The Spatial Relationship of Transportation Infrastructure and Deforestation in Brazil: a Machine Learning Approach

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Abstract

This paper estimates the relationship between transportation infrastructure and deforestation in Brazil with conventional and spatial econometrics. In addition, we contribute to the emerging field of Spatial/Geographic Data Science with an innovative methodology that explicitly consider space in machine learning algorithms based on supervised regression models, aiming to improve the predictive performance of our estimations. The exploratory analysis pointed to spatial concentration for cleared area and road network in the Centro-Sul and Northeast of the country. Then, we assessed econometrically that transportation infrastructures present a significant conditional correlation with deforestation even after controlling for important structural and institutional characteristics. We also confirm the importance of spatial spillovers, interactions and unobservables to understand forest clearings. From Machine Learning, the empirical evidences show that spatial effects improve the models' predictive power, helping to foresaw out of sample deforestation. Finally, we argue that the integration of spatial econometrics with statistical learning may help to design infrastructure projects that mitigate potential environmental impacts.

Keywords: Deforestation; Transportation; Spatial Econometrics; Machine Learning.

Resumo

Este artigo estima a relação entre a infraestrutura de transporte e o desmatamento no Brasil utilizando econometria convencional e espacial. Além disso, contribui para o emergente campo da Ciência de Dados Espaciais / Geográficos com uma metodologia inovadora que considera explicitamente o espaço em algoritmos de *Machine Learning* baseados em modelos de regressão supervisionados, com o objetivo de melhorar o desempenho preditivo de nossas estimativas. A análise exploratória apontou concentração espacial para área desmatada e a malha viária no Centro-Sul e Nordeste do país. Em seguida, avaliamos econometricamente que a infraestrutura de transporte apresenta uma correlação condicional significativa com o desmatamento, mesmo após o controle de importantes características estruturais e institucionais. Também confirmamos a importância de transbordamentos, interações e características espaciais não observáveis para entender o desmatamento. Com *Machine Learning*, as evidências mostram que os efeitos espaciais melhoram o poder preditivo dos modelos, ajudando a prever o desmatamento. Finalmente, argumentamos que a integração da econometria espacial com aprendizado de máquina pode ajudar a projetar projetos de infraestrutura que mitiguem potenciais impactos ambientais.

Palavras-Chave: Desmatamento; Transporte; Econometria Espacial; Aprendizado de Máquina.

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1 Introduction

The Brazil holds an important part of the planet's natural resources and biodiversity. Nevertheless, deforestation in the country has caused concern worldwide due to greenhouse gas emissions, species extinction and forest loss (Dasgupta 2021). The country has six biomes: Amazon, Atlantic Forest, Caatinga, Cerrado, Pampa and Pantanal. The Amazon is the largest tropical forest in the world while the Cerrado is the richest savannah. Although several factors can explain deforestation in Brazil, we can highlight especially the agricultural frontier expansion, which induces considerable land use changes and environmental degradation (Bragança 2018; Barros e Stege 2019). The Amazon, for example, is the most active agricultural frontier in the world in terms of forest loss and CO2 emissions (Assunção, Gandour e Rocha 2015).

However, one of the main drivers of this expansion is the development of a transportation infrastructure, which attracts farmers to agricultural frontier regions, intensifying population pressures on the natural environment. In fact, there is a close relationship between migration and the opening of roads, which enable the creation of access corridors to previously isolated regions, pushing the agricultural frontier further. In this sense, the transportation infrastructure development is an important factor that indicates trends of environmental change, since it facilitates and accelerates human access to natural resources (Pfaff et al. 2007; P. Fearnside 2007; Tritsch e Le Tourneau 2016; Alphan 2017). To make matters worse, it is common in Brazil that infrastructure projects have inadequate Environmental Impact Assessments (EIA), both methodologically and in its enforcement.

Despite its importance, papers analyzing the impacts from the transportation infrastructure on the Brazilian deforestation are concentrated almost exclusively on the Legal Amazon (Pfaff 1999; Nepstad et al. 2001; Soares-Filho et al. 2004; Pfaff et al. 2007; P. Fearnside 2007; Godar, Tizado e Pokorny 2012; Walker et al. 2013). In addition, spatial interactions are a common effect when considering forest conversion and land use changes. In fact, several papers point out that spatial spillovers are relevant to understand deforestation, with a strong positive spatial interaction impacting negatively the environment (Igliori 2006; Robalino e Pfaff 2012; Bouchardet, Porsse e Timofeiczyk Junior 2017; Amin et al. 2019). In this context, this paper aims to contribute to the literature by estimating the spatial relationship between transportation network, especially of roads, and deforestation, in addition to propose an innovative methodology to predict the impacts of transportation infrastructure projects by integrating space in machine learning algorithms. Therefore, we indirectly contribute to the emerging field of Spatial (Geographic) Data Science, which seeks to integrate spatially explicit problems with Data Science. (Anselin 2020; Murray 2020; Singleton e Arribas-Bel 2021). In fact, the explicit consideration of space in predictive modeling, according to Singleton e Arribas-Bel (2021), is one of the most fruitful methodological areas of Geographic Data Science, especially in the context of spatial econometrics.

It is also worth mentioning that the literature has pointed to the impacts of agricultural practices on the Brazilian deforestation. In particular, we can mention activities related to cattle raising and crops that have recently gained market value, such as soybeans, maize and sugarcane, reflecting the increase in the national and international demand for beef, animal feed and biodiesel (Godar, Tizado e Pokorny 2012; Walker 2014; Faria e Almeida 2016). Therefore, on a robustness check, this papers controls for confounding variables and spatial interactions since they may change the spatial relationship between transportation infrastructure and improve the algorithms predictive performance (Choumert, Combes-Motel e Dakpo 2013; Robalino e Pfaff 2012; Pfaff e Robalino 2017; Singleton e Arribas-Bel 2021).

The paper is structured into five sections, including this introduction. In the second section, we outline the theoretical framework on the relationship between infrastructure and the environment. In the third section, we detail the methodology and the database. The results and their analysis are in the fourth section, followed by the final considerations.

2 Theoretical Framework

The investments in infrastructure, in general, and in transportation, in particular, have the potential to generate economic growth and social development (Calderón e Serven 2010; Amann et al. 2016). Despite this, the causal relationship between transportation investment and development is not direct, since, on the one hand, economic growth creates additional incentives for investments in infrastructure and, on the other, the accumulation and quality of infrastructure may impact the pace of economic growth (Amann et al. 2016). In any case, it is undeniable that the infrastructure plays a central role in determining a country's level of economic and social development.

In Brazil, transportation contribute to regional development, to the generation of jobs and income, in addition to improve the population's living conditions. The road network, specifically, has a preponderance on the Brazilian economy due to its expressive participation in the country's cargo and passenger transportation matrix, which reaches 96 % of passengers and 60.5 % of goods (Projeto Infra 2038 2019). Despite this, there are still many challenges to overcome, especially the insufficient supply and quality resulted from low investments. This scenario harms the entire Brazilian productive chain, in addition to inhibit the country's economic development (Bartholomeu e Caixeta Filho 2008).

To aggravate this scenario, transport infrastructure, in general, and roads, in particular, are usually associated with the significant negative environmental externalities (Laurance, Goosem e Laurance 2009; Jiang e Wu 2019). According to the Welfare Economics Theory, "externalities"are defined as a source of market inefficiency and occur whenever production have an unintended positive or negative result on the well-being of others. Therefore, the increase in the supply of transportation infrastructure in a given region can induce not only economic and social gains, but also important externalities, which must be adequately measured to determine the true cost-benefit of the investments (Pfaff 1999). In fact, the expansion of the transportation infrastructure and the subsequent economic development itself are, to a large extent, related to environmental problems, such as deforestation, biodiversity loss and emission of greenhouse gases (Igliori 2006; Choumert, Combes-Motel e Dakpo 2013; Barros e Stege 2019).

In Brazil, the environmental concerns induced by transportation infrastructure has been concentrated especially on the deforestation of primary forests. This reflects the significant participation of forests in the Brazilian territory and the history of deforestation caused by investments in infrastructure. In general, migration, unsustainable exploitation of forest resources, land grabbing and speculation in land prices are important consequences of the expansion in the transportation infrastructure that induce deforestation, especially in agricultural frontier areas as the Amazon (Pfaff 1999; Fearnside e De Alencastro Graça 2006; P. Fearnside 2007; Soares-Filho et al. 2004; Tritsch e Le Tourneau 2016; Ferrante e Fearnside 2020).

Theoretically, a new transport infrastructure increases the demand for forest goods, such as wood and firewood, and for land, in addition to expanding the supply of agricultural goods. These factors create anthropic pressures on forest areas, ultimately resulting in deforestation (Asher, Garg e Novosad 2020). In general, the deforestation process begins with the opening of roads that enable the extraction of noble wood, allowing, later, forest clearings into agriculture or pasture. In practice, logging begins with the opening of side roads derived from a main road, forming the so-called "fish bone" (Paiva et al. 2020). Then, there is the removal of noble wood, which open small voids inside the forest area. Subsequently, trees of lesser value are extracted, contributing to the forest void, which, ultimately, reduces the present value of the forest and creates additional incentives for the agricultural frontier expansion. Finally, the area is often set on fire to clean the soil for later use in agriculture or livestock (Barber et al. 2014; Lawrence e

Vandecar 2015; Jusys 2016).

Therefore, the construction of transportation infrastructure, the exploitation of wood and the advance of the agricultural frontier lead to significant land use changes. To make matters worse, these factors, by increasing the expected economic benefits from deforestation, create incentives for new migratory waves and additional investments in infrastructure, which ultimately increase forest clearings (P. Fearnside 2005). It is worth noting that deforestation is also affected by geographical and climatic conditions, especially due to its impacts on the costs of building and maintaining transport infrastructure. A high level of precipitation can act to make runoff difficult and reduce the potential of agricultural production, compressing the agricultural profitability margin, curbing deforestation.

Empirically, the literature confirms that there are large concentrations of deforestation in the buffer zones around roads, which is aggravated in tropical areas, as shown some papers for Congo, Jamaica and Indonesia (Newman, P. e Wilson 2014; Austin et al. 2018; Kleinschroth et al. 2019). In Brazil, Nepstad et al. (2001) was one of the first to analyze the relationship between deforestation and roads using satellite images. The evidences show that forest areas are negatively correlated with road access. In fact, according to Alves (2002), the 1990s deforestation occurred within a radius of 100km from the main roads and highways in the Amazon and Barber et al. (2014) showed that 95 % of forest loss was located within a radius of 5.5 km on roads and 1 km on rivers.

In this context, P. Fearnside (2005) argues that Brazil must combat the "unsustainable development" induced by investments in infrastructure with environmental cost analysis. The Brazilian Government's decision-making usually prioritizes the construction of highways, dams and large infrastructure projects that do not properly consider the direct and indirect negative environmental impacts that they can generate. As emblematic examples, we can mention some Amazon's highways, such as BR-319 (Manaus-Porto Velho), BR-163 (Cuiabá-Santarém) and BR-364 (Cuiabá-Porto Velho) and the Belo Monte dam (Soares-Filho et al. 2004; Fearnside e De Alencastro Graça 2006; P. M. Fearnside 2006; P. Fearnside 2007).

Therefore, the expansion of infrastructure transportation, despite being essential to the country's economic development, especially in isolated and underdeveloped regions, can also generate important environmental impacts. In this context, projects must undergo Environmental Impact Assessments (EIA), as they are the best way to identify, prevent, mitigate and offset the negative effects of roads on biodiversity. Therefore, the EIA is important to ensure economic development while minimizing possible environmental impacts (Reis e Guzmán 2015; Chi, Ruuska e Xu 2016). Theoretically, EIA is a process of assessing the environmental consequences of a project that could significantly affects the natural and artificial environment, helping the decision makers to define the best alternative. Therefore, it is an anticipatory environmental management tool, making negative externalities more visible. Despite this, in practice, the laws that support environmental licensing in Brazil are recent and inefficient. In addition, EIA also suffers from lack of clear objectives and poor methodological quality. As a negative consequence of this scenario, we can mention the environmental liabilities of many of the main Brazilian highways, especially those located in regions with great environmental assets (Glasson e Salvador 2000; P. M. Fearnside 2002; Sánchez 2013).

3 Methodology

3.1 Empirical Design and Database

To estimate the relationship between transportation infrastructure and deforestation in Brazil, we propose to use data at the microregion-level covering the country's 558 microregions. Our outcome variable is the proportion of deforested area in 2017 from the annual maps of land cover and land use released by MapBiomas, which uses images from Landsat satellites with 30 meters pixel resolution. The initiative was formed in 2015 and cover all the Brazilian biomes: Amazon (49.29%), Atlantic Forest (13.04%), Caatinga (9.92), Cerrado (23.92%), Pampa (2.07%) and Pantanal (1.76%). In addition, we also used vectors data in order to build specific variables and shapefiles to this empirical design. Specially, we use infrastructure data, road and rail network, from the MapBiomas project, in addition to microregions shapefile available in the *Instituto de Geografia e Estatística (IBGE)*.

This paper also uses complementary vector databases in which we perform specific spatial analysis and geoprocessing with Arcmap 10.7 software. First, we employ a Polygon Overlay, particularly the Spatial joint tool, to overlap the infrastructure and microregions vectors data to measure the extension (in kilometers) of the transportation network at the microregion-level. Then, we weight each measure by the area in order to obtain comparable informations for all regions. In addition, we also consider some geographic, agricultural and structural variables for control purpose. The inclusion aims to improve the model specification, avoiding spurious regressions and omitted variable problem. In other words, additional controls may help to establish the relationship and predict the impacts on deforestation. Specifically to this empirical design, we construct: Rainfall, Soil, River, Protected Area. We constructed the controls variables using the spatial joint tool. Some explanations about these variables are worth mentioning.

We construct the Soil variable using the *Mapa de Potencial Agrícola do Brasil*, complied by the *Instituto Brasileiro de Geografia e Estatística (IBGE)* and made available by the *Ministério do Meio Ambiente (MMA)*. The Brazilian territory is classified according to the agricultural potential of its soils, considering factors such as: fertility, physical and morphological characteristics, main limitations and topography. Merging the agricultural potential map with the microregions map, we identified the predominant type of soil that exists in each region. Finally, we calculated a weighted average with higher weights for more suitable soils, which resulted in an indicator that the closer to one, the greater is suitability. This procedure seeks to control for the fact that the impact of transportation infrastructure conditional on soil suitability can change since regions with higher agricultural potential may attract migratory waves, lead to further agricultural frontier expansion and deforestation, increasing demand for infrastructure. In an indirect way, it will be possible to identify if microregions with greater agricultural potential soils have deeper changes in land use.

The Protected Area data vector was made available by the *Centro de Sensoriamento Remoto da Universidade Federal de Minas Gerais (CSR-UFMG)*. The Rainfall is composed of average annual precipitation data (1977 to 2006), from the national hydrometeorological network, compiled by the *Serviço Geológico do Brasil (CPRM)* and made available by the Pluviometric Atlas of Brazil. It is worth mentioning that we check for correlations between the variables and noticed high correlations that could compromise the estimation.

Finally, we also consider social, economic, technology and additional geographic variables that may improve the estimations. From IBGE, we have the demographic density, gini index, GDP, rural GDP (proportion), property area (average), pasture and planted area (proportion), Human Capital (average years of schooling), property rights. We also construct an agricultural technology index with Principal Component Analysis (PCA) using several dimensions of technological access and adoption on agricultural properties: (1) - tractors; (2) - seeders; (3) - limestone and fertilizer distributors; (4) - harvesters; (5) - technical assistance; (6) - irrigation; (7) - fertilization; (8) - soil preparation; (9) - electricity; (10) - limestone; (11) - pesticides; (12) - animal feed.

In addition, the forest conversion and land use changes may present spatial interactions that result in significant spillovers, influencing the economic agent decision. This spatial spillover may occur due to the presence of centripetal forces, generated by productivity difference and transport costs that can cause significant regional differences; attracting productive activities, especially agricultural and livestock. In other words, the presence of spatial spillovers may be one important factor inducing the economic agents to push the agricultural frontier expansion and the demand for transport infrastructure, resulting in deforestation, which highlight the need for its proper control. Therefore, the baseline model estimated is

$$Deforest_i = \beta_0 + \rho W Deforest_i + \beta_1 Road_i + \beta_2 Rail_i + \beta_3 Rivers_i + \beta_k Z_i + \tau WS + \varepsilon_i \quad (1)$$

where $Deforest_i$ is the percentage of the microregion that was cleared; Z is the matrix of k additional explanatory variables included in the model; S is the transportation network. The spatial dependence matrix W, which represents the structural neighborhood between the regions, capture the presence of spatial spillovers in the variables.

3.2 Exploratory Spatial Data Analysis (ESDA)

The ESDA capture effects of spatial dependence and heterogeneity, association patterns (spatial clusters) and indicate how the data are distributed. The Moran's I seeks to capture the degree of spatial correlation between a variable across regions. Mathematically,

$$I = \frac{n}{S_o} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2} \quad (2)$$

where n is the number of regions, S_0 is equal to the sum of all elements of matrix W, z is the normalized value for deforestation. However, the Moran's I statistic can only capture global autocorrelation, not identifying association at a local level. In this context, we use the LISA statistic, which capture local spatial autocorrelation and clusters,

$$I_i = z_i \sum_{j=1}^{J} w_{ij} z_j \quad (3)$$

where z_i represents the variable of interest of the standardized region i, w_{ij} is the spatial weighting matrix element (W) and z_j is the value of the variable of interest in the standardized region j. The local Moran I (LISA) can represent four spatial clusters: High-High (AA), Low-Low (BB), High-Low (AB) and Low-High (BA).

3.3 Spatial Econometrics

In an econometric model, it is possible to incorporate the spatial component through spatially lagged variables. In this paper, we propose to estimate three spatial models: Spatial Autoregressive Model (SAR), Spatial Lag Model (SLX) and Spatial Durbin Model (SDM). The Spatial Autoregressive Model (SAR), which incorporates the the spatial lag of the dependent variable, is

$$y = \rho W y + X\beta + \mu + \epsilon \quad (4)$$

where W is the spatial weighted matrix $n \times n$; a vector $n \times 1$ of the dependent variable, y; X is a matrix $n \times k$ of the regressors and μ is the intercept. The basics hypothesis of the SAR model are $\epsilon_i\ N(0,\ \sigma_\epsilon^2)$ and $E(\epsilon_i \epsilon_j) = 0$ for $i \neq j$. The Spatial Lag Model (SLX), on the other hand, include includes spatial lags of explanatory variables,

$$y = X\beta + W Z_t \theta + \mu + \epsilon \quad (5)$$

where it is possible that $Z \neq X$. Finally, the Spatial Durbin Model (SDM) is a generalization from the SAR and SLX models with independent and dependent variables spatially lagged as explanatory variables,

$$y = \rho W y + X\beta + W Z_t \theta + \mu + \epsilon \tag{6}$$

To estimate the spatial models with endogenous interactions (SAR and SDM), we propose to use an two-stage estimation with instrumental variable, using the exogenous lagged explanatory variables WX for SAR and W^2X for SDM. The SLX model, on the other hand, can be estimated by OLS since the lagged explanatory variables WX are exogenous.

3.4 Machine Learning

The main goal of Machine Learning is to construct a statistical model to predict some outcome of interest. In fact, statistical models are the basis of Machine Learning algorithms; specially regression, classification and mixed models[1]. Differently from standard statistics, that focus on asymptotic theory and casual relationships, the machine learning literature focus on the model's predictive power. In practice, there are two basic algorithms types in the literature, the supervised and unsupervised models. The first is scored based on a known quantity while the later estimate patterns from the data.

In this paper, we use algorithms based on supervised regression models since they are the most common in the Machine Learning literature. In addition, regression models are also widely used in the deforestation literature to access conditional correlations and casual relationship between variables. Therefore, by using supervised algorithms based on regression models, we can combine our approaches to access the predictive power of the spatial models.

To implement such approach, the first step is to train the model to minimize its forecast error and avoid overfitting. In practice, we need to split our data sample in two: one for training and another for testing. In other words, this procedures seeks to test the validity of our model by using the testing sample to access the predictive power of the estimated model. To minimize potential bias, it is important to use sampling techniques to construct the samples. Next, we need to compare the predicted results calculated with the training sample with the actual values from the testing sample. To access the model's predictive power, it is important to use some test metric. In this paper, we use the root-mean-square error (RMSE),

$$\text{RMSE} = \sqrt{\left(\frac{1}{n}\Sigma \left(y_{predicted} - y_{actual}\right)^2\right)} \tag{7}$$

where $y_{predicted}$ is the predicted deforestation, from the trained model, using the actual value from the testing sample; y_{actual} is the actual value from the testing sample; n is the number of observations in the testing sample. In general, a lower RMSE is better than a higher one. In other words, we can access the best model specification and, therefore, test if some variables of interest help to improve the predictive power of the model. In this paper, we test if the transportation variables and the spatial interactions from deforestation help to improve the predictions. In other words, we integrate space, by using spatial econometrics, with supervised machine learning algorithms, indirectly contributing to the emerging field of Spatial/Geographic Data Science (Anselin 2020; Murray 2020; Singleton e Arribas-Bel 2021).

To check the robustness of the results, we use a k-fold cross validation method to ensure that the testing data represents in fact our data sample. This technique splits the data sample in k chunks and create, for each chunk, a training and testing sample and estimate the model. Then, it takes the average of the k predicted errors from each chunk. In other words, the k-fold cross validation enables to access the potential degree of variation in the RMSE and minimize it by averaging the errors.

1. See Burger (2018) for additional information

4 Results and Discussion

Deforestation in Brazil has significant negative impacts on the environment, affecting adjacent localities and potentially global climatic stability. Therefore, the search for its determinants is fundamental in the development of mitigation measures, especially considering the transportation infrastructure expansion that allows access to previously isolated areas, affecting the clearings rhythm. The Figure 1 shows the spatial distribution of deforested area (a) and road network density[2] (b) in Brazil and we can note a spatial concentration for both variables.

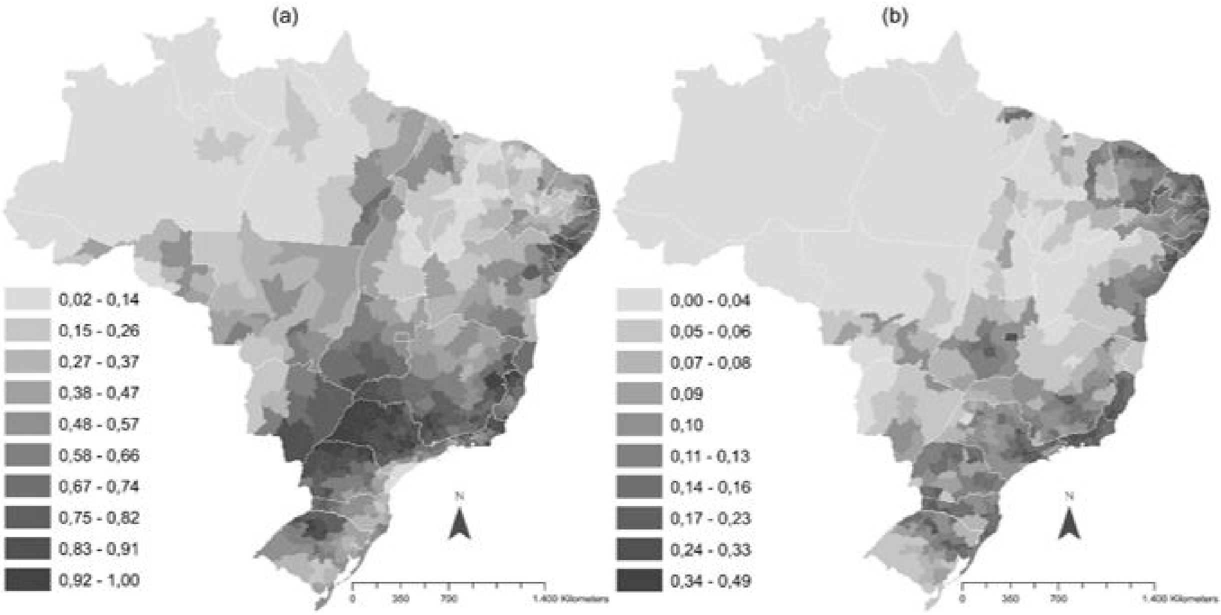

Figura 1: Spatial Distribution of deforested area (a) and road network density (b) in Brazil.

Deforestation and road density are both concentrated in the Centro-Sul and Northeast. This spatial configuration reflects the Brazilian colonization and occupation process that occurred more intensely in Southeast and Northeast. Theoretically, the spatial concentration of deforestation may result from spatial interactions, which can reinforce it, a phenomenon that are evidenced by several empirical papers (Igliori 2006; Pfaff et al. 2007; Bouchardet, Porsse e Timofeiczyk Junior 2017; Pfaff e Robalino 2017; Jusys 2016; Barros e Stege 2019; Amin et al. 2019). Figure 2 confirms this phenomenon for deforestation and road network in Brazil, with similar spatial configuration from Figure 1. We have a High-High cluster for both variables in the Centro-Sul and Northeast along with a Low-Low cluster in the North.

2. We focus our exploratory analysis on the road network due to its central role in the Brazilian transportation infrastructure.

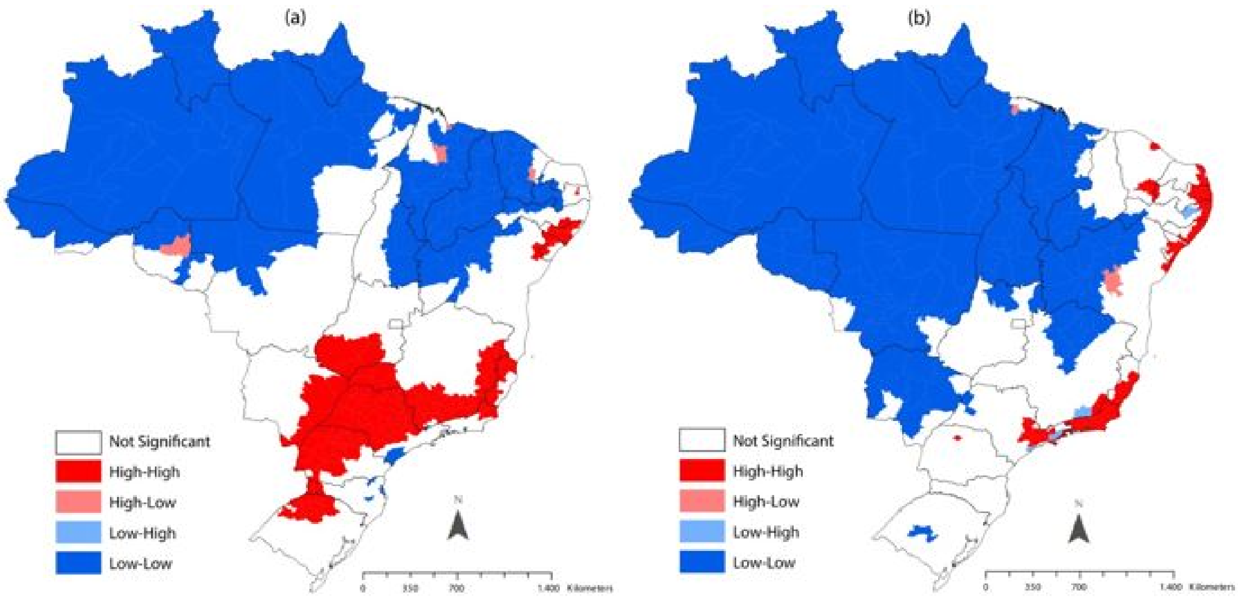

Figura 2: LISA Map for Deforestation and Road Density in Brazil.

With the deforestation basic characteristics identified, in terms of its spatial distribution, the next step is to find its potential determinants. Table 1 presents the Ordinary Least Squares estimations. In the column (1), we estimate the relationship between transportation infrastructure and deforestation in Brazil. In general, the road and rail network presented a positive and statistically significant coefficient, highlighting a positive correlation of transportation network and forest clearings in the country, explaining approximately 13.3% of the variation in the cleared area.

To check the robustness of our results, we include control variables in column (2) to column (6) that proxy characteristics related to social, economic, agricultural, market structure, technology, climate, geography, human capital and institutions. It is worth mentioning that our benchmark model in column (6) explained approximately 75% of the variation in deforestation. Despite the reduction in the road and rail network coefficients as we include control variables in the estimations, they remain statistically significant, highlighting a consistent conditional correlation with clearings. In addition, the river variable turned statistically significant after conditioning its correlation to the control variables.

We further check the robustness of our results by considering potential endogeneity problems. Table A1 in the Appendix presents a endogeneity test[3] for all estimation of Table 1. In general, the variables are statistically insignificant, highlighting no endogeneity concerns. Despite this, our results, by not using an exogenous source of variation for transportation infrastructure, do not allow for casual interpretation due to possible observable confounders. However, it is worth mentioning that one possible explanation for our empirical evidence is that the transportation infrastructure allows access to previously isolated areas by creating corridors to the region, reducing transportation costs and pushing the agricultural frontier further by intensifying the migration and occupation of the territory, leading to deforestation (Pfaff et al. 2007; Tritsch e Le Tourneau 2016; Bragança 2018).

Notwithstanding the consistent of the results, spatial interactions and spillovers can affect deforestation decisions and, in addition, unobservables variables that is related to transportation infrastructure and deforestation may be spatially correlated. In fact, the Moran I test, calculated in each model specification (Table 1), confirm that the residuals are spatially autocorrelated.

3. We estimate an Ordinary Least Square of all variables on the model's residuals from Table 1 to test for potential endogeneity problems

Tabela 1: Ordinary Least Squares

	Dependent variable:					
	Deforestation					
	OLS	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)	(6)
Roads	1.3267***	0.9433***	0.8145***	0.4621**	0.5571***	0.5762***
	(0.2056)	(0.1763)	(0.1730)	(0.2257)	(0.1936)	(0.1861)
Rail	1.0413*	0.7584*	0.7778*	0.6528*	0.4554	0.5173*
	(0.5492)	(0.4425)	(0.4427)	(0.3502)	(0.3102)	(0.2989)
Rivers	−0.0627	−0.0874	−0.0794	−0.0564	−0.0875*	−0.1095**
	(0.0639)	(0.0547)	(0.0557)	(0.0591)	(0.0531)	(0.0511)
GDP		0.00001***	0.00001***	0.000000	0.000003	0.00001**
		(0.000003)	(0.000003)	(0.000002)	(0.000003)	(0.000003)
GDP²		−0.0000***	−0.0000***	0.0000	−0.0000	−0.0000
		(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Population		−0.00004**	−0.00005**	0.0001***	0.0001***	0.0001***
		(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Rural GDP		0.0024***	0.0022**	−0.0020***	−0.0008	−0.0011
		(0.0009)	(0.0009)	(0.0006)	(0.0007)	(0.0007)
GINI		−2.3370***	−2.2422***	−1.0142***	−0.5189***	−0.7587***
		(0.1977)	(0.2043)	(0.1635)	(0.1625)	(0.1733)
Openness Trade			−0.1587***	−0.0471	−0.0563*	−0.0639**
			(0.0482)	(0.0307)	(0.0291)	(0.0268)
Property Area			−0.0001	−0.0002***	−0.0001***	−0.0001***
			(0.00004)	(0.00003)	(0.00003)	(0.00003)
Pasture				0.0085***	0.0081***	0.0080***
				(0.0005)	(0.0005)	(0.0005)
Planted Area				0.0058***	0.0055***	0.0065***
				(0.0004)	(0.0004)	(0.0004)
Soil				0.0631	0.0717*	0.0494
				(0.0397)	(0.0379)	(0.0392)
Technology				−0.0950	−0.1599	−0.0979
				(0.1098)	(0.1165)	(0.1112)
Altitude					0.00005	0.0001**
					(0.00003)	(0.00003)
Precipitation					−0.00005***	−0.0001***
					(0.00002)	(0.00002)
Temperature					0.0185***	0.0180***
					(0.0029)	(0.0029)
Human Capital						−0.0287**
						(0.0130)
Property Rights						−0.00004
						(0.00002)
Environm. Fines						0.0001
						(0.0001)
Rural Credit						−0.0040***
						(0.0010)
Protected Areas						0.1608**
						(0.0636)
Constant	0.4237***	1.5202***	1.4683***	0.7624***	0.1360	0.4051***
	(0.0458)	(0.1196)	(0.1393)	(0.1180)	(0.1320)	(0.1470)
Observations	558	558	558	558	558	558
R^2	0.1380	0.4305	0.4446	0.7041	0.7365	0.7517
Adjusted R^2	0.1334	0.4222	0.4345	0.6965	0.7282	0.7415
Akaike (AIC)	41.9273	-179.3092	-189.3449	-532.6709	-591.4604	-614.6085
Moran I	0.7856***	0.7348***	0.6860***	0.6909***	0.6289***	0.6182***

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors.

Therefore, consider spatial interactions from deforestation in the estimations may improve the results, specially in its predictive capability. To measure such spatial effects, we must consider the endogenous nature of the problem. To overcome these caveat, we instrumentalized neighborhood deforestation using neighbors' exogenous characteristics as described in Section 3.3. To include the spatial effects, we considered out benchmark model (column (6), Table 1), which presented the lowest Akaike information criterion and highest adjusted R^2. Table 2 presents the results for our OLS benchmark model and the SLX, SAR and SDM spatial models.

The ρ coefficients that captures the spatial interaction from deforestation are significant for both SAR and SDM models, highlighting the importance of spatial spillovers in forest conversion and land use changes. Although we can not decompose the channels that the interactions and spillovers operate, its control captures spatially unobservables and potential impacts from input reallocation, leakages, market prices, technology learning and social interactions (Igliori 2006; Pfaff et al. 2007; Robalino e Pfaff 2012; Assunção, Gandour e Rocha 2015; Pfaff e Robalino 2017; Barros e Stege 2019; Amin et al. 2019). The road and rail network coefficients turned statistically insignificant after controlling for spatial interactions and spillovers. One possible explanation for this empirical evidence is that both transportation variables are spatially correlated. Therefore, by controlling for spatially unobservables characteristics, the estimations no longer could decompose a statistically significant conditional correlation for the road and rail variables. This fact, however, does not mean that transportation infrastructure are not important to explain deforestation; it just highlight for its potentially spatial nature, which prompts the need for further investigations.

Tabela 2: Spatial Models

	Dependent variable:			
	Deforestation			
	OLS	SLX	SAR	SDM
	(1)	(2)	(3)	(4)
Roads	0.5762***	0.2951	0.1471	0.1411
	(0.1861)	(0.2216)	(0.1535)	(0.1535)
Rail	0.5173*	0.2964	0.2255	0.1522
	(0.2989)	(0.3277)	(0.2578)	(0.2578)
Rivers	−0.1095**	−0.1205**	−0.0791*	−0.1133***
	(0.0511)	(0.0593)	(0.0423)	(0.0423)
WRoads		0.4205*		−0.0896
		(0.2396)		(0.1691)
WRail		0.7629		0.3565
		(0.4768)		(0.3161)
WRivers		0.0309		0.0886*
		(0.0717)		(0.0519)
WDeforest (ρ)			0.6729***	0.6693***
			(0.0334)	(0.0334)
Constant	0.4051***	0.3143**	0.3143***	0.2528**
	(0.1470)	(0.1488)	(0.1175)	(0.1175)
Controls	Yes	Yes	Yes	Yes
Observations	558	558	558	558
R^2	0.7517	0.7584	0.8722	0.8736
Adjusted R^2	0.7415	0.7471	0.8667	0.8675
Akaike (AIC)	-614.6085	-623.9024	-982.9881	-983.477
Moran I	0.6182***	0.5991***	-0.0129	-0.0121

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors. Column (1) to (4) include all control variables from Table 1, column (6).

Finally, we propose an innovative methodological approach that integrate space with supervised Machine Learning algorithms to improve the predictive performance of our estimations. In other words, we check if the spatial econometric models can be used to improve the predictive power of the impacts of infrastructure projects since most of Environmental Impact Assessments (EIA) are inadequate to measure potential environmental impacts. The results are presented in Table 3. The SAR model presented the lowest root-mean squared error (RMSE), both in the global estimation and in the k-fold cross validation with 10 chunks; despite the fact that the SDM spatial model presented the highest Adjusted R^2 and the lowest Akaike information criterion and Moran I in the residuals. Therefore, the Machine Learning algorithms allowed to access the best predictive model going beyond simple statistical adjustment measures. In practice, this empirical approach may help design infrastructure projects by improving the Environmental Impact Assessments (EIA) to foresaw potential environmental impacts. Indirectly, this innovative methodology contribute to the emerging field of Geographic Data Science, which seeks to integrate spatially explicit problems with Data Science.

Tabela 3: Accessing the model's predictive power with Machine Learning algorithms

	Dependent variable: Deforestation			
	OLS	SLX	SAR	SDM
	(1)	(2)	(3)	(4)
RMSE (*global*)	0.1311	0.1296	0.0904	0.0964
	k-fold Cross Validation: 10 chunks			
RMSE (1)	0.1952	0.1873	0.1138	0.1118
RMSE (2)	0.1915	0.1887	0.1203	0.1185
RMSE (3)	0.1677	0.1765	0.1185	0.1261
RMSE (4)	0.1479	0.1394	0.1041	0.1010
RMSE (5)	0.1255	0.1280	0.0899	0.0900
RMSE (6)	0.1297	0.1283	0.0806	0.0810
RMSE (7)	0.0974	0.1000	0.0825	0.0810
RMSE (8)	0.1794	0.1943	0.1039	0.1018
RMSE (9)	0.2089	0.2122	0.1394	0.1382
RMSE (10)	0.1964	0.2000	0.1194	0.1258
Average RMSE	0.1640	0.1655	0.1072	0.1075

Note: Column (1) to (4) include all control variables from Table 1, column (6).

5 Final Considerations

This paper investigated the relationship between transportation infrastructure and deforestation in Brazil. The exploratory analysis pointed to spatial concentration of deforestation and road network, with both of its high values concentrated in the Centro-Sul and Northeast, indicating a close spatial relationship. This spatial configuration may reflects the Brazilian colonization and occupation process that occurred more intensely in those regions, and the significant correlation between this process and the construction of a transportation infrastructure.

Then, we assessed empirically the relationship using Ordinary Least Squares (OLS) and spatial econometric models. In the OLS estimations, the transportation infrastructure presented a statistically significant conditional correlation with deforestation even after including important structural and institutional controls. On the other hand, with the spatial models, we confirmed the importance of spatial spillovers, interactions and unobservables to understand forest clearings. However, after controlling for this spatial effects, the coefficients from transportation infrastructure turned statistically insignificant, possibly highlighting the spatial nature of transport network, which prompts the need for further investigations.

Finally, we propose an innovative methodological approach by integrating space with Machine Learning algorithms based on supervised regression models to improve the predictive performance of our estimations. The empirical evidences show that considering spatial interactions, spillovers and unobservables from deforestation improve the models' predictive power. Therefore, in addition to the direct contribution to the literature from considering the spatial relationship between transportation infrastructure and deforestation in Brazil by helping to design foresaw potential environmental impacts from infrastructure projects, we also indirectly contribute to the emerging field of Geographic Data Science by integrating spatial econometrics with Machine Learning. In other words, these empirical evidences may help the designing of Environmental Impact Assessments (EIA) of transportation projects while the new methodological development can be adopted by researchers to new predictive modelling in spatially explicit problems.

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A Appendix

Table A1: Endogeneity Test

	Dependent variable:							
	Resid	Resid	Resid	Resid	Resid	Resid	Resid	Resid
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Roads	0.0000	0.0000	−0.0000	0.0000	0.0000	−0.0000	−0.0000	−0.0000
	(0.1633)	(0.1930)	(0.2056)	(0.1684)	(0.1730)	(0.2257)	(0.1936)	(0.1861)
Rail		−0.0000	0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000
		(0.5528)	(0.5492)	(0.4530)	(0.4427)	(0.3502)	(0.3102)	(0.2989)
Rivers			0.0000	−0.0000	0.0000	−0.0000	0.0000	0.0000
			(0.0639)	(0.0559)	(0.0557)	(0.0591)	(0.0531)	(0.0511)
GDP				−0.0000	0.0000	−0.0000	−0.0000	−0.0000
				(0.000003)	(0.000003)	(0.000002)	(0.000003)	(0.000003)
GDP^2				−0.0000	−0.0000	0.0000	0.0000	0.0000
				(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Demographic Density				0.0000	0.0000	0.0000	−0.0000	−0.0000
				(0.00002)	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Rural GDP				0.0000	−0.0000	0.0000	0.0000	0.0000
				(0.0009)	(0.0009)	(0.0006)	(0.0007)	(0.0007)
GINI				0.0000	−0.0000	−0.0000	−0.0000	−0.0000
				(0.2134)	(0.2043)	(0.1635)	(0.1625)	(0.1733)
Openness to Trade					−0.0000	0.0000	0.0000	0.0000
					(0.0482)	(0.0307)	(0.0291)	(0.0268)
Property Area					−0.0000	0.0000	−0.0000	−0.0000
					(0.00004)	(0.00003)	(0.00003)	(0.00003)
Pasture						0.0000	0.0000	0.0000
						(0.0005)	(0.0005)	(0.0005)
Planted Area						−0.0000	0.0000	0.0000
						(0.0004)	(0.0004)	(0.0004)
Soil						−0.0000	−0.0000	−0.0000
						(0.0397)	(0.0379)	(0.0392)
Technology						−0.0000	0.0000	−0.0000
						(0.1098)	(0.1165)	(0.1112)
Altitude							−0.0000	0.0000
							(0.00003)	(0.00003)
Precipitation							0.0000	−0.0000
							(0.00002)	(0.00002)
Temperature							0.0000	−0.0000
							(0.0029)	(0.0029)
Human Capital								0.0000
								(0.0130)
Property Rights								−0.0000
								(0.00002)
Environmental Fines								0.0000
								(0.0001)
Rural Credit								−0.0000
								(0.0010)
Protected Areas								−0.0000
								(0.0636)
Constant	−0.0000	−0.0000	−0.0000	−0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0205)	(0.0209)	(0.0458)	(0.1450)	(0.1393)	(0.1180)	(0.1320)	(0.1470)
Observations	558	558	558	558	558	558	558	558
R^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Adjusted R^2	-0.0018	-0.0036	-0.0054	-0.0146	-0.0183	-0.0258	-0.0315	-0.0411

Note: *** Significant at 1%; ** Significant at 5%; * Significant at 10%. Robust Standard Errors.