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Deforestation drivers in the Brazilian Amazon: assessing new spatial predictors

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A R T I C L E I N F O

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Spatial variability
Amazon biome
Conditions of deforestation

A B S T R A C T

Researches on the deforestation of the Amazon have gained prominence in the last recent years, mainly with the change in the policy regarding the facing of this phenomenon by the Brazilian government. Therefore, an understanding about the causes that pressure the occurrence of deforestation remains relevant and has a leading role in the world. Therefore, the aim of this study is to perform the analysis of the spatial variability of the reasons for the deforestation in the Amazon Biome, in Brazil, (2010–2019). To achieve this goal, 14 variables were selected, the choice and adjustment of the regression model were determined and a diagnosis was carried out in order to verify the most appropriate model. To achieve this purpose, a geographic database was structured in a geographic information system environment. The main results revealed that the adjusted R^2 of the Geographically Weighted Regression (GWR) was 0.96, that is, the GWR model explains 96% of the variations in deforestation. Therefore, it was observed a significant gain when using this model. In addition, it was also observed that the average variable of the number of oxen was, among those analyzed, the one that showed the highest correlation with deforestation. Thus, it was found that the livestock sector in southern Amazonia is the main economic agent that pressures large areas of deforestation, since stockfarming is practiced extensively. Finally, it was concluded that the municipalities with the largest areas of deforestation formed a cluster in the southern portion of the Amazon, in the arc of deforestation.

1. Introduction

Several researches have been investigating the removal of natural vegetation in areas of non-indigenous occupation, such as the current area in the Amazon Biome (Ometto et al., 2014; Fearnside et al., 2017). These studies have shown that deforestation triggers significant changes in the hydrological cycle (Vergopolan and Fisher, 2016), for example, the quality of waters and of the aquatic environments (Ríos-Villamizar et al., 2017), on the life of the remaining socio-diversity (Santos, 2018), the rising global and regional average temperature (Prevedello et al., 2019), the intensification of extreme weather events (Boers et al., 2017; Zemp et al., 2017; Leite Filho et al., 2019) and also in the proliferation of infectious diseases and public health (Ellwanger et al., 2020). Thus, according to Nóbrega (2014), the deforestation is the biggest problem in the hydrographic basin of the Amazon River and its impacts can generate several consequences that may affect different geographical scales (local, regional and global).

Some recent researches indicated that the reason of the accelerated deforestation in tropical forests is the growing search for wood (Brandt et al., 2016; Karsenty et al., 2017), biofuels (Edwards et al., 2014),

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agricultural products (Laurance et al., 2014; Miyamoto, 2020) and also the road constructions (William, 2002; Laurance et al., 2006) and. An example of such an assertion is that in the 80s and 90 s decades, almost 55% of new agricultural land in the world was acquired at the expense of intact tropical forests (Gibbs et al., 2010). This increase in the search for wood from tropical forests has been rapidly increasing year after year, due to the increased demand for wood derived products, mainly in the markets of Asia and in developing countries (Brandt et al., 2018). This problem represents a major challenge for the conservation of such areas, since tropical forests occupy a large part of the land required for agriculture (Gibbs et al., 2010).

The Brazilian Amazon deforestation has been monitored since the early 80s by the National Institute for Space Research (INPE) through the project Forest Monitoring of the Brazilian Amazon by Satellite (PRODES), which perform annual annually mapping of the deforestation areas (INPE, 2017a). With that, in the last decade, a tendency of reduction of the deforestation in the Brazilian Amazon has been observed. Unfortunately, this tendency has drastically changed in the recent years, and an increase of the deforestation has started gradually (Silva et al., 2020, 2021; Dang et al., 2019). In this sense, deforestation in the Amazon can be explained by several factors. Assunção et al. (2020) indicated an evidence of the influence of the effect of rural credit on the Brazilian Amazon deforestation. The authors point out that the change in the policy promoted a substantial reduction in deforestation, especially in municipalities that have livestock as their main economic activity.

In addition to this, deforested areas are usually concentrated closer to roads (Pinheiro et al., 2016). Thereby, improvements in the transport infrastructure have intensified deforestation along its route and in places that are more bound to its influence (Silva et al., 2020). In this sense, Oliveira et al. (2020) affirms that the variables of distance from highways and urban centers were the ones that contributed the most to the area of the great probability of deforestation, since, to create these roads and cities, it was necessary to cut down trees and/or change the forest landscape. It is added to that, the increase in the human population density (Laurance et al., 2009). Laurance et al. (2009) also highlighted the factors that can affect physical accessibility to forests, materialized by the linear distances to the nearest paved highway, unpaved roads, and navigable rivers. The roads also facilitate the selective extraction of wood of commercial interest.

Stockfarming is another factor often mentioned in terms of deforestation in Brazil (Walker et al., 2013; Picoli et al., 2020). This is due to the growing demand from the national and international market for bovine meat, which requires larger extensions of area for the development of pastures (Walker et al., 2013; Picoli et al., 2020). In the Amazon, livestock ranching is often practiced in conjunction with agriculture (Santos, 2018). Thus, the areas of pasture and soybean cultivation play a fundamental role in the deforestation of the Brazilian Amazon (Picoli et al., 2020; Mammadova et al., 2020) and this occurs since farmers, ranchers, and lumber traders find ways to get around the agreements and legislation (Carvalho et al., 2019). In this sense, according to Costa et al. (2017), soybean plantations have increased in the south of the Brazilian Amazon, especially in the states of Rondônia and Mato Grosso.

In contrast, there are the inhibiting deforestation areas, such as indigenous lands (BenYishay et al., 2017; Santos, 2018) and the conservation units (Assunção et al., 2015; Folharini et al., 2021; Rudke et al., 2020; West and Fearnside, 2021). As a result, Assunção et al. (2015) attributes 56% of the reduction in the forest loss in the period 2004–2009 to the conservation policies implemented in the Amazon between the years of 2004 and 2008.

Thus, it was chosen as a hypothesis the fact that deforestation in the Amazon Biome occurs predominantly through livestock ranching and agricultural crops in the southern portion of this region. Therefore, it is important to visualize the spatial nature of deforestation in tropical forests and on each area compared to the others. For this purpose, explicit spatially analyses are increasingly been used to solve the problems derived from spatial autocorrelation. For example, the Moran index is the most common statistic test for detecting spatial autocorrelation, which includes tests for visualizing clustering through global testing and creating meaningful and clustering maps using local statistics tests, such as the Local Indicators of Spatial Autocorrelation - LISA (Anselin and Rey, 2014). It was observed that this methodology, for the analysis of deforestation, is not recurrent in the Amazon, but the work from Walker et al. (2000) and Fagua et al. (2019). Walker et al. (2000) performed diagnoses of spatial autocorrelation on land cover data in the Choco-Darien Ecoregion, which occupies part of the areas of Panama, Colombia, and Ecuador. Fagua et al. (2019) used the Moran Index to identify the cities where deforestation, through livestock and reforestation, was significantly clustered in the Brazilian Amazon. Salame et al. (2016), for example, used the Moran Index to analyze forest fires and deforestation in the Brazilian Amazon during the period from 1999 to 2004. In addition, finding a logical statistical relationship between deforestation and its causes is helpful in order to quantify its influence and prioritize this variable in forest conservation programs at the local and national levels.

Common regression methods, such as, Ordinary Least Squares (OLS), can only analyze a relationship between the response variable and the explanatory variables, but do not consider a spatial dependency (Anselin and Rey, 2014). The local spatial analysis creates a relationship between the results of spatial techniques and the visualization capacity of the Geographic Information System (GIS) (Fotheringham et al., 2002), while spatial patterns are ignored in the correlations of global statistics (Wu et al., 2010). Therefore, spatial regression techniques, including geographically weighted regression (GWR) (Leung et al., 2000; Fotheringham et al., 2002) can be used to analyze spatial causes in deforestation (Wu et al., 2010; Naibbi and Healey, 2014).

Although some statistical models, for instance the general regression models, have been applied to study the deforestation and its causes in some studies, models of spatial autocorrelation and spatial regression have rarely been applied. Therefore, first, the spatial trend patterns of deforestation in the Brazilian Amazon were assessed using the Global Moran Index and LISA to detect the spatial autocorrelation between deforestation and its causes. Then, the performance of the OLS and GWR models were compared, in order to explain the relationship between deforestation and its causes. Thus, the aim of this research was to carry out the analysis of the spatial variability of the causes of deforestation in the Amazon Biome, in Brazil, in the last decade (2010–2019).

The article is structured into five parts. The first section presents, respectively, the introduction, which contains the theoretical foundations of the Brazilian Amazon deforestation and its causes. Section 2 describes the materials and methods used in this study. The third part displays the results followed by the discussion section. The fourth section is devoted to discuss the results. Finally, in the last section, the conclusions and recommendations for future research were described.

2. Material and methods

2.1. Study area

The study area included the 550 municipalities located in the Amazon Biome, which are part of the states of Acre, Amapá, Amazonas, Pará, Rondônia, Roraima, and part of the municipalities of Mato Grosso, Maranhão, and Tocantins (Fig. 1). The vegetation is predominantly composed of forests (Ferreira et al., 2005), however, it was identified the transition zones of the Amazon and the Cerrado (Pires and Costa, 2013; Santos, 2018). The Amazon rainforest is crucial for the maintenance of the planetary health, due to its vital role in the regulation of the Earth's climate (Ellwanger et al., 2020). In addition, the Amazon has a unique biome in many aspects, with importance in different spheres of life (Ellwanger et al., 2020), and also, it is extremely rich from a biological point of view, with approximately 420 million ha in Brazil (Simon and Garagorry, 2005).

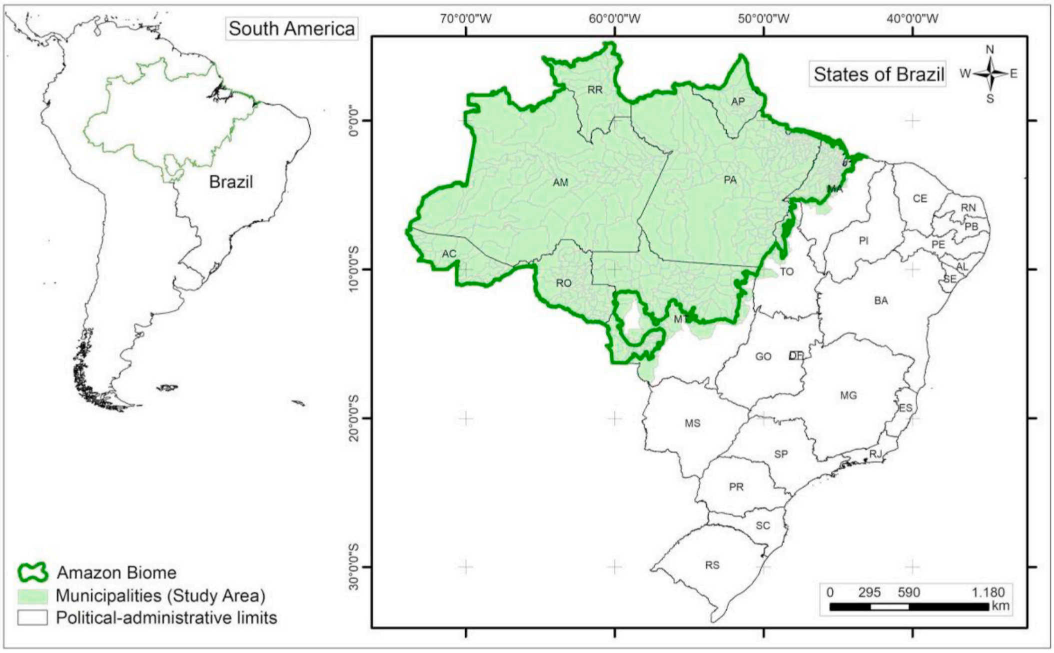

Fig. 1. Study area.

2.2. Data

The data on deforested areas in the Amazon Biome was obtained from the National Institute for Space Research (INPE/TerraBrasilis, 2020) through the Amazon Deforestation Monitoring Satellite Project (PRODES Amazônia). As mentioned before, there are several causes that can help to explain the occurrence of the Brazilian Amazon deforestation. Therefore, it was highlighted researches in the Amazon by Laurance et al. (2002), Aguiar et al. (2007), Diniz et al. (2009) and in the most recent studies by Silva et al. (2020) and Silva et al. (2021) and the research carried out by Trigueiro et al. (2020) for the Cerrado Biome. With this purpose, from the consulted bibliography and from the empirical experience, the variables described in Table 1 were chosen for analysis, classified into Response, Socioeconomic, Ecological, Physical and Climate Variable, according to Trigueiro et al. (2020).

The data of the vector files of the limits of the municipalities located in the Amazon Biome were obtained through the Brazilian Institute of Geography and Statistics (IBGE), which is the official registration agency and for the elaboration of the political-administrative division in the country. This database was processed in Qgis and the statistical analyzes in R.

2.3. Analytical strategy

It was assessed the global spatial autocorrelation of deforested areas by the use of the Moran Index. Subsequently, LISA was applied (Anselin, 1995) for the local deforestation analyses by municipalities.

When choosing and adjusting the models for estimating deforestation, the set of predictor variables were evaluated in order to verify those that best describe the response variable, and thus to be applied to the model. To select the co-variables of the proposed model, the stepwise method of variable selection was used along with the Akaike's criterion (AIC) (the model with the lowest AIC was chosen). This method previously checks partial F statistics for all variables in the model. The determination of the variables that have the greatest influence on the deforestation of environmental preservation areas is necessary to determine the factors that may possibly have a considerable impact on the practice of the Amazon biome deforestation (Trigueiro et al., 2020).

The F statistical tests were performed in order to verify the existence of spatial autocorrelation in the Ordinary Least Square (OLS) model, in which high values of the residuals were observed. Thus, the Geographically Weighted Regression (GWR) was applied. According to Fotheringham et al. (2002) the GWR model can be written as:

$$y_i = \beta_0\ (u_i\ ,\ v_i)\ +\ x_{i1}\beta_1\ (u_i\ ,\ v_i)\ +\ \ldots\ + x_{ip}\beta_p\ (u_i\ ,\ v_i)\ +\ \varepsilon_i \tag{1}$$

In which, y_i is the value of the response variable from the i-th point in space, $x_{i1}, \ldots, x_{ip}$ are the p co-variables of the i-th point, u_i and v_i are the geographic coordinates, $\beta_k\ (u_i\ ,\ v_i)$ represents the value of the effect of the k-th covariable for previously determined geographic co-variables and finally ε_i is any random error. Therefore, the GWR model recognizes that spatial variations in the relationships could exist and provide a way for them to be measured.

In the GWR, an observation is evaluated accordingly to its proximity to the local *i,* in a way in which a ponderation of an observation is no longer constant, but can vary with *i*. The observational data closer to *i* have more influence in relation to the farther observational data. Consequently, it can be estimated the regression parameters as follows:

$$\widehat{\beta}(u_i,\ v_i)\ =\ (\ X^\top W(u_i\ ,\ v_i)X\ )^{-1}X^\top W(u_i\ ,\ v_i)Y \tag{2}$$

In which X is the matrix of co-variables, Y is the values vector of the response variable, $\widehat{\beta}$ represents the estimate value of β and $W(u_i\ ,\ v_i\ )$ is a $n\ \times\ n$ matrix, in which the elements outside the diagonal are zero and the diagonal elements exhibit the geographic ponderation of each one of the n data, observed in the regression point i. In the process of evaluation, an iterative maximization algorithm is required to estimate the parameters model in the local i. In this work, the models were evaluated based on the data from the AIC, R^2 and Moran's I of the residues.

In this paper, a GWR model estimates deforestation controlled by the average forest area (Forest), the average number of oxen (Cattle), average area of temporary cultures (Cultures), the average amount of m^3 of wood extracted (Woods), the agricultural credit (AgriCredit) and distance from the deforested area to the roads (RoadDist) (Selected variables using the Stepwise selection method). Thus, based Eq. (1) we are interested in proposing the following GWR model:

Table 1
Description of the variables with the respective categories, measurement units, and information sources.

Category	Description	Unit	Source
Response variable	Average annual deforested area between 2010 and 2019, standardized by the area of each municipality	km^2	TerraBrasilis INPE (2020)
Socioeconomic	Average number of bovine livestock between 2010 and 2019, standardized by the area of each municipality	Heads/ Unit	SIDRA/IBGE (2020)
Socioeconomic	Number of people residing in the urban zone accordingly to the 2010 census, standardized by the area of each municipality	Count/ Unit	INPE (2017)
Socioeconomic	Number of people residing in rural zone accordingly to the 2010 census, standardized by the area of each municipality	Count/ Unit	INPE (2017)
Socioeconomic	Average of the estimative of the population in 2010 and 2019	Count/ Unit	SIDRA/IBGE (2020)
Socioeconomic	Average agricultural rural credit provided by financial institutions between 2013 and 2019, standardized by the area of each municipality	Each R$ 1000.00	Banco Central do Brasil (2020)
Socioeconomic	Average livestock rural credit provided by financial institutions from 2013 to 2017, standardized by the area of each municipality[a]	Each R$ 1000.00	Banco Central do Brasil (2020)
Socioeconomic	Average area with temporary crops cultivated between 2010 and 2019, standardized by the area of each municipality	km^2	TerraBrasilis INPE (2020)
Socioeconomic	Average Gross Domestic Product between 2013 and 2015, standardized by the total population[a]	Each R$ 1000.00	SIDRA/IBGE (2020a)
Socioeconomic	Wood removal between 2010 and 2019	m^3	SIDRA/IBGE (2020a)
Ecological	Area of native vegetation remnant standardized by the area of each municipality. (2020)	km^2	TerraBrasilis INPE (2020)
Physical	Conservation unit of full-time use. (2020)	km^2	TerraBrasilis INPE (2020)
Physical	Indigenous lands (2020)	km^2	TerraBrasilis INPE (2020)
Physical	Average distance between deforested areas and the closest official roads per municipality wood removal between 2010 and 2019	km	TerraBrasilis INPE (2020) MMA (2017)
Climatic	Average annual precipitation per municipality in the driest month (1970–2002)[a]	mm	Fick and Hijmans (2017)

[a] Data available only for this period.

3. Results

The map shown in Fig. 2 reveals the grouping of municipalities with a high deforested areas average in the municipalities in the southern portion of the Amazon in the last decade, especially in the municipalities in the northern portion of the state of Mato Grosso (MT), southern portion of Pará (PA), and far west of Rondônia (RO). Through Fig. 2, three High-High (HH) clusters are observed, the largest of which has 72 municipalities and has an interconnection with the states of Mato Grosso and Pará. On the other hand, it was possible to identify three Low-Low (LL) LL-type clusters, with a total of 198 municipalities, in Amazonas (AM) and Amapá (AP).

This LISA result indicated the presence of spatial clusters type high-high (HH), which means they form a set of municipalities with high rates of the considered variable that are surrounded by other municipalities with the same characteristics. Contrary, the low-low (LL) clusters form a set of municipalities with low variable rates considered.

On Table 2, it is shown the correlation matrix of the co-variables used in the models. It appears that the average variable in the number of oxen has the greatest correlation with deforestation. In general, co-variables do not show strong correlations with each other, which helps to avoid possible multicollinearity problems. According to Vatcheva et al. (2016), the adverse impact of ignoring multicollinearity in the results and in the interpretation of the data in the regression analysis is very well documented in the statistical literature.

In this way, the Ordinary Least Squares (OLS) regression model was applied. The OLS regression model was used to identify statistically significant associations between the response variable and the co-variables. Thus, the associations between the average Amazon biome deforestation and co-variables (Socioeconomic, Ecological, Physical and Climatic) were evaluated.

Table 3 shows the co-variables selected for the model, the regression coefficients, standard error, significance of the coefficients and finally, the variance inflation factor (VIF), which was calculated in order to identify the existence of multicollinearity. The co-variables chosen for the model are the following: average of the area of forest (Forest), average of the number of oxen (Cattle), average of the area of temporary cultures (Cultures), average amount of m^3 of wood extracted (Woods), the agricultural credit (AgriCredit) and distance from the deforested area to the roads (RoadDist). All covariates were significant (p value $<$ 0.01).

It was identified that the estimated coefficients for the variables Forest, Cattle, Cultures, Wood, and AgriCredit were positive, that is, there is a positive association with the average deforestation. Therefore, in theory, the higher the values of the variables Forest, Cattle, Cultures, Wood, and AgriCredit in the municipality, the greater average of the deforestation is observed. In contrast, the RoadDist variable provides a negative coefficient, which implies that the higher the value of this variable, the lower the deforestation.

Regarding the assumption of multicollinearity, all variables VIF value $<$ 1.5, indicated that there is no multicollinearity in the OLS regression model. The adjusted R^2 indicated that the models were able to explain about 77% of the total variance of deforestation in the Amazon. However, the residues of the OLS model dissipated a significantly

$$
\begin{aligned}
Deforestation_i = {} & \beta_0 (u_i, v_i) + Forest_{i1}\beta_1 (u_i, v_i) + Cattle_{i2}\beta_2 (u_i, v_i) \\
& + RoadDist_{i3}\beta_3 (u_i, v_i) + Agricredit_{i4}\beta_4 (u_i, v_i) + Cultures_{i5}\beta_5 (u_i, v_i) + Wood_{i6}\beta_6 (u_i, v_i) + \varepsilon_i
\end{aligned}
\tag{3}
$$

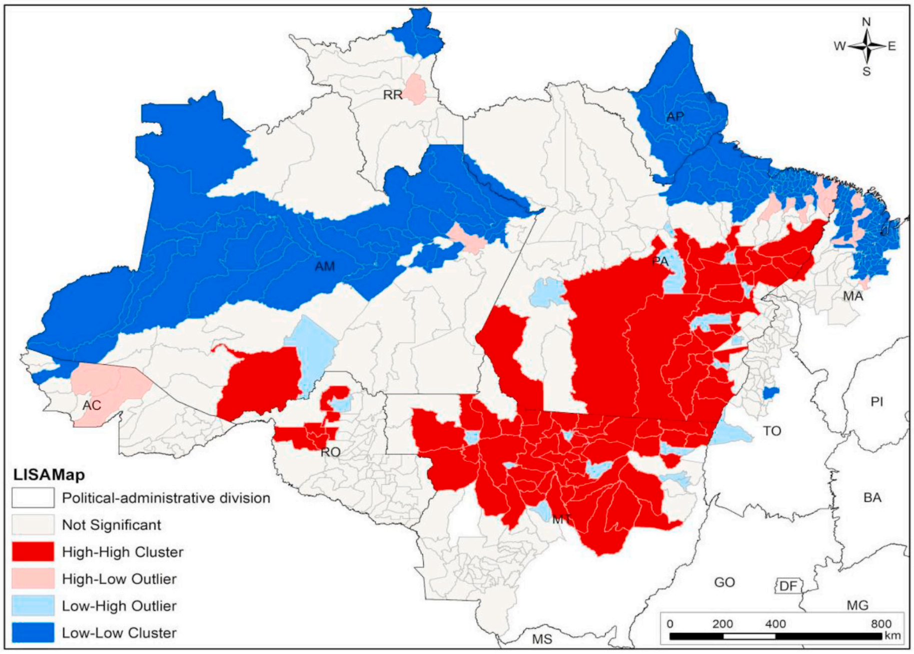

Fig. 2. LISA Map of deforestation in Amazon Biome.

Table 2
Correlation matrix of the OLS regression model.

	Deforestation	Forest	Cattle	Cultures	Wood	Agricredit	RoadDist
Deforestation	1	0.24	0.83	0.21	0.32	0.17	−0.12
Forest	0.24	1	0.16	−0.02	0.18	−0.06	0.39
Cattle	0.83	0.16	1	0.04	0.19	0.13	−0.11
Cultures	0.21	−0.02	0.04	1	0.03	0.06	−0.07
Wood	0.32	0.18	0.19	0.03	1	0.04	−0.02
Agricredit	0.17	−0.06	0.13	0.06	0.04	1	−0.18
RoadDist	−0.12	0.39	−0.11	−0.07	−0.02	−0.18	1

Table 3
Adjustment of the OLS regression model.

Variables	Estimate	Std. Error	t value	p value	VIF
(Intercept)	$2.30E^{+0}2$	$6.15E^{+01}$	3.737	<0.001	–
Forest	$1.56E^{-02}$	$2.87E^{-03}$	5.435	<0.001	1.268
Cattle	$6.58E^{-03}$	$1.85E^{-04}$	35.418	<0.001	1.103
Cultures	$3.44E^{-03}$	$4.08E^{-04}$	8.428	<0.001	1.008
Wood	$3.60E^{-03}$	$5.47E^{-04}$	6.59	<0.001	1.069
AgriCredit	$3.44E^{-05}$	$1.36E^{-05}$	2.527	0.011780	1.052
RoadDist	−3.32	1.44	−2.301	0.021768	1.257
R^2	*0.77*				
AIC	*8888.836*				

positive spatial autocorrelation (Global Moran's I = 0.161, p-value = 0.001), thus, the assumption of the OLS regression, that the residues are independent, is not satisfied. To fill this gap, the GWR spatial model was used to characterize the relationship between deforestation averages and co-variables. Thus, to help understand the results, maps with the distribution of the raw data of the explanatory variables of the GWR model were presented in supplementary material (Figs. S1, S2, S3, S4, S5, S6 and S7).

In Table 4, the GWR coefficients for deforestation are presented in terms of statistical measures, such as: minimum, first quartile, median, third quartile and maximum. The adjusted R^2 of the GWR is 0.96, that is, the GWR model explains 96% of the variations in deforestation. Therefore, there is a significant gain when using the GWR model.

One of the great advantages of the GWR model is that through the local R^2 it is possible to highlight the areas that the model had a better

Table 4
Adjustment of the GWR model.

Variables	Min.	1st Qu.	Median	3rd Qu.	Max.	Global
(Intercept)	$-4.9923E^{+02}$	$-3.8096E^{+01}$	$6.3518E^{+01}$	$1.6818E^{+02}$	$9.0109E^{+02}$	230.0255
Forest	$-1.4265E^{+00}$	$6.5449E^{-03}$	$4.4305E^{-02}$	$3.9817E^{-01}$	$2.1466E^{+00}$	0.0156
Castte	$-4.2193E^{-03}$	$5.2483E^{-03}$	$7.2310E^{-03}$	$9.9752E^{-03}$	$2.1545E^{-02}$	0.0066
Cultures	$-1.6517E^{-01}$	$4.8284E^{-03}$	$2.8306E^{-02}$	$4.7177E^{-02}$	$1.5876E^{-01}$	0.0034
Wood	$-4.9125E^{-01}$	$-6.1970E^{-04}$	$4.0789E^{-03}$	$1.1041E^{-02}$	$1.0244E^{+00}$	0.0036
AgriCredit	$-7.1681E^{-05}$	$-4.1162E^{-06}$	$1.4280E^{-05}$	$4.3302E^{-05}$	$1.9905E^{-04}$	0.0000
RoadDist	$-1.4788E^{+02}$	$-3.2234E^{+00}$	$2.2546E^{+00}$	$1.8890E^{+01}$	$1.2295E^{+02}$	−3.3164
R2	*0.96*					
AIC	*8013.09*					

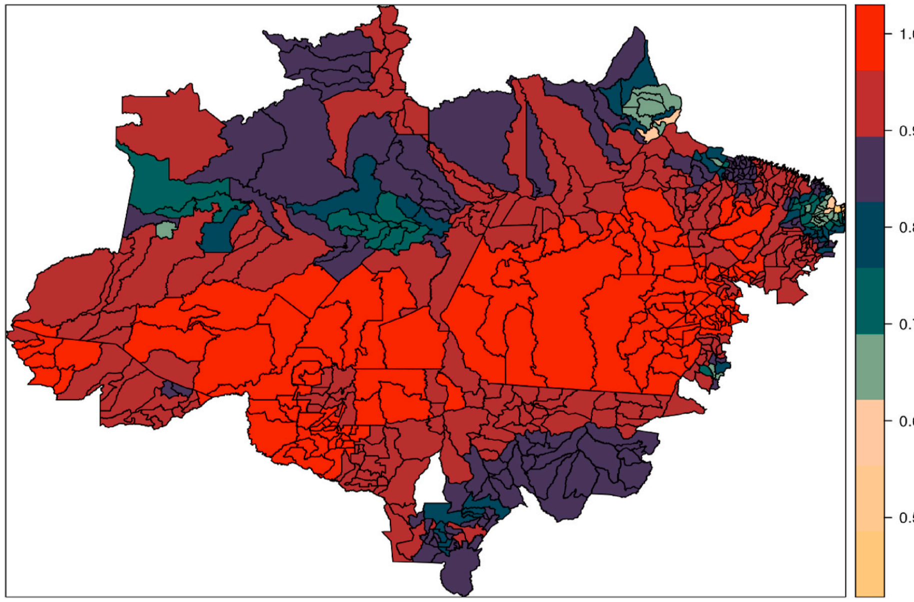

Fig. 3. Local R^2 of the GWR regression model.

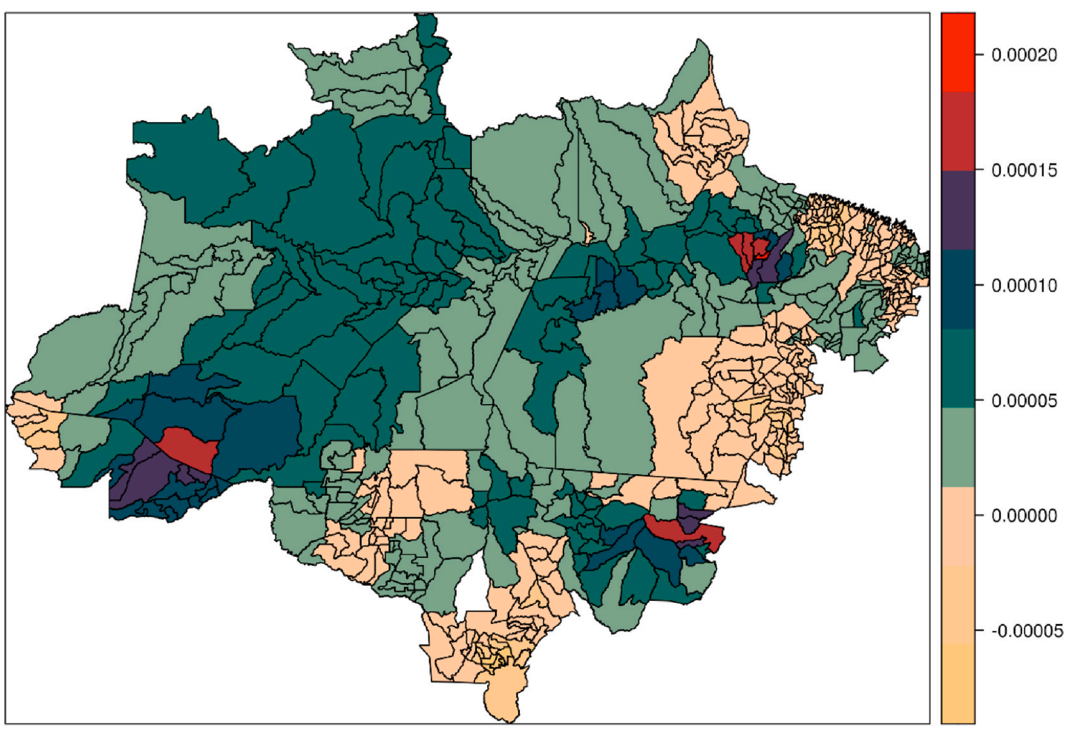

Fig. 4. Regression coefficient for the agricultural credit variable.

performance. Thus, it is possible to have a spatial visualization of the model's performance to explain deforestation. The higher R^2 values were found mainly in the states of Pará, Amazonas (southern portion), Mato Grosso (northern portion), Acre and Rondônia. In the vast majority of municipalities in those states, the R^2 values were higher than 0.8 (Fig. 3).

It is important to mention that the model was able to give a reliable representation of the deforestation in the region, since most of the municipalities that showed a high correlation are inserted in the axis known as the "arc of deforestation". This axis comprises the regions south of AM, north of RO, north of MT, and south and east of PA, and is known by this name due to the current status of the epicenter of deforestation in the Amazon (see Costa and Pires, 2010; Silva et al., 2019).

In this sense, it was evaluated the behavior of the coefficients of the selected co-variables in the GWR model. Fig. 4 shows the significance of the coefficient values for credit to agriculture. In general, on this step, the set of explanatory variables was evaluated to verify those that could best describe the response variable, and thus, that could be applied to the model. Positive coefficients were observed, and the highest values were observed in the states of Acre, Amazonas, Roraima, and Pará (west).

Temporary crops showed positive coefficients (Fig. 5) in most municipalities, with the exception of the states of Roraima and Acre (east/

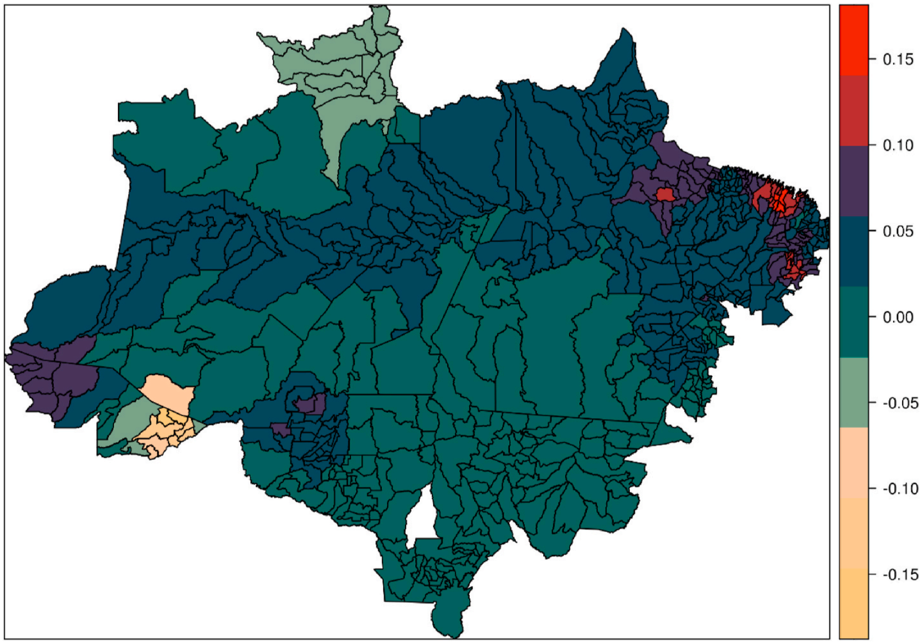

Fig. 5. Regression coefficient for the temporary culture variable.

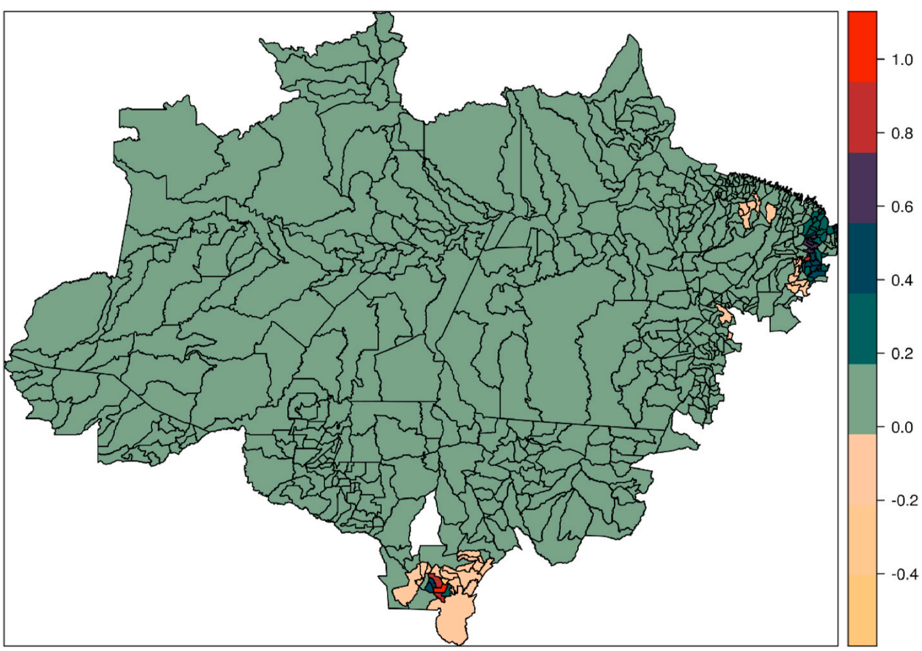

Fig. 6. Regression coefficient for the wood production variable.

south). The highest coefficients were observed in the north and east of the state of Pará, Maranhão, in the central part of the Amazonas and Acre (west/north). The regression coefficients were significant for most regions, with the exception of the states of Amazonas (western/northern portions) and some areas of Tocantins and Maranhão.

All states showed positive coefficients of the average production of wood resulting from the deforestation of the Amazon Biome. The southern portion of Mato Grosso was an exception, contrary to the others states, it had a negative relationship with deforestation (that is, for this region, greater amounts of temporary culture imply less deforestation). The states of Amazonas, Pará, northern Mato Grosso, Roraima and the southern part of Mato Grosso showed significant coefficients (see Fig. 6).

Furthermore, given a hypothetical situation that most of the coefficients are positive and the minority is negative, these regions with negative coefficients are considered to be atypical regions (outliers) and for this reason, should be further investigated.

In the vast majority of states, positive coefficients were found regarding the relationship between the average number of oxen and deforestation. Higher coefficients were identified in the states of Pará (mainly in the north/east portion), Roraima, Amazonas (north) and Amapá (north). Their respective significance is shown in Fig. 7.

One of the advantages of the GWR model is that the direction of the relationship between deforestation and the number of cattle can vary spatially. In some municipalities, this relationship was positive (0.005) that is, the increase in the number of oxen implies an increase in

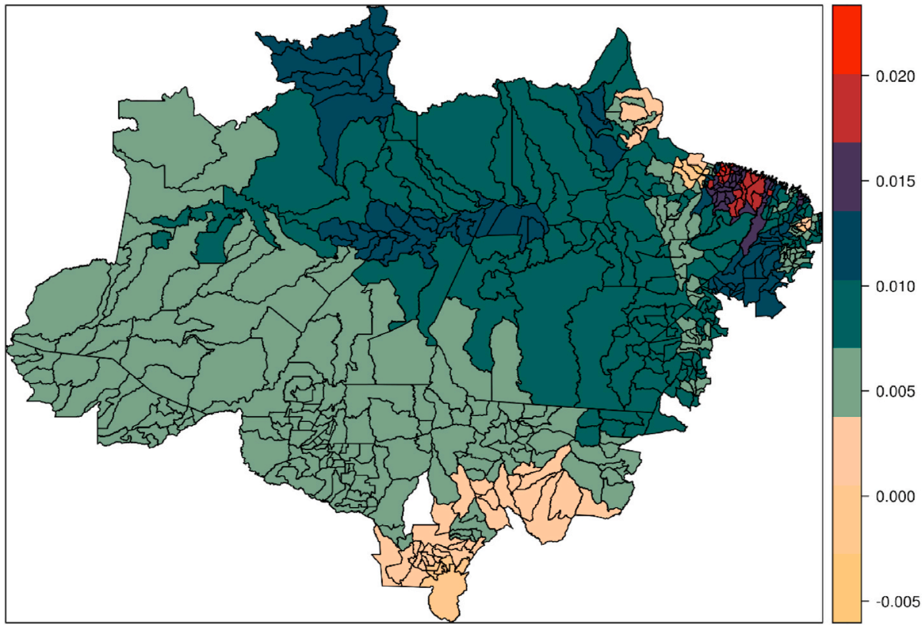

Fig. 7. Regression coefficient for the average oxen variable.

deforestation. However, in the southwestern portion of the state of Mato Grosso, livestock is practiced in natural fields, associated with the Pantanal Biome. So, the increase in the number of cattle do not imply an increase in deforestation (Santos and Mota, 2017; IBGE, 2020b). Therefore, finding regions that show signs of different correlation for the same variable do not imply errors in the model, but they elucidate different behaviors that vary spatially.

In addition, it was mentioned three other aspects: (1) the differences in the size of the areas of the municipalities analyzed, (2) the way of raising cattle, and (3) the location of municipalities in areas of transition between Biomes.

Regarding the size of the municipalities, when looking at Figs. 7 and S3, it was possible to notice that the coefficient values were high (the reddest part of Fig. 7) even in places with a few heads of cattle (Fig. S3). This occurrence can be explained because, even though the municipality has only a few cattle (when compared to larger municipalities), that was the main variable capable of explaining the "little deforestation" that occurred in the region during the analyzed period (Fig. S1).

In the second case, the increase in the ox variable may be more related to the type of cattle production (e.g., intensive production, which is based on the creation of cattle confined in small areas), which does not require the expansion of pasture areas.

In the third case, there are the municipalities located in the transition zones with other biomes. For example, the breeding of cattle in areas of natural pasture, without necessarily occurring deforestation. This occurs in certain phytophysiognomic types of the Cerrado Biome (biome surrounding the Amazon biome), the rural formations, which are culturally used for the breeding of cattle.

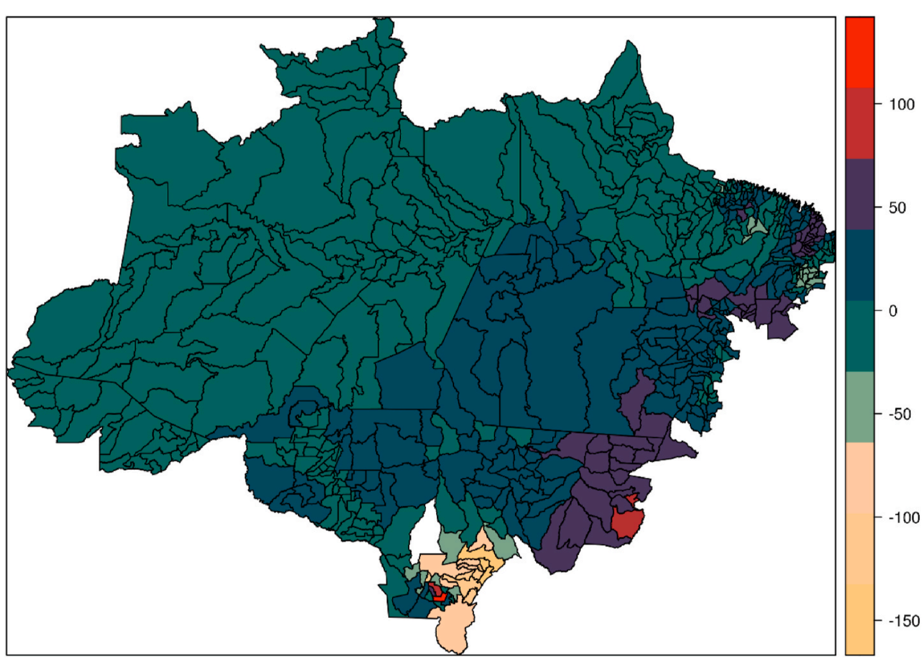

Fig. 8. Regression coefficient for the variable distance from the road.

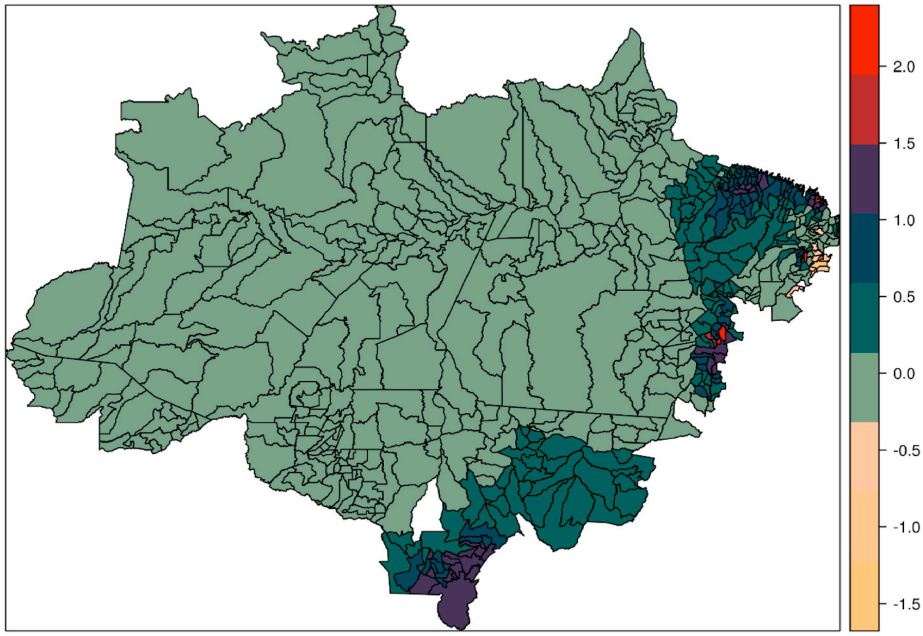

Fig. 9. Regression coefficient for the variable forests.

Regarding the distance from roads to the deforestation area, the municipalities of Mato Grosso presented negative coefficients, that is, the greater the distance to roads, the lower the deforestation. The other municipalities presented positive weights. In Fig. 8, the significance of the coefficients is provided.

The average of the forest area in nearly all regions showed positive coefficients. The highest coefficients were found in the states of Mato Grosso (south), Pará (north/east) and Tocantins. The states of Amazonas, Roraima, Amapá, Acre and Rondônia also had positive coefficients (their respective significance is given in Fig. 9.

Finally, to verify the local significance of each variable of the GWR model, the maps with their respective p-values are presented in the supplementary material (Figs. S8, S9, S10, S11, S12 and S13).

4. Discussions

This can be considered the first analysis that presents the correlation of deforestation with the largest number of variables for all the municipalities in the Amazon Biome area, in Brazil. Generally, most researches focuses on the analysis of 'isolated' spatial clippings, for example, states, municipalities, indigenous lands, or Conservation Units (BenYishay et al., 2017; Ríos-Villamizar et al., 2017; Gollnow et al., 2018; Aldrich et al., 2020; Assunção et al., 2020; Carvalho et al., 2020).

14 variables, classified as socioeconomics, ecological, physical and climatic, were surveyed. Those variables were defined accordingly to the literature, but it was observed that not all of them responded positively to the occurrence of deforestation.

In regards to the ecological data, it was incorporated the covariables: areas of indigenous lands and integral protection conservation units. However, they showed no correlation with the response variable.

The results obtained through the LISA Map indicated the grouping of deforested areas in the southern portion of the Amazon Biome. This region coincides with the states that occupy the top of the list of those with the most deforested areas in the Amazon, Pará (34.46%), Mato Grosso (32.34%) and Rondônia (13.76%) (INPE/Terrabrasilis, 2021), and that region is comprised in the area commonly called as the "arc of deforestation" (Fearnside, 2017; Garcia et al., 2019; Oliveira et al., 2019). In this sense, Fearnside (2017) states that approximately 80% of the forest loss in the Brazilian Amazon had occurred in the "arc of deforestation", which is a crescent-shaped strip along the southern and eastern edges of the forest.

Sathler et al. (2018) studied the dynamics of deforestation and human development in the 211 small and medium-sized municipalities (in population terms) in the Amazonian arc of deforestation in Brazil. The authors' findings shows that there are four well-defined macro-deforestation frontiers that exhibit distinct interactions between forest loss, socio-demographic and economic characteristics, and levels of human development: the stagnant frontier, the dynamic frontier of deforestation, the consolidated frontier, and the internal frontier of deforestation (Sathler et al., 2018). In other words, the results from this paper reinforce that it is needed a policy aimed at containing deforestation must be focused at this area.

According to Reydon et al. (2020), deforestation occurs mainly when property rights are not clearly established, and it occurs mainly on areas which are directly or indirectly under the responsibility of the State. Thus, it is believed that the insertion of a variable on the land-ownership structure would contribute to details of the way in which deforestation occurs. However, it was noted that the availability of land structure variables is still being produced for the Amazon.

In addition to the above, generally, the result of R^2 for the OLS regression was in the order of 0.77. However, the assumption that the residues were independent was not satisfied, and to fill this gap, the GWR spatial model was used. Thus, the adjusted R^2 of the GWR reached 0.96, which means that this model explained 96% of the variations in deforestation. Therefore, there is a significant gain when using the GWR model. In addition, according to Trigueiro et al. (2020), this model supports the use of analyzes that consider spatial variability to assess factors associated with deforestation in the municipal or regional contexts. In the analysis of spatial variability, the highest values for R^2 were found mainly in the states of Pará, Amazonas (southern portion), Mato Grosso (northern portion), Acre and Rondônia, all comprised in the arc of deforestation, as mentioned.

The explanation for this phenomenon is directly related to the expansion of the soy cultivated area, in the state of Mato Grosso, and also the recent advances in the state of Pará. In addition to that, Aldrich et al. (2020) suggested that agriculture has been a profitable sector in recent years, especially for soy exports (Soterroni et al., 2019). On the other hand, according to Gollnow et al. (2018), Brazil's Soy Moratorium solidified the commitment of the world's largest traders to prevent the purchasing of soy from deforested production areas after July 2006.

Furthermore, Oliveira et al. (2020) highlighted the extensive raising of beef cattle (Müller-Hanse et al., 2019; Yanai et al., 2020), as a cause for the occurrence of deforestation. Additionally, Carvalho et al. (2020) claimed that about 60% of all deforested land in the Brazilian Amazon is covered with pasture, placing the livestock ranching in evidence as one of the main causes for deforestation.

The high concentration of deforestation is explained by Yanai et al. (2020), which claimed that after the initial stage of deforestation, medium and large landowners bought lots of settlers to establish farms to raising cattle. In addition, according to the authors, the rate of deforestation per lot was higher among land concentrators compared to non-concentrators, or small landowners, showing the concentration speed of deforestation lots in the Amazon (Yanai et al., 2020).

The results showed that the average co-variable for the number of oxen had the highest correlation with deforestation in three states, Pará, Mato Grosso, and Rondônia, indicating possible cattle-ranching in the southern portion of the Amazon. This phenomenon puts pressure on larger areas of forest, since the practice of cattle-ranching in the Amazon is traditionally performed extensively, where cattle are raised on the loose, requiring large extensions of pasture (Santos, 2014).

In this sense, for 2019, the data on the number of cattle generated by the Brazilian Institute of Geography and Statistics (IBGE) indicated that, among the states of the Brazilian Amazon, Mato Grosso is the one with the largest number of bovine cattle-ranching. Also, according to IBGE (2020a), the states of the Amazon region had the greatest positive variation in the number of cattle between the period of 1985–2019.

It is added to that, the record for the exportation of bovine meat, explained mainly by the Chinese demand, which was reflected in the prices of the entire chain, from the calf to the final consumer (IBGE, 2020a). That occurred due to the low stock of pork, a consequence of a plague that affected the specie, impairing an expanding domestic market, leaving China in the need to supply its domestic demand by importing animal protein. From Brazil only, this country acquired 497.7 thousand tons of beef, between the years of 2018 and 2019 (IBGE, 2020a).

Additionally, it was mentioned that the areas of small fragments of forest were facilitators of new fronts of deforestation in the Amazon, especially at the edges of the east side (Fig. 8). These areas are associated with those already consolidated in the central west portion of the country. Due to this fact, in the last 32 years, fragments of Amazonian forest ranging from 1 to 100 ha have experienced a wide range of ecological changes (Laurance et al., 2011). Laurance et al. (2011), indicated that the effects of fragmentation will probably interact synergistically with other anthropogenic reviews, such as logging, hunting, and, especially, fire, creating an even greater danger for the Amazonian biota. Silva et al. (2014) stated that the impact of fragmentation is greater in the southern portion of the Amazon Biome, since this area is drier than most of the lands to the north of this region, with fragmented seasonal semi-deciduous forests and closed by pasture, and, to a lesser extent, for agricultural crops.

The occurrence of roads also had influence on the fragmentation of forests and consequently deforestation. In this sense, Laurance et al. (2014) affirmed that the rapid proliferation of roads strongly influences agriculture, consequently, leading to newly deforested areas. Additionally, the authors assessed the distances between the roads and major deforestation fires and concluded that the largest areas were close to the roads (Laurance et al., 2014). In addition to the above, there is a cycle in the Amazon in which the roads already structured contribute to the emergence of secondary roads. Barber et al. (2014) evaluated the relationship between deforestation to the existing networks of highways, navigable rivers, and all other roads, including more than 190,000 km of unofficial roads. For the authors, most deforestation occurs closer to the main roads (Barber et al., 2014) that facilitates or schooling of agricultural production.

Thus, temporary crops, mainly of grain cultivation, play an important role in the deforestation of municipalities located in the Amazon Biome. According to CONAB (2018), the areas occupied by the main grains cultivated in the country showed growth in the municipalities of the Amazon. Thus, the expansion of the agricultural commodity still impose a considerable threat to the Amazon and Cerrado biomes (Frey et al., 2018), especially soybeans, in the state of Mato Grosso (Gusso et al., 2017), the largest Brazilian producer of this grain. For Mier and Teran (2016), in general, soy bean production in South America has become a symbol of commodity crops produced on a large scale for the agribusiness aimed at global markets. According to Garret et al. (2018), the intensification of crops occurred more quickly in the regions with shorter distances to the soy processing facilities, as is observed in the state of Mato Grosso and the extreme south of Rondônia. According to Costa Silva (2014), the advance of soy agribusiness in the Brazilian Amazon results from the process of agricultural modernization derived from the action of capital in rural areas. In the case of soybeans, the growth and consolidation of the cultivation area benefit from the guarantee of production flow to the foreign market through the Madeira-Amazonas Waterway.

The activities in the field are financed by agricultural credit (agriculture and livestock). In this study, the results revealed that the variable credit for agriculture has an influence in the deforestation. This is corroborated by the variable quantity of ox, already mentioned. Therefore, it is observed that banks' credit contributes indirectly to deforestation. Despite this, Assunção et al. (2020) stated that in 2008 the Brazilian government conditioned the granting of rural credit in the Amazon to stricter requirements as an attempt to contain deforestation. For example, Low Carbon Agriculture - ABC Program) and financial support from conservation programs (Carvalho et al., 2020) were analized. Despite this, Assunção et al. (2020) observed that the relationship between credit and deforestation can be different between municipalities with different economic activities. Furthermore, it was observed that agricultural production in Brazil has been less dependent on credit and has undergone several technological improvements, allowing the production to increase at the intensive margin (Assunção et al., 2020). In addition to that, when markets are not complete, exogenous credit variations should affect agricultural production decisions and, therefore, deforestation (Assunção et al., 2020).

5. Conclusions and recommendations

This research has revealed the spatial variability of the causes for deforestation in the Amazon Biome, in Brazil, occurred in the last decade (2010–2019). Thus, through the results it is possible to conclude that:

1. The municipalities with the largest deforested areas form a cluster in the southern portion of the Amazon, which is known as the arc of deforestation;
2. In general, the co-variables do not present strong correlations with each other, avoiding multicollinearity problems;
3. The ajusted R^2 with the Geographical Weighted Regression (GWR) was 0.96, that is, the GWR model explains 96% of the variations in deforestation. Therefore, there is a significant gain when using the GWR model compared to the Ordinary Least Squares (OLS) model, in which the R^2 value was 0.77.
4. It was found that the estimated coefficients for the variables Forest, Cattle, Crops, Wood and AgriCredit were positive, that is, there is a positive association with the average of the areas deforested by the municipality; In addition, the co-variable average of the number of oxen, presented the greatest correlation with deforestation;
5. From the analysis of spatial variability, it was concluded that the highest values for R^2 were found mainly in the states of Pará, Amazonas (southern portion), Mato Grosso (northern portion), Acre, and Rondônia, reinforcing that deforestation is consolidated in the deforestation arc.

For future studies, an analysis of co-variables that are related to the land structure in the Amazon Biome and that compose the Rural Environmental Register (CAR), which is a database still under construction in Brazil, is recommended. Additionally, specialized studies on the impact of rural credit, for livestock and agriculture, on deforestation are recommended for future researches. This has a great importance since past studies have pointed out that agricultural credit can help reduce deforestation, a reality that is not observed in this study. It was observed that the AgriCredit co-variable showed a positive association with the average of the areas deforested by the municipality.

Credit author statement

Alex Mota dos Santos: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing. Carlos Fabrício Assunção da Silva: Conceptualization, Methodology, Software, Data curation, Writing- Original draft preparation, Supervision, Software, Validation, Writing- Reviewing and Editing. Pedro Monteiro de Almeida Junior: Conceptualization, Methodology, Software, Software, Validation. Anderson Paulo Rudke: Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing. Silas Nogueira de Melo: Data curation, Writing- Original draft preparation, Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2021.113020.

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