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The influence of rural credit on the conservation of the Amazon biome

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ABSTRACT
The advance of deforestation in the Amazon concerns society, while rural credit stimulates agricultural activity in the region. This study investigates the main drivers of deforestation and analyzes the effects of rural credit restrictions in the Amazon biome, as well as their potential to promote sustainability. Using the Geographically Weighted Regression (GWR) method for 2021, the results show that, in most municipalities, the relationship between deforestation rates, rural credit amounts, and cattle numbers was negative. This suggests that these variables contribute to forest preservation and highlights the effectiveness of Resolution 3545, which limits financial resources for agriculture linked to deforestation. In some areas, rural activities are supporting environmental preservation through the adoption of sustainable and organic farming practices. As a future research direction, the study recommends extending the time frame to capture long-term effects.

KEYWORDS
Deforestation, Sustainability, Preservation

A influência do crédito rural na conservação do bioma amazônico

RESUMO
O avanço do desmatamento na Amazônia preocupa a sociedade, enquanto o crédito rural estimula a atividade agropecuária na região. Por isso, este estudo investiga os principais determinantes do desmatamento e examina os impactos das restrições ao crédito rural no bioma amazônico, bem como seu potencial para promover a sustentabilidade. Utilizando o método de Regressão Geograficamente Ponderada (RPG) para o ano de 2021, os resultados mostram que, na maioria dos municípios, a relação entre as taxas de desmatamento, os volumes de crédito rural e o número de cabeças de gado foi negativa. Isso sugere que essas variáveis contribuem para a preservação florestal e explicita a efetividade da Resolução nº 3.545, que limita os recursos financeiros destinados à agropecuária associada ao desmatamento. Assim, em algumas áreas, as atividades rurais têm contribuído para a preservação ambiental por meio da adoção de práticas agrícolas sustentáveis e orgânicas. Como direcionamento para pesquisas futuras, recomenda-se a ampliação do recorte temporal a fim de captar efeitos de longo prazo.

PALAVRAS-CHAVE
Desmatamento, Sustentabilidade, Preservação

JEL CLASSIFICATION
Q18, Q23, Q56

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1. Introduction

In 2021, an area of 5,238 square kilometers (km²) was deforested in the state of Pará, located in the central region of the Amazon biome. The main cause of forest reduction is agriculture, characterized by cattle husbandry and soybean cultivation, which demand territorial expansion. As a consequence, deforestation reduces the availability and quality of water, climate change, and loss of biodiversity. These impacts have sparked increased interest in protecting forests (INPE – Instituto Nacional de Pesquisas Espaciais, 2022).

Deforestation in the Amazon biome has been a topic of debate in the scientific community, which analyzes the ecosystem threat imposed and the potential unsustainable effects, highlighting, for example, the practice of illegal logging. In addition, other elements, such as agricultural prices and public policies, influence deforestation rates in the region. Although there are negative effects such as the reduction of biological diversity, it is important to note that deforestation can provide economic growth and increase the income of the region's inhabitants through agriculture. To resolve this dichotomy, sustainable production methods can be used, such as organic extractivism, which exploits natural resources without significantly altering the natural state of the forest (Celentano et al., 2018; Ferreira e Coelho, 2015; Oliveira et al., 2011; Ticktin, 2004).

Some governments have tended to reduce deforestation through environmental policy actions, the presence of Non-Governmental Organizations (NGOs), and the implementation of government measures. On the other hand, liberal governments, by guaranteeing individual land rights, end up encouraging uncontrolled forest exploitation. As a result, there are global efforts to protect countries' forests, regardless of the environmental policy adopted, due to the negative effects of reducing forests, such as an increase in global temperatures and the consequent reduction in glaciers. However, estimates of the advantages and disadvantages of deforestation are unreliable when structural factors such as economic development, population density, initial forest area, and international agricultural prices are not considered. Therefore, the economic effects of flora exploitation need to be considered (Wehkamp et al., 2018; Motel et al., 2009).

In this context, access to rural credit can boost deforestation, benefiting farmers who want to replace natural vegetation with crops and make room for animal husbandry. In Brazil, in 2008, a legislative condition was established for access to rural credit aimed at curbing deforestation. Brazil Central Bank's Resolution 3545 defined, through environmental regulation, the criteria for loans of rural resources in the Amazon region. Its purpose was to mitigate the advance of agriculture into the Amazon biome by determining compliance with the productive sustainability criteria to obtain the resources. This gave rise to the opportunity to use rural credit for environmentally beneficial activities, which also benefit farmers, such as pasture recovery (Assunção et al., 2020; Feltran-Barbieri e Féres, 2021).

It is important to note that, even with legal incentives, sustainable development can entail costs, including the need to open new roads and establish rules on property rights and population growth. Despite the challenges associated with such issues, sustainable economic growth can be achieved. The scope of organic production, for example, demonstrates how it is possible to unite financial prosperity with environmental conservation (Jusys, 2016; Saraiva et al., 2020).

Based on the premise that rural credit positively influences sustainable farming in the Amazon, this study sought to answer the following research question: What impact does rural credit have on the productive sustainability of agriculture in Amazon municipalities, particularly concerning environmental preservation? This inquiry addresses the challenge of balancing economic growth from farming with the conservation of the Amazon biome. To answer this question, Geographically Weighted Regression (GWR) was used to identify the effects of the variables in each municipality.

This study provides evidence on the spatially heterogeneous determinants of deforestation in the Amazon biome. It emphasizes local variations in the influence of rural credit on forest loss rates. Importantly, the findings underscore the effectiveness of Brazil's Resolution 3545/2008, which restricts rural credit linked to deforestation, demonstrating its potential to foster environmentally sustainable agricultural practices. Furthermore, the results reveal that rural credit can, under certain conditions, contribute to forest preservation rather than degradation, challenging conventional views in the literature. Collectively, these contributions strengthen the understanding of how credit policy and agricultural dynamics interact with environmental outcomes and illuminate the relevance of designing spatially differentiated public policies for sustainable development in the Amazon.

The research is divided into five stages. The first is composed by the introduction, followed by the theoretical background, which is presented in the literature review. The third section presents the materials and methods used. The discussion of the results is contained in the fourth section and, finally, it closes with final considerations and recommendations for possible extensions of this research in the future.

2. Theoretical foundation

2.1 Economic studies on deforestation

The literature addressing the relationship between governance and deforestation reduction reveals a variety of results, including positive, inconclusive, and negative findings. In a study conducted by Wehkamp et al. (2018), the researchers investigated the level of governance, and the specific measures adopted by governments. The authors identified that weak governments, characterized by coalitions that prioritize private rights and democracy, are associated with a higher incidence of deforestation.

This finding highlighted the difference in how central agents carry out public administration, suggesting that political contexts can influence environmental outcomes.

Governance can influence not only deforestation but also foreign trade policies. In the Brazilian context, the country is one of the world's leading beef producers and exporters. The activity of slaughtering cattle is directly linked to international prices, and rising prices encourage the expansion of the number of cattle in the country. As evidenced by studies such as Zu Ermgassen et al. (2020), Brazilian beef exports are identified as one of the main drivers of deforestation in the Amazon biome. The interaction between economic, environmental, and trade factors highlights the need for integrated approaches to deal with the environmental challenges associated with agricultural production and international trade.

Among the factors that can cause deforestation, agriculture stands out as one of the main ones, since, just like the international demand for meat, the cultivation of some crops requires physical space. In developing countries, the increase in demand for agricultural products is often perceived as an opportunity to increase the amount of foreign currency entering the country. In this context, regions of native forest are sought after for the expansion of agricultural production, as is the case in the Amazon. Although there are efforts to maintain virgin forests, economic conditions discourage nations from restricting rural activities, highlighting the difficulties related to environmental preservation in the face of income generation (Leblois et al., 2017).

The study by Pfaff et al. (2015) addresses the association between economic development and pressure on land use, emphasizing that protected areas face less incentive to deforest due to the legislation associated with these regions. It also emphasizes that areas close to highways and urban centers are more susceptible to exploitation. Generally, locations that facilitate transportation and reduce costs are often the first to be exploited, as noted by Souza-Rodrigues (2019). The author highlights policies that impose restrictions on land use as part of the effort to combat deforestation, stressing the selection of strategic points, such as areas of closed forest, which facilitate control and inspection. In this way, regulatory measures aimed at promoting sustainability and mitigating the environmental impacts of economic development appear to be effective, although they do not quite represent reality.

Climate change, one of the main concerns related to deforestation, has attracted global attention and worried nations. In Brazil, changes in the Amazon rainforest directly impact the population's quality of life, as pointed out by Balboni et al. (2023). The authors emphasized that the issue of deforestation in developing countries, along with its externalities such as increased pollution and reduced social welfare, has gained prominence in economic literature. An illustrative example is provided by the study by Prem et al. (2020), which revealed how the end of the war in Colombia favored the reduction of deforestation in the Amazon region of the country. It states that socioeconomic, political, and environmental interactions are linked to the context of tropical forests.

The landscape of Brazilian agriculture, predominantly under the control of multinational corporations, shows a concentration of the market in a few companies. This centralization results in the unequal distribution of rural credit, with a low proportion going to rural families who promote sustainable cultivation to a greater extent. Consequently, agroecology has emerged as an alternative for agricultural activities, without the need for deforestation, as highlighted by (Santos et al., 2014). In addition, data presented by Medina e Santos (2017) revealed that less than 20% of the rural credit contracted is directed to rural families, which limits the dissemination of more sustainable practices in areas of deforestation. Finally, it is possible to avoid or reduce deforestation by encouraging family farming participants through credit.

2.2 Rural credit and deforestation

Different methods have been applied to the issue of deforestation, such as the study by Assunção et al. (2020). The study investigated the impact of restrictions on access to rural credit in 2008 when it became more difficult to access rural credit lines for activities related to deforestation. In their research, they used a spatial panel of differences in differences for the period from 2003 to 2011, covering all the municipalities in the Legal Amazon. The results indicated that these requirements were effective in reducing the advance of deforestation by restricting one of the main supports for Brazilian agriculture.

In Brazil, there are degraded pastures due to technical inefficiency in soil maintenance. Recovering these pastures can result in reforestation, making it possible to restore the forest. According to Feltran-Barbieri e Féres (2021), this process is advantageous for both farmers and policymakers, as the land and forest will be recovered and can help increase income in the future. To verify these local economic gains, non-degraded pastures were estimated using the Spatial Error Model (SEM), again using a spatial model.

Another study that used spatial econometric methods to assess the local variability of predictor terms using GWR was carried out by Trigueiro et al. (2020). The biome investigated was the Cerrado, which has high rates of deforestation similar to the amazon. deforestation was associated with socio-economic, environmental, and structural factors on a regional scale. Thus, similar patterns of behavior were observed in the localities, with rural credit being identified as the main driver of deforestation in the northeast of the Brazilian Cerrado. It was concluded that public policies should focus on specific biomes and consider the differences between regions and their specificities.

For Santos et al. (2021), GWR has been used to identify deforestation clusters in the Amazon biome. Fourteen variables were strategically selected, explaining 96% of the phenomenon, including the number of cattle, the Gross Domestic Product (GDP) per capita, the estimated population, rural credit, and the extent of conserved forest. The variable that most influenced the dependent term was the number of cattle, forming a cluster of municipalities to the south of the selected area. However, some variables showed collinearity due to the transmission of similar information. Finally, an arc of deforestation was identified in the south of the biome, demonstrating the effectiveness of the GWR.

The use of spatial and econometric methods for analyzing socioeconomic and environmental phenomena has become increasingly relevant and widespread. Sass et al. (2016) employed spatial techniques, including Spatial Autoregressive (SAR), Spatial Error Model (SEM), Spatial Durbin Model (SDM), and Geographically Weighted Regression (GWR), to investigate the determinants of homicide rates in municipalities across Paraná, Brazil. They emphasized impacts from socioeconomic variables such as poverty rates and urbanization, underscoring the relevance of spatially targeted public policies. In another context, Silva e Arruda (2020) analyzed the effects of rural credit on agricultural labor markets in Brazilian states using Panel Vector Autoregression (PVAR). Their findings indicated a positive effect of rural credit on real wages, while the impact on employment was heterogeneous - positive in the labor - intensive agriculture regions of the North and Northeast and negative in the more capital - intensive regions. Lastly, Gonçalves e Ferreira (2024) applied Seasonal Autoregressive Integrated Moving Average (SARIMA) models to predict deforestation alerts in the Legal Amazon. They identified structural breaks and stochastic seasonality, demonstrating that their proposed model could provide accurate and valuable forecasts to support the formulation of preventive public policies. These studies exemplify how spatial and econometric approaches enhance the understanding and formulation of policies across regional and environmental contexts.

Similar results to those found by Santos et al. (2021) were observed in the research by Jusys (2016). The author also used the GWR method, although, for a wider region, the Legal Amazon covers part of the Brazilian Cerrado. In an alternative study, Saraiva et al. (2020) tried to identify ways of regenerating forests. To do this, they used a panel estimated by the Generalized Method of Moments (GMM), which found that fines for improper land use help to combat deforestation. Corroborating the findings of Saraiva et al. (2020) a panel regressed by double-difference was applied by Cisneros et al. (2015), as well as in Assunção et al. (2020). This shows that land enforcement, environmental registration campaigns, and restrictions on rural credit reduce deforestation.

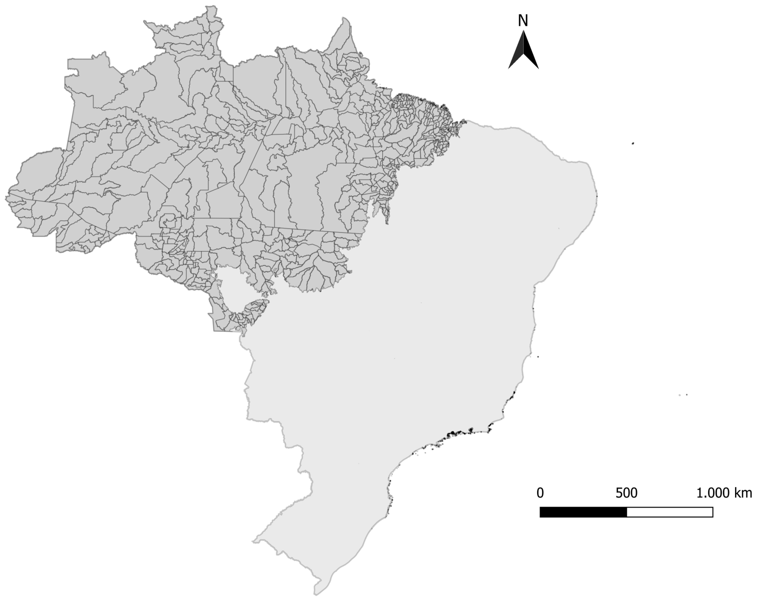
Unlike prior investigations, this research offers novel empirical evidence by employing the GWR framework within the Amazon biome, concentrating on the significance of rural credit as a factor influencing deforestation across various municipalities. By undertaking this approach, it reveals spatial heterogeneities that are frequently neglected by global or panel-based methodologies and illustrates that rural credit may, under certain circumstances, facilitate forest conservation rather than exclusively instigate deforestation. This constitutes a scholarly contribution as it contests the prevailing assumption that the expansion of credit is invariably linked to environmental degradation.

3. Materials and Methods

3.1 Descriptive data analysis

For this study, the 559 municipalities that compose the Amazon biome were selected, as shown in Figure 1. These municipalities are distributed across the states of Acre, Amazonas, Roraima, Rondônia, Mato Grosso, Pará, Amapá, Maranhão, and Tocantins. It is important to note that due to the significant presence of the Cerrado biome in Maranhão and Tocantins, as well as Mato Grosso's coverage of the Amazon, Cerrado, and Pantanal biomes, some areas in these three states were excluded from the study.

Figure 1. Municipalities in the Amazon biome



Source: made by the authors based on IBGE data.

Data were collected from various sources with different units of measurement, as described in Table 1. Monetary variables were adjusted to December 2021 using the Extended National Consumer Price Index (IPCA), provided by the Brazilian Institute of Geography and Statistics (IBGE). Free-access programs such as GeoDa, QGIS, and RStudio were used to display the information and apply the methods.

Also in Table 1, the values of the explanatory variables for each municipality were divided by the number of inhabitants, to remove any possible bias due to the geographical size of the location. On the other hand, the forest deforestation rate was obtained by considering the percentage change in deforestation in the Amazon biome between 2020 and 2021. In addition, the information on the regressors was collected for the year 2021 because it represents the most recent period when these data were updated. Finally, to reduce the variance of the observations, the natural logarithm was applied to all independent terms.

Table 1. Description of the variables chosen

Variable	Description	Measure	Source
def	deforested area rate	%	National Institute for Space Research (INPE)
credit	Credit contracted for rural funding and investment activities	R$	Brazil Central Bank (BCB)
corn	Corn harvested by municipality	Tons	Institute for Applied Economic Research (IPEA)
soy	Soybeans harvested by municipality	Tons	Institute for Applied Economic Research (IPEA)
cattle	Head of cattle per municipality	Unit	Brazilian Institute of Geography and Statistics (IBGE)
flo	Forest area per municipality	Km^2	National Institute for Space Research (INPE)
nflo	Non-forest area by municipality	Km^2	National Institute for Space Research (INPE)
hid	Area covered by water per municipality	Km^2	National Institute for Space Research (INPE)

Source: made by the authors.

The deforestation rate, represented by *def*, reflects the space in kilometers where natural vegetation was removed. This was selected as the dependent term because the aim was to identify the factors that influenced the reduction of the Amazon rainforest, similar to the regressor used by Santos et al. (2021). *Credit*, or rural credit, is a widely used regressor in the literature, also adopted by Santos et al. (2021), Trigueiro et al. (2020), and Assunção et al. (2020). It was expected that the monetary values directed to rural activities would stimulate deforestation, as agriculture is known for using natural resources. Therefore, a positive relationship between rural credit and deforestation in the Amazon was assumed. Both *corn*, tons of corn, and *soy*, tons of soy, were included because they are important representatives of Brazilian agriculture and crops in the region. Given that both require space for cultivation, a positive effect on deforestation was expected. While Santos et al. (2021) and Trigueiro et al. (2020) considered agricultural products in aggregation, in this investigation we chose to separate the two main crops to capture different effects.

The number of head of cattle, *cattle*, is another independent term common in the literature. Cattle husbandry is stimulated by international prices and currency devaluation, which benefits exports. This gives farmers the incentive to expand their herds in search of greater income, making the Amazon region an attractive target. The number of cattle has been included in some other studies as a possible factor causing deforestation, including Assunção et al. (2020), Feltran-Barbieri e Féres (2021), Trigueiro et al. (2020), and Santos et al. (2021), demonstrating its relevance in this approach.

What is new, the variables *flo*, forest area, *nflo*, non-forest area, and hid, area covered by water, were not mentioned in the base literature for this research. Based on this, a positive impact was anticipated for *flo*, considering that a greater extent of forest could suggest greater potential for deforestation. On the other hand, an opposite effect was predicted for *nflo*, based on the assumption that a smaller number of available trees would result in a lower level of deforestation. Finally, a negative relationship between *hid* and *def* was expected, following the same reasoning as for *nflo*, since greater water cover can limit the land's capacity for agricultural use. The purpose of looking at *nflo* was to discover any relationship between the percentage of area deforested and the municipalities' water resources, such as lakes and rivers.

3.2 Spatial Autocorrelation

Before analyzing the local effects using the GWR, the existence of global autocorrelation was verified using the Global Moran's I, a minimum condition to enable spatial inference, since the areas must influence each other, indicating autocorrelation. As Anselin (1995) described, described in spatial statistics, the spatial weighting matrix of dimension n by n must be defined before applying the algorithm. The spatial weight W_{ij} indicates the degree of connectivity between locations i and j. according to some geographical or socio-economic criterion. Defined according to the contiguity and distance between the locations, the geographical basis was chosen because we were working with municipalities. Due to the arrangement of the locations in space, the queen contiguity matrix was used as it considers the vertices to be continuous (Almeida, 2012).

Once the weight matrix was defined, Global Moran's I was applied. According to (Moran, 1948), Global Moran's I is a spatial autocorrelation coefficient that measures the autocovariance of cross-products and is expressed as:

$$I = \frac{z'Wz}{z'z} \tag{1}$$

where $z'Wz$ represents the spatial autocovariance of the standardized variable of interest, z denotes the values of this standardized variable and Wz indicates the mean values of the neighbors of the standardized variable of interest, defined by the spatial weighting matrix W. The index number found, I ranges from -1 to 1. The closer to positive unity, the greater the positive autocorrelation, while the closer to negative unity, the greater the negative autocorrelation. Unlike the classic correlation coefficient, an absence of spatial correlation does not correspond to a value of zero, except when n tends to infinity. Instead, it is represented by $-1/(n-1)$ when the sample size n is finite, as noted by (Chasco e Vallone, 2023).

3.3 Understanding the Geographically Weighted Regression model

As we wanted to verify the causes of deforestation in the Amazon biome by municipality, focusing on the selected variables, we opted for the GWR method to understand the dynamics of deforestation. The concept of GWR was first introduced by Goodchild e Longley (1987) during a congress. On this occasion, they discussed the potential of using geographic information systems for spatial data and emphasized the importance of considering the heterogeneity of regressions, outlining the basic principles of GWR and its applications.

GWR was defined by Fotheringham et al. (2023) and Brunsdon et al. (1996), Equation (1). For each specific location i, the GWR model can be written as:

$$y_i = \beta_{0i} + \sum_{j=1}^{p} \beta_{ji} x_{ji} + e_i \tag{2}$$

where y_i is the response variable for location i, β_{0i} is the intercept that varies spatially in i, β_{ji} is the regression coefficient of the predictor variable j at location i, x_{ji} is the value of the predictor variable j at location i and e_i is the error term for the location i.

For Almeida (2012), GWR creates a succession of linear regressions, estimated for each location, using distance-weighted subsamples. Weights are added to the observations based on a reference point known as the calibration point, and the closer the observation is to this reference, the greater its importance. From Equation (2), the local coefficients can be estimated as:

$$y_i = \beta_0(u_i, v_i) + \sum_{j=1}^{p} \beta_{ji}(u_i, v_i) x_{ji} + e_i \tag{3}$$

where (u_i, v_i) represent the coordinates of point i in space, and $\beta_{ji}(u_i, v_i)$ the local coefficient i. The error term, e_i, follows a normal distribution with zero mean and constant variance. In this way, GWR generates a coefficient for each region i from the distance of the focal point on which the regression is based.

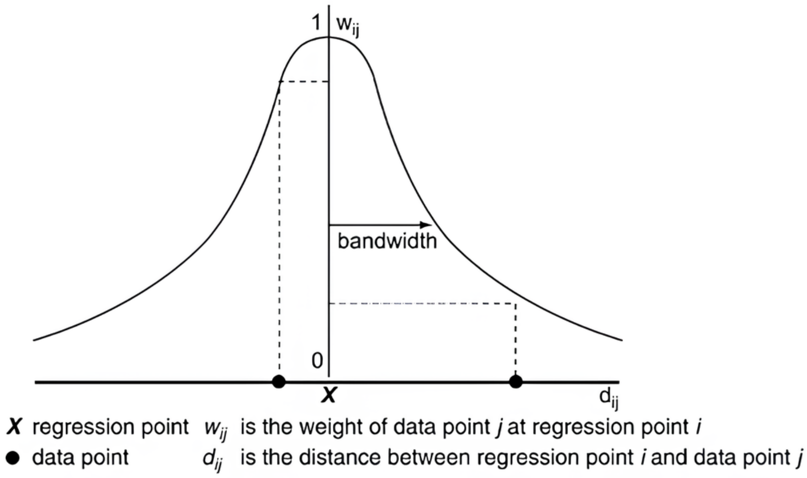
A distinct feature of GWR, the bandwidth, focuses on smoothing the local coefficients. The wider the bandwidth, the greater the smoothing of the local coefficients, because more observations will be selected around the calibration point. In other words, the smaller the band, the greater the heterogeneity in the results, because fewer observations will be used around the reference, Figure 2 represents this idea.

The technique uses a weighting function, Equation (3), which is used to assign higher weights to nearby observations and lower weights to distant observations. The weight assigned to each observation is typically defined using a kernel function, the observation j concerning the location i is given by the Equation (4):

$$W_{ij} = K\left(\frac{d_{ij}}{h_i}\right) \tag{4}$$

where $K(\cdot)$ is the kernel function, d_{ij} is the distance between the location i and observation j, h_i is the bandwidth parameter for the location i which determines the size of the local neighborhood.

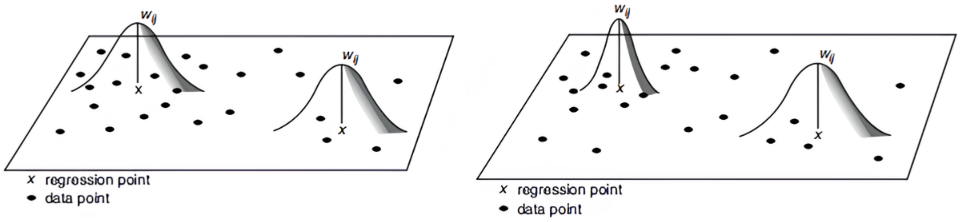
Figure 2. Representation of the bandwidth of a GWR



Source: adapted by the authors based on Fotheringham et al. (2002).

They can be fixed-band or adaptive, and the class that most closely matches the data must be selected. For this reason, the fixed kernel function can be redundant depending on the subsample and is commonly applied in data-dense regions, considering the high number of observations for calibration. The fixed kernel is inefficient in regions where data is scarce and may be smaller than necessary for the calibration of local coefficients. In contrast, the adaptive kernel expands in areas where observations are scarce and shrinks in areas where observations are abundant, i.e., in regions of high data density. The difference between the band types is shown in Figure 3 (Fotheringham et al., 2023).

Figure 3. Fixed and adaptive kernel function band



Source: adapted by the authors based on Fotheringham et al. (2002).

The bandwidth h_i is crucial in GWR, as it determines the spatial extent of the location for each observation. Some methods can be used to select an appropriate bandwidth, such as the Akaike Information Criterion (AIC) or Cross Validation (CV). The procedure is estimated separately for each location, allowing the regression coefficients to vary spatially, and providing information on how the relationships between the variables change in space according to the selected cut-off. Local models are then estimated based on the chosen bandwidth and spatial weighting function. Nonetheless, while Geographically Weighted Regression (GWR) constitutes a compelling empirical methodology, it possesses significant constraints that warrant consideration, including its susceptibility to the selection of kernel type and bandwidth, alongside the impact of outliers, which could jeopardize the consistency and interpretation of the derived results.

3.4 Empirical model

Almeida (2012) argues that GWR estimates each area using distance-weighted subsamples by generating a sequence of linear regressions. It is said that the weights assigned to individual observations are based on a focal point, and the influence of the observations decreases the further away they are from this reference. The representation of the estimated equation, Equation (5):

$$\begin{aligned}\text{def}_i = {} & \beta_0(u_i, v_i) + \rho(u_i, v_i)\text{def}_i^* + \beta_1(u_i, v_i)\text{credit} + \beta_2(u_i, v_i)\text{corn} \\ & + \beta_3(u_i, v_i)\text{soy} + \beta_4(u_i, v_i)\text{cattle} + \beta_5(u_i, v_i)\text{flo} + \beta_6(u_i, v_i)\text{nflo} \\ & + \beta_7(u_i, v_i)\text{hid} + \varepsilon_i\end{aligned} \tag{5}$$

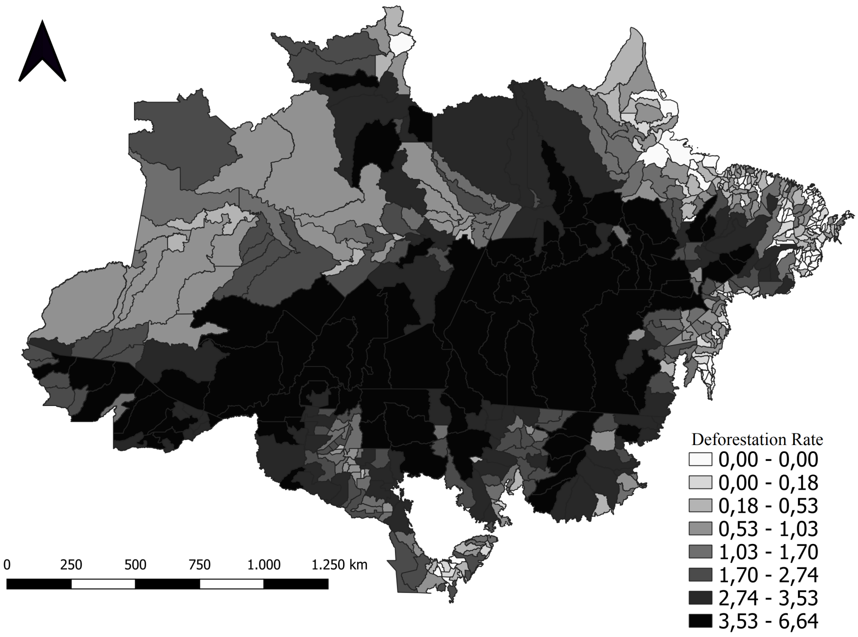
where the term (u_i, v_i) represents the coordinates in the space of location i, def_i^* represents the average deforestation rate of the 10 municipalities closest to i, ε_i is the random error term, and ρ, β_1, β_2, β_3, β_4, β_5, β_6, and β_7 are the coefficients to be estimated.

4. Results and Discussion

4.1 Deforestation area

Before statistical inference, we need to understand the distributional dynamics of deforestation in the Amazon biome. The regression, the deforestation rate by location, is shown in Figure 4. The municipality of Altamira, the only one in the category with 6.64% deforestation, is located in the state of Pará and represents the largest deforested area. It is also possible to see that the regions with the highest rates are concentrated in the central areas of the Amazon biome, with less forest exploitation occurring on the frontiers. According to IBGE – Instituto Brasileiro de Geografia e Estatística (2023), Altamira is prosperous in agriculture and, in 2021, had almost one million head of cattle in its territory. In conclusion, the group that begins in the west of Maranhão and the south of Pará and runs west to the states of Mato Grosso, Rondônia, and Acre, is known as the deforestation belt and stands out as the area with the highest level of deforestation in the entire region, as Domingues e Bermann (2012) say.

Figure 4. Distribution of the deforestation rate by municipality in the Amazon biome



Source: made by the authors based on INPE data.

Having understood the focus of deforestation, the GWR was used to find the significance of the regressor terms in each municipality, considering the deforestation rate as the dependent term, since the results can differ considerably depending on the location. For this reason, GWR was selected to explain the degree of influence of the explanatory terms on the deforestation rate in the Amazon biome. Nevertheless, it is important to recognize that deforestation in Brazil may involve interconnected and spatially interdependent dynamics between the Amazon and the Cerrado biomes. The advance of deforestation in the Cerrado, studied by Trigueiro et al. (2020), may be related to the deforestation in the Amazon.

4.2 Adherence to the Geographically Weighted Regression method

In the test that checks for global spatial autocorrelation, the null hypothesis is spatial randomness. Based on this, the null hypothesis points to spatial autocorrelation, since the calculated value is higher than the tabulated value, as shown in Table 2. The verification was carried out using the residuals of a regression estimated by Maximum Likelihood (ML). According to Almeida (2012), ML or the Generalized Method of Moments (GMM) is preferable to the Ordinary Least Squares (OLS) estimation method when there is spatial correlation in the data. Finally, as the coefficient found was

0.5866, spatial autocorrelation is positive, indicating that municipal interactions occur positively in the global context.

Table 2. Summary of the results of the Global Moran's I test

	Global Moran's I	Expectations	Variance
Values	0.5866***	-0.0095	0.0007

Source: made by the authors.
Legend: "*" = 10%; "**" = 5%; "***" = 1%.

Although some of the variables used in this study have already been used in other studies, it was still necessary to check their quality in the proposed model. To this end, the Variance Inflation Factor (VIF) was used to identify the presence of multicollinearity, as shown in Table 3. It was observed that no regressor exhibits problems of high collinearity. It is interesting to note that the terms related to the quantity of corn produced, *corn* and soybeans, *soy*, showed higher values in the test, but do not indicate a problem of collinearity. In addition to testing for collinearity, a potential endogeneity issue among the variables was also examined. To this end, the Hausman test for endogeneity, as outlined in Wooldridge (2010), was applied. The null hypothesis could not be rejected, indicating that the model does not exhibit the presence of endogenous variables.

Table 3. Global Variance Inflation Factor (VIF)

Variables	**VIF**
credit	1.169531
corn	5.628415
soy	5.555475
cattle	1.450330
flo	1.327409
nflo	1.053562
hid	1.283648

Source: made by the authors based on the survey results.

To assess the quality of the variables studied, some descriptive information is shown in Table 4. The range, mean, and standard deviation indicate the quality of the research data for statistical inference, which seeks to provide information that represents reality. Good adherence is seen in the low mean and standard deviation, as well as the amplitude, where only rural credit showed a high maximum value compared to the other regressors, as did the mean and standard deviation. Most of the terms had a minimum value of zero, attributable to their inherent characteristics that preclude negative values. In conclusion, the variables demonstrate suitability for applying the proposed method.

Table 4 provides an overview of the dataset and allows for an initial assessment of its adequacy for statistical inference. That said, the variables display a range of values, reflecting the heterogeneity of the units under study. For instance, rural credit exhibits a high mean of R$ 3,854.16 million, accompanied by substantial variability, as indicated by the amplitude between its minimum, zero, and maximum, 210,876.33 million. This emphasizes the unequal distribution of credit across the sample. In contrast, the deforestation variable shows a much lower mean value of 1.56%, with a relatively narrow dispersion, suggesting that most observations remain close to the lower bound. Agricultural production variables such as corn, soy, and cattle also display high dispersion, with means of 51,767 tons, 57,717 tons, and 141,571 units, respectively, but with maximum values that underline the concentration of production in specific areas. Similarly, the land use variables, *flo*, 5,504.81 km^2, *nflo*, 506.90 km^2, and *hid*, 185.91 km^2, show notable variation, consistent with the structural differences in territorial composition across the regions studied. Overall, it indicates that while certain variables, e.g., deforestation, are relatively homogeneous, others such as credit, corn, soy, and cattle reveal heterogeneity.

Table 4. Descriptive data analysis

Variables	**Minimum**	**1st Quartile**	**Median**	**Mean**	**3rd Quartile**	**Maximum**
def (%)	0.00	0.18	1.03	1.56	2.74	6.64
credit (R$ - Millions)	0.00	0.00	134.87	3,854.16	2,091.26	210,876.33
corn (ton)	0.00	51.00	469.00	51,767.00	6,328.00	3,182,321.00
soy (ton)	0.00	0.00	0.00	57,717.00	7,251.00	2,111,961.00
cattle (un.)	15.00	11,902.00	64,781.00	141,571.00	178,277.00	2,468,764.00
flo (km^2)	0.00	76.55	568.80	5,504.81	4,279.55	142,657.20
nflo (km^2)	0.00	0.20	39.80	506.90	305.00	16,957.50
hid (km^2)	0.00	0.00	11.00	185.91	94.45	4,500.20

Source: made by the authors based on the survey results.

After ML estimation, the optimum number of neighbors for each location, also known as the bandwidth, was determined before GWR was applied. This was defined using the kernel function and can be fixed or adaptive. In the case of a fixed configuration, sampling is regular, while in the case of an adaptive configuration, the distributive format is irregular. In Table 5, adherence was tested based on Cross Validation (CV) and the Gaussian Kernel (G), according to the test formulated by Leung et al. (2000), in which the lowest score indicates the appropriate model. Therefore, the outputs in Table 5 show that the bandwidth best suited to the data is the Adaptive Gaussian Kernel, i.e., the bandwidth will be greater in areas of sparse observations and smaller in dense ones.

Table 5. Band choice test for GWR

Method	**Kernel**	**Type**	**RMSE / AIC**
CV	Gaussian	Adaptive	0.8604
CV	Bisquare	Adaptive	0.9008
CV	Gaussian	Fixed	0.8773
CV	Bisquare	Fixed	0.9958
AIC	Gaussian	Adaptive	1,540.59
AIC	Bisquare	Adaptive	1,465.62
AIC	Gaussian	Fixed	1,410.68
AIC	Bisquare	Fixed	1,621.78

Source: made by the authors based on the survey results.
Legend: RMSE = Root Mean Square Error.

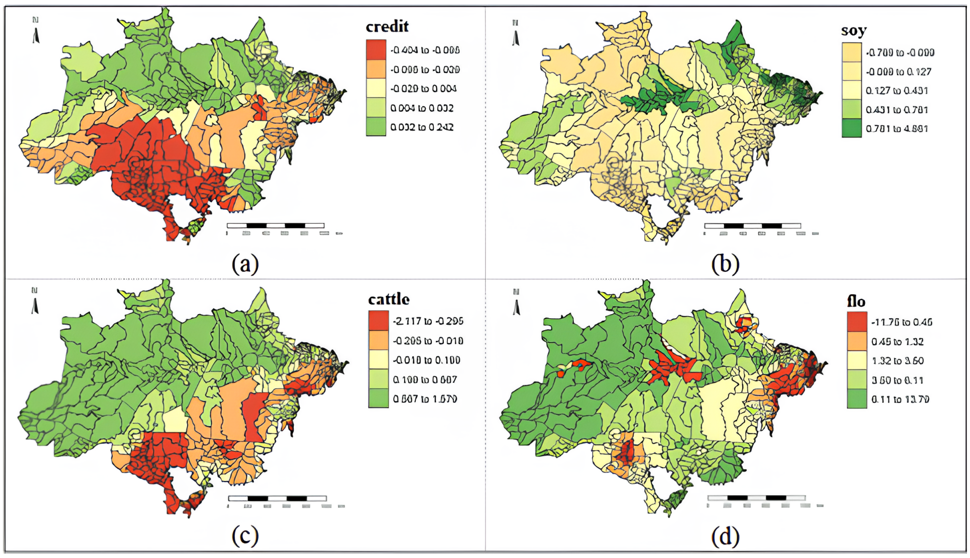
Once the model has been estimated using ML and GWR, Leung et al. (2000) propose another test to check the quality of GWR compared to ML. The Residual Sum of Squares (RSS) is compared between the two proposals, with the lowest value indicating the preferable regression model. An RSS of 206.193 was identified for GWR and 1084.833 for ML, indicating that GWR is favored. In addition, the significance of the F-test at 1% confirms that there is a statistical difference between the procedures. Thus, it can be said that GWR is more adherent to the data. Furthermore, in the significance test of the variance of the GWR regressors, only *credit*, *soy*, *cattle*, and *flo* are statistically relevant for estimating deforestation in the Amazon biome, which is why only these were analyzed.

4.3 Estimated coefficients

The results of the GWR showed that the explanatory variables of *credit*, *soy*, *cattle*, and *flo* were the only ones that were statistically significant in explaining the deforestation rate in the Amazon biome. Therefore, the inference was made around these regressors. Starting with rural credit loans in Figure 5 (a), a term also used by Assunção et al. (2020), it can be seen that in most of the observations, the coefficients are negative. This shows an inverse relationship between the deforestation rate and the level of rural loans taken out, i.e., *credit* has been contributing negatively to deforestation, and the higher the value of loans taken out, the lower the deforestation rate. This finding is in line with Assunção et al. (2020); on this occasion, the authors identified a reduction in the use of rural financing lines for deforestation activities. Thus, the positive effects of Resolution 3545 can be seen.

In this investigation, agriculture is represented by soybeans, which are a common crop in Brazil. Unlike *credit*, *soy* shows higher coefficients in Figure 5 (b) when compared to the cartogram (a). For the most part, the values were low, but at some points on the map, the contribution of the amount of soy produced in tons positively affected tree felling. In this sense, as highlighted by Trigueiro et al. (2020), the dynamics of deforestation in the Amazon may be similar to those in the Cerrado. For this reason, the factors that contribute to deforestation in the Cerrado may be the same as those in the Amazon, such as socio-economic, environmental, and structural factors on a regional scale.

Figure 5. Categories of estimated coefficients by significant variable



Source: made by the authors based on survey data.

Concerning the number of cattle, there were some similarities between the areas highlighted in parts (c) and (a) of Figure 5, particularly in the locations where the coefficients are negative. This suggests that, in a similar way to credit, the increase in the number of cattle is negatively associated with the advance of deforestation. One possible explanation for this result could be the difficulty in accessing rural resources, since cattle husbandry often takes place extensively in Brazil, requiring vast areas of pasture for its activity. This again highlights the effectiveness of Resolution 3545. This finding presents an opportunity, as noted by Feltran-Barbieri e Féres (2021), who emphasize the substantial amount of degraded pastureland in Brazil. Restoring these areas can contribute to reforestation and also provide opportunities for sustainable use in the future.

It is logical to say that the larger the area available for deforestation, the greater the chances of deforestation since it is impossible to deforest without land available for this activity. Despite this argument, it was possible to identify in (d) of Figure 5 some municipalities where the coefficients show negative values. This occurs in forest reserves, industrial areas, or regions where deforestation has already affected most of the municipality's territory. Regardless of the level of deforestation in a given region, some measures such as fines, awareness campaigns, and registration, as well as restrictions on rural credit, can be adopted to combat expansion over the forest, as highlighted by the authors Santos et al. (2021), Jusys (2016), Saraiva et al. (2020), Cisneros et al. (2015), and Assunção et al. (2020).

In conclusion, the results obtained by analyzing Figure 5 reveal changes in the coefficient values between municipalities. However, it is necessary to check their statistical significance, regardless of the regressors in question. Even if a locality shows a positive coefficient, it may not be statistically significant according to the criteria for statistical significance. Therefore, only regions that pass the statistical significance test are explored in the next section.

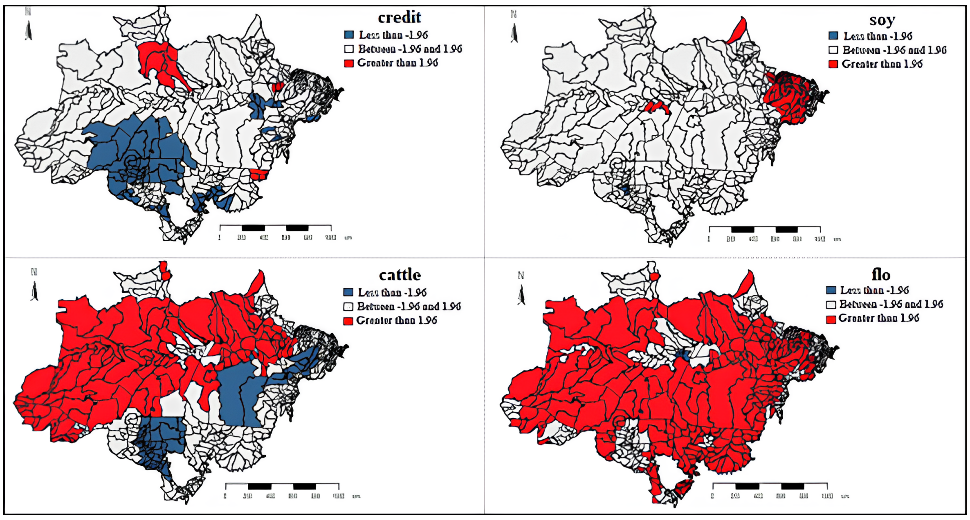
4.4 Discussion of the statistical significance of the results

Based on the coefficient values, an inference analysis was carried out on the statistical significance at 5% in each municipality. Figure 6, divided into (a), (b), (c), and (d), illustrates this relationship using the t-test, highlighting the groups that are significant with negative and positive coefficients and where there was no significance.

Regarding *credit*, most municipalities that showed significant values in (a) exhibited a negative relationship with rural credit, indicating that financing for agricultural activities is not contributing to deforestation. However, there are smaller clusters where the relationship remains positive, suggesting that Resolution 3545 has some benefits, though not without limitations. Consequently, the restrictive policy should be maintained or even strengthened.

In the context of *soy*, (b), it was observed that the locations where the coefficients positively influence the deforestation rate are located in the northeast of the Amazon biome, close to the Cerrado. In this way, soybean cultivation is seen as a factor that contributes positively to deforestation. This observation is in line with previous studies that have looked at both the Legal Amazon region and the Cerrado, such as the works by Assunção et al. (2020), Feltran-Barbieri e Féres (2021), and Trigueiro et al. (2020).

Figure 6. Cartograms of the significance test by municipality



Source: made by the authors based on the survey results.

Cattle husbandry has been shown to have a positive influence on the deforestation of the Amazon biome in part of the municipalities in Figure 6 (c); however, the coefficients are negative in the range where deforestation occurs most intensely. This observation suggests that, despite the significant presence of cattle husbandry in the Amazon region, at least the farmers already established in the area are not contributing to deforestation; on the contrary, a process of forest recovery may be taking place, as argued by Feltran-Barbieri e Féres (2021).

Finally, (d) demonstrates that the available forest area has a positive significance across nearly the entire dataset. This supports the argument that greater forest density has a positive effect on reducing deforestation. Although significant, *flo* did not display an unexpected pattern. Some municipalities with smaller forest areas showed a negative relationship with deforestation, likely because they had less forest available for exploitation.

In short, there was heterogeneity in the results of the variables, and it was not possible to see any common pattern between the regressors. In addition, Organic Sustainable Extractivism (OSE) has emerged as an alternative for allocating rural credit, as OSE combines the concepts of sustainable extractivism and organic agriculture. It is the practice of harvesting natural resources without compromising the long-term recovery of resources, i.e., sustainably, and without the use of synthetic chemicals. OSE is classified as a productive scope of the organic farming method and can help farmers in the Amazon biome to develop the region by using the financial resources earmarked for rural areas without deforesting. The productive scope is defined as the set of activities, processes, and resources to produce goods or services in a given context (Ticktin, 2004; Landau et al., 2020).

5. Final considerations

This study contributed to the literature by identifying the factors that influence deforestation rates, both positively and negatively, in a spatial context. In addition, different patterns were identified in the clipping that do not expose uniformity. Therefore, it was proposed that each municipality be treated considering its specificities. For this reason, the locations with the highest rates of deforestation behaved differently from the others with the lowest rates. This shows the direct impact of the flow of rural credit loans, the number of soybeans in tons, the number of cattle, and the area covered by forest on the deforestation of the Amazon biome.

After the establishment of Resolution 3545 of 2008, which aimed to restrict access to rural financing to curb deforestation in the Amazon rainforest, there was a lower level of deforestation through activities that use financial resources aimed at agriculture. Since access to rural credit is an important driver of agricultural progress, it was pointed out that the resolution has been effective. This is because most of the municipalities that showed statistical significance and are located in the focal region of deforestation showed an inverse relationship between the effects of the use of rural credit and deforestation. In this way, a group of localities was identified in which the greater use of rural resources caused a lower level of deforestation.

Cattle husbandry is present in the Amazon biome, and just like soybean production, it requires financial resources for its activity. Due to credit restrictions, the number of cattle was also indirectly affected by Resolution 3545 of 2008. In this way, some of the municipalities indicated that the increase in the number of cattle causes a reduction in the deforestation rate, although the majority still show a positive relationship with deforestation. However, as with rural loans, the positive effect occurs in places where deforestation is lower. With this argument, the recovery of pastures may be the reason for the reduction in deforestation in areas where cattle are used as an agricultural activity.

The most common sustainable activity in the Amazon biome, Organic Sustainable Extractivism (OSE), combines the characteristics of sustainable extractivism and organic agriculture. This is a form of production in which the benefits of the forest are extracted without deforestation. Among the products that are present in the territory and are extracted sustainably are açaí, Brazil nuts, cupuaçu, and guaraná. This method of production justifies the use of financial resources for the rural sector in such a way that there is no positive contribution to deforestation.

Finally, this research corroborates the literature and contributes by pointing out the municipalities in which the deforestation rate is negatively affected by variables such as the level of rural credit and the number of head of cattle. Thus, allocating financial resources to the rural environment for sustainable activities could represent a viable alternative for preserving the forest, providing social benefits that do not significantly compromise the biome and promote economic development. In addition, production geared towards agro-ecological practices, such as organic farming, allows for this integration.

For future research, a more comprehensive temporal analysis is recommended to capture spatial dynamics over time, such as through the application of Geographical and Temporal Weighted Regression (GTWR), which incorporates the temporal dimension into the modeling framework. As a limitation, it was not possible to include variables recognized in the literature as relevant to deforestation dynamics, such as road infrastructure, population density, environmental enforcement, and international commodity prices, due to the unavailability of consistent data for the selected period of analysis. Therefore, since this study relies on cross-sectional data, it does not allow for the identification of potential dynamic effects. Another aspect to be considered is that deforestation in Brazil may involve interconnected dynamics between the Amazon and the Cerrado, as the expansion of deforestation in one biome may be related to processes occurring in the other.

References

Almeida, E. (2012). *Econometria espacial aplicada*. Editora Alínea, Campinas, Brazil.

Anselin, L. (1995). Local indicators of spatial association—lisa. *Geographical Analysis*, 27(2):93–115.

Assunção, J., Gandour, C., Rocha, R., e Rocha, R. (2020). The effect of rural credit on deforestation: Evidence from the brazilian amazon. *The Economic Journal*, 130(626):290–330.

Balboni, C., Berman, A., Burgess, R., e Olken, B. A. (2023). The economics of tropical deforestation. *Annual Review of Economics*, 15:723–754.

Brunsdon, C., Fotheringham, A. S., e Charlton, M. (1996). Geographically weighted regression: A method for exploring spatial nonstationarity. *Geographical Analysis*, 28(4):281–298.

Celentano, D., Miranda, M. V., Mendonça, E. N., Rousseau, G. X., Muniz, F. H., Loch, V. D. C., Varga, I. V. D., Freitas, L., Araújo, P., Narvaes, I. D. S., e Adami, M. (2018). Desmatamento, degradação e violência no "mosaico gurupi" - a região mais ameaçada da amazônia. *Estudos Avançados*, 32:315–339.

Chasco, C. e Vallone, A. (2023). *Introduction to cross-section spatial econometric models with applications in R*.

Cisneros, E., Zhou, S. L., e Börner, J. (2015). Naming and shaming for conservation: Evidence from the brazilian amazon. *PLOS ONE*, 10(9).

Domingues, M. S. e Bermann, C. (2012). O arco de desflorestamento na amazônia: da pecuária à soja. *Ambiente & Sociedade*, 15:1–22.

Feltran-Barbieri, R. e Féres, J. G. (2021). Degraded pastures in brazil: Improving livestock production and forest restoration. *Royal Society Open Science*, 8(7).

Ferreira, M. D. P. e Coelho, A. B. (2015). Desmatamento recente nos estados da amazônia legal: Uma análise da contribuição dos preços agrícolas e das políticas governamentais. *Revista de Economia e Sociologia Rural*, 53:91–108.

Fotheringham, A. S., Brunsdon, C., e Charlton, M. (2023). *Geographically weighted regression: The analysis of spatially varying relationships*. John Wiley & Sons.

Gonçalves, I. G. e Ferreira, M. D. P. (2024). Modelos para a previsão de alertas de desmatamento na amazônia legal. *Revista Brasileira de Estudos Regionais e Urbanos*, 17(4):537–560.

Goodchild, M. F. e Longley, J. A. T. (1987). The geographical information system and the future of spatial data analysis in social science. *Journal of Regional Science*, 27(4):403–406.

IBGE – Instituto Brasileiro de Geografia e Estatística (2023). Altamira. Accessed on: 15 October 2025.

INPE – Instituto Nacional de Pesquisas Espaciais (2022). A taxa consolidada de desmatamento por corte raso para os nove estados da amazônia legal em 2021 foi de 13.038 km². Accessed on: 15 October 2025.

Jusys, T. (2016). Fundamental causes and spatial heterogeneity of deforestation in legal amazon. *Applied Geography*, 75:188–199.

Landau, E. C., da Silva, G. A., Matrângolo, W., e Pedrosa, M. W. (2020). Variação geográfica do uso de agricultura orgânica. In: *Dinâmica da Produção Agropecuária e da Paisagem Natural no Brasil nas Últimas Décadas*.

Leblois, A., Damette, O., e Wolfersberger, J. (2017). What has driven deforestation in developing countries since the 2000s? evidence from new remote-sensing data. *World Development*, 92:82–102.

Leung, Y., Mei, C. L., e Zhang, W. X. (2000). Statistical tests for spatial nonstationarity based on the geographically weighted regression model. *Environment and Planning A*, 32(1):9–32.

Medina, G. e Santos, A. P. (2017). Curbing enthusiasm for brazilian agribusiness: The use of actor-specific assessments to transform sustainable development on the ground. *Applied Geography*, 85:101–112.

Moran, P. A. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society. Series B (Methodological)*, 10(2):243–251.

Motel, P. C., Pirard, R., e Combes, J. L. (2009). A methodology to estimate impacts of domestic policies on deforestation: Compensated successful efforts for "avoided deforestation" (redd). *Ecological Economics*, 68(3):680–691.

Oliveira, R. C. D., Almeida, E., Freguglia, R. D. S., e Barreto, R. C. S. (2011). Desmatamento e crescimento econômico no brasil: Uma análise da curva de kuznets ambiental para a amazônia legal. *Revista de Economia e Sociologia Rural*, 49:709–739.

Pfaff, A., Robalino, J., Herrera, D., e Sandoval, C. (2015). Protected areas' impacts on brazilian amazon deforestation: Examining conservation–development interactions to inform planning. *PLOS ONE*, 10(7).

Prem, M., Saavedra, S., e Vargas, J. F. (2020). End-of-conflict deforestation: Evidence from colombia's peace agreement. *World Development*, 129.

Santos, A. M., da Silva, C. F. A., de Almeida Junior, P. M., Rudke, A. P., e de Melo, S. N. (2021). Deforestation drivers in the brazilian amazon: Assessing new spatial predictors. *Journal of Environmental Management*, 294.

Santos, C. F. D., Siqueira, E. S., Araújo, I. T. D., e Maia, Z. M. G. (2014). A agroecologia como perspectiva de sustentabilidade na agricultura familiar. *Ambiente & Sociedade*, 17:33–52.

Saraiva, M. B., Ferreira, M. D. P., da Cunha, D. A., Daniel, L. P., Homma, A. K. O., e Pires, G. F. (2020). Forest regeneration in the brazilian amazon: Public policies and economic conditions. *Journal of Cleaner Production*, 269.

Sass, K. S., Porsse, A. A., e da Silva, E. R. H. (2016). Determinantes das taxas de crimes no paraná: Uma abordagem espacial. *Revista Brasileira de Estudos Regionais e Urbanos*, 10(1):44–63.

Silva, J. P. R. e Arruda, E. F. (2020). Impactos do crédito rural no mercado de trabalho da agropecuária dos estados brasileiros. *Revista Brasileira de Estudos Regionais e Urbanos*, 13(3):340–356.

Souza-Rodrigues, E. (2019). Deforestation in the amazon: A unified framework for estimation and policy analysis. *The Review of Economic Studies*, 86(6):2713–2744.

Ticktin, T. (2004). The ecological implications of harvesting non-timber forest products. *Journal of Applied Ecology*, 41(1):11–21.

Trigueiro, W. R., Nabout, J. C., e Tessarolo, G. (2020). Uncovering the spatial variability of recent deforestation drivers in the brazilian cerrado. *Journal of Environmental Management*, 275.

Wehkamp, J., Koch, N., Lübbbers, S., e Fuss, S. (2018). Governance and deforestation: A meta-analysis in economics. *Ecological Economics*, 144:214–227.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data*. MIT Press.

Zu Ermgassen, E. K., Godar, J., Lathuillière, M. J., Löfgren, P., Gardner, T., Vasconcelos, A., e Meyfroidt, P. (2020). The origin, supply chain, and deforestation risk of brazil's beef exports. *Proceedings of the National Academy of Sciences*, 117(50):31770–31779.