Social and Ecological Determinants of Land Clearing in the Brazilian Amazon: A Spatial Analysis

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Abstract
While tropical land clearing in the Brazilian Amazon provides for the livelihoods of Brazilians from a variety of socio-economic backgrounds, it also contributes to changes in climatological and ecological processes at a variety of scales. To develop sustainable approaches that balance the needs of forest users with ecological requirements, further study is needed to investigate the root causes of tropical land clearing. This study uses novel and systematic spatial econometric techniques to estimate the effects of ecosystem productivity, as measured by soil fertility and climate, and strategic interactions on municipal-level land clearing in the Legal Amazon of Brazil between 1970 and 1995. We find a negative relationship between soil fertility and land clearing. Furthermore, there is evidence of positive spatial interactions across municipalities in most specifications.

Keywords: land clearing, deforestation, spatial econometrics, ecosystem productivity, cation exchange capacity
JEL Classifications: Q23, Q24, C31

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1. Introduction

Emissions released as a result of tropical land clearing contribute to climatological and ecological processes at various scales (Fearnside and Laurance 2004, Morton et al. 2005). During the 1980’s and 1990’s clearing in the tropics produced nearly one-fifth of global carbon emissions and activities in the Brazilian Amazon accounted for more than 25 percent of that (Loarie et al. 2009, Okereke and Dooley 2010). Since the link was established between tropical land clearing and global environmental change, the Brazilian government has attempted to curb illegal clearing as a means of economic subsistence with varied success (Andersen et al. 2002). In this paper, we conduct a spatial econometric analysis of land clearing in the Brazilian Amazon to better understand some of the spatial, ecological, and socio-economic mechanisms that drive tropical land clearing decisions.

Starting in 1990, Brazilian officials implemented a suite of policies to reduce rainforest loss using a combination of monitoring, zoning, and private land restrictions (Fearnside 2005). However, enforcement has been plagued by an inability to compete with the short-term economic incentives to clear land, ineffective monitoring of large remote areas and a perceived low probability that violators will be caught (Laurance 1999, Fearnside 2003). Despite the intervention, frontier farmers continued to increasingly deforest the Brazilian Amazon through the early 2000’s (Laurance et al. 2002, 2004).

While recent satellite data shows that land clearing in Brazil peaked in 2004 and has since decreased, it is unclear whether the reduction is attributable to policy measures addressing the local causes of deforestation or price decreases in global food markets (Regalado 2010). If Brazil is to maintain lower levels of clearing and progress towards sustainable use of their land resources, they must develop policies that address the root causes and drivers of land clearing instead of reacting to and mitigating the consequences. Continued research is required to investigate how interactions between Brazilian frontier colonists, socio-economic conditions, and the dynamics of the surrounding ecosystem drive land clearing decisions.

In this paper we investigate the impacts of spatial, ecological, and socio-economic characteristics on tropical land clearing between 1970 and 1995. Specifically, we wanted to better understand how the ecosystem's natural productivity and strategic interactions due to neighbors' rates of land clearing contribute to both the total amount of land cleared and the rates of land clearing over time in the Brazilian Amazon.

Farmers in Brazil are highly dependent on natural resources from the environment to produce agricultural products and generate income (Andersen et al. 2002). Identifying how ecological characteristics affect land clearing decisions could facilitate novel agricultural adaptations that increase the sustainability of the system. Further, research suggests that land clearing decisions may be highly influenced by the actions of others in proximity (Mena et al. 2006, Caldas et al. 2007). Accounting for strategic interactions could help the Brazilian government more successfully prioritize locations for policy intervention.

The objectives of this paper are twofold. First, we examine the effects of ecosystem productivity on land clearing. A function of soil fertility and climate, productivity may play a crucial role in the land clearing decisions made by Brazilian farmers (Huston 1993). While researchers have investigated the influence of soil characteristics and climatic variables on land clearing, this study is the first to our knowledge that builds upon recent advances in ecology by using a new indicator of crop and forest productivity—cation exchange capacity (CEC) of the soil collected in soil surveys since 1981 (FAO et al. 1998). We find a negative relationship between CEC and land clearing.

Secondly, we improve on past literature by introducing methods to systematically account for the effects of spatial interactions inherent in land clearing patterns. While potentially important to explain the influences of neighbors' actions on land clearing decisions; failing to account for spatial interactions when present can lead to biased coefficient estimates of other predictor variables. In our analysis we estimate the OLS, the spatial lag, the spatial error, and the spatial mixed models. Additionally, we present formal test statistics for choosing between them. In our analysis we find that spatial econometric models are always statistically superior to OLS models, highlighting their importance for estimating unbiased coefficients. When longer than one period effects are modeled, the spatial lag is positive and significant suggesting that increased land clearing in one municipality facilitates land clearing in nearby municipalities.

Section two discusses contextual background including the history, the ecological and economic consequences, and potential causes of land clearing in Brazil. Section three provides a description of the dataset used in our model. Section four explains the modeling methodology. Section five presents results and Section six concludes our study.

2. Contextual Background

2.1 Rainforest and Economics in the Brazilian Amazon

The Amazon rainforest extends over an area of 5.5 million square kilometers, 60 percent of which is in the northern region of Brazil. While land clearing occurred in the Brazilian Amazon for hundreds of years, the modern era began in the late 1960's and early 1970's as Brazil implemented the economic development program Operation Amazonia (Cochrane 2009, Banerjee et al. 2009). Operation Amazonia used fiscal and credit based agricultural subsidies, colonization and regional incentive programs, and road/infrastructure expansion to create integrated growth poles. As a result of the policies, per capita income tripled and population grew by more than five percent per year between 1970 and 1980. Average annual farm area grew by six percent, crop area by 11 percent, and cattle stocks by 8.9 percent per year throughout the decade (Andersen et al. 2002).

Economic expansion during the 1970s preceded national recession in the 1980s. While per-capita income continued to grow at 3.3 percent per year, hard economic times led to an important sectoral shift from industry and infrastructure development to agriculture as the main economic activity (Fujisaka et al. 1996). Barbosa (2000) stated "Brazil almost overnight became an environmental villain when the eco-politics of the world-system changed in the mid-1980s." In 1990, responding to international perceptions, Brazil implemented the Commission for Coordination of Ecological-Economic Zoning in the Northern Territory (CCZEE). The policy partitioned public rainforest into several land use zones based on the amount of deforestation deemed acceptable. Land use in the zones ranged from complete protection of the most ecologically beneficial and fragile areas, to unhindered development. Since implementation, Brazil expanded the zoning system to include portions of private land. They further mandated that all private landowners must maintain 50 percent of their land in a natural state, and in 1996 that figure was increased to 80 percent (Andersen et al. 2002).

In the late 1990s Brazil attempted to merge development and environmental protection into cohesive policy. Known as Avança Brazil, the measure promised approximately 74 billion dollars of investment dedicated to developing the Amazonian region. While the government allocated the majority of the money to fund infrastructure and development programs, about five percent supported environmental projects. Although the ecological and socio-economic consequences of Avança Brazil remain unknown, researchers predict everything from responsible forest use (Andersen et al. 2002) to significant environmental damage (Laurance et al. 2001).

2.2 Ecological and Economic Consequences of Land Clearing

Land clearing in the Brazilian Amazon significantly alters ecological processes, with local to global implications (Aragão et al. 2008, Gardner et al. 2008, Grau and Aide 2008). The Brazilian rainforest accounts for 40 percent of the remaining tropical forests on earth (Rodrigues et al. 2009). Conversion of atmospheric carbon to plant biomass as a result of photosynthesis in tropical forests contributes to global climatic stability, moderating local hydrology and weather dynamics (Gibbs et al. 2007).

The Amazon also houses the most concentrated biodiversity found on earth, accounting for approximately 25 percent of the world's plants and animals (Betts et al. 2008). Land clearing threatens the survival of many species in the Amazon. Large scale activities like cattle ranching and industrial development can drive species and populations to extinction by eliminating entire habitats. However, even incorrectly conducted clearing at very small scales can put biodiversity at risk by causing spatial fragmentation. Spatial fragmentation or heterogeneous mosaic patterns of forest alternated with open fields and roads, impedes animal movements, limits their reproductive capabilities, and may genetically isolate populations (Broadbent et al. 2008). Genetic isolation reduces variation in the population gene pool and potentially lowers individual fitness. Additionally, fragmentation can decrease seed recruitment and plant biomass, increase carbon emissions, decrease rainfall, and contribute to a greater likelihood of fire (Perz et al. 2007).

Economically, the forest provides for the livelihoods of Brazilians from a variety of socio-economic backgrounds (Perz 2001, Pacheco 2009). Until recently, landless migrants could acquire property rights under Brazilian law by showing residency and productivity on a plot of land. Normally, this entailed clearing the land for agricultural development (Fearnside 2008, Nepstad et al. 2002).

Tropical soils are typically low in available plant nutrients as compared to other biomes, so farmers supplement existing below ground plant nutrients by slashing and burning the above ground vegetative biomass. Burning vegetation releases critical nutrients stored in live plant material. However, bi-products of burning plant biomass also include the release of greenhouse gases like nitrogen oxides and carbon dioxide into the atmosphere (Zarin et al. 2005). Known as swidden agriculture or slash and burn farming, soil fertility is increased for a short time until the combination of crop uptake and leaching by rainfall depletes the soil nutrients to their original levels in approximately three to four years (Andersen et al. 2002). After which, farmers must either rely on fertilizer to maintain productivity or abandon the land for new property.

Slash and burn farming is responsible for two-thirds of past tropical land clearing (Wright and Mueller-Landau 2006). Traditionally used practices conducted in large forest areas with low agricultural density and long fallow periods are considered sustainable and do not compromise soil fertility or forest regeneration capability (Johnson et al. 2001, Pedroso-Junior et al. 2009). However, as agricultural methodologies shift and production intensifies, slash and burn farming can dramatically degrade land quality, alter hydrological processes, and intensify wildfire risk (Nepstad et al. 2008).

Following colonization of frontier forest, economic opportunities evolve as people increasingly migrate into the area looking for land. Slash-and-burn farming transitions to larger scale activities such as ranching, commercial logging, and mining (Fearnside 2008). Resulting from the establishment of commercial enterprises, investment in infrastructure creates access to previously undisturbed forest. Population pressures increase, agricultural land is exhausted, and frontier farmers are forced deeper into the tropical forest in search of new economic opportunities. Research shows that during the initial establishment and expansion of the land use cycle, indicators of socio-economic development and human wellbeing increase as a function of deforestation extent. However, as land clearing continues, resources supporting the communities become scarce, indicators of societal health deteriorate, and the unsustainable nature of development forces people to move on and clear new land (Rodrigues et al. 2009).

2.3 Environmental Characteristics in Land Clearing Literature

Ecosystem productivity is a function of climatic and soil characteristics (Huston 1993). A variety of studies have investigated the influence of such factors on land clearing in the tropics. In a small scale study of one county in the eastern part of the Amazon basin, Caldas et al. (2007) find a significant positive relationship between soil quality, as measured by soil type and water availability, and land clearing. While studying 51 conservation units throughout the state of Rondonia, Brazil, Pedlowski et al. (2005) fail to identify a relationship between soil type and land clearing; however they suspect this is due to the uniformly low soil fertility throughout the study sites. In the tropical forests of Mexico however, soil quality increases forest conversion (Deininger and Minten, 2002). Contrary to these studies, Andersen et al. (2002) use a variety of properties to classify soil into different quality categories throughout the Brazilian Amazon. They find that increasing the amount of good soil in a given area decreases land clearing. Our study area and the spatial scale of our study units are similar to Andersen et al. We are therefore likely to find similar results.

Andersen et al. (2002) also find that annual precipitation above 2200 mm has mixed effects on land clearing and warmer seasonal temperatures increases the growth of land clearing.

Chomitz and Thomas (2001, 2003) however, show in a cross sectional study of the Brazilian Amazon using data from 1995 that the majority of clearing occurs in dryer areas and the number of agricultural establishments decreases as precipitation increases. Sombroek (2001) finds that the areas in the Brazilian Amazon with the most active agriculture have at least five consecutive months a year with less than 100 mm of rain. The author suggests that increasing precipitation decreases land clearing due to impacts on agricultural productivity related to the proliferation of pests and plant diseases, the challenges of maintaining infrastructure, and the inability to harvest crops mechanically (Schneider et al. 2002).

Individual factors that determine ecosystem productivity have been relatively well addressed; however the effect of ecosystem productivity on land clearing decisions in the Amazon needs further study. In ecological theory, debate exists about the best measures of terrestrial ecosystem productivity. Net primary productivity (NPP), or the production of plant biomass per unit area per unit time, is the traditional indicator. New global analysis suggests that there are major problems with current models of NPP and that soil fertility may better predict an ecosystem's productivity than currently used models (Huston and Wolverton 2009). Ecologists have traditionally believed that there are opposing global productivity gradients in marine and terrestrial ecosystems based on NPP models. Huston and Wolverton argue that the terrestrial and marine latitudinal patterns are virtually identical. Their research suggests that soil fertility is a more accurate indicator of terrestrial ecosystem productivity and solves the paradox of opposed gradients. In our analysis we measure soil fertility using cation exchange capacity (CEC), or the capacity of soil to hold and provide plant nutrients. Using this indicator of soil fertility provides important information not only on natural terrestrial ecosystem productivity, but also on potential productivity after conversion to agricultural use.

Climatic variables must also be accounted for when considering ecosystem productivity. Factors such as precipitation may be a key determinant in soil nutrient availability. As precipitation increases, soil fertility decreases due to higher rates of soil weathering and nutrients leaching out of the soil profile with increased water movement (Hölscher et al. 1997). Heimann and Reichstein (2008) suggest that on a variety of scales, changes in the timing, frequency and amount of rainfall can have profound effects on terrestrial ecosystem productivity.

2.4. Spatial Econometrics in Land Clearing Literature

Few studies in the land clearing literature include spatial econometric techniques to account for spillover effects of neighbors' land clearing and ensure unbiased estimation of coefficients. We organize our discussion of past research based on the types of spatial econometric models estimated by each study. In a contribution to spatial econometric theory, Mur and Angulo (2009) suggest specification tests are more robust when moving from a general model (the spatial mixed model) to a specific model (OLS) if the data generating process involves anomalies, such as heteroskedasticity with a spatial pattern. The only study in related literature that estimates the spatial mixed model is that of Pattanayak and Butry (2005). They model farm labor demand, a weak complement of deforestation, and find statistically significant spatial lag and spatial error coefficients only when included separately in the model. Their study uses a cross-sectional dataset at the farm level and therefore cannot exploit time-series variation as we do using a panel dataset to provide a more contextually rich understanding of land clearing over time. We also present formal test statistics for choosing between the spatial lag, the spatial error and the spatial mixed models to help tease apart the mechanisms driving spatial processes in our model.

Most of the previous spatial econometric land clearing literature, discussed below, focuses on moving from the specific-to-general approach. This technique uses the Lagrange Multiplier tests in OLS regression to choose between the spatial lag and the spatial error models. While estimating deforestation on producer properties throughout the Brazilian Amazon, Walker et al. (2000) find no evidence of the spatial lag or the spatial error in their sample using contiguity-based weighting matrices. As a result they do not estimate the spatial models. Employing a similar methodology Caldas et al. (2007) do find evidence of a spatial lag and estimate a positive spatial lag coefficient in their full model. While Mena et al. (2006) do not consider the spatial error term in a study of deforestation at the farm and parish levels in northern Ecuador; they do estimate a positive spatial lag in deforestation rates. Nelson et al. (2001) discuss the possibility of the spatial lag and the spatial error but do not explicitly estimate or test for these effects. None of the studies described here consider land clearing growth rates to better understand the short-term effects of explanatory variables on land clearing or control for cross-sectional unit fixed effects as we do.

Chomitz and Thomas (2003) and Klemick (2011) both estimate cross-sectional spatial error models while studying the effects of rainfall on land clearing in the Brazilian Amazon and valuating fallow land in an eastern state of Brazil. Neither examines the presence of spatial lags in their models. Not accounting for relevant spatial lags may bias the coefficients of the included explanatory variables. We, as well as two of the previous studies discussed above, find a statistically significant spatial lag coefficient in many of our specifications, highlighting their potential importance when modeling tropical land clearing. While the studies mentioned previously use methods that do consider the effects of spatial processes, our study is the first to our knowledge that systematically evaluates spatial effects in tropical land clearing and presents formal test statistics to do so.

3. Study Area and Data Sources

Our study focuses on the 6 million square kilometers defined by the Brazilian government as the Legal Amazon. Covering portions of ten interior states, the Legal Amazon acts as an administrative boundary including the Brazilian portion of the Amazon Basin. Seven of these states make it to our sample. Delineated in 1953, it was originally created as part of an effort to spur development and infrastructure in the northern regions of Brazil. As a result, the Legal Amazon encompasses a variety of other land cover types in addition to dense rain forest. These include but are not limited to open rainforest, transitional forest, and bushy savannah (Fearnside and Ferraz 1995).

This paper explores the relationships between cleared land in the Legal Amazon and a suite of spatial, environmental, demographic, and socio-economic variables. The majority of data used in this analysis come from an agricultural census conducted by the Brazilian government roughly every five years between 1970 and 1995. Our sample contains 4 time periods: 1970-1975, 1975-1980, 1980-1985 and 1985-1995. Data were compiled and made available by the Institute of Applied Economic Research in Brazil (IPEA 2010). The IPEA acts as a clearinghouse with the intention of providing pertinent, clear and accessible data for academics, NGOs, and governments on topics related to Brazilian economics, society, and environment. The agricultural census categorized land at the municipal level as either private agricultural establishments or publicly held. Since 1970, the government has redrawn municipality boundaries several times accommodating population growth and frontier expansion. To maintain consistent units of analysis over the study period, municipalities were aggregated into areas of minimum comparison (MCAs). Our sample contains 256 MCAs.

In our analysis, we defined cleared land as the logarithm of the number of new agricultural establishments created approximately every five years during the study period. Agricultural establishments are any continuous section of land under single ownership, urban or rural, used to produce some sort of plant or animal product such as crops, livestock, or lumber. The census considers all public land as un-cleared. As Andersen et al. (2002) point out; this assumption may prove tenuous because until recently Brazilian citizens could obtain ownership rights on public land by converting and farming it. However, quantifying cleared land as the number of agricultural establishments provides a valuable alternative to satellite based binary land classification that may miss small-scale activities and selective logging. For our analysis we calculated both the total levels of land clearing and the adjusted growth of land clearing every five years during the study period. For several MCAs we found fewer new agricultural establishments than recorded five years prior. To avoid negative values for the growth of land clearing, we scaled this measure by the observation with the largest decrease in the level of agricultural establishments over a five-year period. As a result, the smallest adjusted growth of land clearing is zero. This leaves our results unchanged and removes the odd implication that the growth of land clearing could be negative. Figure 1 presents a map of land clearing by MCA between 1985 and 1995.

Our data on CEC come from updates to the FAO et al. (1998) "soil and terrain digital database for Latin America and the Caribbean at 1:5 million scale", conducted by Batjes et al. (2004). Large-scale soil mapping describes soils in a region according to a number of characteristics, and then aggregates like areas into soil units. Once mapped, the authors use a combination of soil surveys, expert knowledge, and statistical techniques to further characterize properties of that soil unit including CEC. Using the "extract by mask" and "calculate statistics" tools in Arc GIS Desktop 9.3 we calculated the mean CEC value for each MCA (ESRI 2008). While in reality CEC may vary widely within any given MCA, we believe our measurements are the most consistent representation of soil fertility at the scale of the study. As CEC remains largely constant over time, we use a single CEC value per MCA that does not change across study periods. Figure 2 provides a map of mean CEC by MCA collected in soil surveys conducted since 1984.

Weather is controlled by annual precipitation, summer temperature and winter temperature averaged over 1961-1990. These variables are obtained from the IPEA database. While seasonal weather can vary greatly from year to year, using averages calculated over a 30 year period provides important information on the long-term, characteristic weather patterns for each MCA.

Demographic and socio-economic variables in our model include the number of cattle, local and national transportation costs, value added rural and urban GDP per capita, and percent of MCA population living in a rural setting. We incorporate the number of cattle per MCA in our analysis to distinguish between the effects of small-scale slash and burn agriculture and industrial cattle production on land clearing. Previous research shows that a large proportion of the Brazilian rainforest is cleared for cattle, and how ranchers choose where they clear may be fundamentally different from other colonists (Walker et al. 2000).

We also include indices of local and national transportation costs to account for the cost of selling produced goods at market in each MCA as well as to control for the distance of each MCA to Brazil's more industrialized eastern coast. The local transportation index measures the cost of transporting goods to the nearest municipal capital. The national transportation index measures the cost of transporting goods to São Paolo, the country's commercial center.

Finally, we account for both the proportion of rural to total population as well as rural and urban value added GDP per capita. Value added GDP measures the value of a MCA's final output minus the value paid for intermediate consumption. This measure of GDP may be negative if people consume more at the intermediate levels than the final product is worth. For example, crop failures or lower than expected agricultural prices can lead to lower final output than the cost of creating the product (Andersen et al. 2002). A demographic census was conducted every ten years during our study period in which they measured population size. For our mid-decade periods we interpolate population values. The Brazilian government collected mid-decade GDP data in an economic census.

4. Empirical Model

In this analysis our two dependent variables of interest are the level and the growth rate of land clearing. The equations for the level of land clearing provide information on the effects of explanatory variables in the longer-term and the growth rate equations provide insight into the shorter-term effects. Central to our study is the maximum likelihood estimation of the spatial mixed model which includes both spatial lag and spatial error terms:

$$(1)\ Y_{i,t} = \rho \sum_{i \neq j} \omega_{ij} Y_{j,t} + \beta_1 X_i + \beta_2 Z_{i,t} + \gamma Trend_t + u_{i,t}\text{ , where}$$

$$(2)\ u_{i,t} = \lambda \sum_{i \neq j} \omega_{ij} u_{j,t} + \varepsilon_{i,t}\ .$$

In equation (1), $Y_{i,t}$ is the log transformed level or growth of land clearing in MCA *i* over time period *t*. In regressions with the state fixed effects, X_i is a vector of independent variables that vary by MCAs but remain constant over time as well as state fixed effects. Time invariant variables include the logarithm of CEC, logarithm of area, precipitation, summer temperatures, and winter temperatures. In regressions with the MCA fixed effects, X_i stands for MCA fixed effects alone. $Z_{i,t}$ is a vector of independent variables that vary by MCAs and across time, including the logarithm of number of cattle, two log transformed transportation indices, the logarithm of rural and urban per capita GDP and rural population percent. The variables in vector Z are included in either levels or growth rates depending on the form of the dependent variable. In the growth rate equations, we include the lagged level of land clearing. Clearly, growth rates of land clearing cannot be high for MCAs that have already experienced significant land clearing in the past. The model also includes a time trend and an i.i.d. random error term, $\varepsilon_{i,t}$.

The spatial lag, $\sum_{i \neq j} \omega_{ij} Y_{j,t}$, is the weighted average of the other MCAs land clearing, where the weights are based on inverse distance between MCAs.[3] It is the spatial lag coefficient, ρ, that lends itself to interpretation of strategic interactions between MCAs. In other words the coefficient ρ describes how land clearing in an average MCA is influenced by neighboring MCAs' land clearing. For example, if neighboring MCAs develop infrastructure for transporting lumber to different markets then a positive spatial lag in land clearing may be induced. Spatial interactions could also be driven by proximity of equipment and increased demand by neighboring colonists for more land to clear.

[3] To create the matrices necessary for modeling spatial spillovers, we calculated the x,y coordinates for the centroid of each MCA using the "polygon to centroid" tool in the XTools Pro extension of Arc GIS Desktop 9.3 (ESRI 2008). Coordinates were converted into a text file and imported into R.gui (R development Core Team 2005). Using the spatial package "Fields" to calculate the Euclidian distances between all of the centroids in km we generated a distance matrix for each agricultural census year (Furrer et al. 2009). We then used Stata software to aggregate the matrices into one with each census year matrix on the diagonal and the rest filled with null values (Stata 2007).

The spatial error, $\sum_{i \neq j} \omega_{ij} u_{j,t}$, is the weighted average of the other observations' error terms, using the same weights as for the spatial lag. The spatial error coefficient, λ, does not lend itself for interpretation as a strategic interaction estimate but rather provides evidence of inherent similarity ($\lambda > 0$) or dissimilarity ($\lambda < 0$) between MCAs located near one another.[4]

As a baseline, we begin our analysis assuming that both the spatial lag and the spatial error coefficients equal zero. Then we separately estimate the spatial lag and the spatial error models that allow one of the two spatial coefficients to take on non-zero values. Finally, the full model presented in this section is estimated. This methodology is executed for both level and growth rate of land clearing.

5. Results

We conducted a spatial econometric analysis to better understand how spatial, ecological, and socio-economic characteristics drive tropical land clearing in the Legal Amazon between 1970 and 1995. This section discusses the estimated models for levels and growth rates of land clearing. For each dependent variable, we first include state fixed effects and time-invariant characteristics of MCAs. Then we substitute state fixed effects for MCA fixed effects, which force us to exclude the time-invariant variables. In our analysis OLS models are always rejected in favor of the spatial models using the likelihood-ratio (LR) tests.[5] Thus, we focus our discussion on the spatial models.

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[4] We use Jeanty's (2010) Stata code *spmlreg* to run our models on the Social Science Gateway hosted by the NSF grant SES-0922005.

[5] We use Hendry's methodology outlined by Florax et al. (2003), a general-to-specific (Gets) approach, in choosing our statistically preferred econometric model. The Gets approach's robustness to anomalies in the data generating process is discussed in Mur and Angulo (2009).

5.1. Level of Land Clearing

Table 2 presents the estimated models for level of land clearing with state fixed effects and the time-invariant variables. These regressions provide estimates of the longest-term effects on land clearing. The spatial lag model dominates in this form of the regression providing evidence of positive spatial interactions between MCAs' land clearing levels. An increase in the proximate MCAs' land clearing levels by one percent increases the MCA's land clearing by 0.636 percent on average. This result is consistent with the transportation and equipment networks as well as the new colonists' demand hypotheses.

We find a small negative effect of soil fertility as measured by CEC, on land clearing. An increase in CEC levels by one percent decreases land clearing by 0.09 percent. This finding matches the Andersen et al. (2002) result that an increase in the share of good soil decreases land clearing. Additionally, we find an increase in precipitation by one percent increased levels of land clearing by 0.345 percent. While there may be interactions between soil fertility and precipitation, the benefit of regression analysis is that we can isolate these two effects.

As expected, larger MCAs had larger levels of land clearing during the study period. An increase in area by one percent increased levels of land clearing by about 0.07 percent. Economic activity indicators also impact land clearing. Increase in the number of cattle or rural per capita GDP by one percent also increase level of land clearing by about 0.07 percent.

Continuing to use level of land clearing as the dependent variable, Table 3 presents the results with MCA fixed effects. Therefore, the time-invariant variables drop out of the equation. In this form of the regression the spatial mixed model dominates. Now we find a positive spatial lag as well as a positive spatial error coefficient. MCA fixed effects control for everything that is constant within each MCA, we are now unable to include variables that would be similar for

MCAs nearby—such as CEC and the weather controls that do not vary across time. That is likely the reason why the spatial error becomes statistically significant. The size of the spatial lag coefficient is comparable with the spatial lag model from Table 2.

The other two variables that are statistically significant in Table 3 are rural per capita GDP and rural population percent. The estimated effect of rural per capita GDP is twice as large as that in Table 2. Increasing rural population percent by its standard deviation or about 20 percentage points increases land clearing levels by 1.746 percent. Both of these findings are intuitive, as most of the land clearing would take place in rural areas.

5.2. Growth of Land Clearing

Results for growth rates of land clearing with state fixed effects are in Table 4. Here, similar to the results from Table 2 we find that the spatial lag model performs the best when the state fixed effects are included. Just as before, there is a positive spatial interaction in land clearing between MCAs and a negative effect of CEC on land clearing. Further, MCAs with higher levels of precipitation also experienced higher growth of land clearing.

Contrasting the results of Table 2 where we found that the larger the MCA area the higher the level of land clearing, in Table 4 an increase in area by one percent decreases the growth rate of land clearing by 0.043 percent. While the level of land clearing is higher, the growth rate is lower in larger MCAs. In the state fixed effects models, the time-invariant weather variables are all statistically significant. MCAs with higher winter temperature have higher growth of land clearing whereas MCAs with higher summer temperatures exhibit lower growth rates of land clearing. As expected, MCAs with larger levels of land clearing in the previous time period exhibit lower growth rates of land clearing. Also as expected, increasing rural GDP increases growth of land clearing whereas growth in urban GDP lowers growth of land clearing.

Similar to the move from Table 2 to Table 3, when we replace state fixed effects with MCA fixed effects in Table 5 the spatial error term becomes more prevalent. This time to the extent that the spatial error model cannot be rejected at the traditional significance levels and it dominates the other spatial models. When we estimate growth rates and control for MCA fixed effects, coefficients are based on time-series variation alone. This suggests that the economically interpretable spatial lag effects take longer than one time period to present themselves.

The effects of lagged land clearing on the growth rate in this model with MCA fixed effects are even larger than those in the model with state fixed effects. Furthermore, we find that larger growth in national transportation costs increases land clearing. This is counterintuitive for land clearing involving commercial enterprises such as cattle ranching and logging that ship products to world markets. Yet, slash-and-burn land clearing is likely to move into more and more remote locations. If national transportation costs proxy for remoteness, then we find that land clearing is growing fastest in remote areas of the Amazon.

6. Conclusions

Past research on land clearing in the tropics has largely overlooked the influence of terrestrial ecosystem productivity. Our spatial econometric analysis suggests that soil fertility as measured by CEC and the effects of annual precipitation play statistically significant and counter-intuitive roles in land clearing processes throughout the Legal Amazon. We present several speculative hypotheses that may explain our findings.

One explanation for these results may be that farmers make land clearing decisions not based on the productivity of the natural ecosystem but based on the ease of clearing. If a farmer has the choice between two plots, one heavily overgrown with large amounts biomass per hectare and another more moderately vegetated plot, the farmer may choose the lower productivity plot because they can clear it more easily. A farmer will potentially pick a lower productivity plot if the costs of clearing a productive piece of land outweigh the agricultural benefits accrued from farming more fertile soil (Pichón 1997).

Another possibility is that frontier colonists clear land more slowly when farming on productive plots because the land remains agriculturally viable for longer. A higher CEC and lower precipitation means that soil is better able to retain plant nutrients as they enter the soil and prevents them from leaching out. As a result, when areas with higher productivity are slashed and burned it may be that farmers are able to raise crops for longer periods of time, reducing the need for continued clearing (Barbier 2000).

Additionally, we provide strong evidence for spatial methods in modeling land clearing decisions. Our results indicate that under many specifications, land clearing decisions made in neighboring MCAs can influence both the level and growth of land clearing in a given MCA. Further, it is important to test and account for spatial interactions to ensure unbiased estimation of model coefficients. For levels of land clearing, we find positive strategic interactions between MCAs regardless of the choice of fixed effects. For growth of land clearing the choice between state and MCA fixed effects determines the importance of the spatial lag versus spatial error models. With state fixed effects, sufficient cross-sectional variation remains to identify a positive spatial lag. With MCA fixed effects our results are fully driven by time-series variation and only the spatial error remains significant in the growth rate regression.

Recognizing the presence of spatial interactions in land clearing processes has direct policy application. Providing enforcement and monitoring of government protected natural forest is a major roadblock to effective conservation policy in the Brazilian Amazon. The areas are too large and resources are unavailable for effective comprehensive monitoring. When Brazil formulates new regulation, they may find greater success if they prioritize locations for policy intervention based upon spillover effects between municipalities.

Understanding the influences of ecosystem productivity and spatial interactions on land clearing decisions could provide important information on how to formulate a more sustainable solution to the current environment-development conflict. The push to end the cycle of unsustainable forest conversion in the Legal Amazon may benefit from a combination of highly targeted and effective government policy intervention and innovation in agricultural methodologies. Incorporating spatial interactions into land clearing analyses can help direct current policy intervention. Further, better understanding the interactions between terrestrial ecosystem productivity and agricultural methodologies could help improve the agricultural life span of the land that is cleared. Creating small, highly productive plots might help to increase development effectiveness by maximizing the ratio of agricultural output to field area. The ecosystem's natural productivity may play an integral role in formulating this more productive land clearing strategy.

Ecologically, agricultural strategies based on farming the most productive land could have positive effects for both the maintenance of tropical biodiversity and atmospheric carbon sequestration. From a biodiversity perspective, the highest number of plant and small animal species tend to be in lower productivity areas. This is a result of reduced competition that allows for a greater number of different plant species to co-exist in a given area (Huston 1993, 2005, Huston and Marland 2003). Further, studies show that even lower productivity forest stands can effectively sequester atmospheric carbon and help mitigate climatic change (Huston and Marland 2003, Schlamadinger and Marland 1996). This suggests the potential for a social and ecological win-win. Targeting areas with high terrestrial ecosystem productivity for agriculture could improve agricultural output and sustainability while bolstering biodiversity and carbon sequestration capacity.

The results of this study highlight the need for future research to systematically consider and incorporate spatial interactions when modeling tropical land clearing. Further study is also needed regarding the relationships between land clearing and ecosystem productivity. First, researchers must improve NPP models to better measure ecosystem productivity at regional and global scales. In lieu of improved NPP models we need to investigate other measures of soil fertility and climate, as different indicators have costs and benefits that may influence land clearing decisions. For example, while CEC measures the potential capacity of soil to hold on to critical plant nutrients now and in the future, it provides little information on fluctuations of the actual availability of nutrients over time. Other indicators like total exchangeable bases estimates the amount of nutrients available at a given time based on a location's soil properties and external environmental factors, but provides little information on future nutrient availability. Finally, we need to better understand the mechanisms that drive relationships between terrestrial ecosystem productivity and land clearing decisions. This will require more detailed analysis of interactions between economic and ecological variables at various scales and feedbacks amongst those scales.

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Figure 1 Land Clearing by MCA, Measured by the Adjusted Number of New Agricultural Establishments (1985-1995)

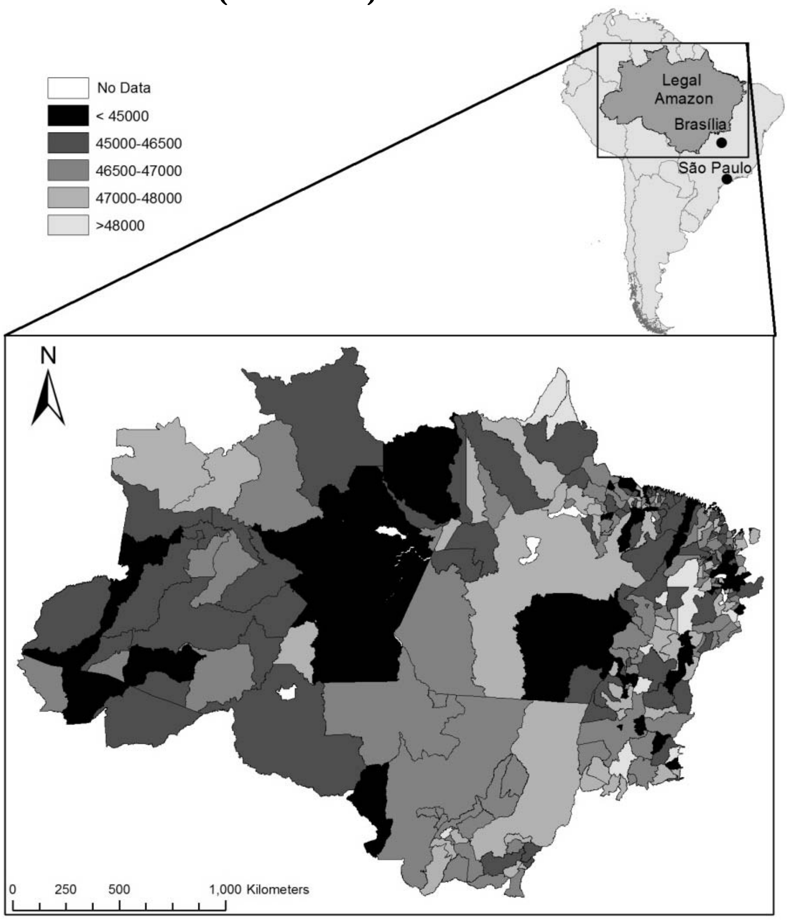

Figure 2 Mean Cation Exchange Capacity by MCA, Measured by cmol/kg

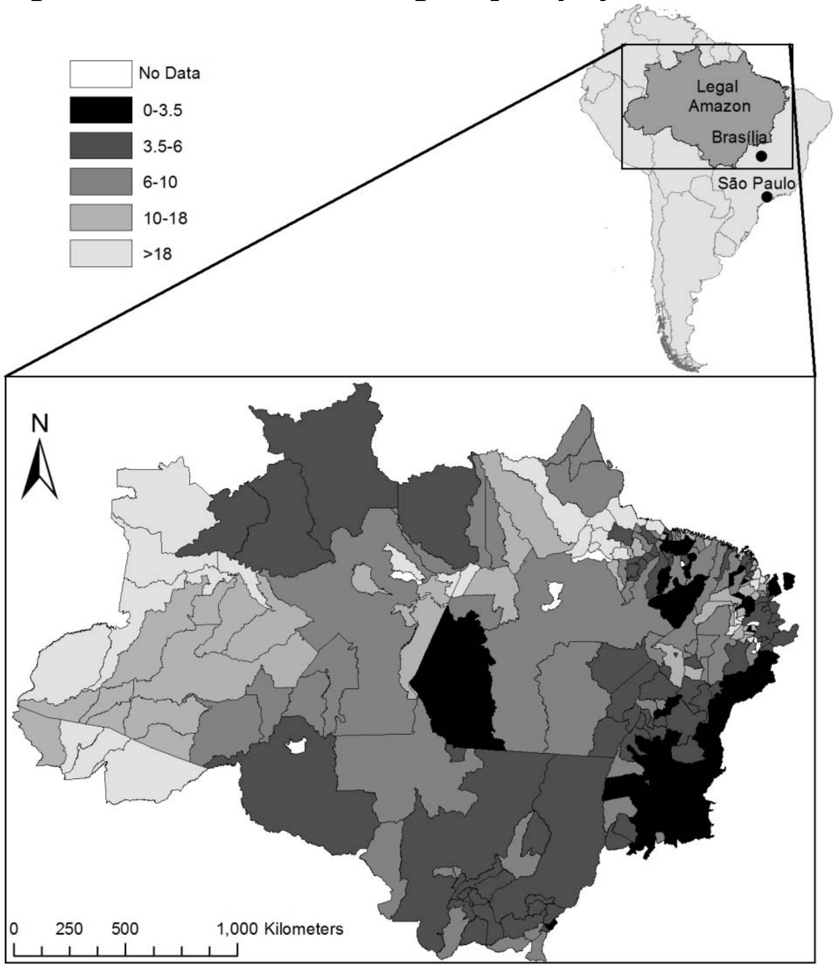

Table 1 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max	Data Source
Ln(Land Clearing)[a]	1263	7.50	1.09	3.71	11.30	IPEA (2010)
Ln(Land Clearing) growth[b]	998	3.30	0.83	0.00	9.41	IPEA (2010)
Ln(CEC)	1263	1.76	0.91	-1.47	4.33	Batjes et al. (2004)
Ln(Area)	1263	8.32	1.75	4.65	13.18	IPEA (2010)
Precipitation[c]	1263	1.98	0.51	1.09	3.27	IPEA (2010)
Summer Temp[c]	1263	26.35	0.72	23.51	28.15	IPEA (2010)
Winter Temp[c]	1263	26.16	0.72	22.56	27.13	IPEA (2010)
Ln(Cattle)	1263	9.36	2.21	1.10	15.39	IPEA (2010)
Ln(Local Transp)	1263	6.77	0.79	3.53	8.69	IPEA (2010)
Ln(National Transp)	1263	8.33	0.45	7.15	9.64	IPEA (2010)
Ln(Rural GDP/Pop)	1263	0.25	0.78	-5.19	4.19	IPEA (2010)
Ln(Urban GDP/Pop)	1263	1.29	0.77	-0.57	5.32	IPEA (2010)
Rural Pop Percent	1263	0.66	0.20	0.04	0.98	IPEA (2010)
Ln(Land Clearing) lagged	998	7.53	1.08	4.01	11.30	IPEA (2010)
Ln(Cattle) growth	998	0.29	0.68	-3.67	5.53	IPEA (2010)
Ln(Local Transp) growth	998	-0.11	0.12	-0.69	0.10	IPEA (2010)
Ln(National Transp) growth	998	-0.15	0.07	-0.50	-0.02	IPEA (2010)
Ln(Rural GDP/Pop) growth	998	0.18	0.62	-3.02	2.98	IPEA (2010)
Ln(Urban GDP/Pop) growth	998	-0.04	0.63	-4.24	3.96	IPEA (2010)
Rural Pop Percent growth	998	-0.06	0.06	-0.43	0.25	IPEA (2010)

Notes:

[a] Land clearing is proxied by the number of new agricultural establishments.

[b] For several MCAs we found fewer new agricultural establishments than recorded five years prior. The largest decrease in the log of new agricultural establishments was 3.30. To avoid negative values for growth rates of Ln(Land Clearing), we scaled up the calculated growth rates by 3.30.

[c] The precipitation and temperature data originated from a global 10 minute latitude/longitude model of several climatological variables interpolated from weather station readings between 1961-1990 (New et al. 2002).

Table 2 Ln(Land Clearing), State Fixed Effects

	(1)	(2)	(5)	(8)
VARIABLES	OLS	Spatial Lag	Spatial Error	Spatial Mixed
Rho		0.636***		0.675***
		(0.096)		(0.189)
Lambda			0.654***	-0.085
			(0.104)	(0.390)
Ln(CEC)	-0.093***	-0.086**	-0.084**	-0.086**
	(0.036)	(0.034)	(0.040)	(0.038)
Ln(Area)	0.063**	0.069***	0.069**	0.069**
	(0.027)	(0.026)	(0.029)	(0.028)
Precipitation	0.391***	0.345***	0.423***	0.338***
	(0.115)	(0.113)	(0.136)	(0.124)
Summer Temp	-0.000	-0.035	-0.016	-0.036
	(0.113)	(0.111)	(0.135)	(0.124)
Winter Temp	0.058	0.071	0.045	0.073
	(0.113)	(0.111)	(0.133)	(0.120)
Ln(Cattle)	0.064***	0.066***	0.072***	0.066***
	(0.020)	(0.019)	(0.021)	(0.020)
Ln(Local Transp)	-0.011	-0.021	-0.029	-0.020
	(0.055)	(0.053)	(0.059)	(0.056)
Ln(National Transp)	-0.200	-0.187	-0.168	-0.185
	(0.161)	(0.157)	(0.179)	(0.167)
Ln(Rural GDP/Pop)	0.103**	0.072*	0.064	0.072
	(0.042)	(0.040)	(0.048)	(0.045)
Ln(Urban GDP/Pop)	0.027	-0.000	-0.013	0.001
	(0.044)	(0.042)	(0.046)	(0.044)
Rural Pop Percent	-0.048	-0.031	-0.020	-0.033
	(0.185)	(0.179)	(0.182)	(0.182)
Trend	0.010**	0.010*	0.008	0.010**
	(0.005)	(0.005)	(0.010)	(0.005)
Constant	5.270***	1.119	5.744***	0.809
	(1.557)	(1.649)	(1.857)	(2.237)
Sigma		1.002***	1.002***	1.001***
		(0.023)	(0.020)	(0.020)
Observations	1263	1263	1263	1263
R-squared	0.126			
Log-likelihood	-1812.571	-1798.0869	-1798.8603	-1798.0648
LR chi2 (vs. OLS)		28.968	27.421	29.012
P-value		(0.000)	(0.000)	(0.000)
LR chi2 (vs. Spatial Lag)				0.044
P-value				(0.834)
LR chi2 (vs. Spatial Error)				1.591
P-value				(0.207)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3 Ln(Land Clearing), MCA Fixed Effects

	(1)	(2)	(3)	(4)
VARIABLES	OLS	Spatial Lag	Spatial Error	Spatial Mixed
Rho		0.906***		0.738***
		(0.040)		(0.113)
Lambda			0.915***	0.702***
			(0.035)	(0.128)
Ln(Cattle)	0.017	0.020	0.020	0.020
	(0.045)	(0.036)	(0.032)	(0.031)
Ln(Local Transp)	0.585**	0.095	-0.092	-0.082
	(0.228)	(0.183)	(0.212)	(0.206)
Ln(National Transp)	-0.174	0.557	0.799	0.627
	(0.436)	(0.370)	(0.504)	(0.467)
Ln(Rural GDP/Pop)	0.222***	0.145***	0.133***	0.134***
	(0.044)	(0.036)	(0.042)	(0.042)
Ln(Urban GDP/Pop)	0.066	0.014	-0.002	-0.004
	(0.044)	(0.036)	(0.042)	(0.041)
Rural Pop Percent	0.749	0.808**	0.856**	0.873**
	(0.474)	(0.393)	(0.357)	(0.350)
Trend	-0.008	-0.018**	-0.030	-0.019
	(0.011)	(0.009)	(0.026)	(0.012)
Constant	4.583	-4.766	1.495	-2.837
	(3.491)	(3.033)	(3.656)	(3.435)
Sigma		0.595***	0.596***	0.591***
		(0.022)	(0.012)	(0.012)
Observations	1263	1263	1263	1263
R-squared	0.657			
Log-likelihood	-1221.9011	-1148.0125	-1150.5497	-1139.4731
LR chi2 (vs. OLS)		147.777	142.703	164.856
P-value		(0.000)	(0.000)	(0.000)
LR chi2 (vs. Spatial Lag)				17.079
P-value				(0.000)
LR chi2 (vs. Spatial Error)				22.153
P-value				(0.000)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 4 Growth of Ln(Land Clearing), State Fixed Effects

	(1)	(2)	(3)	(4)
VARIABLES	OLS	Spatial Lag	Spatial Error	Spatial Mixed
Rho		0.828***		0.881***
		(0.079)		(0.064)
Lambda			0.825***	-0.384
			(0.076)	(0.374)
Ln(CEC)	-0.069**	-0.050*	-0.049	-0.054*
	(0.028)	(0.026)	(0.032)	(0.029)
Ln(Area)	-0.044**	-0.043**	-0.049***	-0.041**
	(0.017)	(0.017)	(0.018)	(0.017)
Precipitation	0.259***	0.211**	0.251**	0.208**
	(0.092)	(0.087)	(0.106)	(0.086)
Summer Temp	-0.266***	-0.250***	-0.256**	-0.250***
	(0.091)	(0.090)	(0.105)	(0.089)
Winter Temp	0.166*	0.161*	0.144	0.168*
	(0.090)	(0.088)	(0.107)	(0.089)
Ln(Land Clearing) lagged	-0.278***	-0.243***	-0.227***	-0.255***
	(0.031)	(0.030)	(0.023)	(0.025)
Ln(Cattle) growth	-0.011	0.005	0.004	0.002
	(0.034)	(0.031)	(0.038)	(0.034)
Ln(Local Transp) growth	0.318	0.108	0.036	0.159
	(0.197)	(0.181)	(0.265)	(0.205)
Ln(National Transp) growth	0.653*	0.168	0.342	0.073
	(0.342)	(0.332)	(0.615)	(0.348)
Ln(Rural GDP/Pop) growth	0.076*	0.069*	0.068*	0.069*
	(0.040)	(0.038)	(0.041)	(0.040)
Ln(Urban GDP/Pop) growth	-0.063*	-0.067**	-0.070*	-0.064*
	(0.034)	(0.032)	(0.041)	(0.038)
Rural Pop Percent growth	0.634	0.538	0.545	0.550
	(0.445)	(0.425)	(0.455)	(0.425)
Trend	0.015***	-0.001	0.024	-0.002
	(0.004)	(0.005)	(0.018)	(0.003)
Constant	4.595***	4.160***	4.412***	4.105***
	(1.087)	(1.042)	(1.267)	(1.028)
Sigma		0.695***	0.703***	0.693***
		(0.030)	(0.016)	(0.016)
Observations	998	998	998	998
R-squared	0.236			
Log-likelihood	-1094.0033	-1060.2332	-1070.8384	-1059.6852
LR chi2 (vs. OLS)		67.5402	46.330	68.636
P-value		(0.000)	(0.000)	(0.000)
LR chi2 (vs. Spatial Lag)				1.096
P-value				(0.295)
LR chi2 (vs. Spatial Error)				22.306
P-value				(0.000)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 5 Growth of Ln(Land Clearing), MCA Fixed Effects

	(1)	(2)	(3)	(4)
VARIABLES	OLS	Spatial Lag	Spatial Error	Spatial Mixed
Rho		0.288***		0.128
		(0.049)		(0.086)
Lambda			0.744***	0.672***
			(0.082)	(0.112)
Ln(Land Clearing) lagged	-0.981***	-0.954***	-0.974***	-0.970***
	(0.019)	(0.017)	(0.014)	(0.014)
Ln(Cattle) growth	0.011	0.016	-0.012	-0.009
	(0.017)	(0.015)	(0.016)	(0.017)
Ln(Local Transp) growth	-0.073	-0.172*	-0.143	-0.168
	(0.114)	(0.100)	(0.118)	(0.117)
Ln(National Transp) growth	1.162***	0.981***	0.611**	0.660***
	(0.181)	(0.156)	(0.260)	(0.255)
Ln(Rural GDP/Pop) growth	0.049***	0.046***	0.041**	0.042**
	(0.018)	(0.015)	(0.017)	(0.017)
Ln(Urban GDP/Pop) growth	-0.036*	-0.038**	-0.041**	-0.041**
	(0.019)	(0.016)	(0.017)	(0.017)
Rural Pop Percent growth	0.308	0.261	0.063	0.069
	(0.268)	(0.229)	(0.208)	(0.208)
Trend	0.006***	0.001	0.008*	0.005
	(0.002)	(0.002)	(0.005)	(0.004)
Constant	7.645***	7.424***	7.480***	7.475***
	(0.219)	(0.190)	(0.195)	(0.190)
Sigma		0.275***	0.271***	0.271***
		(0.014)	(0.006)	(0.006)
Observations	998	998	998	998
R-squared	0.887			
Log-likelihood	-140.33366	-126.89069	-118.40284	-117.37463
LR chi2 (vs. OLS)		26.886	43.862	45.918
P-value		(0.000)	(0.000)	(0.000)
LR chi2 (vs. Spatial Lag)				19.032
P-value				(0.000)
LR chi2 (vs. Spatial Error)				2.056
P-value				(0.152)

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1