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Modelling drivers of Atlantic Forest dynamics using geographically weighted regression

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Abstract

Despite its ecological importance and anthropogenic pressures, only a few studies have modeled deforestation and regeneration dynamics within Brazil's Atlantic Forest biome. In this article, we propose an econometric approach to model these landscape dynamics. Based on public available data, the model was first processed using a STEPWISE procedure in the software SPSS Statistics, with *ad hoc* selection of the most relevant model. Next, we used Geoda software to account for spatial dependence and compared its results to a geographically weighted regression executed in ArcGIS software using a 25-municipality neighborhood distance. The amount of forest remnants, percentage of private protected land, expansion of pastures and planted forests can significantly explained the dynamics of deforestation and regeneration in the Atlantic Forest. The geographically weighted regression improved the model adjustment, and also illustrated localities where model performance was not satisfactory, and demonstrated where variables were more or less significant. The model can be used to inform conservation policies. It can also be used to create scenarios for simulations, allowing assessment of how possible market and policy changes, such as cattle rising and reforestation suffering market pressures, and changes in the national Forestry Code, would impact future deforestation and regeneration rates.

Keywords: Deforestation. Econometric model. Forest regeneration. Landscape dynamics. LUCC model.

Modelagem da dinâmica do desmatamento da Mata Atlântica usando regressão geograficamente ponderada

Resumo

Apesar da reconhecida importância ecológica e elevado grau de fragmentação, há poucos esforços para modelagem da dinâmica do desmatamento e regeneração da Mata Atlântica. Esse artigo contribui propondo uma abordagem econométrica para modelar a dinâmica da paisagem no bioma. Primeiramente foi executado um teste *stepwise* no software SPSS Statistics com uma seleção *ad hoc* do modelo mais relevante. Em seguida foi feito um teste para detecção de autocorrelação espacial no *software* Geoda e seus resultados foram comparados à uma regressão geograficamente ponderada executada no *software* ArcGIS com uma vizinhança de 25 municípios. Quantidade de remanescentes florestais, porcentagem de áreas protegidas, expansão de pastagem e expansão de florestas plantadas explicaram significativamente o desmatamento e regeneração no bioma. A regressão geograficamente ponderada melhorou o ajuste do modelo, indicou regiões em que o mesmo não teve uma performance satisfatória e onde as variáveis se mostraram mais ou menos significantes. O modelo pode ser usado como suporte para políticas de conservação e para a criação de cenários para simulações, permitindo uma avaliação das possíveis mudanças sobre as taxas de desmatamento e regeneração, geradas, por exemplo, pela força de mercado sobre a criação de gado e plantio de florestas, e as mudanças no Código Florestal.

Palavras-chave: Desmatamento. Modelo econométrico. Regeneração florestal. Dinâmica da paisagem. Modelagem de mudança de uso da terra.

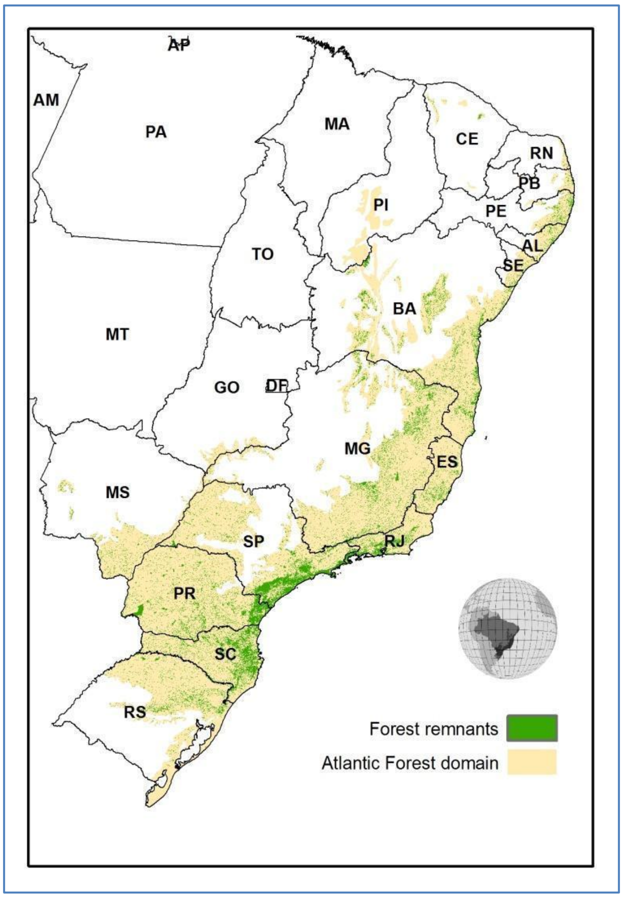
Introduction

The Atlantic Forest was once one of the largest tropical forests of the American continent (Tabarelli, et al. 2005, Ribeiro, Metzger et al. 2009). Its domain was over one million square kilometers, crossing different climatic conditions, relief, soils and vegetal physiognomies (IESB 2007) (Figure 1). The biome is biodiverse (Myers et al. 2000) and provides important environmental services, such as water supply maintenance for ~70% of the Brazilian population (IESB 2007). Human impacts on native vegetation within the Atlantic Forest began more than 10,000 years ago, when its area was occupied by indigenous groups (DEAN 1995). However, the Atlantic Forest suffered its greatest period of conversion, during the European colonization. Large tracts of land were cleared to transform original vegetation into pastures and sugarcane crops. In the mid-twentieth century, particularly after the economic crisis of 1929, the modernization of the country was implemented, with development of the urban and industrial land uses (RODRIGUES, 2008), leading to deforestation of vast areas and intensification of fragmentation. Today, approximately 14% of original Atlantic forest remains, highly fragmented remnants: 80% of the remaining forest patches are smaller than 50 ha (RIBEIRO et al., 2009).

Some recent studies indicate that the biome may be at the peak of forest transition (BECKER et al., 2004; KRONKA et al., 2005; BAPTISTA and RUDEL, 2006; LIRA et al., 2012), with regeneration rates surpassing those of deforestation. The forest transition theory which is based on the Environmental Kuznets Curve (EKC) describes the relationship between economic development and deforestation. According to this theory, in the early stages of economic development of a region, there is a high demand for natural resources and consequently high deforestation. However, in the later stages of development, when income increases, environmental degradation is reduced, while regeneration and reforestation processes take place (DINDA, 2004). The Robertsen (2011) study indicate that forest transition is an empirical regularity, but there is no consensus on which variables determine it, most likely depending on the region and socioeconomic background (ROBERTSEN, 2011).

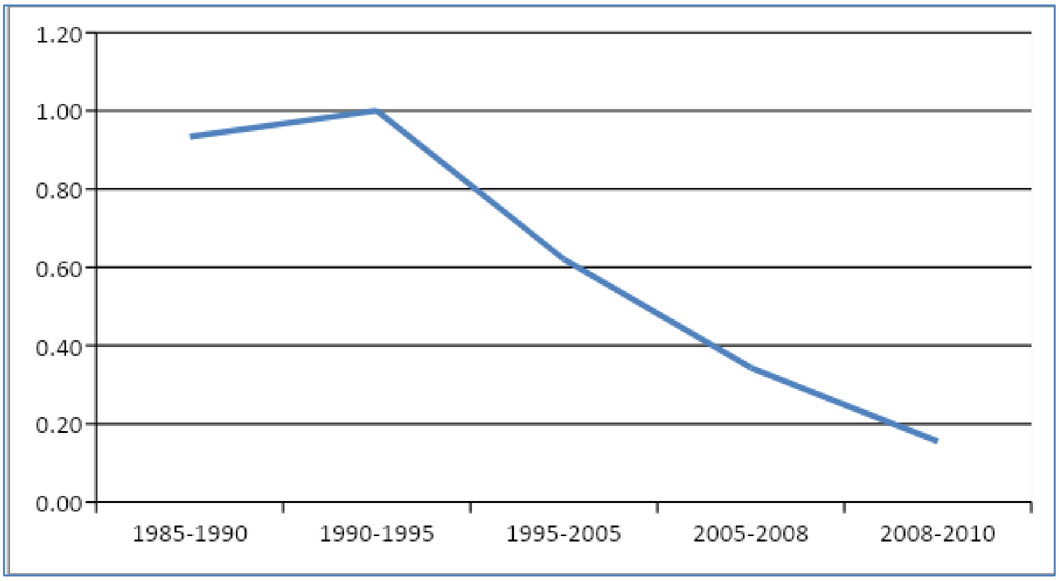
For the Atlantic Forest, The hypothesis of forest transition is consistent with the data available in the Atlantic Forest Atlas (INPE / SOS Atlantic Forest Foundation 1993, 2000, 2008, 2011) (Figure 2), which show deforestation rates have decreased from in recent decades. However, the variables that influence and determine this trend remain unknown.

Figure 1: The Brazilian Atlantic Forest domain and remnants



Source: INPE/SOS Mata Atlântica Foundation 2012.

Figure 2: Annual deforestation in the Atlantic Forest by period



Source: INPE / SOS Mata Atlântica Foundation (1993, 2000, 2008, 2011).

Identifying and analyzing the factors that drives the dynamics of deforestation and regeneration within the Atlantic Forest is essential to ensure conservation of its biodiversity and environmental services. Despite this, modeling initiatives to achieve this goal have been restricted to a few examples with local case studies (SONTER, BARRETT and SOARES-FILHO, 2014; TEIXEIRA et al., 2006; FREITAS and METZGER, 2009). To the best of our knowledge, no model has been proposed to describe the dynamics of the entire biome.

An important point must be taken into consideration when modeling the Atlantic Forest: relationships between deforestation, regeneration and their drivers are not evenly distributed across the landscape. The Atlantic Forest is a biome of continental dimensions, with complex social, physical and biological characteristics that result in spatial non-stationarity. Geographically Weighted Regression (GWR, FOTHERINGHAM, BRUNDSON and CHARLTON, 2002) is a useful approach to account for modeling heterogeneous relationships between rates and drivers throughout space. This statistical approach is a simple, yet effective tool to explore spatial heterogeneity (HUANG and LEUNG, 2002).

In this context, this study aims to develop a model for the Atlantic Forest that synthesizes the behavior of its rates of deforestation and regeneration, given the influence of economic and ecological factors, allowing for spatial heterogeneity.

Methodology

Preliminary analysis

As a preliminary assessment, we investigated the availability of data sources for the Atlantic Forest biome. Three sources were found: i) census information from the Brazilian Institute for Geography and Statistics (IBGE), ii) times series maps elaborated by INPE and SOS Mata Atlântica Foundation, and iii) maps of the biome from the monitoring program of the Ministry of Environment and the Brazilian Institute of Environment and Renewable Natural Resources (MMA / IBAMA).

The data from MMA / IBAMA is only available from the year 2002, a period of at least a decade was necessary to analyze the dynamics of the biome, therefore not used in this study.

While the IBGE Census is based on the statement of landowners, the other sources use mapping by visual interpretation. Both methods are subject to error. It is expected that mapping underestimates the forest amount, due to constraints of resolution, and that the Census may overestimate it, considering small patches of forests and forests in the early stages of regeneration, which are not represented on maps. The divergence of results obtained by these different methods is well demonstrated when comparing the amount of remaining forest, for 1995 and 2005 according to the two sources of information, as shown in Table 1. Despite the inherent limitations, IBGE data was chosen to be used for the models here proposed, since it is the most complete for land-use quantitative information and is also an official source.

Table 1: Quantity of Remaining Forest and Deforestation

(km²)	INPE/SOS MA	IBGE
Remaining forest 1995	141,590.53	250,266.90
Remaining forest 2005/2006	136,419.30	235,139.42
Deforestation1995-2005/2006	5,407.88	15,206.08

Source: According to IBGE and INPE / SOS Mata Atlântica Foundation

Ordinary linear regression model (OLR)

A simple econometric model is represented by equation (1). The variable Y is the rate of variation in the amount of forests. Y is a function of one or more independent variables that influence Xn, usually represented as a matrix.

$$Y_{t+v} = \beta_{0} + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_m + E \qquad (1)$$

Where:

Y = dependent variable

X = independent variable

β = coefficients

E = error term

To calculate the econometric model for the Atlantic Forest dynamics, a datasheet was prepared by municipality, based on public available data published by the IBGE, with complementary data from the Institute of Applied Economics (IPEA). This table included 126 potential explanatory variables, such as social, economic and geographic descriptors, and all data were from the period between 1995 and 2005.

The dependent variable corresponded to the annual variation in the amount of forest, according to data from the Agricultural Census (IBGE, 1998, 2006). Negative values indicated a decrease in forested area, while positive values indicated an increase in forests (2).

$$Y = (F_{(t+n)} – F_{(t)}) / n \qquad (2)$$

Where:

Y = rate of change in the stock of forests

Ft = percentage of the municipality covered by forests

t = initial time

n = number of years in the period

We applied a filter to the list of municipalities in the biome, withdrawing the cases with no information on the dependent variable. This database was processed using SPSS Statistics 17.0 software using the linear regression tool. Thus, it was possible to select the most relevant independent variables significantly correlated to the rate of change of forest. After the first loop, we implemented a control for outliers, excluding cases that contained residuals greater than 2 standard deviations (+ or -). This sample was resubmitted to the STEPWISE procedure, which results were used to select the best model to represent the dynamics of the biome. Among the models obtained with coefficient of determination R^2 above 0.5, a four-variable model was selected ad hoc. The ad hoc selection was based on the significance levels and theoretical coherence of relations between the dependent variable and the independent variables suggested by the method as more explanatory.

To increase the coefficient of determination obtained in the simple regression model, as well as due to the hypothesis that some spatial pattern existed in the distribution of the data analyzed, a spatial dependence test was performed using the GeoDa software 0.9.9.11. A queen type neighborhood of first order, was used, i.e., considering as neighbors only directly adjacent municipalities, (horizontal, vertical or diagonal neighbors). After confirming spatial dependence, using the selected variables in regression model overall, geographically weighted regressions were performed using the software ArcGIS 10. This statistical analysis reveals spatial variability among the behavior of variables in the model, because of that it allows a better understanding of uses and mechanisms of forest cover change (JAIMES et al., 2010).

Geographically weighted regression (GWR)

To improve the OLR model, we used Geographically Weighted Regression to account for the spatial non-stationarity inherent to the biome, due to its physical and historical heterogeneity. Many techniques have been proposed for measuring spatial non-stationarity: expansion method (CASETTI, 1972; JONES and CASETTI, 1992; FOTHERINGHAM, CHARLTON and BRUNSDON, 1998), the method of spatial adaptive filtering (SAF; FOSTER and GORR, 1986; GORR and OLLIGSCHLAEGER, 1994), the random coefficients model (AITKIN, 1996), the multilevel modeling (GOLDSTEIN, 1987), the moving window approach (FOTHERINGHAM, CHARLTON and BRUNSDON, 1997) and geographically weighted regression (GWR; BRUNSDON, FOTHERINGHAM and CHARLTON, 1996; FOTHERINGHAM, CHARLTON and BRUNSDON, 1997; FOTHERINGHAM, CHARLTON and BRUNSDON, 1998; LEUNG, MEI and ZHANG, 2000). Among all of them, Huang and Leung (2002) chose GWR as a simple and effective method. One of the advantages of Geographically Weighted Regression is that it is implemented in the popular Geographic Information System software ArcGIS, making this statistical procedure more user-friendly than others.

Geographically Weighted Regression is a common tool used in studies of land use change, but there are few examples of applications for the investigation of deforestation (JAIMES et al., 2010). It is a method of local statistics in which a linear regression is performed for each location (FOTHERINGHAM, BRUNDSON and CHARLTON, 2002). In this way, the coefficients are specific to location, rather than assumed to be constant throughout the study area. Therefore, GWR allows different relationships to exist at different points in space, being a useful technique to examine situations of spatial non-stationarity (HUANG and LEUNG, 2002), as is the case for the Atlantic Forest.

$$Y_{t+v(i)} = \beta_{0(i)} + \beta_1 X_{1\,(i)} + \beta_2 X_{2\,(i)} + \ldots + \beta_n X_{m(i)} + E_{(i)} \qquad (3)$$

Where:

Y = dependent variable

(i)= location

X = independent variable

β = coefficients

E = error term

Different from the global regression, in which the model is calibrated considering the whole landscape, GWR parameters are calibrated in accordance with the values of vicinity of each location. Weights are assigned according to the distance of each point to the locality analyzed. Higher weights are distributed to the nearest points and smaller weights for more distant points (FOTHERINGHAM, BRUNDSON and CHARLTON, 2002). The model results in a set of parameters adjusted for each location in the geographic region analyzed.

There are different possibilities of weighting functions to calibrate the GWR model. One way is to give the same rule for all locations, defining a constant bandwidth at each regression point across the study area, choosing to exclude observations that are further than some distance to the locations or implementing a continuous function across the space. Another way to calibrate the model is to vary the bandwidth throughout space according to the density of the observations: smaller bandwidths where data is dense and larger bandwidths where data is sparse. The adaptive method includes the possibilities to decrease the weights with the distance, to define a constant value for the sum of the weights or define a number of neighbors (FOTHERINGHAM, BRUNDSON and CHARLTON, 2002).

The choice of the weighting scheme is an important setting for this method which greatly influences the GWR results (JAIMES, et al. 2010). In this study an adaptive Kernel was used with a fixed number of neighbors. To define the optimal size of the bandwidth, several neighborhood were tested, within a reasonable interval, considering the entire study area (15 to 30 neighbors), and thus the neighborhood to be used was chosen such that the results confer high values of local adjustment models preserving a high overall adjustment.

A first geographically weighted regression was performed with all municipalities selected after the first filtering described in previous section, with a neighborhood of 25 municipalities. From the results, municipalities with residuals greater than 2 standard deviations were removed from the data set, and a second regression was performed using the same vicinity of the first model.

Results

The OLR model had an overall fit of $R^2 = 0.725$, as shown in Table 2, indicating that over 70% of the variability in deforestation and regeneration across municipalities can be explained by the variables selected.The independent variables obtained indicate that deforestation (negative growth of forests) is related to the municipalities with greater amounts of forest remnants and increased grazing areas. On the other hand, increases in forests are related to the percent of legally protected areas (APP/RL = Permanent Preservation Areas and Legal Reserves in accordance with the Brazilian Forest Code), as well as the increase in planted forests, as Eucalyptus spp. and Pinus spp.

Tests of spatial autocorrelation showed the existence of spatial dependence in the dependent variable and the error term, indicating that rates of deforestation and regeneration are directly influenced by the rates of neighboring municipalities, as well as the influence of other factors not measured by the model.

The geographically weighted regression showed a general fit of $R^2 = 0.90$. Thirty-three percent of the local municipalities had R^2 greater than 0.90. After adjusting for outliers, these values increased to 0.95, with 21% of the municipalities having higher than average fit. The model explained 80% of the variability in 67% of municipalities and more than 90% in 42% of municipalities.

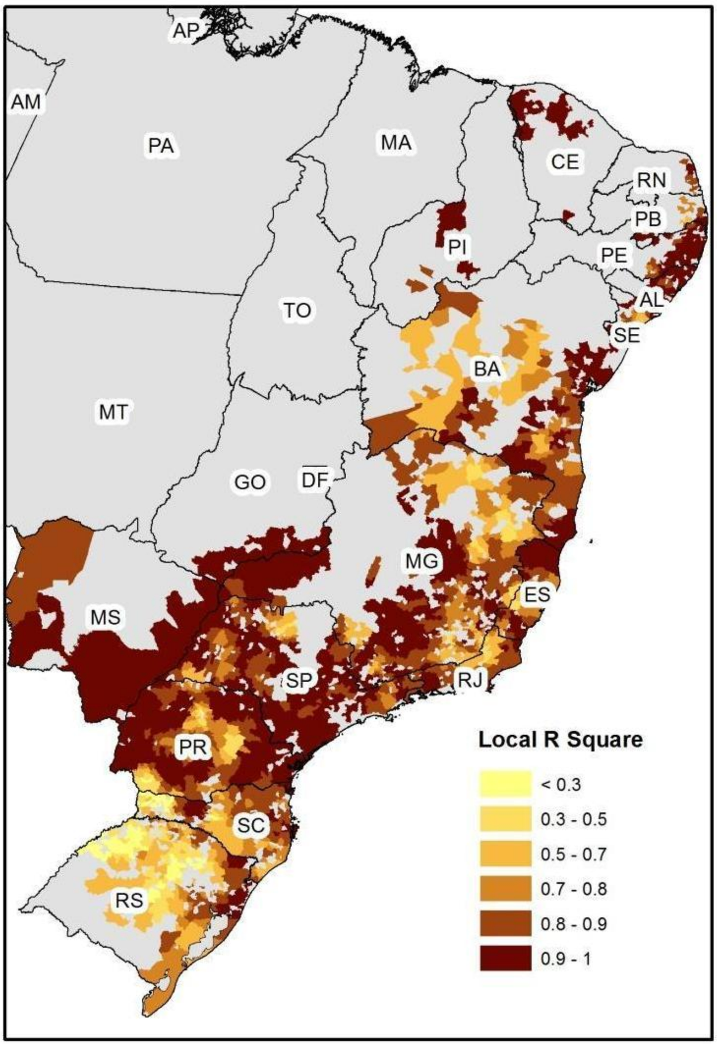
Table 2: Econometric Models with and without Outliers Control and Test for Spatial Dependence

Model without outliers control	**Value**	**P-value**
Intercept	0.001	0.000
Forest remnants	-0.052	0.000
APP / RL[1]	0.077	0.000
Increase of planted forests (*Pinus* spp. / *Eucalyptus* spp.)	0.013	0.000
Increase of pastures	-0.001	0.008
R^2 = 0.544		
Nº valid cases: 2164		
Model with outliers control	**Value**	**P-value**
Intercept	0.001	0.000
Forest remnants	-0.053	0.000
APP / RL[1]	0.074	0.000
Increase of planted forests (*Pinus* spp. / *Eucalyptus* spp.)	0.017	0.000
Increase of pastures	-0.001	0.008
R^2 = 0.725		
Nº valid cases: 2079		
Test for spatial dependence	**Value**	**P-value**
Lagrange Multiplier (lag)	5.6973649	0.0169904
Robust LM (lag)	71.6555039	0.0000000
Lagrange Multiplier (error)	232.9386912	0.0000000
Robust LM (error)	298.8968302	0.0000000
Lagrange Multiplier (SARMA)	232.9386912	0.0000000
Geographically Weighted Regression		
General R^2 = 0.90		
Geographically Weighted Regression with outliers control		
General R^2 = 0.95		
Local R^2 > 0.80 in 67% of municipalities		
Local R^2 > 0.90 in 42% of municipalities		

Source: Prepared by the authors, according to IBGE and INPE / SOS Mata Atlântica Foundation

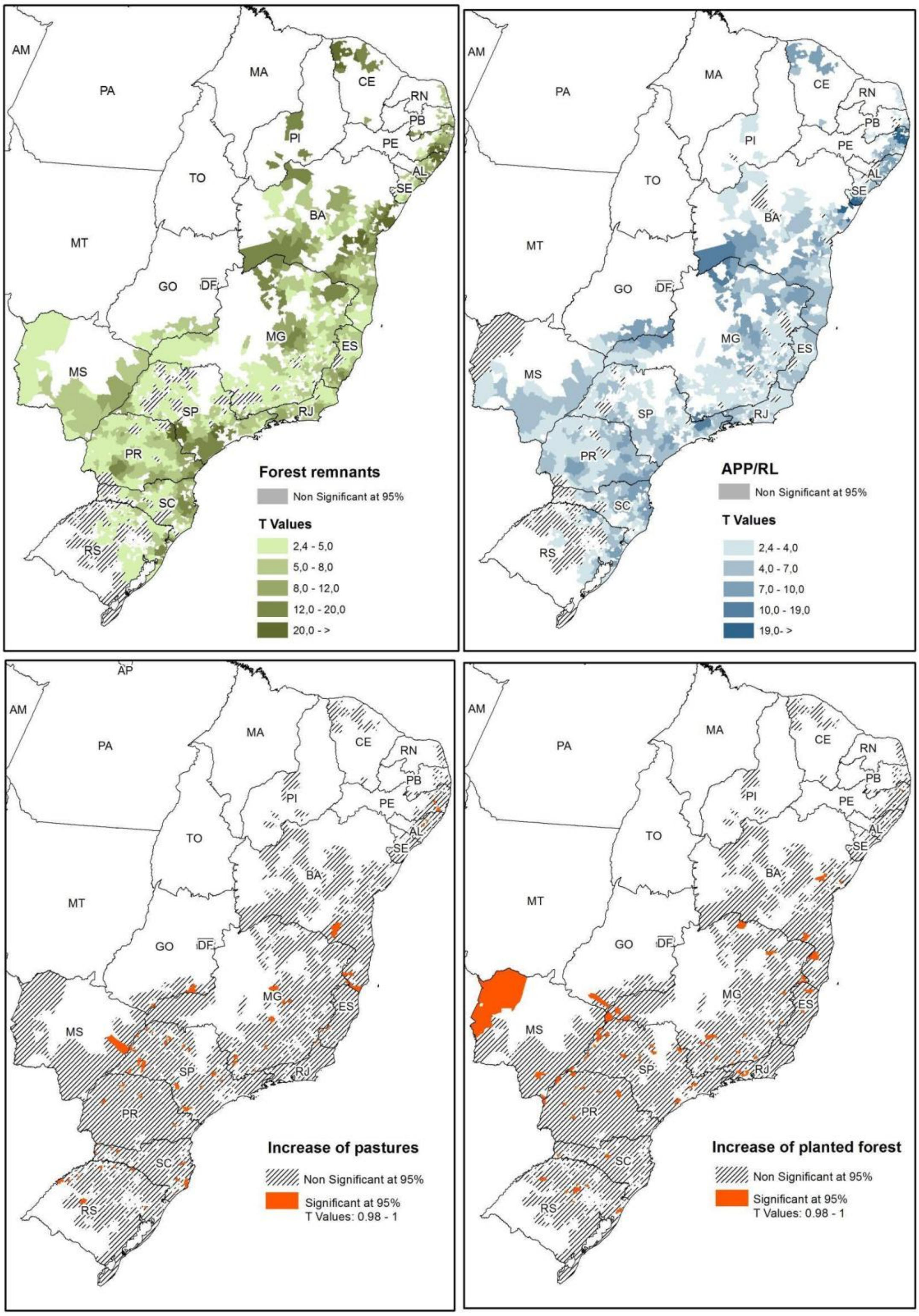
Among municipalities the local models had heterogeneous fits, and also heterogeneous relations with the independent variables (Figure 3 and Figure 4). Analyzing the results of the significance tests, it is possible to conclude that the amount of forests and the amount of private protected areas are the variables that usually have more influence on the dependent variable, both for the local and overall regressions (Figure 4). Lower fits were found in southern Brazil (Rio Grande do Sul and Santa Catarina states), overall in these areas more explanatory variables were not significant. The model also showed lower fits in northeast of Minas Gerais and interior region of Bahia, however, without coinciding with independent variables non-significance.

Figure 3: Distribution of GWR model fits along the municipalities of the Atlantic Forest.



Source: Prepared by the authors, according to IBGE and INPE / SOS Mata Atlântica Foundation

Figure 4: Relations and significances between explanatory variables and variation of forests (dependent variable)



Source: Prepared by the authors, according to IBGE and INPE / SOS Mata Atlântica Foundation

Discussions and conclusion

Global pattern

The regression obtained by STEPWISE procedure indicated four main variables related to forest growth rate. The higher the percentage of remaining forests in a municipality, the greater the tendency for deforestation. This is the expected pattern in highly fragmented landscapes: deforestation occurs where there are still forests to be removed. Moreover, the amount of private protected areas[1] is positively related to an increase in forests, which may correspond either to spontaneous regeneration processes in abandoned portions of lands or to induced reforestation efforts for legal compliance. This indicates that environmental policies effectively constraints deforestation and promotes ecological regeneration. This observation is highly relevant considering the recent polemic changes on the Brazilian Forest Code.

Pasture and reforestation behaved differently in relation to the variation of forest. The increase in pasture areas is negatively related to the amount of forest, i.e., is positively related to deforestation and negatively related to regeneration. On the other hand, planted forests are positively related to regeneration and negatively related to deforestation. These factors indicate that, in the Atlantic Forest, cattle rising are less favorable for forest conservation than planting forests, which may be more subject to regulation by environmental agencies and consumer's choice of green products.

Regional patterns

As previously discussed, the Atlantic Forest encompasses heterogeneous socioeconomic and ecological realities, so local analysis becomes essential to the proper understanding of the biome landscape dynamics. It is expected that deforestation and regeneration are influenced differently by drivers in each region, depending on its physical characteristics, land use history, and current political and economic context. This is the reason why local statistics, such as GWR, which accounts for spatial heterogeneity, are especially important to model the dynamics of the biome. Another advantage of the

[1] Permanent Preservation Areas and Legal Reserves that landowners are obliged to maintain, according to the Brazilian Forest Code.

geographically weighted regression is that it is capable of demonstrating where the model does not provide a good fit, so that further research can seek other drivers for landscape behavior in these regions. In this study, low settings were found concentrated in southern Brazil, where private protected land and amount of forest remnants were not significant as explanatory variables. It is possible that this finding is due to the flatter topography and less dense hydrographic net of the region, leading to fewer Permanent Preservation Areas (APPs). Overall, the municipalities with non-significance for forest remnant as explanatory variable almost do not have forest remnants, and therefore this variable does not appear to be relevant for the fate of the municipality in achieving a forest transition.

Despite the eastern region of Minas Gerais and the countryside of Bahia state present lower coefficients of determination, the explanatory variables do not have an abnormal behavior. However, new variables should be investigated, to better fit in these regions. It is possible that the chosen four variables do not have a relevant impact on deforestation and regeneration of municipalities in the border of the biome. In these areas, it is more difficult to apply the more rigorous legislation specific for the Atlantic Forest, as the vegetation in the ecotones is harder to distinguish.

Using GWR to analyse the relationship between each variable and resulting deforestation (Figure 4), we found that an increase of pastures and planted forests showed significant values in only few municipalities of Atlantic Forest domain. This fact was not visible from the OLR results, demonstrating the importance of the GWR analysis to display in the specifics in the spatial patterns of deforestation. Although the four variables were significant related to forest variation in the global model, GWR results stressed where it is important to consider increase of pastures and increase of planted forests as relevant potential drivers.

This difference in the spatial pattern of the influence of variables suggests that the variables increase of pastures and of forest plantations suffer more influence by the heterogeneity of land-use in the Atlantic Forest. For instance, in the southeast of Brazil, rural properties are larger and more dependent on the international market than those in the northeast region (SONTER et al. 2014). In the south of Brazil, the production is also focused on the external market, but lands are smaller.

On the other hand, the variables amount of forests and private protected land shows consistent significance over the entire biome domain, demonstrating that they can be more homogeneously applied throughout the biome domain in the explanation of its landscape dynamics. It can be explained by the character of the variable forest remnants (more deforestation where there are more forests left) and by the nation-wide legislation that supports the variable private protected land.

Limitations and recomendations

The proposed model reflects exclusively the rural reality, since the rate calculated is based on data from the agrarian census (Censo Agropecuário) of IBGE. As it only represents the amount of rural forests on private property, urban forests and public protected areas were not considered in the model calibration. However, we believe it is not a significant constraint for this model application, since it can be assumed that it is in the private lands where most of the landscape dynamics occur.

The model proved to be capable of integrating ecological and socioeconomic data to compute the dynamic behavior of the biome, including the heterogeneity among municipalities. The global model developed with geographically weighted regression, not considering outliers, was able to explain 95% of the variability of the rate of change in forested areas, using only four explanatory variables. This can be considered an optimum synthetic model for such a complex landscape dynamics such as the one of the Atlantic Forest. The substantial improvement in model fit from the regression without spatial dependence to the geographically weighted regression confirmed the spatial-dependent character of the dynamics studied.

It is also important to highlight the limitations of the data for monitoring land cover in the Atlantic Forest. There are several studies on the biota of the biome but consistent information on the quantity of its remaining natural vegetation is lacking. Ribeiro et al. (2009) highlight this issue on spatial data, and the divergence between the data and census maps appear clearly in our preliminary analyzes. When comparing rates of deforestation according to IBGE and INPE / SOS Mata Atlântica Foundation (2000, 2008), we find a significant difference: an annual rate of deforestation 1.3% versus 0.4%, respectively, based on data from 1995 to 2005/2006. This difference is probably related to differences in methods of data collection. This fact is a serious limitation to model the Atlantic Forest biome, especially when trying to integrate ecological and socioeconomic data. Still, we believe it is necessary to develop models for the biome, in order to better understand the process of forest transition that is likely to be happening in its domain. In this sense, improving the reliability of quantitative data of land-use, in time series, will be essential to give sound basis for new modeling efforts, and, therefore, for evidence-based conservation strategies.

Besides the model indicated indicating which variables are currently acting on the landscape dynamics of the Atlantic Forest, it can be used to create alternative scenarios for simulations. The effects of national and international demand for meat and wood, for example, can be assessed by analyzing the consequences of variations in growth trends of livestock and planting forests on deforestation and regeneration rates. Similarly, the impact of the recent changes in the Brazilian Forest Code can be assessed modifying the amount of the expected private legally protected areas in each municipality. Such uses can be useful for estimating the future of forest transition in the biome, as well as for developing effective conservation strategies.

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