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Beyond Local Effects: Spatial Spillovers of Transportation Infrastructure and Deforestation in Brazil

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ABSTRACT

This paper examines the relationship between transportation infrastructure and deforestation in Brazil. We combine exploratory spatial data analysis with standard econometric, spatial econometric, and machine learning using spatially disaggregated data covering all Brazilian biomes. Exploratory analysis reveals a strong spatial concentration of both deforestation and transportation networks, particularly in the Centro-Sul and Northeast regions. Conventional econometric results indicate a positive conditional association between transportation infrastructure and deforestation after controlling for a broad set of structural and institutional characteristics. However, explicitly accounting for spatial effects highlights the central role of spatial spillovers, interactions, and spatially correlated confounders, suggesting that the environmental impacts of transportation infrastructure extend beyond local boundaries. Finally, results from the machine learning evaluation show that incorporating spatial structure substantially improves out-of-sample predictive accuracy. Overall, the findings underscore the importance of spatially informed empirical approaches for understanding, anticipating, and monitoring deforestation patterns associated with infrastructure expansion.

KEYWORDS

Deforestation, Transportation Infrastructure, Spatial Econometrics, Machine Learning

Além dos Efeitos Locais: *Spillovers* Espaciais da Infraestrutura de Transporte e do Desmatamento no Brasil

RESUMO

Este artigo examina a relação entre infraestrutura de transporte e desmatamento no Brasil. Combina análise exploratória de dados espaciais com métodos econométricos tradicionais, econometria espacial e aprendizado de máquina, utilizando dados espacialmente desagregados que cobrem todos os biomas brasileiros. A análise exploratória revela forte concentração espacial tanto do desmatamento quanto das redes de transporte, especialmente nas regiões Centro-Sul e Nordeste. Os resultados econométricos convencionais indicam uma associação condicional positiva entre infraestrutura de transporte e desmatamento, mesmo após o controle por um amplo conjunto de características estruturais e institucionais. No entanto, ao incorporar explicitamente efeitos espaciais, os resultados destacam o papel central de spillovers espaciais, interações e fatores não observados espacialmente correlacionados, sugerindo que os impactos ambientais da infraestrutura de transporte extrapolam os limites locais. Por fim, a avaliação baseada em aprendizado de máquina mostra que a incorporação da estrutura espacial melhora substancialmente o desempenho preditivo fora da amostra. Em conjunto, os resultados ressaltam a importância de abordagens empíricas sensíveis à dimensão espacial para compreender, antecipar e monitorar padrões de desmatamento associados à expansão da infraestrutura.

PALAVRAS-CHAVE

Deforestation, Transportation Infrastructure, Spatial Econometrics, Machine Learning

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1. Introduction

Brazil holds a substantial share of the planet's natural resources and biodiversity. The country comprises six major biomes—Amazon, Atlantic Forest, Caatinga, Cerrado, Pampa, and Pantanal—with the Amazon representing the largest tropical forest in the world and the Cerrado the most biodiverse savannah. Despite this ecological richness, deforestation in Brazil has raised global concern due to its contributions to greenhouse gas emissions, forest degradation, and biodiversity loss Dasgupta (2021). While deforestation is driven by multiple factors, the expansion of the agricultural frontier and broader territorial occupation stand out as central mechanisms, with transportation infrastructure playing a key enabling role by reducing access costs and inducing substantial land-use change and environmental degradation Bragança (2018); Barros and Stege (2019). As a result, the Amazon has become the most active agricultural frontier globally in terms of forest loss and associated CO2 emissions Assunção et al. (2015).

More specifically, the expansion of transportation infrastructure attracts farmers to agricultural frontier regions by reducing the opportunity cost of territorial occupation, thereby intensifying population pressures on the natural environment and leading to forest clearings. There is a close relationship between migration, territorial occupation, and road construction, as new transport links create access corridors to previously isolated areas and push the agricultural frontier outward. For this reason, transportation infrastructure constitutes an important indicator of broader environmental change Pfaff et al. (2007); Fearnside (2007); Tritsch and Le Tourneau (2016); Alphan (2017). Compounding this issue, infrastructure projects in Brazil frequently suffer from inadequate environmental impact assessments, both in methodological design and in their enforcement.

Empirical evidence shows that deforestation tends to be highly concentrated in buffer zones surrounding transportation infrastructure, a pattern that is particularly pronounced in tropical regions. Studies focusing on countries such as the Congo, Jamaica, and Indonesia document strong associations between road proximity and forest loss Newman et al. (2014); Austin et al. (2018); Kleinschroth et al. (2019). For Brazil, the literature similarly indicates that the expansion of the road network is closely associated with increased forest clearing Pfaff (1999); Soares-Filho et al. (2004); Fearnside and De Alencastro Graça (2006); Fearnside (2007); Pfaff et al. (2007); Barber et al. (2014). Much of the Amazon deforestation observed during the 1990s occurred within a 100 km radius of major roads Alves (2002) with approximately 95% of forest loss being located within 5.5 km of roads and 1 km of rivers Barber et al. (2014). This scenario is compounded by significant spatial spillovers from road investments, affecting not only directly connected areas but also neighboring regions Pfaff (1999); Pfaff et al. (2007).

Despite its relevance, the literature analyzing the impacts of transportation infrastructure on deforestation in Brazil remains largely concentrated on individual biomes, particularly the Amazon Pfaff (1999); Nepstad et al. (2001); Soares-Filho et al. (2004); Pfaff et al. (2007); Fearnside (2007); Godar et al. (2012); Walker et al. (2013); Araujo et al. (2025). In parallel, forest conversion and land-use change are well known to exhibit strong spatial interactions and spillovers. Empirical evidence documents significant positive spatial spillovers associated with forest clearings Igliori (2006); Robalino and Pfaff (2012); Bouchardet et al. (2017); Amin et al. (2019), as well as spillovers arising from road investments Pfaff et al. (2007), both of which tend to amplify deforestation beyond local boundaries. However, to the best of our knowledge, no study has jointly analyzed transportation infrastructure and deforestation across all Brazilian biomes while explicitly accounting for spatial interactions in deforestation outcomes. This paper seeks to fill this gap by estimating the relationship between transportation networks and deforestation at the national level, controlling for spatial dependence in deforestation decisions. Additionally, we draw on tools from the machine learning literature to assess whether spatial models improve the out-of-sample prediction of deforestation patterns Anselin (2020); Murray (2020); Singleton and Arribas-Bel (2021); Kopczewska (2022).

The literature also emphasizes the role of agricultural practices in driving deforestation in Brazil. In particular, activities related to cattle ranching and the expansion of high-value crops—such as soybeans, maize, and sugarcane—have been closely associated with forest conversion, reflecting growing domestic and international demand for beef, animal feed, and biodiesel Godar et al. (2012); Walker (2014); Faria and Almeida (2016). Accordingly, this paper controls for a broad set of confounding variables and spatial interactions related to these agricultural practices.

The paper is organized into five sections, including this introduction. Section 2 presents the theoretical framework linking transportation infrastructure and environmental outcomes. Section 3 describes the methodology and data. Section 4 reports and discusses the empirical results, and Section 5 concludes with final considerations.

2. Theoretical Framework

Investments in transportation infrastructure have the potential to foster economic growth and development Calderón and Serven (2010); Amann et al. (2016). Nevertheless, the causal relationship between transportation investment and development is not straightforward: on the one hand, economic growth generates additional incentives for infrastructure investment; on the other, the accumulation and quality of infrastructure may influence the pace of economic growth Amann et al. (2016). Regardless of this bidirectional relationship, transportation infrastructure plays a central role in shaping a country's economic and social development.

In Brazil, transportation infrastructure contributes significantly to regional development, job creation, and income generation, while also improving the population's living conditions. The road network, in particular, plays a predominant role in the Brazilian economy due to its substantial share in the national transportation matrix, accounting for approximately 96% of passenger transport and 60.5% of freight movement Projeto Infra 2038 (2019). Despite its importance, the sector still faces considerable challenges, especially those related to insufficient supply and low quality resulting from chronic underinvestment. This situation undermines the efficiency of the entire productive chain and constrains the country's economic development Bartholomeu and Caixeta Filho (2008).

Compounding this scenario, transportation infrastructure is commonly associated with significant negative environmental externalities Laurance et al. (2009); Jiang and Wu (2019), reflecting market inefficiencies that adversely affect social welfare Bartholomeu and Caixeta Filho (2008). Consequently, expansions in transportation infrastructure can generate not only economic and social benefits but also substantial negative externalities, which must be properly accounted for in order to assess the true cost–benefit of such investments Pfaff (1999). Indeed, the expansion of transportation infrastructure and the economic activity it facilitates are closely linked to environmental pressures, including deforestation, biodiversity loss, and greenhouse gas emissions Igliori (2006); Choumert et al. (2013); Barros and Stege (2019).

Theoretically, the expansion of transportation infrastructure increases the demand for forest goods—such as timber and firewood—and for land, while simultaneously expanding the supply of agricultural goods. These forces generate anthropogenic pressures on forested areas, ultimately leading to deforestation Asher et al. (2020). In many contexts, the deforestation process begins with road construction aimed at extracting high-value timber, which subsequently facilitates forest clearing for agricultural or pasture use Paiva et al. (2020). This initial extraction opens gaps within the forest canopy, followed by the removal of lower-value tree species, further degrading forest cover. As forest quality deteriorates, the present value of standing forests declines, strengthening incentives for agricultural frontier expansion. Finally, cleared areas are often burned to prepare the land for crop cultivation or livestock production Barber et al. (2014); Lawrence and Vandecar (2015); Jusys (2016).

Consequently, transportation infrastructure development, timber extraction, and the advance of the agricultural frontier jointly drive land-use change by increasing the expected economic returns to forest conversion. These processes can trigger additional migratory flows and further infrastructure investments, reinforcing deforestation dynamics through self-reinforcing feedbacks Fearnside (2005). At the same time, deforestation outcomes are shaped by geographic and climatic conditions that influence both agricultural profitability and infrastructure costs. In particular, high precipitation levels can raise construction and maintenance costs and limit agricultural productivity, thereby reducing incentives for forest clearing.

Deforestation associated with transportation infrastructure in Brazil has generated substantial environmental externalities, reflecting both the large share of forested areas in the national territory and the historical role of infrastructure investments in shaping patterns of land conversion. In particular, migration flows, the unsustainable exploitation of forest resources, land grabbing, and land price speculation have been identified as key mechanisms through which the expansion of transportation infrastructure contributes to deforestation, especially in agricultural frontier regions such as the Amazon Pfaff (1999); Fearnside and De Alencastro Graça (2006); Fearnside (2007); Soares-Filho et al. (2004); Tritsch and Le Tourneau (2016); Ferrante and Fearnside (2020).

In this context, Fearnside (2005) argues that Brazil must confront the "unsustainable development" associated with infrastructure investments through rigorous environmental cost analysis. Public decision-making in Brazil has often prioritized the construction of highways, dams, and large-scale infrastructure projects without adequately accounting for their direct and indirect environmental impacts. Emblematic examples include major Amazonian highways—such as BR-319 (Manaus–Porto Velho), BR-163 (Cuiabá–Santarém), and BR-364 (Cuiabá–Porto Velho)—as well as the Belo Monte hydropower project Soares-Filho et al. (2004); Fearnside and De Alencastro Graça (2006); Fearnside (2006, 2007). Thus, while transportation infrastructure expansion is frequently justified as essential for economic development, particularly in isolated and underdeveloped regions, it can also generate substantial environmental costs.

For these reasons, infrastructure projects are subject to Environmental Impact Assessments (EIAs), which aim to identify, prevent, mitigate, and offset negative environmental externalities associated with transportation infrastructure. In theory, EIAs serve as anticipatory environmental management tools that assess the potential impacts of projects on natural and built environments, thereby supporting decision-making that reconciles economic development with environmental protection Reis and Guzmán (2015); Chi et al. (2016). In practice, however, environmental licensing in Brazil is relatively recent and often ineffective, and EIAs frequently suffer from unclear objectives and weak methodological standards. As a result, major infrastructure projects—particularly highways located in environmentally sensitive regions—have accumulated significant environmental liabilities Glasson and Salvador (2000); Fearnside (2002). In this context, the results of this paper can help inform and improve future environmental impact assessments of transportation infrastructure in Brazil.

3. Methodology

3.1 Empirical Design and Database

To estimate the relationship between transportation infrastructure and deforestation in Brazil, we use data at the microregion level covering the country's 558 microregions. Our outcome variable is the proportion of deforested area in 2017, derived from the annual land cover and land use maps produced by the MapBiomas project, which are based on Landsat satellite imagery with a spatial resolution of 30 meters. The initiative was launched in 2015 and covers all 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 use vector data to construct specific variables and shapefiles for the empirical analysis. In particular, we rely on transportation infrastructure data—road and rail networks—from the MapBiomas project, as well as microregion shapefiles provided by the *Instituto Brasileiro de Geografia e Estatística (IBGE)*.

We use microregions as the unit of analysis because finer spatial aggregation could bias the results, as many areas lack official transportation infrastructure or contain only a small proportion of forest cover. In addition, we rely on a cross-sectional dataset because the machine learning literature has not yet converged on standard approaches for handling panel data structures, particularly when combined with spatial models. Therefore, given the cross-sectional nature of the data, the results should be interpreted with caution, and their potential limitations should be carefully considered.

This paper also relies on complementary vector databases to perform spatial analysis and geoprocessing using ArcMap 10.7. First, we employ polygon overlay procedures—specifically the Spatial Join tool—to intersect transportation infrastructure and microregion vector data, allowing us to measure the length (in kilometers) of the transportation network at the microregion level. We then normalize these measures by area to obtain comparable indicators across regions. In addition, we include a set of geographic, agricultural, and structural variables as controls. The inclusion of these variables aims to improve model specification and to reduce the risk of spurious correlations and omitted variable bias. In other words, additional controls help both to better characterize the relationship between transportation infrastructure and deforestation and to improve predictive performance. For this empirical design, we construct the following control variables: rainfall, soil characteristics, rivers, and protected areas. These variables are derived using the Spatial Join tool, and further details are provided below.

We construct the Soil variable using the Mapa de Potencial Agrícola do Brasil, compiled by the *Instituto Brasileiro de Geografia e Estatística (IBGE)* and made available by the *Ministério do Meio Ambiente (MMA)*. This classification assigns agricultural potential to Brazilian soils based on factors such as fertility, physical and morphological characteristics, main limitations, and topography. By merging the agricultural potential map with the microregions map, we identify the predominant soil type in each region. We then compute a weighted average that assigns higher weights to more suitable soils, resulting in an indicator bounded between zero and one, where higher values indicate greater agricultural suitability. This procedure controls for heterogeneity in soil quality, as the impact of transportation infrastructure may vary with agricultural potential. In particular, regions with more suitable soils may attract migratory flows, promote agricultural frontier expansion, and experience higher deforestation pressures, thereby increasing demand for infrastructure.

The Protected Area vector data were provided by the *Centro de Sensoriamento Remoto da Universidade Federal de Minas Gerais (CSR-UFMG)*. The Rainfall variable is constructed from average annual precipitation data for the period 1977–2006, obtained from the national hydrometeorological network, compiled by the *Serviço Geológico do Brasil (CPRM)*, and made available through the Pluviometric Atlas of Brazil.

We also include a set of social, economic, technological, and additional geographic variables that may improve the estimation. From IBGE, we obtain demographic density, the Gini index, GDP, the share of rural GDP, average property size, the proportion of pasture and planted areas, human capital (measured as average years of schooling), and indicators of property rights. In addition, we construct an agricultural technology index using Principal Component Analysis (PCA), based on multiple dimensions of technological access and adoption at the farm level, including: (1) tractors; (2) seeders; (3) limestone and fertilizer distributors; (4) harvesters; (5) access to technical assistance; (6) irrigation; (7) fertilization; (8) soil preparation; (9) electricity; (10) use of limestone; (11) pesticides; and (12) animal feed.

In addition, forest conversion and land-use change may exhibit spatial interactions that generate significant spillovers, influencing economic agents' decisions. Such spatial spillovers can arise from the presence of centripetal forces driven by differences in productivity and transportation costs, which may generate substantial regional disparities and attract productive activities, particularly in agriculture and livestock production.

The baseline model estimated is:

$$\text{Deforest}i = \beta 0 + \rho, W\text{Deforest}i + \beta 1\text{Road}i + \beta 2\text{Rail}i + \beta 3\text{Rivers}i + \beta k Z_i + \tau W S + \varepsilon_i, \quad (1)$$

where Deforest$i$ denotes the percentage of the microregion that was deforested; Zi is a matrix of k additional explanatory variables included in the model; and S represents the transportation network. The spatial dependence matrix W, which represents the neighborhood structure across regions, captures the presence of spatial spillovers in the variables. We adopt a k-nearest neighbors spatial weights matrix, selected to minimize the model's Akaike Information Criterion (AIC).

3.2 Exploratory Spatial Data Analysis (ESDA)

ESDA captures patterns of spatial dependence and heterogeneity, as well as spatial association patterns (clusters), and provides insights into how the data are distributed across space. Moran's I is used to measure the degree of spatial autocorrelation of a variable across regions. Formally,

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} z_i z_j}{\sum_{i=1}^{n} z_i^2}, \tag{2}$$

where n denotes the number of regions, S_0 is the sum of all elements of the spatial weights matrix W, and z represents the normalized value of deforestation. However, Moran's I captures only global spatial autocorrelation and does not identify local association patterns.

To address this limitation, we also employ the Local Indicators of Spatial Association (LISA), which capture local spatial autocorrelation and spatial clustering:

$$I_i = z_i \sum_{j=1}^{J} w_{ij} z_j, \tag{3}$$

where z_i represents the standardized value of the variable of interest in region i, w_{ij} denotes the (i, j)-th element of the spatial weights matrix W, and z_j is the standardized value of the variable in neighboring region j. The local Moran's I (LISA) identifies four types of spatial association: High–High (HH), Low–Low (LL), High–Low (HL), and Low–High (LH).

3.3 Spatial Econometrics

In this paper, we estimate three spatial models: the Spatial Autoregressive Model (SAR), the Spatial Lag of X Model (SLX), and the Spatial Durbin Model (SDM). The Spatial Autoregressive Model (SAR), which incorporates a spatial lag of the dependent variable, is specified as

$$\boldsymbol{y} = \rho \boldsymbol{W} \boldsymbol{y} + \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}, \tag{4}$$

where $\boldsymbol{y}$ is an $n \times 1$ vector of the dependent variable, $\boldsymbol{W}$ is an $n \times n$ spatial weights matrix, $\boldsymbol{X}$ is an $n \times k$ matrix of regressors, $\boldsymbol{\mu}$ is an intercept term, and $\boldsymbol{\epsilon}$ is an error vector. The standard assumptions of the SAR model are $\epsilon_i \sim \mathcal{N}(0, \sigma_\epsilon^2)$ and $E(\epsilon_i \epsilon_j) = 0$ for $i \neq j$.

The Spatial Lag of X Model (SLX), in contrast, includes spatial lags of the explanatory variables and is given by

$$\boldsymbol{y} = \boldsymbol{X} \boldsymbol{\beta} + \boldsymbol{W} \boldsymbol{Z} \boldsymbol{\theta} + \boldsymbol{\mu} + \boldsymbol{\epsilon}, \tag{5}$$

where $\boldsymbol{Z}$ may differ from $\boldsymbol{X}$.

Finally, the Spatial Durbin Model (SDM) generalizes the SAR and SLX models by allowing both the dependent and explanatory variables to be spatially lagged:

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

To estimate spatial models with endogenous spatial interactions (SAR and SDM), we employ a two-stage instrumental variables approach, using spatially lagged exogenous regressors as instruments—specifically, $W\boldsymbol{X}$ for the SAR model and $W^2\boldsymbol{X}$ for the SDM. The SLX model, by contrast, can be consistently estimated by ordinary least squares, as the spatially lagged explanatory variables are exogenous.

3.4 Machine Learning

Our machine learning approach aims to optimize predictive performance and is grounded in statistical methods. Machine learning models differ from traditional econometric approaches by prioritizing out-of-sample prediction rather than asymptotic properties or causal identification[1]. Broadly, machine learning methods can be classified as supervised methods, which are trained using labeled outcomes, or unsupervised methods, which aim to uncover latent patterns in the data.

In this paper, we focus on supervised regression-based algorithms, which are standard in the machine learning literature. Because regression models are widely used in empirical studies of deforestation to assess conditional relationships between outcomes and covariates, this approach allows us to complement the spatial econometric analysis by evaluating the predictive performance of models that incorporate transportation infrastructure and spatial interactions.

Model implementation follows a standard training–testing framework. The sample is partitioned into a training set, used to estimate model parameters, and a testing set, used to evaluate out-of-sample predictive accuracy and to mitigate overfitting. To assess predictive performance, we employ the root mean squared error (RMSE), defined as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i^{\mathrm{predicted}} - y_i^{\mathrm{actual}}\right)^2}, \tag{7}$$

where $y_i^{\mathrm{predicted}}$ denotes the predicted level of deforestation generated by the trained model, y_i^{actual} is the observed value in the testing sample, and n is the number of observations in the testing set. Lower RMSE values indicate superior predictive performance. This metric allows us to compare alternative model specifications and to assess whether transportation infrastructure variables and spatial dependence improve predictive accuracy.

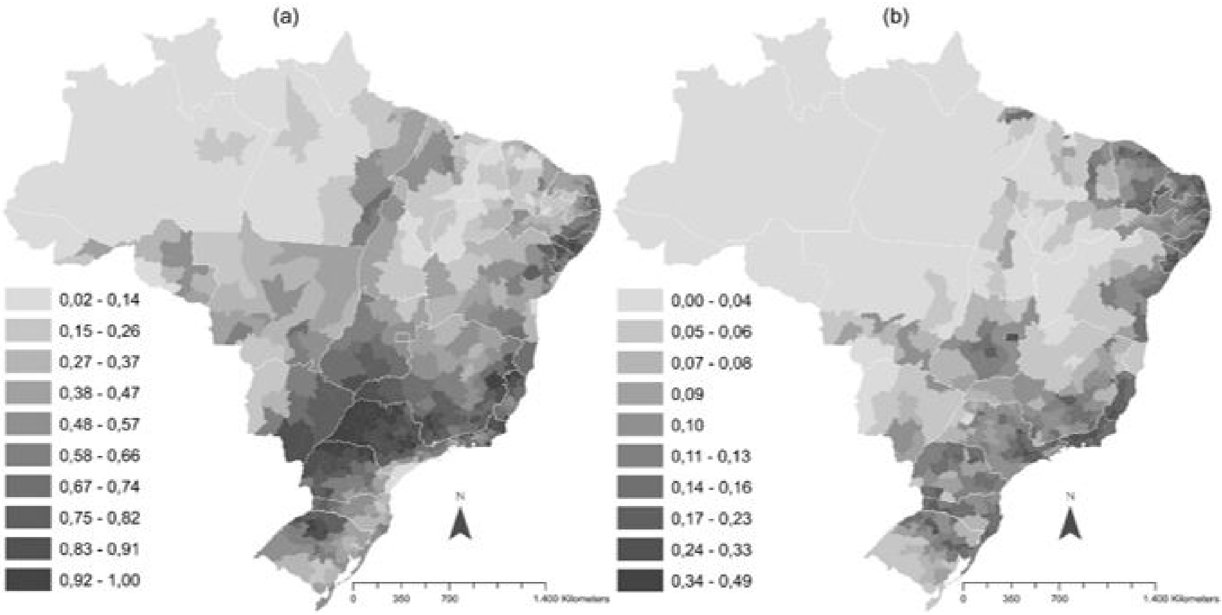
To ensure robustness, we apply a k-fold cross-validation procedure. The dataset is divided into k mutually exclusive subsamples, each of which is used once as a testing set while the remaining $k-1$ subsamples form the training set. The model is estimated k times, and the average RMSE across folds is reported. This procedure reduces sampling variability in the evaluation metric and provides a more reliable assessment of out-of-sample predictive performance.

[1] See Burger (2018); Kopczewska (2022) for overviews.

4. Results and Discussion

Deforestation in Brazil has significant negative environmental impacts, affecting neighboring localities and potentially undermining global climatic stability. Identifying its determinants is therefore essential for the design of effective mitigation measures, particularly in the context of transportation infrastructure expansion, which facilitates access to previously isolated areas and accelerates the pace of forest clearing. Figure 1 presents the spatial distribution of deforested area (panel a) and road network density[2] (panel b) across Brazil, revealing a clear spatial concentration in both variables.

Figure 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 regions. This spatial configuration reflects Brazil's historical colonization and occupation processes, which were more intense in the Southeast and Northeast. From a theoretical perspective, the spatial concentration of deforestation may arise from spatial interactions that reinforce deforestation dynamics, a phenomenon documented in several empirical studies Igliori (2006); Pfaff et al. (2007); Bouchardet et al. (2017); Pfaff and Robalino (2017); Jusys (2016); Barros and Stege (2019); Amin et al. (2019). Figure 2 confirms this pattern for deforestation and the road network in Brazil, exhibiting a spatial configuration similar to that shown in Figure 1. In particular, High–High clusters for both variables are observed in the Centro-Sul and Northeast, while Low–Low clusters dominate the North.

[2]The exploratory analysis focuses on the road network due to its central role in Brazilian transportation infrastructure.

Next, Table 1 reports the Ordinary Least Squares (OLS) estimations. Column (1) presents the baseline specification estimating the relationship between transportation infrastructure and deforestation in Brazil. Both road and rail network densities exhibit positive and statistically significant coefficients, indicating a positive association between transportation infrastructure and forest clearing. However, this specification should be interpreted as descriptive, as it is likely subject to endogeneity arising from omitted variables and reverse causality, given that infrastructure placement is correlated with unobserved economic and institutional factors. Even so, the model explains approximately 13.3% of the variation in deforested area across microregions.

Figure 2. LISA Map for Deforestation and Road Density in Brazil

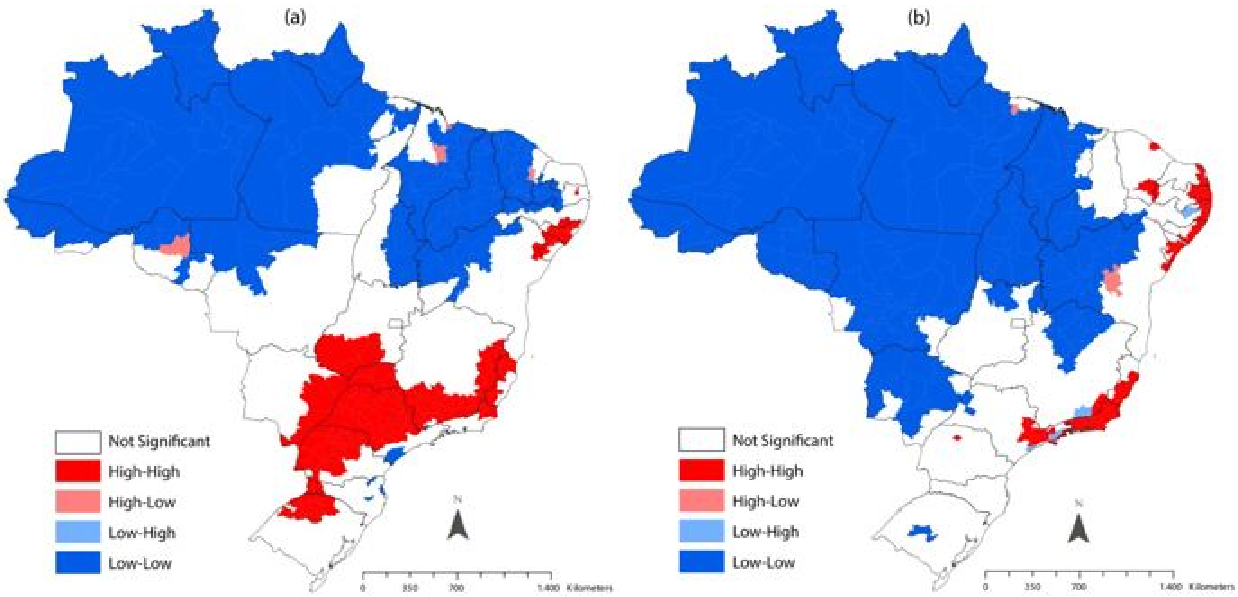


Table 1. Ordinary Least Squares

	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)
GDP^2		−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.

To mitigate potential biases arising from omitted variables and correlated unobservables, columns (2) through (6) progressively incorporate control variables capturing social, economic, agricultural, market structure, technological, climatic, geographic, human capital, and institutional characteristics. The benchmark specification in column (6) explains approximately 75% of the variation in deforestation across microregions. As additional controls are included, the estimated coefficients on road and rail network density decline in magnitude but remain statistically significant, indicating a stable conditional association with forest clearing. Moreover, the river variable becomes statistically significant once its correlation with the full set of controls is accounted for.

We further examine potential endogeneity concerns by conducting a set of diagnostic checks. Table A1 in the Appendix reports an endogeneity test[3] for each model specification. Overall, the estimated coefficients are statistically insignificant, suggesting no strong evidence of endogeneity according to this diagnostic procedure. However, we explicitly emphasize that this test has a diagnostic rather than identificational role and does not rule out reverse causality or unobserved confounding factors. Because our empirical strategy does not rely on an exogenous source of variation in transportation infrastructure, the estimated relationships should not be interpreted causally. Instead, the results should be understood as documenting robust conditional associations, consistent with the hypothesis that transportation infrastructure is spatially and conditionally correlated with deforestation outcomes.

Spatial interactions and spillovers may play a central role in deforestation decisions, while unobserved factors related to both transportation infrastructure and deforestation are likely to be spatially correlated. Indeed, Moran's I tests computed for each specification in Table 1 indicate that the residuals exhibit significant spatial autocorrelation. This evidence suggests that ignoring spatial dependence may lead to model misspecification and that explicitly modeling spatial interactions can improve model performance, particularly in terms of predictive accuracy.

To capture these spatial effects, it is necessary to address the endogenous nature of spatial dependence. Accordingly, we instrument neighborhood deforestation using spatial lags of exogenous characteristics, as described in Section 3.3, and estimate the spatial models using a k-nearest neighbors spatial weights matrix with $k = 5$[4]. We adopt as a reference specification the benchmark model reported in column (6) of Table 1, which yields the lowest Akaike Information Criterion and the highest adjusted R^2. Table 2 reports the results for this benchmark OLS model alongside the SLX, SAR, and SDM spatial specifications.

The estimated ρ coefficients are statistically significant in both the SAR and SDM

[3]The test consists of estimating auxiliary Ordinary Least Squares regressions of the explanatory variables on the residuals from the baseline specifications in Table 1.

[4]We tested alternative k-nearest neighbors matrices with k ranging from 3 to 100. The specification with $k = 5$ yielded the lowest Akaike Information Criterion among the alternatives considered.

specifications, indicating the presence of endogenous spatial dependence in deforestation outcomes, whereby forest clearing in one region is systematically related to deforestation in neighboring regions. Once this endogenous spatial interaction is explicitly modeled, the coefficients on road and rail network density become statistically insignificant. Importantly, this result should not be interpreted as evidence of a null conditional correlation between transportation infrastructure and deforestation. In spatial models such as the SDM and SLX, transportation infrastructure may affect deforestation through two distinct channels: indirectly, via endogenous feedback effects captured by the spatial lag of the dependent variable ($\rho W y$), and through spatial spillovers associated with the exogenous characteristics of neighboring regions, captured by the spatially lagged covariates (WX). Because transportation infrastructure is itself spatially clustered, its association with deforestation may be redistributed across these spatial channels once spatial effects are taken into account. Finally, it is important to emphasize that, in SAR and SDM models, the reported coefficients reflect only the estimated direct effects.[5] A full interpretation of infrastructure impacts would therefore require a formal decomposition, as well as exogenous variation in infrastructure placement to support causal inference, which lies beyond the scope of this article.

Table 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 adopt an alternative approach based on the machine learning literature to evaluate the predictive performance of our estimations. Specifically, we assess

[5] Indirect and total effects were not reported, as they did not qualitatively alter the main conclusions.

whether the estimated models can be used to improve the prediction of deforestation. Following standard practice in supervised machine learning, we split the sample into two subsets, one used to train the model and the other to test its predictive performance[6].

The results are reported in Table 3. The SAR model yields the lowest root mean squared error (RMSE), both in the full-sample estimation and in the 10-fold cross-validation exercise, despite the SDM specification exhibiting the highest adjusted R^2 and the lowest Akaike Information Criterion and Moran's I statistic for the residuals. These findings indicate that machine learning–based evaluation provides useful insights into the predictive capacity of the estimated spatial models. In practical terms, this approach may help inform the design of public policies by improving the anticipation of potential forest clearings.

Table 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 examines the relationship between transportation infrastructure and deforestation in Brazil using microregional data covering all national biomes. The analysis combines exploratory spatial data analysis with standard econometric, spatial econometric, and machine learning models to characterize the spatial distribution of both transportation networks and forest clearing, assess their conditional relationship across regions, and evaluate their predictive capacity. By explicitly modeling spatial effects, the empirical strategy allows for the identification of spatial interactions and spillovers affecting transportation infrastructure and deforestation outcomes, and leverages this information to improve predictive performance.

[6]For further details, see Section 3.4.

First, we assess this relationship empirically using Ordinary Least Squares (OLS) and spatial econometric models. In the OLS specifications, transportation infrastructure exhibits a statistically significant conditional association with deforestation, even after controlling for a broad set of structural and institutional characteristics. However, the spatial econometric results highlight the central role of spatial spillovers, interactions, and spatially correlated unobservables in explaining forest clearing. Once these spatial effects are explicitly accounted for, the direct coefficients on transportation infrastructure become statistically insignificant, suggesting that its influence on deforestation operates primarily through spatial channels.

We then adopt an alternative approach from the machine learning literature to evaluate the predictive performance of the estimated models. Overall, the results indicate that incorporating spatial effects improves predictive accuracy. Taken together, these findings provide evidence that can be useful for policy design, implementation, and monitoring. Despite these findings, it is important to acknowledge several caveats and opportunities for further research. First, this study relies on a parsimonious measure of transportation infrastructure based on linear density (kilometers per unit of area), which provides a transparent and tractable proxy for network presence at the microregional level and is well suited to a national-scale analysis. While the literature emphasizes richer dimensions of accessibility—such as travel time or cost to markets and ports, proximity to major corridors, road hierarchy, and infrastructure quality—explicitly modeling these dimensions lies beyond the scope of this paper. Rather than offering a comprehensive assessment of all mechanisms linking transportation infrastructure to land-use change, our objective was to document robust conditional associations between infrastructure presence, spatial interactions, and deforestation across Brazilian biomes, and to evaluate whether these relationships have predictive value. Incorporating more detailed accessibility and quality measures therefore represents a natural extension of this research.

Second, the analysis is based on conditional correlations between transportation infrastructure and forest clearing. While this approach is informative for understanding how spatial effects mediate the relationship and for improving predictive performance—both of which are relevant for policy design, implementation, and monitoring—it does not allow for causal interpretation. Identifying causal effects would require exogenous variation in infrastructure placement, which would also enable a more precise investigation of the spatial mechanisms through which transportation infrastructure influences deforestation outcomes.

Third, the empirical analysis relies on cross-sectional data, which may be affected by omitted variable bias and does not capture dynamic processes that are likely important in explaining deforestation patterns. This choice reflects technical considerations, as the primary objective of the paper was to integrate spatial econometric models within a machine learning framework. Methodological approaches that jointly accommodate spatial effects, dynamics, and machine learning remain relatively underdeveloped, particularly in panel settings. As these methods advance, a promising avenue for future research will be to extend this framework to dynamic spatial models that capture the temporal evolution of infrastructure expansion and forest clearing.

Taken together, these considerations highlight both the contributions and the limits of the present analysis. By explicitly accounting for spatial effects and evaluating predictive performance, the paper advances the understanding of how transportation infrastructure and deforestation are spatially interconnected in Brazil. Although the results do not support causal claims, they provide robust evidence that modeling spatial structure improves both explanatory coherence and predictive accuracy, reinforcing the importance of spatially informed empirical approaches for environmental policy analysis.

References

Alphan, H. (2017). Analysis of road development and associated agricultural land use change. *Environmental Monitoring and Assessment*, 190(5):145–159.

Alves, D. S. (2002). Space-time dynamics of deforestation in brazilian amazônia. *International Journal of Remote Sensing*, 23:2903–2908.

Amann, E., Baer, W., Trebat, T., and Villa Lora, J. (2016). Infrastructure and its role in brazil's development process. *The Quarterly Review of Economics and Finance*, 62:66–73.

Amin, A., Choumert-Nkolo, J., Combes, J.-L., Combes Motel, P., Kéré, E., Ongono-Olinga, J.-G., and Schwartz, S. (2019). Neighborhood effects in the brazilian amazônia: Protected areas and deforestation. *Journal of Environmental Economics and Management*, 93:272–288.

Anselin, L. (2020). *Spatial Data Science*, pages 1–6. American Cancer Society.

Araujo, R., Assunção, J., and Bragança, A. (2025). Transportation infrastructure and deforestation in the amazon. *Journal of Development Economics*, 177:103559.

Asher, S., Garg, T., and Novosad, P. (2020). The ecological impact of transportation infrastructure. *The Economic Journal*, 130:1173–1199.

Assunção, J., Gandour, C., and Rocha, R. (2015). Deforestation slowdown in the brazilian amazon: prices or policies? *Environment and Development Economics*, 20(6):697–722.

Austin, K., Schwantes, A., Gu, Y., and Kasibhatla, P. (2018). What causes deforestation in indonesia? *Environmental Research Letters*, 14:0–10.

Barber, C., Cochrane, M., Souza, C., and Laurance, W. (2014). Roads, deforestation, and the mitigating effect of protected areas in the amazon. *Biological Conservation*, 177:203–209.

Barros, P. H. B. and Stege, A. L. (2019). Deforestation and human development in the brazilian agricultural frontier: an environmental kuznets curve for matopiba. *Revista Brasileira de Estudos Regionais e Urbanos*, 13(2):161–182.

Bartholomeu, D. B. and Caixeta Filho, J. V. (2008). Impactos econômicos e ambientais decorrentes do estado de conservação das rodovias brasileiras: um estudo de caso. *Revista de Economia e Sociologia Rural*, 46(3):703–738.

Bouchardet, D. d. A., Porsse, A. A., and Timofeiczyk Junior, R. (2017). Analyzing the spatial dynamics of deforestation in brazilian amazon. *Geographical Analysis*, 49(1):23–35.

Bragança, A. (2018). The Economic Consequences of the Agricultural Expansion in Matopiba. *Revista Brasileira de Economia*, 72:161 – 185.

Burger, S. V. (2018). *Introduction to machine learning with R*. Beijing, [China], 1st edition edition.

Calderón, C. and Serven, L. (2010). Infrastructure in latin america. Policy Research Working Paper Series 5317, The World Bank.

Chi, C., Ruuska, I., and Xu, J. (2016). Environmental impact assessment of infrastructure projects: a governance perspective. *Journal of Environmental Planning and Management*, 59(3):393–413.

Choumert, J., Combes-Motel, P., and Dakpo, H. K. D. (2013). Is the environmental kuznets curve for deforestation a threatened theory? a meta-analysis of the literature. *Ecological Economics*, 90:19–28.

Dasgupta, P. (2021). The economics of biodiversity: The dasgupta review. Technical report, London: HM Treasury.

Faria, W. R. and Almeida, A. N. (2016). Relationship between openness to trade and deforestation: Empirical evidence from the brazilian amazon. *Ecological Economics*, 121:85–97.

Fearnside, P. (2005). Deforestation in brazilian amazonia: History, rates, and consequences. *Conservation Biology*, 19:680 – 688.

Fearnside, P. (2007). Brazil's cuiabá- santarém (br-163) highway: The environmental cost of paving a soybean corridor through the amazon. *Environmental Management*, (601):39.

Fearnside, P. and De Alencastro Graça, P. M. (2006). Br-319: Brazil's manaus-porto velho highway and the potential impact of linking the arc of deforestation to central amazonia. *Environmental Management*, 38:705–16.

Fearnside, P. M. (2002). Avança brasil: environmental and social consequences of brazil's planned infrastructure in amazonia. *Environ Management*, 30(6):735–747.

Fearnside, P. M. (2006). Dams in the amazon: Belo monte and brazil's hydroelectric development of the xingu river basin. *Environmental Management*, 38:16.

Ferrante, L. and Fearnside, P. (2020). The amazon: biofuels plan will drive deforestation. *Nature*, 577:170–170.

Glasson, J. and Salvador, N. N. B. (2000). Eia in brazil: a procedures–practice gap. a comparative study with reference to the european union, and especially the uk. *Environmental Impact Assessment Review*, 20(2):191–225.

Godar, J., Tizado, E., and Pokorny, B. (2012). Who is responsible for deforestation in the amazon? a spatially explicit analysis along the transamazon highway in brazil. *Forest Ecology and Management*, 267:58–73.

Igliori, D. C. (2006). Deforestation, Growth And Agglomeration Effects: Evidence From Agriculture In The Brazilian Amazon. Anais do XXXIV Encontro Nacional de Economia 102, ANPEC - Associação Nacional dos Centros de Pós-Graduação em Economia.

Jiang, R. and Wu, P. (2019). Estimation of environmental impacts of roads through life cycle assessment: A critical review and future directions. *Transportation Research Part D: Transport and Environment*, 77:148–163.

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

Kleinschroth, F., Laporte, N., Laurance, W., Goetz, S., and Ghazoul, J. (2019). Road expansion and persistence in forests of the congo basin. *Nature Sustainability*, 2:628–634.

Kopczewska, K. (2022). Spatial machine learning: new opportunities for regional science. *The Annals of Regional Science*, 68.

Laurance, W., Goosem, M., and Laurance, S. (2009). Impacts of roads and linear clearings on tropical forests. *Trends in ecology & evolution*, 24(12):659–669.

Lawrence, D. and Vandecar, K. (2015). Effects of tropical deforestation on climate and agriculture. *Nature Climate Change*, 5:174–174.

Murray, A. T. (2020). Spatial analysis and modeling: Advances and evolution. *Geographical Analysis*, pages 1–18.

Nepstad, D., Carvalho, G., Barros, A., Alencar, A., Capobianco, J., Bishop, J., Moutinho, P., Lefebvre, P., Silva Júnior, U., and Prins, E. (2001). Road paving, fire regime feedbacks, and the future of amazon forests. *Forest Ecology and Management*, 154(3):395–407. New Directions in Tropical Forest Research.

Newman, M. E., P., M. K., and Wilson, B. S. (2014). Assessing deforestation and fragmentation in a tropical moist forest over 68 years; the impact of roads and legal protection in the cockpit country, jamaica. *Forest Ecology and Management*, 315:138–152.

Paiva, P., Ruivo, M., Marques da Silva Junior, O., Maciel, M., Braga, T. G., Andrade, M., dos Santos Junior, P., Rocha, E., Freitas, T., Leite, T., Gama, L., Santos, L., Silva, M., Silva, E., and Ferreira, B. (2020). Deforestation in protect areas in the amazon: a threat to biodiversity. *Biodiversity and Conservation*, 29:19–38.

Pfaff, A. (1999). What drives deforestation in the brazilian amazon?: Evidence from satellite and socioeconomic data. *Journal of Environmental Economics and Management*, 37(1):26–43.

Pfaff, A. and Robalino, J. (2017). Spillovers from conservation programs. *Annual Review of Resource Economics*, 9(1):299–315.

Pfaff, A., Robalino, J., Walker, R., Aldrich, S., Caldas, M., Reis, E., Perz, S., Bohrer, C., Arima, E., Laurance, W., and Kirby, K. (2007). Road investments, spatial spillovers, and deforestation in the brazilian amazon. *Journal of Regional Science*, 47(1):109–123.

Projeto Infra 2038 (2019). Relatório infra (19): Acompanhamento do avanço da infraestrutura no brasil. Technical report, Infra 2038.

Reis, E. J. and Guzmán, R. M. (2015). An Econometric Model of Amazon Deforestation. Technical Report 34, Instituto de Pesquisa Econômica Aplicada - IPEA.

Robalino, J. A. and Pfaff, A. (2012). Contagious development: Neighbor interactions in deforestation. *Journal of Development Economics*, 97(2):427–436.

Singleton, A. and Arribas-Bel, D. (2021). Geographic data science. *Geographical Analysis*, 53(1):61–75.

Soares-Filho, B., Alencar, A., Nepstad, D., Cerqueira, G., Vera Diaz, M. C., Rivero, S., Solórzano, L., and Voll, E. (2004). Simulating the response of land-cover changes to road paving and governance along a major amazon highway: the santarém–cuiabá corridor. *Global Change Biology*, 10(5):745–764.

Tritsch, I. and Le Tourneau, F. (2016). Population densities and deforestation in the brazilian amazon: New insights on the current human settlement patterns. *Applied Geography*, 76:163–172.

Walker, R. (2014). Sparing land for nature in the brazilian amazon: Implications from location rent theory. *Geographical Analysis*, 46(1):18–36.

Walker, R., Arima, E., Messina, J., Filho, B., Perz, S., Vergara, D., Sales, M., Pereira, R., and Castro, W. (2013). Modeling spatial decisions with graph theory: Logging roads and forest fragmentation in the brazilian amazon. *Ecological applications : a publication of the Ecological Society of America*, 23:239–54.

Appendix:

A.1. Endogeneity Test

	Dependent variable:							
	Residuals	Residuals	Residuals	Residuals	Residuals	Residuals	Residuals	Residuals
	(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.