Space versus Place in Complex Human-Natural Systems: Spatial and Multi-level Models of Tropical Land Use and Cover Change (LUCC) in Guatemala

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David López-Carr[a] Jason Davis[a], Marta Jankowska[b], Laura Grant[c], Anna Carla López-Carr[b], Matthew Clark[d]

[a] **Department of Geography, University of California, Santa Barbara, Human-Environment Dynamics Lab,** 4836 Ellison Hall UC Santa Barbara (UCSB)Santa Barbara, CA 93106-4060
[b] **Department of Geography, San Diego State University,** 5500 Campanile Drive, San Diego, CA 92182
[c] **Department of Economics and Bren School of the Environment,** UC Santa Barbara (UCSB)Santa Barbara, CA
[d] **Department of Geography and Global Studies, Sonoma State University,** Stevenson Hall 3066, 1801 E. Cotati Avenue, Rohnert Park, CA 94928

Abstract

The relative role of space and place has long been debated in geography. Yet modeling efforts applied to coupled human-natural systems seemingly favor models assuming continuous spatial relationships. We examine the relative importance of place-based hierarchical versus spatial clustering influences in tropical land use/cover change (LUCC). Guatemala was chosen as our study site given its high rural population growth and deforestation in recent decades. We test predictors of 2009 forest cover and forest cover change from 2001-2009 across Guatemala's 331 municipalities and 22 departments using spatial and multi-level statistical models. Our results indicate the emergence of several socio-economic predictors of LUCC regardless of model choice. Hierarchical model results suggest significant differences exist at the municipal and departmental levels but largely maintain the magnitude and direction of single-level model coefficient estimates. They are also intervention-relevant since policies tend to be applicable to distinct political units rather than to continuous space. Spatial models compliment hierarchical approaches by indicating *where* and to what magnitude significant negative and positive clustering associations emerge. Appreciating the comparative advantages and limitations of spatial and nested models enhances a holistic approach to geographical analysis of tropical LUCC and human-environment interactions.

Key words: land use/cover change (LUCC), human-environment dynamics, deforestation, coupled human-natural systems.

1. Introduction

1.1 Modeling space and place in coupled human-natural systems and land change research

A “coupled human-natural systems” (CHANS) approach builds on complexity theory, to incorporate feedbacks, multiple equilibria, and unstable dynamics in coupled human-environment dynamics (Liu et al., 2007; Manson, 2003; Turner and Robbins, 2008). Land use/cover change (LUCC) is a central research initiative of CHANS research, with important implications to both human and natural systems (Turner et al., 2007). A large LUCC literature has investigated LUCC drivers (Lambin et al., 2003; Carr, 2004). Recent empirical studies have uncovered feedbacks among migration and LUCC (Carr, 2009), population change and LUCC (Liu et al., 2001), and between socio-economic development, consumption, and LUCC (Rudel et al 2009). All of these prior studies, however, imperfectly capture the influence of space and place in modeling land use outcomes.

Spatial and hierarchical models may usefully complement contemporary human-environment research tools such as agent-based modeling (ABM). To investigate coupled natural-human linkages, researchers have increasingly turned to ABM (An et al., 2002) while hierarchical approaches remain scarce (Rindfuss et al., 2008; Verburg et al., 2004). While ABM can model cumulative effects of actor-environment interactions, it fails to explicitly integrate multiple spatial scales. Modeling spatial behavior at the individual level may fall victim to the atomistic fallacy, where the contextual surroundings of individual behaviors are ignored (Alker, 1969; Diez-Roux, 2002). A hierarchical approach, in contrast, offers the potential to examine structure as manifested in space versus agency by explicitly locating the agents of environmental change within larger meaningful geographical units and contexts (Chowdhury and Turner, 2006). A further strength of multi-level analysis is its ability to overcome inherent bias due to autocorrelation by separating out spatial or temporal similarity at various levels of analysis. However, a potential drawback of the hierarchical modeling approach is its dependence on a priori definitions of discrete spatial units (Fotheringham and Brunsdon, 1999). Lastly, a nested model allows us to distinguish one place from another rather than to model space continuously (Nelson, 2001). This is appropriate when units of interest are naturally place based such as a village or a county. In turn, since policy is made at village, county, state, and national levels – not continuously over space – policy implications of hierarchical models can be particularly applicable.

ABM and other CHANS tools may also be usefully accompanied by spatial regression approaches. The modifiable areal unit problem (MAUP) and associated ecological fallacy have been both a bane and a raison d’être for geographers for many years. MAUP is a potential source of variation associated with aggregating data into arbitrarily bound groups resulting in summary values and statistical properties of variables that are influenced by the boundaries themselves as much as by on-the-ground phenomena (Openshaw, 1984; Fotheringham and Wong, 1991; Greenland, 2002). Since entirely objective boundaries are impossible to derive, researchers are challenged to justify the most feasible and appropriate areal unit to analyze. At times, this is done for them, especially when data are available only for pre-defined units (e.g. county data). As a result, modeling of LUCC has been plagued by the natural occurrence of spatial or temporal autocorrelation—the fact that areas that occur closer in space or time to one another respond more similarly to a stimulus than areas that are further apart (Getis, 2010). Such dynamics violate the independence assumptions of many statistical analyses, particularly regression analysis (Geary, 1954). While multi-level models can reveal relationships of nested parameter measures, they cannot reveal a parameter’s spatial distribution.

Relationships that are liquid over space, in other words exhibit spatial non-stationarity, will not be modeled well by global parameter estimates (Fotheringham and Brunsdon 1999), as found in ordinary lease-squares (OLS) and hierarchical regression techniques. Measures of LUCC are often inherently spatially dependent, and necessitate consideration of how geography will influence model parameters (Overmars et al., 2003; Kupfer and Farris, 2007). Furthermore, incorporating parameter variability over space will lead to better understanding of the connections between geography and LUCC drivers. Geographically Weighted Regression (GWR), is a regression method that accounts for spatial non-stationarity by running a local regression at each spatial unit while incorporating weighted values of surrounding spatial neighbors (Brunsdon et al. 1998). While GWR has been applied in LUCC studies, its use in deforestation research, particularly in Latin America, is rare (Witmer, 2005; Pineda Jaimes et al., 2010).

This paper examines space versus place in a comparison of GWR (i.e., space) versus multi-level models (i.e., place) applied to tropical land change in Guatemala. The case study examines spatial and nested predictors of change in woody cover from 2001-2009 and absolute woody cover in 2009 for Guatemala's 331 municipalities nested within 22 departments. We first describe the importance of the study site for the examination of LUCC and the related data sets, followed by a discussion of multi-level and spatial analytical methods in coupled human-environment research. We then describe our data sources and analytical methods before reporting results for predicting woody cover in Guatemala using OLS, multi-level, and GWR approaches and compare the way these procedures model data and the estimates they generate. Following the discussion of similarities and contrasts between nested and spatial approaches, we elaborate potential implications for enhanced modeling of tropical LUCC and the significance for the theoretical, methodological, and political dimensions of human-environment dynamics.

1.2 Tropical LUCC in Latin America and Guatemala

According to Houghton et al. (1991), 28% (370 x 10^6 ha) of Latin America's forests were replaced by some form of agricultural operation, or fragmented to provide building and fuel supplies for nearby settlements between 1850 and 1985. Forest conversion to pasture represents 44% of this change while conversion to cropland, fragmented land, and fallow each represent 25, 20 and 10% respectively. The rate at which Latin American forests conversion took place remained low and stable prior to 1940, but rapidly accelerated thereafter (Houghton et al., 1991). In the 1990s, forest conversion for agriculture and settlement construction continued to alter large tracts of forested land. Two sets of authors, Achard et al. (2002) and Mayaux et al. (2005), report Latin American deforestation rates of 2.2 and 2.5 x 10^6 ha per year, respectively, during the 1990s. These rates equate to a 0.33 and 0.38% loss of forest cover per year.

Deforestation trends in Central America conform to those seen throughout Latin America. Following human settlement, Central America has suffered an estimated 82% loss of total forest cover and an 89% loss in primary forest cover (Myers, 1991). In the 1990s, Achard et al. (2002) and Barbier (1997) reported continued deforestation throughout Central America with rates ranging from 0.8 to 1.5%. This is down from the 1.8% deforestation rate (3,000km^2/year) for the region reported by Myers (1991) for the late 1980s.

While much of Central American forests continue to be exploited for their timber, fuelwood, and agricultural resources, some are experiencing small but significant re-growth. For example, the mountainous region of La Champa, Honduras experienced a shift from slash and burn agriculture to more sedentary and intensive farming practices from 1987 to 1996, resulting in a net increase in reforestation as marginal lands were abandoned (Southworth and Tucker, 2001; Monroe et al., 2004). Additional examples can be found in Panama (Wright and

Samaniego (2008) reported a 0.36%/year increase in total forest cover in Panama, but a 1.3/year loss of primary forests for the entire nation between 1992 and 2000) and Costa Rica (Kleinn et al. (2002) described a declining rate of deforestation in Costa Rica between the 1940s and the 1980s that eventually flattens out and starts to curve upward in the early 1990s).

Within Guatemala, rapid population growth and shifting agricultural practices have inscribed visible impacts on its biologically diverse landscape. According to Loening and Markussen (2003), Guatemala's total forest cover shrunk from 65% to 26% during the second half of the twentieth century (1950-2000). Deforestation rates were especially high in the 1990s (1.7% per annum) (Carr and Bilsborrow, 2001, Brooks *et al.,* 2002), where most deforestation can be directly attributed to rural-frontier migration by cattle ranchers (Colchester, 1991) and subsistence farmers (Carr, 2004; 2005) who often convert their land to cattle ranches following a few years of row cropping (Sader *et al.*, 1997). The extreme concentration of landholdings and underemployment, combined with the country's very high fertility rate has led to a fragmentation of Guatemalan farm plots and rural poverty, thus stimulating rural out-migration to cities, international destinations, and the forested frontier (Bilsborrow and Stupp, 1997; Cincotta *et al.,* 2000; UN, 2003).

A vast majority of Guatemala's current deforestation is occurring within the northern frontier regions of the north, in the Department of Petén. This deforestation is mainly undertaken by economically and demographically displaced subsistence farmers migrating from southeastern and southwestern rural areas of Guatemala who desire to own farmland (Carr, 2008). However, not every displaced farmer—actually, only a small minority—is ready to travel to the uncomfortably hot, humid, and malaria-ridden lowland tropical forests that dominate the Petén to practice subsistence agriculture. Interestingly, this minority of migrants spurn more economically advantageous rural-urban migration to travel to the frontier, even though urban centers are geographically closer to their places of birth than the Petén—in many cases, the migrant has to travel to Guatemala City to catch a northward bus to reach the Petén.

2. Methods

2.1 Data

Data used for this analysis come from three sources: (1) 2000 Guatemalan Living Standards Measurement Survey, (2) 2003 Guatemala National Agriculture Census, and (3) a 2001-2009 Forest Cover Change database for all municipalities in Latin America. The three data sources provide detailed information regarding land use and management at the municipality and department levels. A description of each dataset follows:

2000 Guatemala Living Standards and Measurement Survey

This rich source of household and community data covers 20,969 (11,302 rural) households and over 100,000 individuals. The surveys were implemented by the Guatemalan National Statistics Institute (INE), with technical guidance from the World Bank Living Standard Measurement Surveys (LSMS) research team. The nationally representative survey includes demographic, economic, and community characteristics modules. For our project, we aggregate mean household fertilizer use and tractor ownership to the municipality and department levels (Table 1).

2003 Agriculture Census

Due to political conflict that ravaged Guatemala during its multi-decade civil war, national-level agricultural and land use data had not been gathered since 1979. Therefore, the 2003 Agricultural Census represents the first large-scale collection of agricultural land use data in 24 years. These data were collected by the INE and contains information from 822,188 farmers—roughly 90% of all producers within the country. Among the many subject areas covered by the agricultural census, our project used information gathered on 2003 crop yields for four of Guatemala's main commodities (coffee, sugar, white corn, yellow corn) and fallowed land (Table 1). These were also aggregated to the municipality and department levels.

Forest Cover Change 2001-2009

The dependent variables are woody forest cover and change in woody forest cover. A NSF-funded project produced LUCC estimates for all of Latin America for the years 2001 and 2009, based on methods developed in Clark et al., (2010) for the Dry Chaco ecoregion of South America and expanded to include Latin America using methods in Clark and Aide (2011). Eight land cover types were mapped using the MODIS MOD13 Vegetation Indices product (Huete et al., 2002), including agriculture, herbaceous vegetation, built-up areas, bare areas, water, plantations, woody vegetation (≥80% cover) and mixed woody vegetation (<80% woody cover with bare, herbaceous or agriculture). Maps were produced for eastern moist forests and western conifer and dry forests separately, with boundaries defined using the majority cover of biomes (Olson et al., 2001) within municipalities. Reference data for classifier training and accuracy were collected across Central America with visual interpretation of Google Earth high resolution imagery within a custom web-based tool (Clark and Aide, *accepted with revisions*). There were 2,082 and 1,422 reference samples for the moist and conifer/dry forests, spanning years 2001 to 2010. We focused our analyses on the more conservative measure of forest in our maps, the woody vegetation class, which had 99.8% and 70.6% class producer and 93.6% and 80.3% class user accuracy for moist and conifer/dry forests, respectively. The area of woody vegetation was summarized for Guatemala's 331 municipalities and used to calculate our two dependent variables: (1) percent woody cover in 2009 and (2) percent change in woody cover from 2001 to 2009 (i.e. woody cover in 2009/woody cover in 2001). Furthermore, we used the project's 1990 and 2000 population census and density information for each of Guatemala's 331 municipalities (Table 1).

Our independent variables presented in Table 1 were selected based on our prior work in Guatemala (Carr, 2008), in Latin America more generally (Carr et al., 2009; Aide and Grau, 2004), and following the literature on proximate and underlying causes of tropical deforestation (Geist and Lambin, 2002). Two sets of variables are tested; demographic and technological-economic. We recognize additional household, municipal, and departmental level socio-economic, political and ecological variables as potentially influential as well but we have insufficient data richness to pursue all of these potential LUCC drivers. In prior models we tested a host of demographic and socio-economic variables that were insignificant in bivariate regressions and trimmed from our final models. Under demographic factors, population density from 1990-2000 and its squared form are examined to probe potential linear and non-linear relations between demographic change in the decade prior to the land cover analysis. Population density in 2000 is also examined in relation to LUCC outcomes. The technological-economic variables tested are directly related to land use intensity in the cases of household fertilizer and tractor use, and subsequent output in the cases of corn production. The converse of intensification is also tested as measured by the percentage of land in fallow.

Table 1. Explanatory Variables Used in the Models

Explanatory Variable	*Definition*	*Mean*	*Standard Deviation*	*N*
Population Density 1990	Year 1990 Municipal Population Density in Persons per Square Kilometer	185.91	311.54	329
Population Density 2000	Year 2000 Municipal Population Density in Persons per Square Kilometer	275.14	483.42	329
% Population Density Δ (1990 to 2000)	Percentage of Municipal Population Change from 1990 to 2000	1.48	0.32	329
% Population Density Δ (1990 to 2000)^2	Percentage of Municipal Population Change from 1990 to 2000 Squared	2.18	0.10	329
% HHs Using Fertilizer	Percentage of Municipal Farming Households that Use Fertilizer in 2000	0.83	0.36	330
% HHs Owning a Tractor	Percentage of Municipal Farming Households that Own a Tractor in 2000	0.038	0.089	300
Café Production	Municipality Café Production in Kilograms per Hectare in 2003	536.95	1243.40	331
Sugar Production	Municipality Sugar Production in Kilograms per Hectare in 2003	2885.79	14192.98	331
White Corn Production	Municipality While Corn Production in Kilograms per Hectare in 2003	85.14	125.09	331
Yellow Corn Production	Municipality Yellow Corn Production in Kilograms per Hectare in 2003	28.39	67.69	331
% Fallow Land	Percentage of Municipal Farmland in Fallow in 2003	0.21	0.13	330

2.2 Multi-level Statistical Analysis

For this investigation, we employ 2-level random intercept models to separate out inherent spatial error in land cover at the municipal level from that found at the department level. Instead of assuming that the regression line for land cover change at the department level passes through the same intercept, a random intercept formulation allows this higher level variable to conform to different regression intercepts to more accurately model the outcome of interest and to overcome some issues of spatial dependence (Vance and Iovanna, 2006). To estimate the models, the event categories are treated as a multivariate response vector using dummy variables with no variation at level 1, rather level 1 covariance specified at level 2. In addition to analyzing variance across nested scales, i.e., the municipality and the department scales, we also explore an independent dummy variable in the models to test potential significant differences between experimental versus control regions (i.e., 0=experimental municipalities/departments, 1=control municipalities/departments). Adequate estimation of cross-level interactions and tests of random effects has generally been found by simulation studies to require 30 groups with 30 observations, 60 groups with 25 observations, or 150 groups with 5 observations (Kreft and de Leeuw, 1998). Our sample generally meets these criteria (Van der Leeden et al., 1997). The two-level random-intercept linear regression model is written as follows:

$$y_{ij} = \beta_1 + \beta_2 x_{2ij} + \cdots + \beta_p xp_{ij} + \varsigma_j + \varepsilon_{ij}$$

For model 1, y_{ij} is the percentage of land identified by satellite imagery as woody vegetation in 2009, where *i* represents municipalities within j^{th} departments. For model 2, y_{ij} is the percentage change in municipal woody vegetation from year 2001 to 2009 (natural log transformed to normalize the long-tailed distribution of these data), where *i* represents municipalities within j^{th} departments. β_1 is the intercept along with its independent error term ς_j while β_2 through β_p are regression coefficients with corresponding explanatory variables x_{2ij} through xp_{ij} with their independent error term ε_{ij}.

We employ municipalities nested within departments as the two multi-level categories and use four specifications of heterogeneity among the groups: ordinary least squares (not multilevel), maximum-likelihood estimator, least squares random effects, and least squares fixed effects. The distinction between maximum-likelihood and generalized least squares is important: the former is more flexible when the underlying intercept distribution remains unknown. There are also important differences between random and fixed effects models. In the random effects models, each intercept is modeled as random deviations from a common mean intercept. Therefore, estimating random effects requires many groups, so that the draws from the hypothetical distribution of intercepts can identify the parameters. In these circumstances, the estimates are more efficient than fixed effects. Another property of the random effects model is the ability to estimate explanatory covariates that do not vary over time by group, such as a region's size. The most important factor when using random effects is the relationship between the categories/groups and the other explanatory variables. First, the model requires numerous covariates; otherwise we have concern that omitted variables are biasing the remaining coefficients. Second, group effects need be uncorrelated with the other independent variables for appropriate estimation of random effects. In other words, this model assumes the observations pertain to the entire population regardless of the group characteristics.

In fixed effects, we estimate a parameter for each group's intercept as an average deviation from the remaining groups. Because explanatory variables that do not vary across time in each unit will be perfectly collinear with the fixed effects we cannot estimate their effects. While estimation removes all cross-section variation in the dependent and independent variables, the advantage is controlling for unavailable, omitted variables. Furthermore, if group effects by department are correlated with the covariates, then the fixed effects model is more consistent than the random effects model. We ensure that random effects models are not mis-specified compared with the fixed effects model by employing a Hausman test.

2.3 Spatial Analysis and Modeling

GWR is employed to examine spatial distributions of parameter estimates for the two models detailed in section 2.1. As commonly available software, with easily replicable results, we utilize ArcMap 10.0 for the GWR model. The ArcMap GWR tool results in global and local R^2 values, local parameter estimates, standard errors, and standardized residual values. However, ArcMap GWR does not provide global parameter estimates or statistical significance measures. While available from the GWR software created by Fotheringham, Charlton, and Brunsdon, the problem of global p-values for parameter estimates is discussed in the corresponding software white paper (Charlton et al., 2005). Additionally, local variation in parameter estimates rather than global estimates is of interest to this study for exploring spatial distributions.

The two dependent variables, woody vegetation in year 2009 and percent change in municipal woody vegetation from year 2001 to year 2009, were assessed for global clustering using Moran's I with inverse distance weighting and Euclidean distance calculation method. Local cluster was examined using the Getis-Ord Gi* statistic for local spatial autocorrelation hot and cold spot analysis (Getis and Ord, 1992). To assess spatial stationarity of variables utilized in the multi-level model, two OLS regression model predicting the dependent variables were run at the municipality spatial scale. Resulting standardized residuals were measured for clustering using Moran's I (Cliff and Ord, 1972).

To account for residual spatial non-stationarity in the multi-level model, GWR was performed. GWR is a variation on the basic linear regression model by accounting for variations in space throughout the parameter surfaces. The GWR for this study is stated as:

$$y_i = \beta_{i0} + \sum_{k=1}^{n} \beta_{ik} x_{ik} + \varepsilon_i$$

where β_{i0} is the intercept at location *i* with latitude and longitude coordinates, *n* is the number of model independent variables, and β_{ik} is value of β_k at point *i* (Fotheringham et al., 2000). For this section y_i is the percentage of land identified by satellite imagery as woody vegetation in 2009 in model 1, and the percentage change in municipal woody vegetation from year 2001 to 2009 in model 2. β_k is *n* regression parameter estimates displayed in Table 1 with corresponding explanatory variables x_k, with independent error term ε at location *i*. It is important to note that parameters are estimated with a weighting function based on distance, resulting in locations closer to the estimated point having more influence on the projected value than locations farther away. Using different weighting functions can have some impact on the model, however this impact is often small (Brundson et al., 1998). A matrix form parameter estimate equation is shown (Cahill and Mulligan, 2007):

$$\hat{b}_{ik} = (X_T W_i X)^{-1} X_T W_i y$$

where $\hat{b}_{ik}$ is the estimate of the location-specific parameter b_k, and W_i is a spatial weights matrix. ArcGIS 10.0 allows for the user to provide a weights matrix, or creates one for the regression model. For this study the weights matrix was used from the adaptive (Gaussian) kernel option in the GWR Tool, which allows each point's spatial context to vary by feature density. Therefore, the weighting matrix varies by *k*. An AIC bandwidth was applied for both models (a discussion of appropriate bandwidth and kernel choice can be found in Fotheringham et al., (2000)). The ArcGIS GWR tool performs a multicollinearity diagnostic before running the model, and variables that are locally collinear are thrown out. Therefore, the percentage population density change from 1990 to 2000 variable was dropped due to high local multicollinearity within the GWR model only.

3. Results and Discussion

3.1 Multi-level/Grouped Models

The model results for percent woody cover in 2009 are given in Table 2. The number of groups is 22, which is a relatively small amount for determining random effects parameters. The number of observations per group varies from 5 to 27, allowing sufficient averaging for the fixed effects estimator. As for time-invariant covariates, we do not have data available over time with sufficient variation in the independent variables to consider estimating invariant factors. Finally, the covariates that are available are likely correlated within groups; for example, population density is related to region. These aspects point to using fixed effects.

Table 2. Multi-level results for modeling percent woody cover in 2009 with socio-economic variables. The estimates are from 298 data points grouped by 22 departments.

	OLS (Not Multilevel)	*Maximum Likelihood Estimator*	*Random Effects*	*Fixed Effects*
PopDen_2000	-0.000	-0.000	-0.000	-0.000
	(0.005)**	(0.017)*	(0.014)*	(0.030)*
PrctChgPopDensity1990-2000	0.565	0.324	0.401	0.185
	(0.001)**	(0.053)+	(0.015)*	(0.282)
PrctChgPopDensity19902000^2	-0.131	-0.077	-0.094	-0.046
	(0.003)**	(0.075)+	(0.030)*	(0.293)
% HHs Using Fertilizer	-0.059	-0.058	-0.059	-0.054
	(0.073)+	(0.072)+	(0.070)+	(0.121)
% HHS Owning a Tractor	-0.404	-0.293	-0.326	-0.242

	(0.004)**	(0.032)*	(0.019)*	(0.097)+
Café Production	0.000	0.000	0.000	0.000
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
Sugar Production	-0.000	-0.000	-0.000	-0.000
	(0.008)**	(0.025)*	(0.019)*	(0.058)+
White Corn Production	-0.000	-0.000	-0.000	-0.000
	(0.005)**	(0.001)**	(0.002)**	(0.001)**
Yellow Corn Production	0.000	0.000	0.000	0.000
	(0.184)	(0.166)	(0.177)	(0.181)
% Fallow Land	-0.565	-0.524	-0.543	-0.479
	(0.000)**	(0.000)**	(0.000)**	(0.000)**
R-squared	0.286		0.282	0.236
Log likelihood		77.51		
Random Intercept Standard Deviation (ς_j)		0.08	0.05	0.10
Residual Standard Deviation (ε_{ij})		0.18	0.18	0.18
Interclass Correlation (ρ)		0.16	0.07	0.23
Likelihood Ratio Test of ς_j		17.71		
Chi-squared		(0.000)		
F-test of Model Significance				3.27
Chi-squared				(0.000)
Hausman Test			24.32	
Chi-squared			(0.002)	

p values in parentheses: + significant at 10%; * significant at 5%; ** significant at 1%

Multilevel formulations are significantly more descriptive than single-level formulations as shown by the highly significant Likelihood Ratio Test for the MLE model and F-Test of Model Significance for the fixed effects model. However, the highly significant Hausman test suggests the random effects models are mis-specified compared with the fixed effects model. Therefore, further discussion of 2009 percent woody cover results will pertain to the fixed-effects multilevel model only.

Multiple coefficients are significant but exhibit values below 0.00001—below the level of practical significance (2000 population density, café production, sugar production, and white corn production). Percentage of land in fallow was highly significant for the percent woody cover in 2009 model with a coefficient of -0.479, meaning for every percentage increase in fallow land at the municipality level, there was a 0.48% decline in woody cover in 2009. Percentage of households owning a tractor was marginally significant with a coefficient of -0.242, meaning for every percentage increase in households that own a tractor at the municipality level, there was 0.24% less woody cover in 2009.

The models of change in woody cover between 2001 and 2009 are shown in Table 3. As in the 2009 woody cover model, a multilevel formulation was significantly more descriptive than a single-level model. Furthermore, the Hausman Test again indicates mis-specified random effects models; therefore, subsequent interpretations of this model pertains to the fixed effects multilevel model only.

As in the 2009 woody cover model, 2000 population density and café production remain significant but below the level of practicality with coefficients below 0.00001. Also consistent with the 2009 woody cover findings, percentage of households that own a tractor remains significant and negatively correlated with the change in woody cover from 2001 to 2009. However, unlike 2009 woody cover, for woody cover change we observe a significant and positive relationship between both the percentage of households that use fertilizer and percentage of the municipality in fallow. Specifically, every one percent rise in the number of households that use fertilizer was correlated with a 0.07% increase in woody vegetation between 2001 and 2009. Furthermore, each percent rise in fallow land at the municipality level was correlated with a 2.76% increase in woody cover between 2001 and 2009. A likely explanation for such a large corresponding increase in woody cover with a rise in fallowed land is the "fallow" category captures abandoned land that is reverting back to forest as argued under Forest Transition Theory (Mather and Needle 1998).

Table 3. Multi-level Results for (natural log) percent change in woody cover from 2001 to 2009 with socioeconomic variables. Estimates are from 278 data points grouped by 22 departments.

	Not Multilevel (OLS)	*Maximum Likelihood Estimator*	*Random Effects*	*Fixed Effects*
PopDen_2000	0.001 (0.000)**	0.000 (0.003)**	0.000 (0.003)**	0.000 (0.011)*
PrctChgPopDensity1990-2000	-0.243 (0.312)	0.093 (0.658)	0.086 (0.688)	0.122 (0.575)
% HHs Using Fertilizer	1.226 (0.000)**	0.623 (0.001)**	0.641 (0.001)**	0.536 (0.005)**
% HHS Owning a Tractor	-2.399 (0.009)**	-2.777 (0.000)**	-2.755 (0.000)**	-2.890 (0.000)**
Café Production	0.000 (0.000)**	0.000 (0.003)**	0.000 (0.003)**	0.000 (0.009)**
Sugar Production	-0.000 (0.464)	-0.000 (0.814)	-0.000 (0.820)	-0.000 (0.793)
White Corn Production	0.003 (0.001)**	0.001 (0.049)*	0.001 (0.045)*	0.001 (0.114)
Yellow Corn Production	0.001 (0.308)	0.001 (0.231)	0.001 (0.240)	0.001 (0.257)
% Fallow Land	-0.221 (0.757)	1.134 (0.079)+	1.094 (0.096)+	1.325 (0.048)*
R-squared	0.307		0.252	0.158
Log likelihood		-406.32		
Random Intercept Standard Deviation (ς_j)		0.96	0.87	1.07
Residual Standard Deviation (ε_{ij})		0.94	0.96	0.96
Interclass Correlation (ρ)		0.51	0.45	0.56
Likelihood Ratio Test of ς_j		86.32		
Chi-squared		(0.000)		
F-test of Model Significance				9.65
Chi-squared				(0.000)
Hausman Test			22.25	
Chi-squared			(0.002)	

p values in parentheses: + significant at 10%; * significant at 5%; ** significant at 1%

3.2 Spatial Analysis and Modeling

Both the global and localized clustering measures indicate significant spatial dependence for the two variables of interest. Figure 1 shows percent woody cover in 2009 and change in woody cover from 2001-2009. Table 4 displays the Moran's I and Z scores for the independent variables, with larger significant Z scores indicating greater clustering. Both dependent variables show statistically significant clustering at the 99% confidence interval. Percent woody vegetation in year 2009 has more global clustering with a Z score of 12.59 as opposed to the change in woody vegetation with a Z score of 3.78. This may point to less spatial non-stationarity for the change model than the 2009 model, however it is difficult to draw conclusions about the residuals for an ill-fit model. Results from the GWR showed improvement in global adjusted R^2 values from 0.016 to 0.024 for the percent change in woody cover from 2001 to 2009 model, and a rise in adjusted R^2 from 0.251 to 0.471 for the percent woody cover in 2009 model. By accounting for spatial non-stationarity, the GWR model outperformed both models, although better results were seen for the percent woody cover in 2009 model likely due to the higher spatial clustering of OLS residuals that were accounted for by the GWR. Standardized residuals from both Model #1 and Model #2 were measured for spatial autocorrelation using Moran's I, and results confirm the lack of clustering (Table 4).

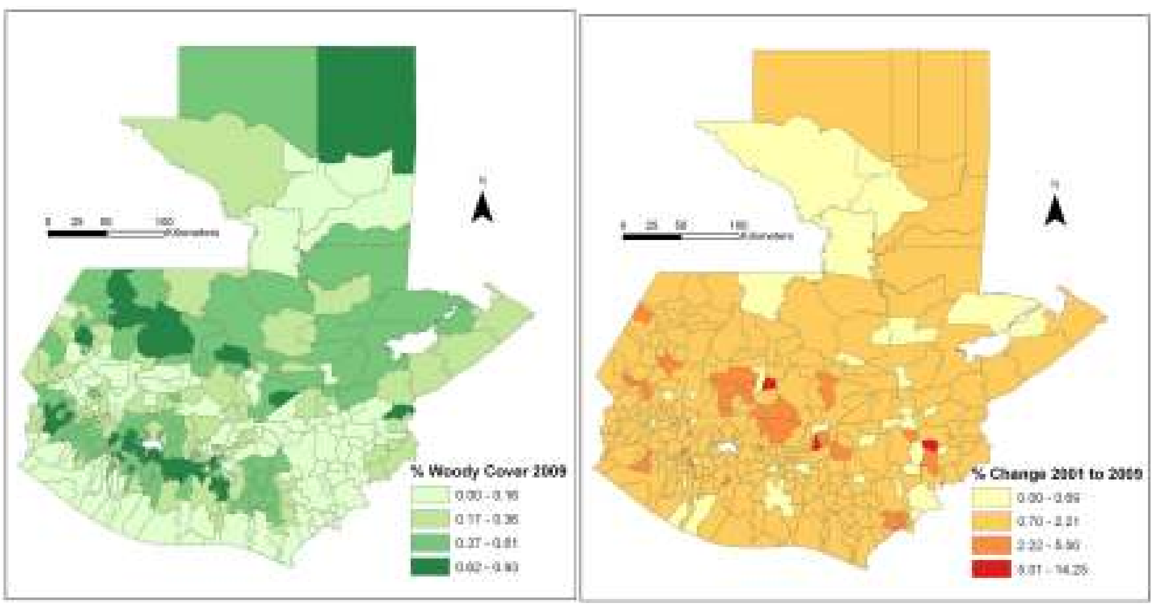

Figure 1. Percent woody cover in 2009 (left) and percent change in woody cover from 2001 to 2009 (right).

Table 4. Moran's I for Change in Woody Vegetation 2001-2009

Variable	*Moran's I*	*Z Score*	*P Value*	*Autocorrelation*
Change in Woody Vegetation 2001 – 2009	.02	3.77	< .0001	Strongly Clustered
Woody Vegetation 2009	.09	12.59	< .0001	Strongly Clustered
OLS Change 2001 – 2009 Standardized Residuals	.01	1.78	.07	Clustered
OLS 2009 Standardized	.07	9.42	< .0001	Strongly

Residuals				Clustered
GWR Change 2001 – 2009 Standardized Residuals	.01	1.16	.25	Random
GWR 2009 Standardized Residuals	.00	.72	.47	Random

A global pattern of woody clustering for 2009 is confirmed when examining local clustering using G*i** (Figure 2) hot and cold spot analysis. Hot spots are spatial units of high values surrounded by other units of high values (with cold spots the reverse), which are statistically significant (measured by Z scores) when compared to a random distribution. Percent woody cover in 2009 exhibits three hot spot regions with high forest cover for diverse reasons. The northeast portion of the country forms part of the Maya Biosphere Reserve and is devoid of roads and settlements; the area in the northwest was severely affected by civil war until the late 1990s and experienced some forest regrowth as a result of out-migration and farm abandonment. The central hotspot is covered by steep volcanoes and has been a priority conservation area by The Nature Conservancy during recent years. There is also a significant cold spot in the south-eastern area of the country. Change in woody cover from 2001 to 2009 shows one hot spot in the central area of the western region of the country, indicating an area that experienced significantly clustered high values of change between 2001 and 2009. Change here was rapid in association with high indigenous population density and high natural population growth.

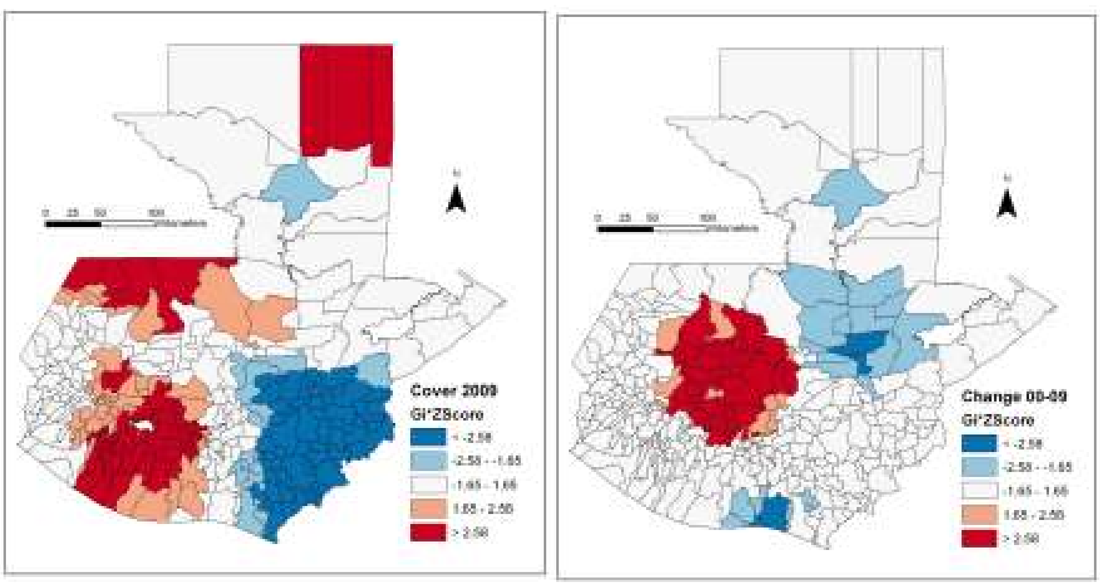

Figure 2. Getis-Ord G*i** maps for woody vegetation in 2009 and change in woody vegetation with significant clusters of high values in red and significant clusters of low values in blue.

Figure 3 presents coefficient estimates from the GWR model of percent population density change from 1990 to 2000 on the left and percent of land in fallow as related to woody cover in 2009 on the right. Population density change has a positive impact on percent woody cover in 2009 in the southern parts of Guatemala, but a negative impact in the northern parts of Guatemala. This result logically follows those prior on intensification. Southern areas where population density increases is likely related with urbanization and thus some land abandonment, whereas in the north the population is overwhelmingly rural and thus increasing population density here increases the number of farm workers and subsistence consumers, leading to less woody cover. Percent fallow land has a negative impact on percent of woody cover in 2009 country-wide, however this effect grows moving east through the country. Eastward and northward the countryside is more rural and practicing semi-subsistence agriculture and more forest cover which can be converted to fallow. Conversely, the more densely populated and urban areas of the southwest are largely deforested, and so fallow land is more likely to be associated with regrowth.

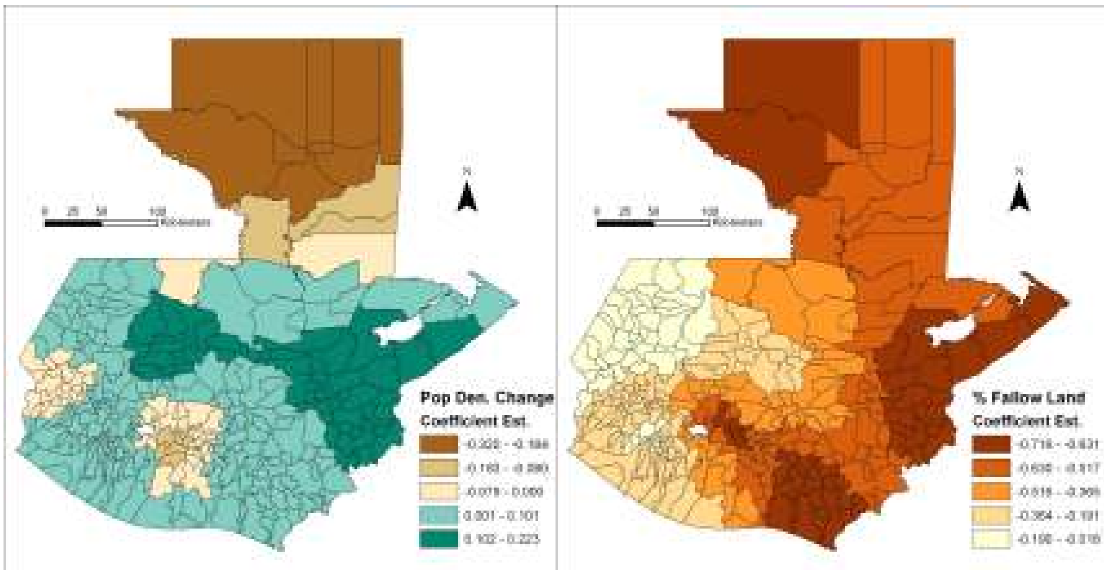

Figure 3. GWR coefficient estimates for percent population density change from 1990 to 2000 (left), and percent of land in fallow (right) for the percent woody cover in 2009 model.

We now turn to analyzing the parameter coefficient distributions resulting from the GWR regression. Figure 4 illustrates the parameter estimates for percentage of households using fertilizer for both models. Both the 2009 and 2001-2009 change models show similar spatial patterns of coefficient estimates increasing moving northward through the country, however in the 2009 model the percent of households using fertilizer has an increasingly negative model impact moving north, and in the 2001-2009 change model the percent of households using fertilizer has an increasingly positive impact moving north. The southern portion of the country is intensively managed in export crops such as sugar cane with high fertilizer inputs but low forest cover at the initial time period and low change in forest cover during the period. Conversely, moving northward, agriculture is generally more small scale, characterized by semi-subsistence maize swidden with relatively less inputs of fertilizers. Within this context, the more wooded remote northern regions are more likely to have recently cleared forest or secondary growth in order to intensify and extensify production simultaneously.

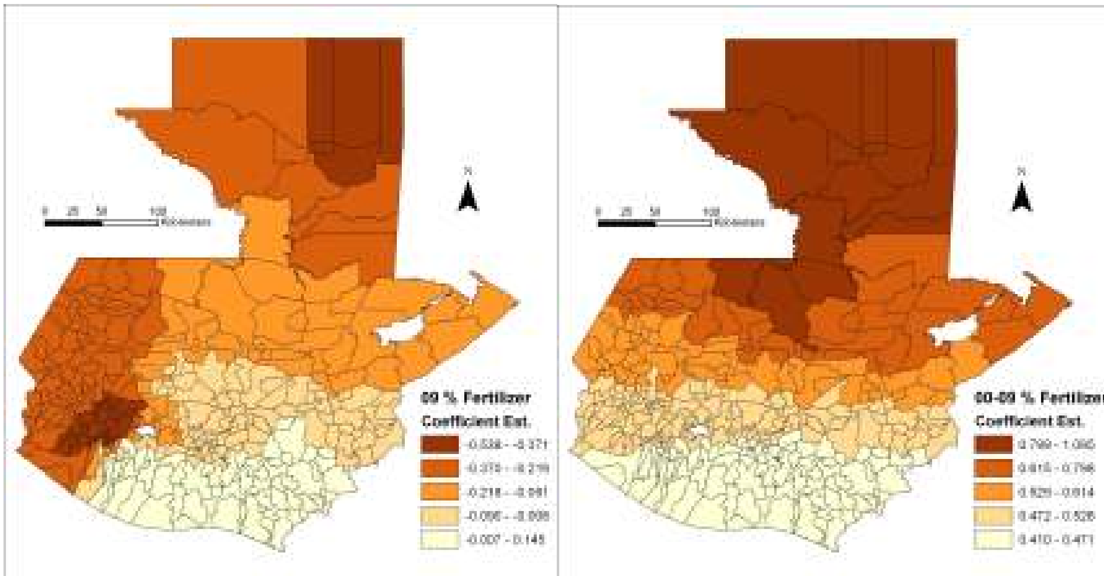

Figure 4. GWR coefficient estimates for percent households using fertilizer for the percent woody cover in 2009 model (left) and percent change in woody cover from 2001 to 2009 model (right).

Figure 5 displays mapped coefficient estimates for percent of households owning a tractor. Coefficient estimates for the 2001-2009 change model are higher, and follow a similar spatial pattern to the percent of households using fertilizer coefficient estimates with values increasing to higher negative values northward through the country. The pattern follows the simultaneous extensification and intensification relationship observed with fertilizer inputs described above. The percent woody cover in 2009 model provides an interesting spatial view of the households owning tractors variable. Here, coefficient estimates have higher negative values both in the north and south-western parts of the country. However, there is a patch of *positive* coefficient estimates in the central and north-western areas demarcated in a green color. In these areas, the little forest that does remain may be preciously coveted for fuelwood and intensification with tractors may help increase agricultural production and therefore benefit forest preservation through intensification.

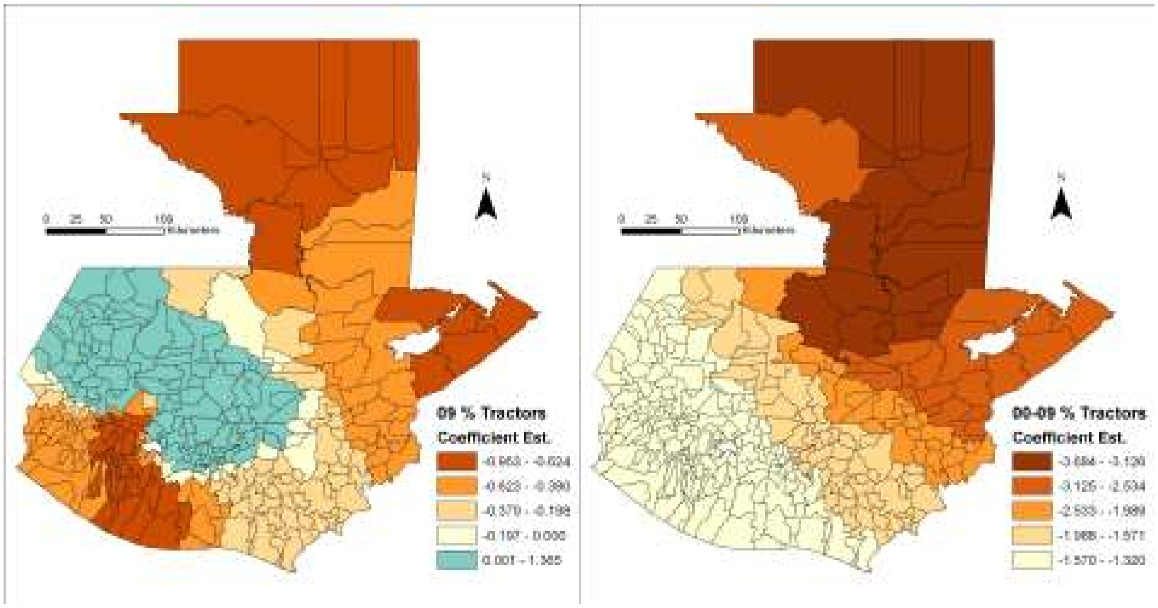

Figure 5. Coefficient estimates for percent households owning tractors for the percent woody cover in 2009 model (left) and percent change in woody cover from 2001 to 2009 model (right).

Local GWR R^2 values for the percent woody cover in 2009 and percent change in woody cover from 2001 to 2009 are displayed in Figure 6. In the 2009 model, values range from 0 in the western-central area of the country where model variables did not predict any woody cover in 2009, to 0.70 in the south-eastern area of the country, where it can be concluded that the variables selected for the model were best able to predict percent of woody cover in 2009. Local R^2 values were equal to 0 in a much larger portion of the country in the percent change in woody cover from 2001 to 2009, and comparatively good model fit, although the highest it achieved was R^2 value of 0.15, was in the northern part of the country. The maps in Figure 6 give an understanding of how the models are able to perform throughout Guatemala.

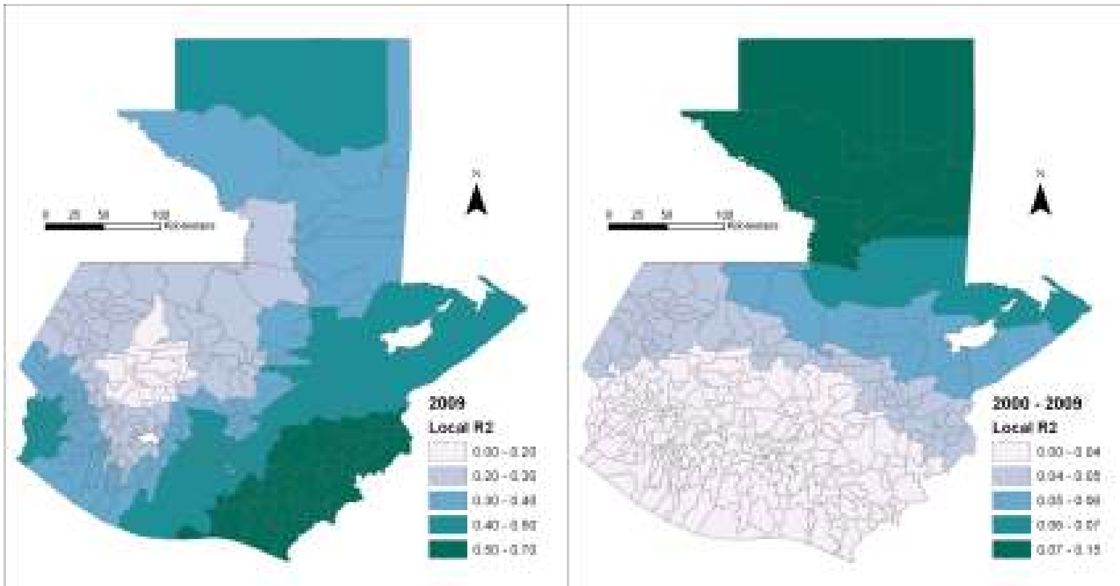

Figure 5. Local GWR R^2 values for 2009 woody vegetation (left) and 2001/2009 change woody vegetation (right).

4. Conclusion

This paper examines GWR versus multi-level models as applied to tropical LUCC and considers theoretical and practical implications to the two approaches. Together, these models allow us to draw a more complete picture of land cover change patterns in Guatemala, and to elaborate more comprehensive implications for theory, empiricism, and policy. While the data sources remain the same, each model provides comparative advantages, highlighting both possibilities and limitations when determining an appropriate statistical approach.

OLS regression suggested that agricultural intensification in the form of fertilizers and tractors and higher levels of fallowed land are negatively associated with forest cover in 2009 while increased population density is positively associated with higher forest cover. Examining forest change during the first decade of the 2000s, we observe that areas that increasingly rely upon mechanized equipment—which is relatively rare—and/or fertilizers have more thoroughly captured and put into agricultural production available agricultural land—especially white and yellow corn. By taking into account spatial heterogeneity at the municipal and department levels, the multilevel model results modify our OLS findings to allow the analysis to better comply with the spatial independence assumptions of OLS regression. Thus, the fixed effects multilevel model results differ OLS by only finding negative relationships between both tractor ownership and percent fallowed land with 2009 woody cover. However, multilevel model results for change in woody cover from 2001 to 2009 capture a positive trend between percentage of land in fallow with woody cover change in addition to previously mentioned OLS relationships with tractor ownership and fertilizer use.

Multi-level effects and spatial clustering were significant. Results from the two approaches corroborated each other synergistically yet also evinced important differences among nested versus spatial manifestations of predictor and outcome variables. Our use of the hierarchical model separated the effects of municipal versus departmental variables, allowing us to distinguish the scale at which variables were most influential. The GWR, conversely and additionally, indicated *where* these associations of changes are most salient. The GWR model controlled for spatial autocorrelation in the geographic distribution of woody cover and woody cover change across the Guatemalan landscape. It indicated that estimated coefficients vary over space, and visually displays where these positively influence the outcome in some areas, while negatively influencing the outcome in others. A clear trend emerges: The southwest to northeast gradient of decreasing population density, higher but decreasing forest cover, and lower but increasing technological inputs are particularly illuminated by the GWR.

The debate in geography and cognate sciences over the importance of space vs. place is often investigated with quantitative or qualitative research, respectively. It need not be so. Place can be quantified and measured. Doing so reveals information that is lost with the assumption of continuous space in spatial regression analysis (Nelson, 2001). Nested or hierarchical effects are often more descriptive of the phenomena of interest. Importantly, they are also more policy-applicable. Policy is not formulated or applied in continuous space but within a nested structure of political units from neighborhoods, to towns, counties, states, and nations. No one model is correct. Rather, appreciating the comparative advantages and limitations of each enhances a holistic approach to geographical analysis of tropical LUCC and human-environment interactions.

Great care should be taken in constructing any model, whether OLS, MLE, random, fixed, multi-level, or spatial in order to ensure the most parsimonious and sensible final model and interpretation of model coefficients. Future research should fruitfully consider spatial versus nested effects and combine both for a more holistic measurement and interpretation of complex coupled human-natural systems.

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