Spatial analysis of deforestation factors in the Atlantic Forest Biome/Brazil

Análise espacial dos fatores condicionantes do desmatamento do Bioma Mata Atlântica/Brasil

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Abstract

Deforestation is a phenomenon that generates social, environmental, and economic impacts and endangers the sustainability of natural resources. The Atlantic Forest is one of the most biodiverse and threatened biomes in the world. Despite its enormous importance, the Atlantic Forest is the most deforested region in Brazil since its European colonization. Therefore, given the relevance of identifying the drivers of deforestation in Brazilian biomes, the objective of this paper is to analyze the factors that conditioned deforestation in the Atlantic Forest Biome in Brazil between the years 2010 and 2020. Land use and land cover data and socioeconomic data processed in a Geographic Information System (GIS) environment were used, through correlation analysis and Geographic Weighted Regression (GWR). The covariates that presented the highest correlation values were the average number of cattle, area of temporary crops, and agricultural credit, with 0.708, 0.516, and 0.418 respectively. The GWR model presented an adjusted R² of 0.94, confirming the model's

capability to explain 94% of the variations in deforestation. The variable ranching was the one that displayed the highest correlation with deforestation. In addition, the area under temporary crops and agricultural credit also had a significant influence on the occurrence of deforestation.

Keywords: tropical forests, socioeconomic impacts, spatial statistics.

Resumo

O desmatamento é um fenômeno que gera impactos sociais, ambientais e econômicos e coloca em risco a sustentabilidade dos recursos naturais. A Mata Atlântica é um dos biomas mais biodiversos e ameaçados do mundo. Mesmo com tamanha importância, a Mata atlântica foi a região mais desmatada do Brasil desde sua colonização europeia. Assim, dada a relevância de identificar os impulsionadores de desmatamento nos biomas brasileiros, o objetivo deste artigo é analisar os fatores que condicionaram o desmatamento no Bioma Mata Atlântica no Brasil entre os anos de 2010 e 2020. Foram utilizados dados de uso e cobertura das terras e dados socioeconômicos processados em ambiente de Sistema de Informação Geográfica (SIG), através da análise de correlação e da *Geographic Weighted Regression* (GWR). As covariáveis que apresentaram maiores valores de correlação foram as de média de número de bovinos, área de lavouras temporárias e crédito agrícola, com 0,708, 0,516 e 0,418, respectivamente. O modelo GWR apresentou um R² ajustado de 0,94, comprovando a capacidade do modelo em explicar 94% das variações do desmatamento. A variável pecuária foi a que apresentou a maior correlação com o desmatamento. Além disso, a área cultivada com lavouras temporárias e o crédito rural agrícola também influenciam significativamente para ocorrência de desmatamentos.

Palavras–chave: florestas tropicais, impactos socioeconômicos, estatística espacial.

Introduction

Deforestation in Brazil began with European colonization, in the 16th century, through the Atlantic Forest Biome on Brazil's coastal coast. At the beginning of colonization, there was an intense exploitation of Pau-Brasil (*Paubrasilia echinata*), a native and endemic species of the Brazilian Atlantic Forest that was officially included in the list of endangered species in 1992 (BASTOS et al., 2022). After that, the deforestation process was intensified due to large-scale agricultural activities (for example, cultivation of corn, wheat, soybeans, and coffee), cattle breeding, forestry, mining, energy production (construction of large dams for hydroelectric power production and sugarcane cultivation for ethanol production), and others (RUDKE et al., 2022).

The results from the impacts of the occupation process in the Brazilian Atlantic Forest Biome are still the subject of several studies (SCARANO; CEOTTO, 2015; JOLY et al. 2014; DAVIS et al., 2019; REIS et al. 2021). In this regard, Joly et al. (2014) reported that the Atlantic Forest harbors one of the most diverse and threatened tropical forest biotas in the world. In their study on deforestation and regeneration in the Atlantic Forest, Davis et al. (2019) discovered that forest remnants, the percentage of private protected land, the

expansion of pastures, and planted forests play a significant role in explaining the dynamics of deforestation and regeneration within the Atlantic Forest. For Reis et al. (2021), landscape-scale habitat loss can change the floristic composition of forest fragments. Scarano and Ceotto (2015) stated that 11.6% of the remaining Atlantic Forest cover is intensely fragmented, resulting in high vulnerability to climate change. Additionally, Bellard et al. (2013) indicated that the Atlantic Forest is one of the three biodiversity hotspots most vulnerable to climate change. Great enthusiasm was observed for the region that expected to experience conversion from a hotspot to a hope spot (a place with a history of degradation potentially transformed into a sustainable future) but given recent dismantlement in environmental policies saw a possible and obscure proximity to the ecological tipping point (REZENDE et al., 2018; LIRA et al., 2021). Thus, given the uncertain scenario of conversion of the Atlantic Forest, it is becoming essential to understand the spatial configuration of the factors driving its deforestation in the biome.

In the present days, the driving activities behind deforestation are revealed under various aspects of environmental degradation in tropical forests, for example cattle ranching (JOLY et al., 2014; BAUMANN et al., 2017; KRÖGER, 2020) agricultural expansion (FEHLENBERG et al., 2017; DE OLIVEIRA et al., 2017; GARRETT et al., 2018), agricultural credit (TRIGUEIRO et al., 2020; SANTOS et al., 2021), mining (RUDKE et al., 2020; SIQUEIRA-GAY; SÁNCHEZ, 2021; SONTER et al., 2017), urbanization (DA SILVA et al., 2017; RAMOS et al., 2018), road opening (MILIEN et al., 2021; PFAFF et al., 2018), among others.

As mentioned, after five centuries of human expansion, most landscapes of the Atlantic Forest are archipelagos of small forest fragments (JOLY et al., 2014). This scenario prompted the creation of specific legislation that provides for the use and protection of the native vegetation of the Atlantic Forest Biome (BRAZIL, 2006). Therefore, according to this legislation, the Atlantic Forest is considered a national heritage, and its primary and secondary vegetation, in any stage of regeneration, cannot be the target of fire, deforestation, or any other type of unauthorized or unlicensed intervention (BRAZIL, 2006).

Despite this, the pattern of deforestation of the Atlantic Forest is not uniform, as there are different stages of exploitation of the vegetation. In this sense, according to Metzger and Sodhi (2009), the Atlantic Forest region includes some communities that live in different socioeconomic conditions, from large urban areas (such as metropolitan regions of São Paulo and Rio de Janeiro) to rural regions, especially in the Northeast and Southeast regions of the

country. Furthermore, at least 70% of the Brazilian population (which is about 120 million people) lives in this biome (METZGER; SODHI, 2009).

Thus, spatial statistics methods (e.g., Spatial Autocorrelation Models and Spatial Regression) have been presenting great robustness in helping to identify deforestation drivers (TRIGUEIRO et al., 2020; SANTOS et al., 2021; SILVA et al., 2022). An example of such application is the method based on Geographically Weighted Regression (GWR), which is one of the most widely used techniques to explore the relationship of spatial heterogeneity of datasets, that is, the relationship of dependencies of variables (LU et al., 2014; DAVIS et al., 2019).

Given this observation, the objective of this paper is to analyze the factors that conditioned deforestation in the Atlantic Forest Biome between the years 2010 and 2020, supported by a Geographically Weighted Regression (GWR) model. In this way, deforestation was adopted as the dependent variable and as explanatory variables the active agents of deforestation (number of cattle, population estimate, number of people residing in rural and urban areas, rural agricultural credit, are with temporary crops, Gross Domestic Product and area destined for forestry).

Materials and Methods

Study área

The study area (Figure 1) encompasses 3,034 municipalities distributed in 15 Brazilian states (Alagoas, Bahia, Espírito Santo, Goiás, Minas Gerais, Mato Grosso do Sul, Paraíba, Pernambuco, Paraná, Rio de Janeiro, Rio Grande do Norte, Rio Grande do Sul, Santa Catarina, Sergipe, and São Paulo). Thus, the scope of the analysis occupies an area of approximately 1,404,000 km² (INPE, 2020).

The Atlantic Forest Biome is composed of a mosaic of vegetational formations of floodplain and mountainous areas, such as evergreen forest, semideciduous and deciduous forest, mixed forest, mangroves, and restingas. According to Eisenlohr et al. (2015), the forest fragments that are still present in this biome, except in protected areas such as National Reserves and Biological Reserves, are concentrated on the tops of mountains and/or on the steepest slopes. In these areas, agricultural practice is difficult or impractical, either due to access to the site or due to low soil fertility. However, in large Brazilian coastal cities, areas of steeper slopes are identified and occupied by the economically vulnerable population,

which results in the formation of large subnormal settlements (MACHADO; FREITAS, 2022).

Figure 1. Study area.
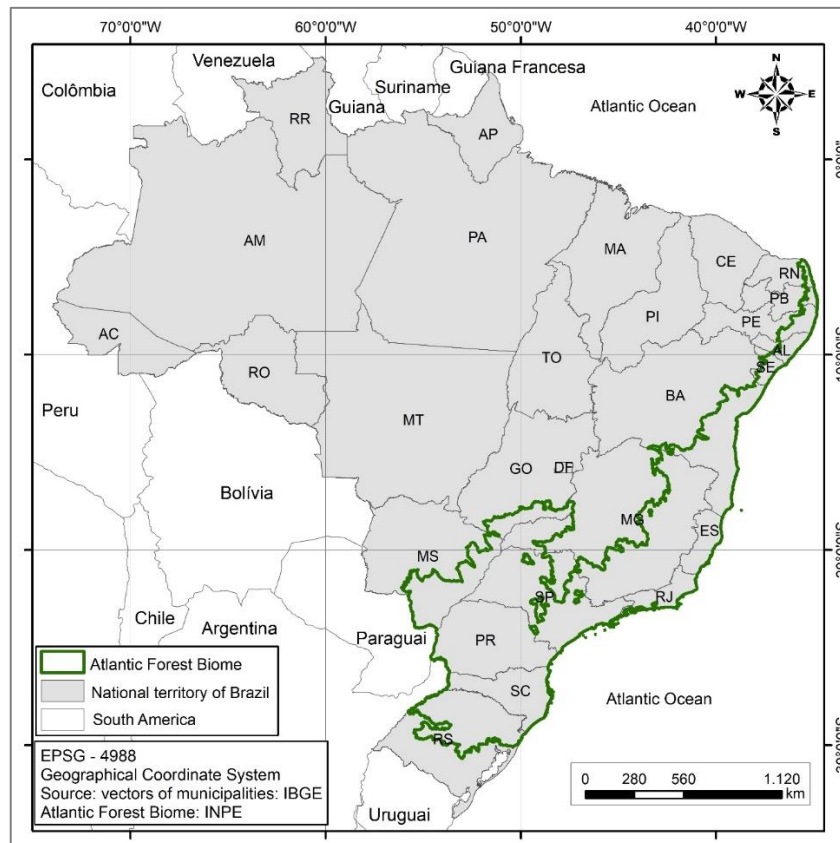
Source: Elaborated by the author

Data source

The Brazilian biomes are monitored by the National Institute for Space Research (INPE), which provides data and information that can be used in studies assessing deforestation–for example, a study by Trigueiro et al. (2020) on the Cerrado biome and by Santos et al. (2021) on the Amazon biome. Besides INPE, the European Space Agency (ESA) also produced a relevant mapping of land uses and land covers on a global scale. This data and information, along with socioeconomic data, can be applied to spatial models in order to clarify the possible causes and spatial variability of deforestation.

Several active agents influence deforestation in the Atlantic Forest. Therefore, the socioeconomic variables, described in Table 1, were obtained from the Database of the Brazilian Institute of Geography and Statistics (SIDRA/IBGE) and the Central Bank of

Brazil. The data and information are selected from the year 2010 to the year 2020, according to Table 1.

The response variable data were obtained from the ESA, WorldCover 10 m 2020 v100 project (ZANAGA et al., 2021). According to Ghassemi et al. (2022), this project provides satellite data, which enables the mapping of all continents with a spatial resolution of 10 meters and 11 different typologies of land use and land cover classes.

Table 1: Variables, their abbreviations, and sources.

Explanatory variables	Abbreviation	Source
1. Average number of cattle between 2011 and 2020	BOIS	SIDRA / IBGE (2021)
2. Average of 2011 and 2020 population estimate	POP_EST	SIDRA / IBGE (2021)
3. Number of people living in rural areas according to the 2010 census	POP_RUR	SIDRA / IBGE (2021)
4. Estimated population in urban areas according to the 2010 census	POP_URB	SIDRA / IBGE (2021)
5. Average rural agricultural credit between 2013 and 2020	CRED_AGRI	Banco Central do Brasil / (2021)
6. Average area with temporary crops cultivated between 2011 and 2020	LAVO_TEMP	SIDRA / IBGE (2021)
7. Average gross domestic product between 2011 and 2019	PIB	SIDRA / IBGE (2021)
8. Average area under forestry 2013 and 2020	SILVI	SIDRA / IBGE (2021)

Source: Elaborated by the author

Data processing

The tabulated data from IBGE and the Central Bank of Brazil were coupled to the vector files of the municipalities that make up the study area. The ESA data were grouped and converted to vectors. From the ESA data, only the land use and land cover classes referring to deforested areas were selected and later re-projected to the official Brazilian system (SIRGAS 2000).

Analytical Strategy

Through the Spearman correlation coefficient (ρ), we verified the existing relationship between deforestation with all active variables of deforestation. This indicator can range from $-1 \leq \rho \leq 1$, with values far from 0 revealing a stronger correlation between the variables, and values close to 0 revealing a weaker correlation, becoming even nonexistent, when they assume the value 0. Hence, it can reveal the association between the conduct of the variables (CHEN; POPOVICH, 2002).

The equation can be described as:

$$\rho = 1 - \frac{6 \sum d_i^2}{n(n^2-1)} \qquad (1)$$

Where, di is the difference in paired ranks and n is the number of cases.

Afterward, we applied the Geographic Weighted Regression (GWR) model. The GWR is a local regression method, which generates spatially diverse parameters that express the variation in the relationships between variables (NAIBBI; HEALEY, 2014). This model allows the identification of variations in these relationships in space, considering spatial variations, between independent explanatory variables and a dependent variable. This model is widely used in various types of studies, including deforestation (NAIBBI; HEALEY, 2014; SANTOS et al., 2021; DA SILVA et al., 2021).

The GWR method has emerged as the most appropriate for studies in larger areas, where there is more spatial variation (DE SOUSA et al., 2012). According to Fotheringham et al. (2003), the GWR model can be determined by the following equation:

$$y_i = \beta_0(u_i, v_i) + x_{i1}\beta_1(u_i, v_i) + \ldots + x_{i1}\beta_p(u_i, v_i) + \varepsilon_i \qquad (2)$$

Where, y_i is the value of the response variable, $x_{i1}, \ldots, x_{ip}$ are the p covariates, u_i e v_i are the geographic coordinates, $\beta_k(u_i, v_i)$ means the value of the effect of the covariate for given graph coordinates, and ε is a random error.

Thus, we can estimate the regression parameters using equation 3:

$$\hat{\beta}(u_i, v_i) = (X^T W(u_i, v_i) X)^{-1} X^T W(u_i, v_i)Y \qquad (3)$$

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Where, X denotes the covariate matrix, $\hat{\beta}$ characterizes the estimate of β e $W(u_i, v_i)$ is a matrix $n \times n$ matrix whose off-diagonal elements are zero and whose diagonal elements denote the geographic weighting of each of the n observed data for regression point i.

In this article, after the diagnosis of Spearman's correlation test, only the variables that showed the most association with the degree of deforestation were selected to be applied to the GWR model. This procedure was carried out through ArcMap, the student version.

Results and discussion

Spearman's correlation coefficient was applied with the significance level being set at 0.05. From Table 2 it can be observed that all variables are statistically significant when correlated with deforestation. Mitra and Lankford (1999) suggested that the degree of correlation between variables be classified into the following categories: very weak (0.00 to 0.20); weak (0.20 to 0.40); moderate (0.40 to 0.60); and strong (above 0.60).

Table 2: Spearman's correlation matrix

|	Test	SILVI	POP_RUR	POP_URB	CRED_AGRI	LAVO_TEMP	BOIS	PIB	POP_EST
Deforest ation	Spearman's rho	0.256^*	0.360^*	0.308^*	0.418^*	0.516^*	0.708^*	0.324^*	0.319^*
	p-value	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$	$< .001$

Notas. * p < .001

Source: Elaborated by the author

The correlations between the variable deforestation and the variables areas of temporary crops (LAVO_TEMP) and agricultural rural credit (CRED_AGRI) displayed values of 0.516 and 0.418, respectively, being rated as a moderate positive correlation. Meanwhile, the average number of cattle (BOIS) showed a correlation of 0.708, being considered a strong positive correlation. The dispersion diagrams (Figure 2) illustrate the positive correlation between the increase in rural agricultural credit, temporary crops, and cattle herds, and the consequent increase in deforestation.

The study conducted by Davis et al. (2019), employing various variables, indicated that pasture expansion is a variable that correlates with the increase in deforestation. Similar results were also found in other Brazilian biomes, such as those demonstrated by Trigueiro et al. (2020) for the Cerrado Biome, and Rivero et al. (2009) and

Santos et al. (2021) for the Amazon Biome. Thus, as observed by Santos et al. (2021), in the Amazon, the cattle ranching sector is the main economic driver that pressures large areas of deforestation. The correlations reveal that a similar process occurs in the Atlantic Forest, which has the same practice of extensive cattle ranching.

Figure 2. Dispersion diagrams.
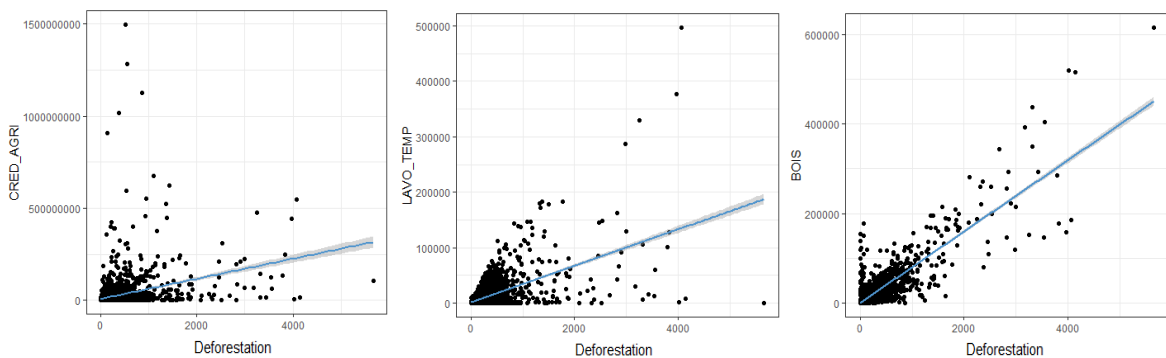
Source: Elaborated by the author

The effectiveness criteria for the GWR regression model are the R^2 coefficient and Akaike Information Criterion (AIC) (NAZARPOUR et al., 2022). The adjusted R^2 stays between values of 0 to 1, and the closer to 1, the higher the percentage of explanation the model has achieved. The applied GWR model obtained an adjusted R^2 coefficient of determination of 0.9415, indicating that the model was able to explain 94%, according to the data used, the drivers of deforestation in the Atlantic Forest (Table 3).

Table 3: Model data.

Model	R^2	Ajusted R^2	AICc
GWR	0.944381	0.941466	36385.688

Source: Elaborated by the author

The GWR model presents several advantages, including the possibility of mapping, through the coefficient of the local R^2, the areas in which the model obtained a more favorable performance (SANTOS et al., 2021). In this case, the highest R^2 values (Figure 3) were observed for the groupings of municipalities located in the eastern and southwest portions of the state of Mato Grosso do Sul, southeast Goiás, the Triângulo Mineiro region, extreme southwest Minas Gerais, central-west Rio Grande Sul; northwest and central portions of Paraná, and in the municipalities of northwest and southeast São Paulo. In these mentioned regions, the R^2 results were higher than 0.93.

On the other hand, in the south and extreme south of the state of Bahia, along with the east coast of Brazil, there are clusters of municipalities with lower R² values, between 0.01 and 0.57 (Figure 3). In this region of Bahia, natural and agroforestry cocoa (Theobroma Cacao) shaded forests (locally known as "cabruca") coexist and ensure extensive vegetated areas (ROLIM; CHIARELLO, 2004; SAGASTUY; KRAUSE, 2019). Although "cabruca" plays an important role in biodiversity conservation (CASSANO et al., 2009), it might mask the real situation of deforestation in the region, due to its spectral similarity with native forests, suggesting the existence of Atlantic Forest remnants where a cultivation system intercalated with native species occurs. For Saatchi (2001), there is difficulty in distinguishing Atlantic Forest from secondary forests, mangroves, and agroforestry systems, by optical remote sensing.

Figure 3. Location R² of the GWR regression model.
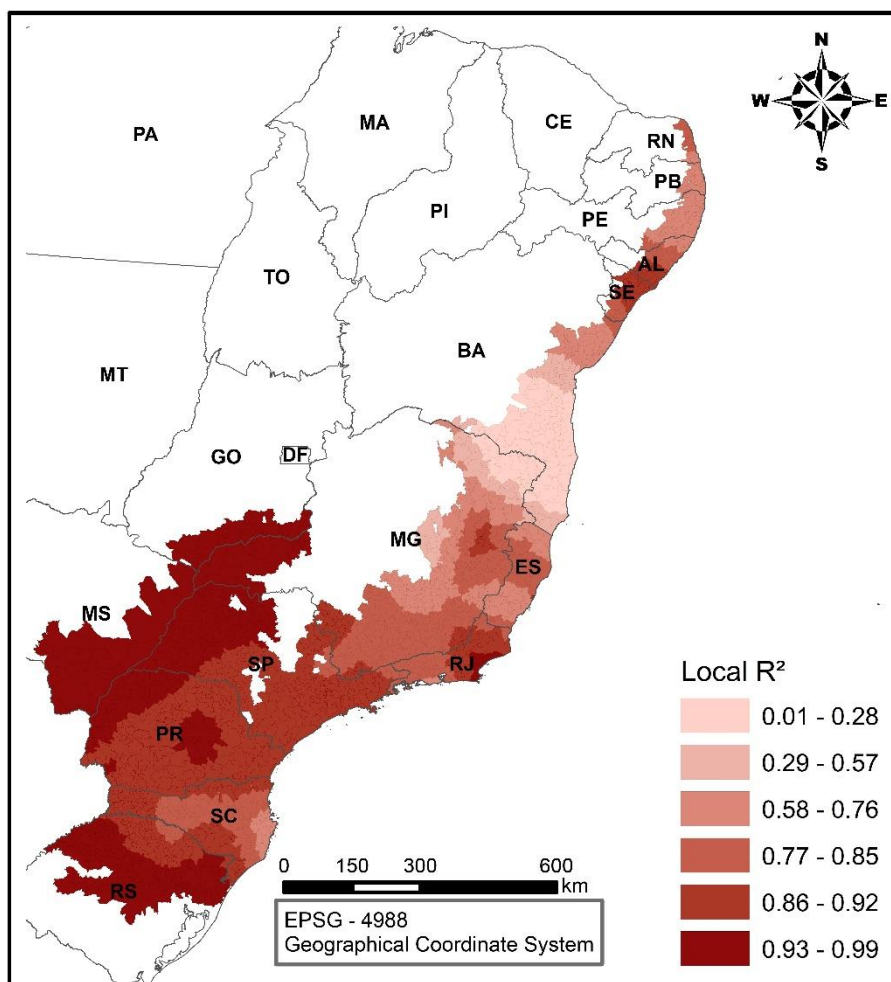
Source: Elaborated by the author

The local R² coefficients calculated by the GWR model indicate the direction and influence of each variable for the occurrence of deforestation, in clusters of municipalities. The results were presented in this manner as it is common for adjacent municipalities to develop socioeconomic relationships with one another and to practice similar economic activities (TRIGUEIRO et al., 2020). Such relationships become evident when the coefficient maps are observed (Figures 4a-c); they allowed for the identification of the main factors (explanatory variables) that influence deforestation in each location when compared to the important content of the spatially distributed variable for the biome.

Figure 4. Coefficients of the explanatory variables in the GWR model.
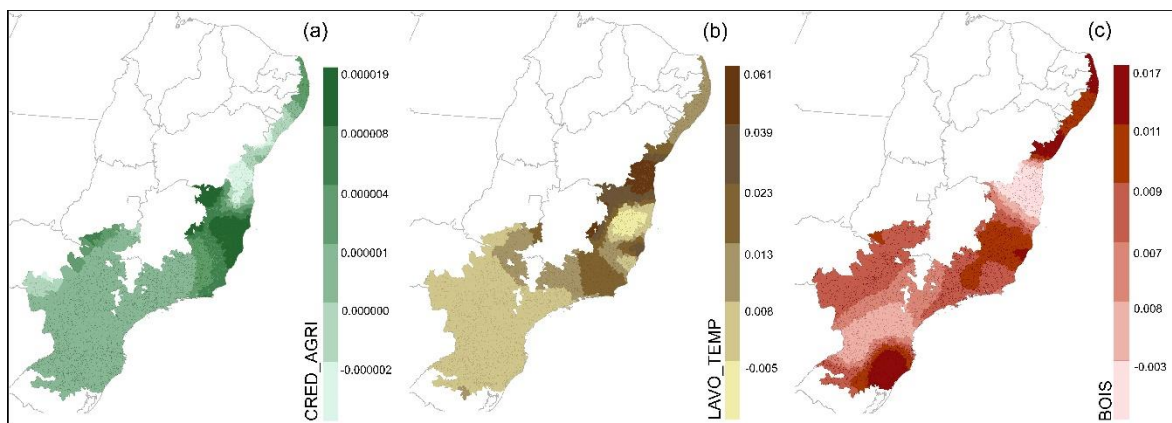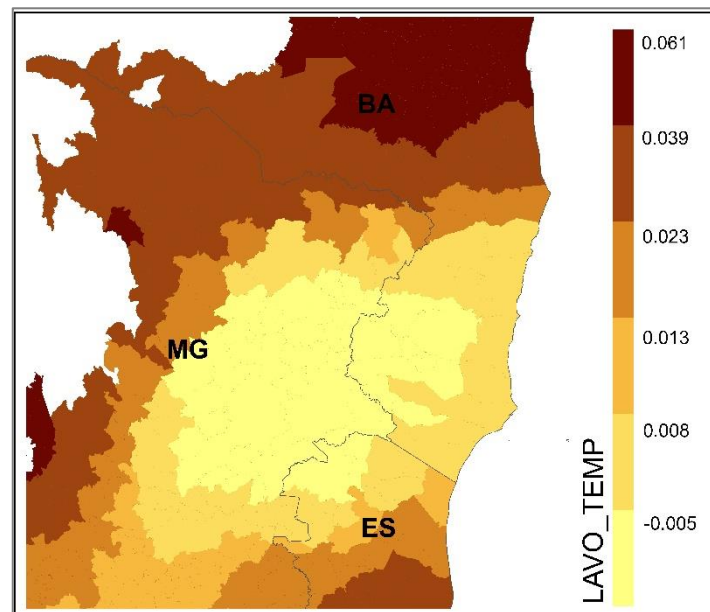

Source: Elaborated by the author

Through Figure 4, one can observe, for example, that rural credit for agriculture (CRED_AGRI) showed a negative relationship with deforestation for the municipalities located in the southeast and northeast regions of Bahia and in the south of the state of Sergipe. In the remaining municipalities, rural credit presented a positive relationship, especially in the southeast and south of the state of Goiás, as well as in the states of Espírito Santo, Rio de Janeiro, east and northeast of Minas Gerais, Rio Grande do Norte, Paraíba and the regions of Mata and Metropolitan of Pernambuco (Figure 4a).

Ferreira and Coelho (2015) verified that rural credit is endogenous, that is, it is capable of funding deforestation, as well as deforestation can raise the demand for credit to finance subsequent economic activities. Assunção et al. (2013) pointed out that the extent of the impact of agricultural credit on deforestation can vary depending on the main economic activity developed in the region. The distribution of such credit is well delimited to certain types of crops, with soybean, corn, and sugarcane production being the most benefited from agricultural credit (FREITAS; SANTOS, 2017).

Temporary crop areas (LAVO_TEMP) were negatively related to deforestation in the extreme southeast region of Bahia, north of Espírito Santo, and in the Mucuri Valley and Rio Doce Valley regions of Minas Gerais (Figure 5). With the remaining municipalities in the states, it presented a positive relationship (Figure 4b). Commonly, the agricultural border advances at the expense of forest clearing (JUSYS, 2016).

Figure 5. Location of north of Espírito Santo, and in the Mucuri and Rio Valley and Rio Doce Valley regions of Minas Gerais.

Source: Elaborated by the author

This positive relationship can be intensified by several other factors, such as the opening of roads (FERREIRA et al., 2005), input prices (MARGULIS, 2002), agricultural prices (FERREIRA et al., 2005), or subsidized agricultural credit policies (FEARNSIDE, 2020), once more incentives are given for the expansion of the agricultural frontier, there will be a greater projection of deforested areas.

Regarding the cattle ranching variable (BOIS), a strong correlation with deforestation was observed for the municipalities of the Brazilian coast, except for southern and extreme southern Bahia (Figure 4c). Therefore, cattle herds presented positive relationships throughout almost the entire biome. For Jusys (2016) the economy and the export trade convert cattle ranching into a profitable business, which puts strong pressure on Brazilian rainforests.

The State of Espírito Santo has 1.5 million hectares of pastures, with 156,400 hectares being deemed degraded (IBGE, 2019). A portion of this amount belongs to the

mountainous region of the Atlantic Forest (SOUZA et al., 2021). The highlight in milk production occurs in the municipalities of the Southern Region of the country (GALEAZZI et al., 2021), thus, in this region, the productivity of dairy cattle, when compared to other Brazilian regions, is above the observed (CARVALHO, 2017).

The spatial cutout of deforestation areas, when compared to the number of cattle by municipality mapped, tend to overlap, from being so familiar in much of the biome. This fact is demonstrated in Figure 6, where the municipalities in the southeast of Goiás and the northeast and southeast regions of Mato Grosso do Sul present high rates of deforestation, as well as high numbers of cattle herds, forming a deforestation corridor in the Atlantic Forest.

Figure 6. Spatial clipping of deforestation, compared to the number of cattle.
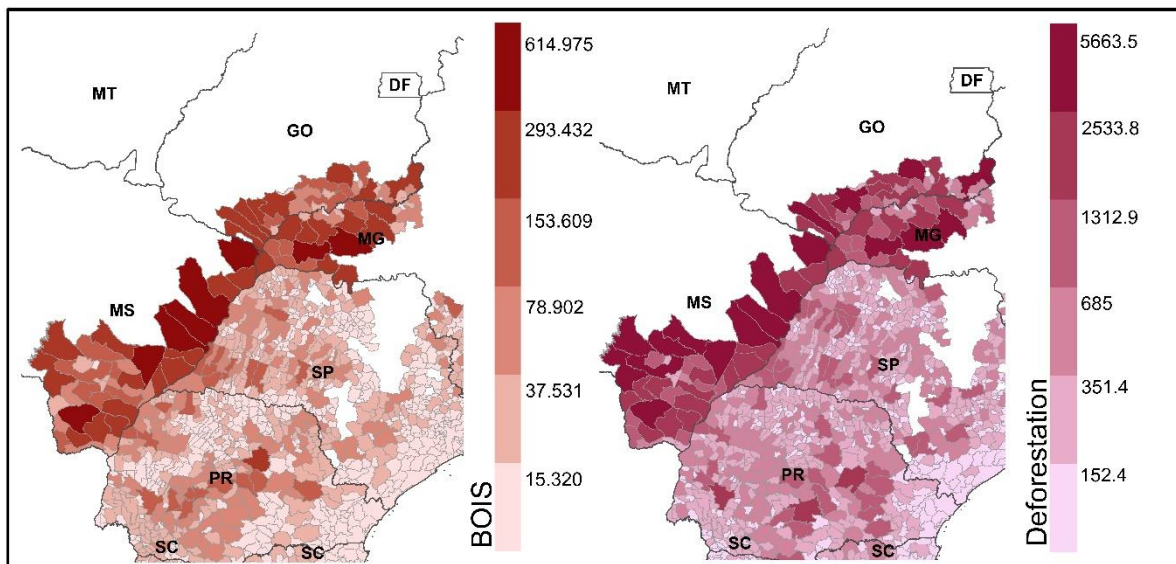
Source: Elaborated by the author

According to Teixeira and Hespanhol (2014), the Central-West region of the country was highlighted in the production of cattle with the arrival of the 1960s, developing extensive character. For Oliveira and Couto (2018), the cattle ranching activity in the center of the country exhibits gross and net margins and profitability consistent with its economic sustainability both in the short and long term.

In this way, and driven by the privileged localization in the center of Brazil, its municipalities expanded the production in the territory, through the addition of new breeding areas. Consequently, other associated problems arise, such as an increase in wildfires. For Pinto (2013), Brazil has a high incidence of burnings. The burning practice is seen as an outdated method, but it is fast and cheap (GABARDO et al., 2021). Moreover, it represents

a central role in carbon emissions in the tropical region (SILVA JUNIOR et al., 2018). When this fire escapes the burning or is started criminally in the forest, the so-called forest fires are set (ALENCAR et al., 2020), triggering a series of other socioeconomic and environmental problems.

Conclusions

This paper revealed the spatial dynamics of the variables that drive deforestation in the Atlantic Forest Biome, in Brazil, between the years 2010 and 2020. However, all the variables initially pointed out in this study were statistically significant when correlated with deforestation. The average number of cattle, the average area of temporary crops cultivated, and rural agricultural credit were the conditioning factors that showed the greatest relationship with deforestation.

The adjusted R² with the GWR was approximately 0.94, meaning that the GWR model explains 94% of the deforestation variations. Values greater than 0.9 of the R² were observed in the states: Mato Grosso do Sul, east and southwest portions; southeast Goiás; Triângulo Mineiro in Minas Gerais; center-west Rio Grande Sul; northwest and central portion of Paraná; northwest and southeast São Paulo. The number of oxen was the covariate that showed the highest correlation with deforestation. On the other hand, lower values were observed in southern Bahia, associated with the development of agroforestry systems practiced in this region of the state.

For future studies, will be necessary to analyze the municipalities that did not configure clusters of deforestation or preservation of the Atlantic Forest, that is, that escape the patterns, the so-called outliers, to understand what makes these municipalities, different from the other municipalities that form clusters.

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