a number of contextual or mediating factors representing political, human, and landscape ecology theory (Bilsborrow, 1987, 2003; Marquette and Bilsborrow, 1994; Moran and Brondizio, 1998; Wood and Skole, 1998; Walsh et al., 1999, 2001, 2003). Political ecology describes forces and factors that are imposed upon a local system from a regional or global context (Blaikie and Brookfield, 1987). Human ecology argues that people are active agents, within the interplay between population and the environment, who both shape and are shaped by the environment (Pattison, 1969). Landscape ecology describes how landscape structure, function, and change are influenced by ecological processes (Forman and Godron, 1986). From a spatial perspective, political, human, and landscape ecology function at multiple scales through exogenous and endogenous factors to alter the spatial organization of landscapes, which are assessed at a variety of grains and extents, and whose effects are scale-dependent. To define the context and mechanisms of these theoretical LULC processes, "characteristic" scales—ranges of spatial and/or temporal scales in which scale–pattern–process relationships are autocorrelated—are defined such that coarser scales above the characteristic scale define context, and finer scales below the characteristic scale define mechanisms.

Based upon these theories and prior research, the examination of human–environment interactions is extended to the Oriente or Northern Amazon region of Ecuador through a Geographic Information Science (GISc) perspective linked to multivariate statistical models. In this research, we demonstrate the integration of spatial information (i.e., remote sensing images and GIS coverages) with household survey data, and statistically explore different models of landscape complexity in two different time periods. Specifically, using farms surveyed in 1990 and 1999, and located within three selected ISAs in the larger regional study area, three types of pattern metrics have been computed to serve as dependent variables: patch density, landscape shape, and contagion. Patch density is a metric of patch configuration and composition, whereas landscape shape and contagion capture patch complexity, fragmentation, and landscape texture. The pattern metrics were computed from 1986 and 1999 Landsat Thematic Mapper (TM) images and linked to a set of independent variables extracted from 1990 and 1999 longitudinal household surveys, and derived from GIS coverage data to represent hypothesized effects of household characteristics on the spatial structure or organization of LULC patterns. The collected and derived data were integrated through multiple regression models developed for 1990 and 1999, and interpreted relative to population–environment theories and our direct observations of how farms are evolving in the Oriente and how LULC is being altered. The statistical models presented here are more statistically robust (than previous models) to dependencies between nearby *fincas*, because of the inclusion of within sector correlation when computing parameter estimates. In addition, GIS coverage and pattern metrics are more complete, since we analyzed data collected from three ISAs rather than only the NISA.

The broad goals of this paper are to explore the relevance of spatial patterns of LULC at the farm-level, and how socio-economic, demographic, biophysical, and geographical variables explain the observed variation in LULC patterns, described through a 1986 and 1999 satellite classification of LULC, and the application of selected pattern metrics to quantify the spatial structure of LULC patterns for the two time periods. The primary goals are to explicitly consider the spatial landscape patterns on surveyed farms and to associate landscape form with landscape function through the regression models. The aim is not to develop an ultimate model of forces driving the spatial re-organization of LULC in the Oriente, but rather is more methodological to explore the nature of spatial patterns of land use at the farm-level and to assess the factors associated with landscape pattern in 1990 and 1999. Therefore, parameters and coefficients for the 1990 and 1999 models were individually interpreted through separate regressions and collectively compared to examine their relative importance in the two time periods. How the socio-economic, demographic, biophysical, and geographical variables affect LULC patterns at two different stages of frontier development (i.e., at the two selected dates) were explicitly addressed. In the course of this analysis, the nature of the LULC classification scheme and the choice of pattern metrics were implicitly considered.

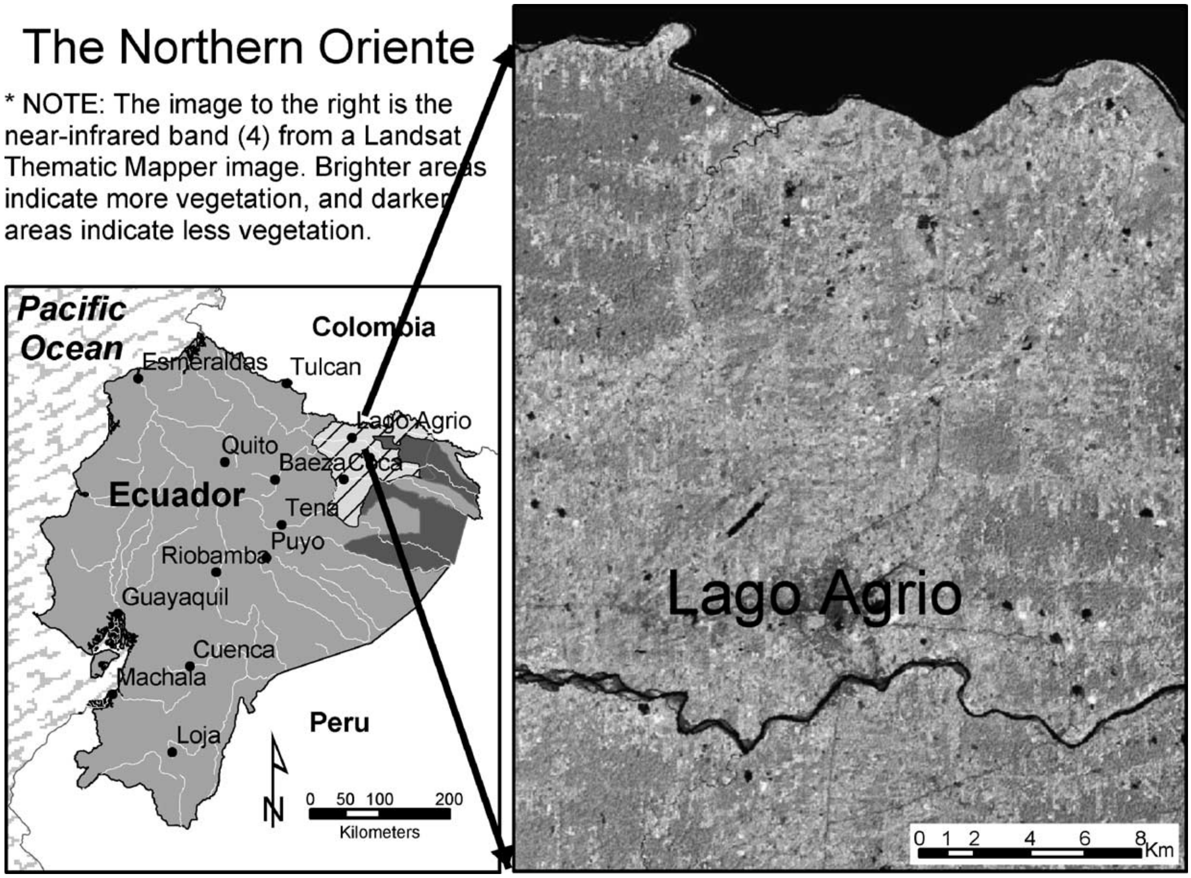

Fig. 1. Study area location, northeastern Ecuadorian Amazon.

2. Methods

2.1. Contextual background—Ecuador

The northern Ecuadorian Amazon (Fig. 1) is an extraordinarily biologically diverse region and one of the 11 ecological "hot spots" in the world (Myers, 1988; Myers et al., 2000). Rapid migration into this region began in the early 1970s when petroleum companies built roads to explore for oil, and subsequently, to extract it by laying pipelines. Once the region became accessible through the road network, colonists migrated to the region in search of land, spurring rapid population growth. Over the past three intercensal periods, population for the Amazon region as a whole (provinces of Napo, Sucumbios, Orellana, Pastaza, Morona Santiago, and Zamora Chinchipe) has grown at over double the national rates, at 8% per year from 1974 to 1982, 5% per year from 1982 to 1990, and 3.5% per year from 1990 to 2001.

Migrants claimed farms or *fincas*, normally configured as 0.25 km × 2.0 km plots (approximately 50 ha), initially along roads due to geographic accessibility and subsequently on parallel rows of farms or *lineas* extending up to 16 km back from the main roads. Once established, a group of farmers living in one area or *sector* would seek to have their land boundaries surveyed by the Ecuadorian land titling agency, IERAC, to establish plot boundaries as the first step towards purchasing provisional land titles and ultimately full land titles. As a result, small-scale farmers have been the primary direct agents of land conversion from forest to agriculture in Ecuador (Bromley, 1989; Rudel and Horowitz, 1993; Southgate and Whitaker, 1994; Pichón and Bilsborrow, 1999).

The Oriente, unlike the Brazilian Amazon: (1) has no large urban areas—Lago Agrio is the largest city with a 2001 census population of only 34,000; (2) settlers are predominantly poor farmers; (3) no government subsidies or other major policies were developed to encourage ranching; and (4) there has been no large-scale timber extraction by commercial logging companies. In addition, the Oriente has no season without rain, resulting in little slash-and-burn agriculture, and generally appears to have more fertile soils, reducing the abandonment of land plots following agricultural cultivation. The agricultural system in the region involves annual crops such as corn and rice; semi-perennials such as plantains, bananas, and yucca; and perennial tree cash crops, mainly coffee (on over 80% of all farms) with modest production of cacao.

2.2. Northern Ecuadorian Amazon study area and prior research

Based on the northern-most provinces of Sucumbios and Orellana, a study was initiated in 1990 to examine the household factors affecting LULC. Data were collected subsequently consisting of: (1) household surveys of farm plots in 1990 and 1999; (2) a time-series of satellite imagery from 1973 to 2002; and (3) a community survey in 2000 to provide regional infrastructure and other contextual information. Analyses indicate widespread land subdivision since 1990 on sample *fincas* located along main roads. Subdivision has occurred because of sales of parts of a *finca* to new in-migrants or through inheritance by children of settlers. The result has been a significant decline in farm size, leading new owners to reduce land in forest and pasture and increase more in the intensive forms of land use—perennials (mostly coffee) and annual crops. Other important changes since 1990 include the expansion of the road network and electrification grid, and an increase in off-farm employment.

Statistical models have been developed to examine the variation in LULC as reported in the 1990 and 1999 socio-economic and demographic surveys. Pichón (1997), Pichón and Bilsborrow (1999) and Pan et al. (2001) conducted cross-sectional multivariate regression analyses to examine the determinants of LULC dynamics at the farm-level. Findings suggest that a number of demographic (i.e., education level, household size), socio-economic (i.e., land title, household labor), biophysical (i.e., soil and terrain), and geographical (i.e., distances to roads and markets) factors significantly influence land use. Pattern metrics and cellular automata models utilizing the satellite time-series (Messina et al., 1999; Messina and Walsh, 2001; Walsh et al., 2002) suggest that the Oriente as a whole, but the Northern Intensive Study Area (NISA) in particular, is undergoing a conversion of LULC types from high-density forest to agriculture and to low and medium density forest. The sequence of changes over time has been attributed to initial deforestation along roads, second stage forest clearing to expand subsistence agriculture to commercial activities, renewed deforestation on *fincas* whose ownership patterns have changed through land subdivision, and modest secondary plant succession of agricultural lands related to declining soil fertility and land conversion to pasture.

2.3. The household longitudinal survey and socio-economic variables

To help understand the processes affecting change in the region, a representative sample of migrant settler household plots was selected in 1990 and revisited in 1999. In the 1990 household survey, 470 *fincas* were selected from 64 sectors. Two questionnaires per household farm were administered separately to the household head and spouse to acquire information regarding land use, labor, technical assistance, household composition, fertility, household assets, etc. Data were successfully collected for 418 farm subdivisions located on 398 *fincas*, with a response rate of 95% (most non-responses were farms that lacked economic activity and either lacked a dwelling or a respondent). A follow-up survey was administered in 1999 on the same *fincas* interviewed in 1990 using similar questionnaires for the household head and spouse. During the intervening 9 years, an extraordinary process of subdivision and fragmentation of many of the *fincas* occurred, resulting in more than twice as many families on the same plots as in 1990 (823 farms, plus 111 *solares* or houseplots with 1 ha or less of land). Data were successfully collected for 767 of the 823 farm plots on 392 *fincas*, with a response rate of 95% (most non-responses were either refusals ($N = 21$) or uninhabited farms with no agricultural activity ($N = 22$)).

From the original data collection, we performed analyses on a select group of *fincas* located within sectors inside three ISAs, each approximately 90,000 ha—the NISA, which contains Lago Agrio, the central city within the region and capital of the Sucumbios province; the southern ISA (SISA), which is geographically positioned in a more rolling physical environment containing two small cities—Coca and La Joya de Los Sachas;[1] and the eastern ISA (EISA), containing the main town of Shushufindi. Each ISA is composed of sample sectors containing a cluster of original *fincas*: the NISA contains 7 sectors with 51 *fincas*, the SISA contains 8 sectors and 49 *fincas*, and the EISA includes 8 sectors and 60 *fincas*. The maximum sample size was 23 sectors and 160 *fincas* for each time period, from which GIS coverage data were available. Survey data were complete for 155 *fincas* in 1990 and 157 *fincas* in 1999. Sectors may be at different stages of deforestation and agricultural extensification, due to the spatial diffusion of roads, population growth, and accessibility between *fincas* within a sector and communities; therefore, multilevel sector effects were modeled to control for correlation between *fincas* located within the same sector.

Variables derived from the household survey for the statistical model were categorized as biophysical, socio-economic/demographic, and geographic (Table 1). Since the observation of interest for the present analysis is the original *finca* and not the individual subdivision, it was necessary to aggregate information for all farms on a subdivided plot (i.e., compute mean age of household heads, soil quality, topography, ownership title status, etc.). Categorical (binary) variables were defined according to the *proportion* of the *finca* characterized by each variable. Thus, if the owner of a 30 ha plot held legal title to the land, but the owners of a subdivision totaling 15 ha did not, the proportion of the *finca* characterized as having a land title was 0.66 (30/45). In addition, since many of the biophysical and geographic variables were defined from remote sensing imagery, the inclusion of similar alternative variables qualitatively defined by the farmer provided a comparison of the accuracy of measures of land characteristics. Specifically, variables on soil quality, topography, and distance extracted from the survey and GIS coverage data were compared in the statistical models. Qualitative assessments of land (good/black soil and flat land) are often reported by farmers for areas that are already cleared or intended to be cleared, while areas considered unusable are sometimes ignored (see Table 4—the increase in flat plots from 1990 to 1999, compared to mean and median slopes that do not change). In addition, distance measures are sometimes more accurately reported by a farmer due to an incompletely digitized road network. This is especially true for walking distances to the road, whereby the GIS derivation used a straight-line Euclidean path between the household and the road, which may not coincide with the actual path taken by household members.

[1] Coca is the capital of the Orellana Province, smaller than Lago Agrio, and is located in the extreme southwestern corner of the SISA. La Joya is a growing community—yet smaller than Coca—centrally located in the SISA.

2.4. GIS coverages and variable derivatives

Independent variables derived within the GIS from spatial data of the study area include four topographic aspects, three distance calculations to measure accessibility and connectivity of farms to other farms and communities, and six indicators of farm subdivisions on neighboring *fincas*. Table 2 defines each variable derived from the GIS coverage data. Slope statistics, which help identify the more desirable flat terrain, were computed in degrees. The potential wetness index (PWI) layer was generated using three raster layers created in ArcInfo GRID from the DEM, and converting the PWI equation into GRID commands. The equation for PWI is

$$\mathrm{PWI} = \ln\left(\frac{A}{\tan B}\right) \tag{1}$$

where A is the flow accumulation from uphill cells into the target cell, and B the slope of the cell. The PWI variable indicates the level of soil wetness assuming equal rainfall across the entire study area. Values near zero indicate potentially dry areas, such as hill tops and ridges, while higher values indicate areas that could potentially be much wetter, such as valleys, low lying areas, and riverine locations.

The distance from the *finca* to the nearest water source was derived by overlaying a point coverage of

Table 1
Variables derived from the household surveys

Variable category	Variable name	Variable description
Biophysical		
Topography	Flat land	Percent of *finca* classified as flat or flat and rolling
Soil	Good Soil	Percent of *finca* classified with good soil
	Black Soil	Percent of *finca* classified with black soil
Land measures	Area (ha)	Total area of the *finca*
	Number of Crops	Number of different crops found on the *finca*
SES/demographic		
Household	Age of head	Average age of household heads on the *finca*
	Education of head	Average education of household heads on the *finca*
	Number of adult males	Number of males at least 12 years old
	Number of adult females	Number of females at least 12 years old
	Number of children	Population under 12
	Year plot established	Year *finca* first inhabited or cleared for agricultural use
	Technical Assistance	Percent of *finca* that reports TA for crops, cattle, agricultural inputs, or agroforestry
Labor pool	Number of subdivisions	Number of subdivisions on a *finca*
	Number of households	Number of households located on the *finca*
	Original sector size	Number of *fincas* in the 1990 sample sector
	Person-months of hired labor	Total hired labor (day and contract labor)
	Person-months of OFE	Months of off-farm employment among any household members living on the farm
Wealth	Title	Percent of *finca* holding full land title
	Certificate of possession	Percent of *finca* holding provisional land title
	Receipt of credits/loans	Whether any subdivision on a *finca* received credits
	Access to electricity	Whether electricity is available in the home
	Average assets per HH	Mean number assets owned by households on a *finca* (weighted by plot size)
Geographic/spatial		
Distance and plot access	Road access to *finca*	*Finca* has year-round vehicular access, regardless of rain/flooding
	Walking distance to road	Walking distance from household to road (km)
	Road/boat distance to community	Road/boating distance from road to community (km)

the *finca* centroids with a hydrography arc coverage digitized from 1:50,000-scale topographic maps, and containing rivers and lakes. A simple Euclidean distance, in meters, was calculated from each centroid to the nearest hydrography arc. Network distance, in kilometers, from each household to a reference community (one of the four large communities—Lago Agrio, Shushufindi, La Joya de Los Sachas, or Coca—serve as references) in the study area was computed using a road network digitized from 1:50,000 topographic maps. Network analysis required that all *From* and *To* points be on the road network. Because none of the household and GPS points were actually on the network, a modification to their locations had to be made. The community (center) GPS points were moved to the nearest road segment, in most cases a distance of a few meters. For the households, a point was placed midway between the two front corner points of the *finca* and then snapped to the nearest vertex of the nearest road segment. This point represented the *From* point for the *finca*, and the network distance was calculated between each *From* point and community *To* point. As an alternative to Network distance, Euclidean distance from each household to a reference community was also computed in a similar fashion, however, actual household locations were used as the *From* point.

The six neighborhood variables consisted of the number of subdivisions within 3, 5 and 10 km of each

Table 2
Variables derived from GIS coverages

Variable category	Variable name	Variable description
Biophysical		
Topography	Mean slope	Mean degrees of slope characteristic of a *finca*
	Median slope	Median degrees of slope characteristic of a *finca*
Soil	Mean PWI[a]	Mean potential wetness index
	Median PWI	Median potential wetness index
SES/demographic		
Labor pool	Number of subdivisions within 3 km	Number of subdivisions within 3 km of *finca* centroid
	Number of subdivisions within 5 km	Number of subdivisions within 5 km of *finca* centroid
	Number of subdivisions within 10 km	Number of subdivisions within 10 km of *finca* centroid
Geographic/spatial		
Distance and plot access	Network distance community	Network road distance from road access point to the reference community (km)
	Euclidean distance community	Euclidean distance from household to the reference community (km)
	Distance to water (m)	Euclidean distance from *finca* centroid to nearest source of water (m)

[a] Potential wetness index.

finca for 1990 and 1999. The centroid of each *finca* was used as the reference point for the distance calculations and an Avenue program was used to perform the calculations.

2.5. Image classification and pattern metrics

Landsat TM images in 1986 and 1999 of the three ISAs were classified into five generalized LULC classes: forest, non-forest vegetation, urban/barren, water, and cloud/shadow (Fig. 2a–c). A hybrid classification approach, using ERDAS Imagine, was used (Messina, 2001) to characterize LULC in 1986 and 1999 using Landsat TM digital data.[2] The approach involved the ISODATA decision-rule operating within an unsupervised classification mode to define 100 “naturally” occurring spectral classes that were subsequently reduced to approximately 30 classes through the interpretation of the transformed divergence and divergence statistics generated as output from the classification. Then, a supervised classification was applied using a maximum likelihood classifier to associate the unclassified pixels to one of the 30 spectral classes defined through the unsupervised classification. This approach allowed for the generalization of classes to several key LULC types, as well as the expansion of cover types to additional classes as needed. The approach did not rely upon in situ data and/or aerial photography for class definition, but emphasized statistical measures to guide the process so that it would be repeatable for images across the time-series. It thereby lacked the spectral, spatial, and thematic control that was available for more recent images.

Pattern metrics were calculated at the landscape (*finca*) level to assess the nature of landscape composition and spatial organization and to generate spatial/temporal signatures of landscape patterns as part of the scale–pattern–process paradigm (Walsh et al., 2002). The regional spatial context in which sites exist (landscape function) affects the properties, or form, of that landscape (Walsh et al., 2002). The derivation of the metrics was achieved through algorithms contained within FRAGSTATS (McGarigal and Marks, 1995), which calculates the spatial structure of nominal classes of LULC types at the landscape, class, and patch levels. Landscape-level metrics represent patterns occurring within a preset boundary, such as a sector or *finca*; class-level metrics represent the patterns of an LULC class (e.g., forest class) that exist within a defined unit boundary; and patch-level metrics represent the patterns associated with a single contiguous class relative to other classes.

[2] 1986 was the closest useful image date to the 1990 survey that covered all three ISAs used in this study, due to a predominance of clouds and their shadows masking most landscape features.

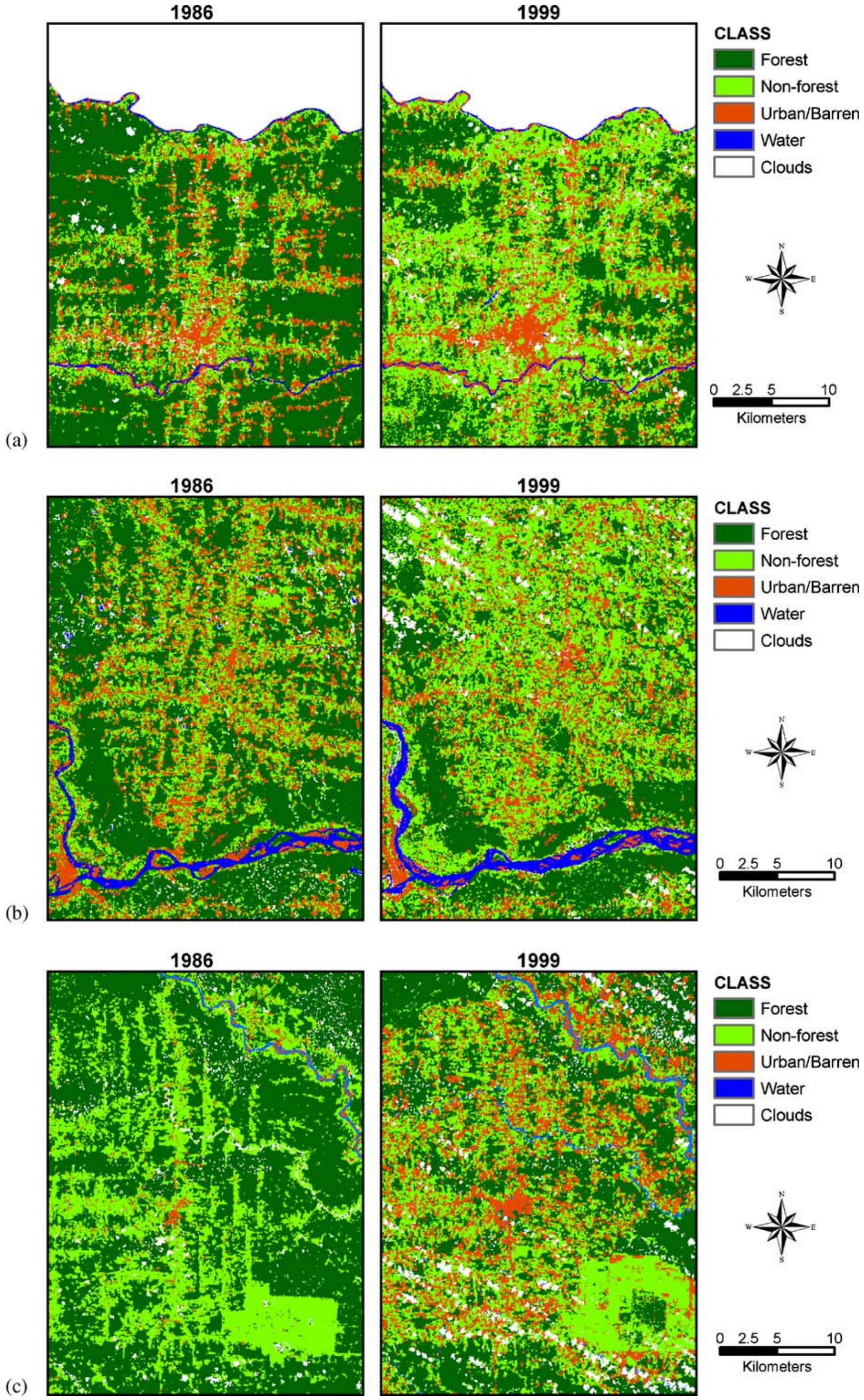

Fig. 2. (a) Classified Landsat TM image for 1986 and 1999 for the Northern ISA. (b) Classified Landsat TM image for 1986 and 1999 for the Southern ISA. (c) Classified Landsat TM image for 1986 and 1999 for the Eastern ISA.

The digital *finca* boundary files were used in ArcInfo GRID to clip the *fincas* out of the 1986 and 1999 classified TM images. The resultant grids were then input into FRAGSTATS to compute the selected landscape metrics for each of the survey *fincas*. Although FRAGSTATS can compute numerous pattern metrics, patch density, landscape shape index, and contagion were used in regression models based upon hypotheses about the spatial organization of LULC and the determinants of landscape dynamics. *Patch density* (PD) expresses fragmentation, but on a per unit area basis by dividing the number of patches in a class by total area, then converting to the number of patches per 100 ha. An increase in PD indicates that a particular *finca* has increased the number of land uses or has fragmented the plot into separate non-contiguous land uses (i.e., broken up a large area of forest into 2 or 3 non-adjacent patches of crops). *Landscape shape index* (LSI) is a standardized measure of total edge, a key factor affecting spatial patterns in landscape ecology, where smaller values indicate fewer patches, more aggregated forms of land use, and less evidence of human alteration of the landscape. It compares the shape of a landscape to that of a simple landscape of the same size by summing the landscape boundary and all edge segments of a particular patch type, then dividing by the square root of the total area. It is essentially a standardized measure of connectivity, insularity, and spatial heterogeneity in the landscape, which in this case is altered by human interaction. *Contagion* (CTGN) is the probability that two adjacent cells belong to different patch types, and therefore measures patch type interspersion and patch dispersion. Interspersion refers to the intermixing of patches of different types and is based solely on patch rather than cell adjacencies, while dispersion refers to the spatial distribution of a patch type. Therefore, holding interspersion constant, a *finca* with large contiguous patches will generally have higher CTGN than one with patches fragmented into smaller patches. Similarly, since dispersion is defined using cell adjacencies rather than patch adjacencies, large contiguous patches will also have high CTGN due to the proportion of total like adjacencies. Table 3 illustrates the high correlation among various metrics computed in FRAGSTATS for our data and the decrease in correlation from 1990 to 1999, reflecting the differences between the two time periods. It is not surprising that the metrics are strongly correlated, given that the equations used to compute them are similar. However, PD, LSI, and CTGN standardize the metrics for easy comparison within a metric (i.e., compare PD vs. the number of patches between two farms, the latter of which is dependent upon plot size), making interpretation more reasonable.

2.6. Statistical methods

The statistical model applied to assess the biophysical, demographic, and geographic factors influencing landscape characterization based on pattern metrics, was a generalized linear mixed model (GLMM; Harville, 1977; Laird and Ware, 1982; Goldstein, 1986, 1995; Bryk and Raudenbush, 1992). GLMMs

Table 3
Correlation matrix of Pattern Metrics computed in 1986 and 1999[a]

Metric	Number of patches		PD		Total edge		Edge density		LSI		CTGN	
	86	99	86	99	86	99	86	99	86	99	86	99
Number of patches												
Patch density	0.84	0.68										
Total edge	0.85	0.61	0.55	0.17								
Edge density (m/ha)	0.85	0.43	0.86	0.54	0.79	0.72						
LSI	0.91	0.61	0.8	0.51	0.88	0.78	0.92	0.84				
Contagion	−0.68	−0.27	−0.71	−0.36	−0.63	−0.47	−0.83	−0.67	−0.76	−0.58		
Interspersion/ juxtaposition[b]	0.24	0.13 NS	0.25	0.19	0.15 NS	0.15 NS	0.22	0.23	0.21	0.21	−0.39	−0.64

[a] PD: patch density, LSI: landscape shape index, CTGN: contagion all correlations are significant at the $P = 0.01$ level, except for those labeled “NS”, which have $P > 0.05$.
[b] $N = 129$ in 1990, 154 in 1999.

rely upon hierarchical theory where higher level units influence lower level sample units. The model combines these multiple-level effects under one model equation with the assumption that random effects (higher level units) are normally distributed and uncorrelated with the fixed effects (lowest level) of the model. The present application assumes that random *sector* effects influence the mean predicted pattern metric on a *finca*. The model is written as in Eq. (2), where Y_{ij} is the outcome of interest (pattern metric) for farm i in sector j and k indexes the p known and unknown independent variables and corresponding parameters, respectively ($\boldsymbol{X}$ and $\boldsymbol{\beta}$—the fixed effects):

$$Y_{ij} = \sum_{k=0}^{p} X_{kij}\beta_k + Z_j\delta_j + e_{ij} \tag{2}$$

Z_j represents the jth sector, δ_j the corresponding random sector effects, and e_{ij} the fixed effects residual error, similar to traditional linear regression. The assumptions, that e_{ij} and δ_j are independently, normally distributed with means of 0 and variances of σ_e^2 and σ_δ^2, respectively, imply that the covariance between e_{ij} and δ_j is 0. Therefore, the covariance structure can be succinctly written:

$$\mathrm{Var}(Y_{ij}) = Z_j^2\sigma_\delta^2 + \sigma_e^2 \tag{3}$$

Estimation of the GLMM differs from traditional linear regression in that maximum likelihood leads to biased estimates. Therefore, restricted maximum likelihood is typically used to reduce bias (Bryk and Raudenbush, 1992). Model selection is also slightly different in that GLMM proceeds in two repeating steps: (1) model the expected value (fixed effect) of the equation, and (2) model the random effects, which essentially models the random variation. Model selection began by choosing a maximum model of non-collinear variables from Tables 1 and 2, examining high influence and high leverage observations, then removing variables not significant at the 0.3 probability level. In the second step, $-2\log$ likelihood ($-2\log L$) and Akaike criterion (AIC) statistics were used to select the best variance model for the random sector intercepts and concluded that an unstructured covariance proved to be the most stable and efficient structure.

The integration of pattern metrics, GIS coverages, and household characteristic data was performed using unique identifiers for each *finca* within SAS 8.0. All descriptive statistics and GLMMs were also computed using SAS (Littell et al., 1996). Although GLMM is well suited to perform analyses of changes over time, the focus of this particular research is methodological and exploratory, rather than primarily inferential; therefore separate models for each year are fit and not modeling the changes that occur over time.

3. Results and discussion

The usual sequence of land conversion begins with the cultivation of small areas of food crops for subsistence, followed by the cultivation of cash crops, particularly coffee, and finally conversion to pasture as soil fertility declines. While land abandonment is uncommon in the Oriente, experience suggests that this “usual” sequence differs in the Ecuador Amazon, especially among newly established *fincas* and subdivisions of existing *fincas*. New subdivisions of a *finca*, generally further from the road and created since 1990 by new migrants or children of the original migrants, demonstrate initial clearing for cash crops (mostly coffee) or taken over parts of the *finca* already cleared for cash crops or pasture. This has important implications when interpreting regression results since land conversion is strongly influenced by the household composition and age structure (i.e., the stage of the household lifecycle), the year plot clearing began, and the socio-economic level of the household. Generally, we conclude that 1990 land use reflects initial clearing, while 1999 represents extensification and second-generation clearing.

3.1. The changing landscape from 1990 to 1999

Tables 3 and 4 compare means and standard deviations for variables entered into the GLMMs. A few key variables were selected here to interpret through descriptive statistics generated for 1990 and 1999. The dramatic increase in farm subdivisions is evident, only 11% of *fincas* in 1990 were subdivided compared to 54% in 1999 (1.1 vs. 2.5 farms per *finca* in 1990 and 1999, respectively). The increase in subdivisions is a result of high population growth—the population density increased 55% from 1.62 persons per ha in 1990 to 2.51 in 1999. Other than higher *finca* population,

Table 4
Descriptive statistics for biosphysical, socio-economic, and geographic variables reported from the survey data: 1990 vs. 1999

		1990 (N = 155)		1999 (N = 157)	
		Mean	S.D.	Mean	S.D.
Biophysical					
Topography	Mean slope[a]	1.16	1.46	1.12	1.45
	Median slope[a]	0.78	1.27	0.75	1.25
	Flat (proportion of *finca*)	0.59	0.49	0.68	0.43
Soil	Mean potential wetness index[a]	6.02	1.10	6.05	1.10
	Median potential wetness index[a]	5.75	1.20	5.78	1.19
	Good (proportion of *finca*)	0.43	0.49	0.40	0.44
	Black (proportion of *finca*)	0.78	0.41	0.58	0.47
Land measures	Area (ha)	51.89	41.10	46.66	13.54
	Number of crops	3.03	1.64	3.55	2.06
SES/demographic					
Household	Average age of head	46.80	12.42	46.84	10.24
	Average education of head	1.49	0.71	2.67	0.94
	Number of adult males (≥12 years)	3.06	1.82	4.43	3.38
	Number of adult females (≥12 years)	2.32	1.63	3.31	2.59
	Number of children (<12 years)	2.99	2.43	3.99	3.83
	Year plot established	1980	4.66	1979	5.45
	Technical assistance (proportion of *finca*)	0.41	0.48	0.27	0.41
Labor pool	Number of subdivisions	1.13	0.41	2.46	1.96
	Number of households on *Finca*	1.10	0.44	2.01	1.48
	Number of subdivisions within 3 km[a]	7.74	2.95	18.48	10.07
	Number of subdivisions within 5 km[a]	9.19	3.50	20.92	10.70
	Number of subdivisions within 10 km[a]	26.45	12.54	67.32	43.79
	Original sector size	31.36	11.79	31.42	11.88
	Person-months of hired labor	8.07	15.73	3.21	5.59
	Person-months of off-farm employment	4.15	8.54	25.53	48.21
Wealth	Title (proportion of *finca* with title)	0.66	0.46	0.62	0.43
	Certificate of possession (proportion of *finca*)	0.32	0.46	0.12	0.29
	Receipt of credits/loans	0.28	0.45	0.45	0.50
	Access to electricity	0.21	0.41	0.73	0.44
	Average assets per household	7.91	2.42	6.81	2.13
Geographic/spatial					
Distance and plot access	Road access to *finca*	0.65	0.48	0.71	0.46
	Walking distance to road (km)	2.11	2.97	0.56	0.92
	Road/boat distance to community (km)	16.85	11.33	13.83	8.81
	Network distance to reference community[a]	26.73	17.32	26.27	17.40
	Euclidean distance to reference community[a]	10.36	7.25	10.29	7.21
	Distance to water (m)[a]	394.81	303.73	402.35	301.75

[a] Variable was derived from a GIS.

smaller plots in 1999 also caused an increase in density, which in turn resulted in an increase in participation of off-farm employment and a decreased need for hired labor.

Among household variables, mean education of household heads rose substantially (from 1.5 to 2.7 years), primarily due to the creation of new plots and thus new household heads who were typically younger and received more education as part of the secular rise in school enrollments in Ecuador. The numbers of adult males, adult females, and children rose by 45, 42 and 34%, respectively, with the smaller increase in children a reflection of declining fertility (Carr and Pan, 2002).

Household wealth has also changed considerably over time. The percent of the land area in sample *fincas* with legal or provisional title (certificate of possession) fell from 96 to 74% as new subdivision owners did not have their status legitimized due to the lack of an active government institution to process land title requests.[3] At the same time, the proportion of farmland on which the holder received credit increased, and the electrical grid expanded rapidly along the main roads so that the proportion of land held by households with electricity in their dwellings rose from 21 to 73%. Such an increase was much greater than that which occurred over the entire study area, and reflects the fact that the three ISAs surround the four major towns and primary roads, where new electric lines have been built during the 1990s.

Geographic/spatial measures reveal increased road access through improved road conditions and an expanded network. The mean walking distance from households to roads declined substantially, from 2.1 km in 1990 to 0.6 km in 1999. Although additional road construction continued throughout the 1990s, much of this decrease was attributed to new subdivisions occurring on *fincas* located on main roads. At the same time, the computed Euclidean and network distances to four reference communities remained necessarily constant over time even as the reported road distances by farmers declined by 3 km (20%).

Biophysical measures for sample *fincas* in both 1990 and 1999 are compared at the top of Table 4. While substantial changes occurred between 1990 and 1999 in many of the other variables, the inherent biophysical characteristics *should* remain steady because of the static site conditions of terrain and soil characteristics. Variables derived from GIS coverages reflect these static conditions, however, perceived site conditions changed. The percent reporting flat land increased, while those reporting black and better quality soils fell over time. These two changes reflect two key ingredients to qualitative data: (1) perceptions can change over time and (2) assessments are sometimes made only to lands that have been cleared already—not the entire landscape.

[3] IERAC was replaced in 1993 by a much weaker land-titling agency, INDA.

Table 5
Descriptive statistics for land use classifications and Pattern Metrics derived from satellite imagery: 1986 vs. 1999

	1986 ($N = 155$)		1999 ($N = 157$)	
	Mean	S.D.	Mean	S.D.
Land use classes[a]				
Forest	26.82	11.66	14.50	9.31
Non-forest vegetation	14.34	9.88	21.96	10.97
Urban/barren	7.15	8.74	10.85	7.60
Water	0.02	0.13	0.10	0.43
Clouds/shadows	0.99	1.97	2.07	3.68
Pattern Metrics				
Number of patches	10.34	5.22	13.09	3.16
Patch density (number/100)	21.12	10.29	26.93	6.56
Total edge	3143.00	2200.82	3830.25	1296.48
Edge density (m/ha)	62.33	32.24	77.71	21.20
Landscape shape index	2.79	0.66	3.04	0.42
Contagion	45.63	16.44	38.61	9.13
Interspersion/juxtaposition index[b]	77.67	21.78	76.64	17.52

[a] All classes are measured in hectares.
[b] $N = 129$ in 1986, 154 in 1999.

Table 5 compares change among measures of the land classifications used to compute metrics as well as the change in the metrics for images from 1986 and 1999. According to the images, hectares of forest dropped considerably over time primarily due to the increase in non-forest vegetation. Pattern metrics reflect this change through increases in PD and LSI, combined with the decrease in CTGN, which are indicative of the rapid increase in plot subdivisions, population growth, and second-generation human-induced landscape change. In addition, standard errors are much larger in 1990 than 1999, reflecting more homogenous landscapes and spatial spillover (land uses among neighbors and within sectors becoming more correlated) in 1999 than 1990.

3.2. GLMM regression results

Results of the six GLMMs are shown in Table 6. Fixed effects are listed in the top three panels, while covariance estimates and goodness of fit are listed in the bottom panel (rho is the proportion of total variance that occurs between sectors). There is a strong presumption that farms in a particular sector

Table 6
GLMM results for contagion, landscape shape, and patch density in 1990 and 1999

Classification	Variable description	Contagion		Landscape shape		Patch density	
		1990	1999	1990	1999	1990	1999
	Intercept	55.35**	37.74**	2.39**	3.08**	18.53**	27.41**
Biophysical							
Topography	Median slope	1.96*	1.04	−0.05	−0.07*	−0.17	−0.90
	Flat (proportion of *finca*)	−5.61†	0.70	0.12	−0.02	2.16	1.93
Soil	Black (proportion of *finca*)	0.76	−1.22	0.01	0.00	−1.18	−0.68
Land measures	Area (ha)	−0.02	0.05	0.01**	−0.003	−0.01	−0.15**
SES/demographic							
Household	Average age of head	−0.22**	−0.01	0.01†	−0.001	0.08*	0.02
	Number of adult males	1.33	0.54	−0.04	−0.008	−0.65	0.10
	Number of adult females	1.89*	−3.50	−0.07†	−0.0094	−0.35	0.12
	Number of children (<12 years)	1.20	−0.27	−0.01	0.02	−0.30	0.51†
	Year plot established	−0.61**	−0.17	0.01	0.001	0.23*	−0.02
	Population density	−67.51†	6.97†	1.23	0.001	21.85	−5.67†
	Technical assistance (proportion of *finca*)	−4.26	−1.57	−0.02	0.05	2.78	1.86
Labor pool	Number of subdivisions	−4.99*	−0.27	0.28†	0.02	5.14**	0.36
	Number of subdivisions within 3 km	1.15**	0.05	−0.03	0.003	0.18	0.02
	Person-months of hired labor	−0.02	−0.06	−0.01**	0.01	0.06	0.03
	Person-months of off-farm employment	0.39**	−0.001	0.00	0.0001	−0.12*	−0.01
Wealth	Title (proportion of *finca* with title)	−5.45†	2.68	0.19†	−0.04	1.78	0.84
	Receipt of credits/loans	0.35	−0.19	0.14	0.06	−0.55	0.54
	Access to electricity	−3.42	−4.09†	0.10	0.12	−0.10	0.72
Geographic/spatial							
Distance/access	Road access to *finca*	3.23	−0.63	−0.21	0.01	−8.14**	0.02
	Road/boat distance to community (km)	−0.11	0.01	0.01	−0.01	0.41†	−0.08
	Euclidean distance to reference community	1.23†	−0.65*	−0.01**	0.02	−1.48**	0.32
	Distance to water (m)	3.72	7.68**	−0.05	−0.32**	−1.84	−2.57
Covariance and goodness of fit							
Covariance	Random intercept	42.38	4.67	0.15	0.05	50.01	3.37
	Residual	112.37	71.93	0.15	0.12	36.13	35.00
Goodness of fit	Rho	0.27	0.06	0.50	0.29	0.58	0.09

† $P < 0.10$.
* $P < 0.05$.
** $P < 0.01$.

will tend to have similar patterns of land use, even controlling for similarities in biophysical and locational conditions though the other variables, due to the spatial diffusion of information (sharing information between neighbors). This presumption holds true for 1990, but not necessarily in 1999, as reflected in the large decrease in variance explained by sectors in 1999 compared to 1990 (large decreases in rho). One therefore concludes that GLMMs are better models for 1990 than 1999. In addition, a larger set of independent variables predicting PD, CTGN, and LSI were found significant in 1990, indicating the vast changes in landscape, household dynamics, and regional infrastructure, which have become more homogenous over time (therefore sector-level variance declined). These results indicate that the inter-regional connection between farms in 1999 (located within the ISAs) are stronger than 1990 due to the expanded road network, improved communication, and access to information. In other words, land use choices in 1990 appeared more independent between sectors, yet highly correlated within sectors, while in 1999 land use appeared correlated both between and within sectors. This relates to evidence that the choice for particular land uses has spatially diffused (become more correlated) from 1990 to 1999. This implies that the model used in 1999 would be more efficient if the correlation structure was modeled using either a covariance function based upon distance between *fincas* or a spatial weight matrix to represent the diminishing correlation as *fincas* are further separated in space.

3.2.1. Contagion

Results from the CTGN models generally reflect more interspersed and dispersed patches in 1999 than 1990. The effects of flat terrain (and high median slopes) on CTGN were significant and negative in 1990, but not significant in 1999. This implies that flat terrain impelled farmers to diversify plots in 1990 (add additional types of land use), but by 1999, increasing pressure led to more extensification on both flat and steep land. Older heads of household and plots significantly reduced CTGN in 1990 since both reflect the time a plot has been exposed to land clearing and agricultural use (i.e., older plots are more likely to have a greater number of patches of different land uses). Neither of these variables was significant in 1999, suggesting a more mixed composition of household heads including second-generation heads and new migrants, which decreases the mean age of the household head and typically increases interspersion and dispersion of patches. Higher population density was one of two variables that remained significant in both the 1990 and 1999 CTGN models, however, the sign changed to positive (higher density implies more CTGN) in 1999. This is likely due to the 55% increase in population density—as *fincas* become more populated, more land clearing occurs. At some point a threshold is likely reached whereby human-induced changes cause *more* aggregation of patches due to more patches of, say, pasture and coffee, which are more likely to be contiguous.

Labor pool variables were generally significant in 1990, but not 1999, probably due to the more widespread availability of labor and better access in 1999. The negative effect on CTGN of the number of subdivisions indicates the effects of more available local labor on the few *fincas* that had it on the ability to clear land for agricultural use. *Finca* households engaging in off-farm employment (OFE) were expected to have higher CTGN since they either have less labor to clear land or they have large contiguous patches that require little daily on-farm labor. OFE significantly increased CTGN in 1990, likely because households that participated in OFE were well developed with large patches of pasture. In contrast, OFE in 1999 was not significant since OFE was much more common overall in 1999.

Fincas with more land under legal title in 1990 had significantly less CTGN, likely due to having more incentive and ability to clear the plot for agricultural use. However, in 1999 the effect of land title was not significant and changed sign. This is reasonable due to the fact that most title-holders had received loans by 1999, which they usually used to purchase cows and form pasture that require large swaths of land, thus decreasing the number of patches and increasing CTGN (more aggregation). *Finca* access to electricity increased from 21 to 73% from 1990 to 1999, resulting in a significant effect of electricity on CTGN in 1999, but no effect in 1990. It is likely that *fincas* with electricity were more developed (more types of land uses) than those without due to the ability to increase work output on the farm, increased knowledge of farming techniques from radio or television informational broadcasts, and/or improved regional connection with neighboring farms and communities.

Geographic/spatial variables have two significant effects—Euclidean distance to the nearest primary reference community and distance to water, both derived from GIS coverage data and relatively static over time. The positive effect of a greater Euclidean distance in 1990 is plausible, because isolation of farms is indicative of less development or clearing. The change in sign in 1999 may be indicative of the improved road network and the expansion of agricultural production in general. One would expect better water access to be associated with more interspersed and dispersed patches since access to water can limit the ability to extensify a plot. In 1999, distance to water significantly increased CTGN, but was not significant in 1990. This is reasonable given that most plots in 1990 were in the initial stages of development and clearing, therefore water access was not a major factor.

3.2.2. Landscape shape index

The results in Table 6 generally indicate that total edge has increased from 1990 to 1999, but the set of independent variables only slightly influence LSI, and not consistently for the two time periods. This is likely due to the fact that total edge (and thus LSI) on a *finca* does not change as quickly over time as CTGN or PD. The value of rho shows this slow change—a slight reduction from 0.5 to 0.3, indicating a decrease in the proportion of sector variation from 1990 to 1999, but remaining relatively high.

High median slope (steeper terrain) was significantly related to smaller LSI in 1999, but not in 1990, which is reasonable given that median slope is a measure for the entire landscape (and not just cleared land). Therefore, since 1990 land use was primarily initial land clearing close to the road or on an easily cleared parcel of land (flat terrain is easier to clear), clearing was less dependent upon overall slope of the *finca* and less edge was created. In contrast, land use in 1999 expanded clearing to other parts of the *finca* that were more affected by higher median slopes. In other words, 1990 forest clearance occurred mostly on flat land along the road, while 1999 likely involved further clearing, both on flat land for crops and steeper land previously in forest. In a similar vein, total plot size significantly increased LSI in 1990, but had no effect in 1999. This discrepancy was likely caused by the spatial and household data merge—when pattern metrics are computed, they are done so for a defined polygon in 1999, not 1990. Therefore, the plot in 1990 with computed LSI does not necessarily correspond to the *whole* plot on which the household was located in 1990—in other words, metrics computed in 1990 correspond only to the *finca* (polygon) in 1999.

As with CTGN, age of the household head results in higher landscape complexity (more edge/patches). More adult females significantly reduced LSI in 1990, but did not have effects in 1999. Females are typically associated with less pasture and more coffee or annual crops, therefore, since more people lived on the *fincas* in 1999 than 1990, the addition of a female in 1990 had a stronger impact on land use than in 1999 when perhaps the law of diminishing returns applied.

Labor supply variables are again significant for 1990 but not 1999. More land subdivisions positively influence LSI, indicating both the increasing complexity due to more farm managers as well as the increased pressure on the land from a higher *finca* population. However, person-months of hired labor, which was used primarily to convert forests, coffee plots, and annual crop areas to pasture in 1990, reduces LSI, resulting in lower landscape complexity in 1999. This is probably due to labor being so widespread in 1999 that variations in the supply no longer are important.

Title holding and electricity both significantly affected LSI—positively in 1990 for title and positively in 1999 for electricity. Holding a full title to the land reflects the ability (economically) to change the landscape, probably due to the greater availability of credit to those with a title. Similarly in 1999, electricity serves both as a proxy for regional infrastructure expansion as well as the household's ability to develop their farm. Thus, greater access to credit and electricity facilitates more human footprints on the landscape.

The effect of Euclidean distance changes sign from 1990 to 1999, but the effects in 1999 are not significant. The expected negative sign in 1990 supports the idea that the region in 1990 was relatively undeveloped, therefore isolated farms had few opportunities to engage in the local market. This changed in 1999, when few farms were isolated due to general improvements in the road network.

3.2.3. Patch density

Results of the PD model show an increase in patchiness of the landscape from 1990 to 1999, thus an increase in complexity as plots have become more fragmented by population growth and subdivision. Rho is substantially lower in 1999 (0.08) than in 1990 (0.58), indicating that sectors are not explaining a large proportion of variance in 1999, but did so in 1990. This is consistent with results reported for CTGN and LSI—all indicators of increasing sector homogeneity from 1990 to 1999, ironically as the landscape became more fragmented, but likely because the fragments are of similar types of land use.

Older household heads and older plots are linked significantly to more PD in 1990, reflecting the effect of duration of residence on patch creation. However, by 1999 these variables are no longer significant, perhaps due either to a leveling off in the creation of new patches or an increase in patch size to subsume smaller patches of the same type (i.e., multiple coffee or crop patches expanding to form one patch). In

1999, the number of children has a strong association with PD while population density has a negative linkage. A plausible explanation is that more children on the *finca* may indicate the need for a wider variety of crop types—particularly in 1999 when plots have already been initially cleared and are at the cash-crop or pasture creation stage of land development. Therefore, if households have more children, they likely require more patches of subsistence crops for their families. For population density, the same argument applies as for CTGN—that some kind of threshold is reached whereby more population density initially increases the need for a larger variety of patches, but eventually leads to combining patches on a *finca*, which then reduces the number of patches.

Since subdivision was rare in 1990, their presence strongly influenced PD, as seen from the significantly positive effect. As more subdivisions are formed on a plot, it is reasonable to presume that land uses become more mixed (i.e., adjacent neighbors within a *finca* share a large patch of pasture or coffee)—particularly on *fincas* subdivided among families. Therefore, the non-significant result in 1999 is reasonable. OFE reduces the available labor on a *finca* to clear land—likely the cause of the significantly negative effect of OFE on PD.

The geographic-spatial variables have mixed and contradictory effects. First, the strong negative effect of *finca* road access and positive effect of road distance to the nearest community on PD are contrary to expectations. Greater distance should be linked to less patchiness of land use, if that patchiness reflects more intensive land use. On the other hand, the even stronger negative effects on PD of (greater) Euclidean distance to a primary community in 1990 are consistent with theory, and even exist in attenuated form in 1999 as well.

3.3. Overall results

The models that integrated these data, approaches, and technologies proved more insightful for 1990 conditions than for 1999. There appear to be three reasons. First, land uses became more homogenous in 1999—as farms extensify their agriculture, they tend to evolve similarly to their neighbors. The rho statistic for each model indicated a decreasing proportion of variance explained by differences between sectors, which implies that both *fincas* and sectors in the study region became more alike (i.e., more spatially autocorrelated). A better model in 1999 would be a GLMM that estimates or controls for the spatial covariance structure. Second, the selection of independent variables, the manner of their measurement and/or collection, and the hypothesized effects that they represented may have been too simply defined, thereby lacking the landscape clarity and statistical power of more robust measures. Third, the dependent variables (measures of pattern metrics) were directly associated with LULC classification; however, in an effort to keep things simple by choosing a classification scheme that included only forest, non-forest, urban/barren, water, and clouds/shadows, specificity was reduced by generalizing the LULC types. While such a classification scheme worked well in 1990, by 1999 the deforested landscape had undergone subsequent land conversion that involved changes in crop types and an alteration in the spatial organization of non-forest classes. For instance, land plots devoted to subsistence crops were transformed to commercial crops, crop land to pasture, and forest cleared for mixtures of uses. Because our classification scheme thematically aggregated all non-forest categories into a single class, we smoothed the landscape and reduced landscape complexity. This had more of an impact in the 1999 models, where landscape change was occurring on lands deforested years before.

Finally, modeling two independent cross-sectional analyses is obviously not the best choice to gain inference on changes occurring over time. The difficulty of combining spatial and survey data into one model proved to be a challenging undertaking, however, as pointed out by our reviewers, in order to gain more meaningful inference on specific factors influencing land use, a better model would implement a panel analysis. However, since the type of data integration and model application demonstrated in this research has not been utilized, it is a logical first step and lays the foundation to develop a longitudinal approach.

4. Conclusions

In this research, variables were integrated that represent socio-economic/demographic, biophysical, and geographical variables collected and analyzed through: (1) a longitudinal household survey, conducted in 1990 and 1999; (2) GPS measures of survey respondent locations (dwelling units) and farm plot layouts; (3) satellite images processed for mapping LULC types for multiple time periods; (4) a GIS for representing thematic coverages within a spatially explicit database and deriving measures of geographic accessibility and resource endowments; (5) the computation of pattern metric measures to characterize the composition and spatial organization of LULC types at the farm-level mapped through remote sensing techniques; and (6) the estimation of the determinants of LULC through statistical models. While these approaches and technologies have been used elsewhere to consider population–environment interactions, using ecological pattern metrics as dependent variables in generalized linear mixed models is new and exciting.

The basic intent was to examine the nature of landscape structure, using principles of landscape ecology, and to associate landscape form to landscape function in a frontier environment. In so doing, we sought to make a contribution to the GIScience and population–environment communities as a consequence of how the dependent and independent variables and the nature of the models and their interpretations were derived. The research affirmed the power of longitudinal surveys, the efficacy of a satellite time-series and GIS tools, the relevance of pattern metric measures, and the value of fixed and random effects models for relating multi-thematic and spatially explicit descriptions of people, place, and the environment within a population–environment and LULC context.

The analyses indicate rapid population growth caused substantial subdivision of plots, which in turn created a more fragmented landscape in 1999 than in 1990. The underlying factors which seem to be most important in predicting landscape complexity are population size and composition, plot subdivisions, expansion of the road and electricity networks, age of plot (for 1990 only), and topography. The inconsistencies over time among the significance levels for these factors address the subsequent complex changes in landscape form and function. The methods and models presented in this research demonstrates a useful exploratory tool to help begin to untangle the population–environment threads that are inherently linked within sophisticated GIS coverage data, satellite imagery, and household surveys.

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