Relationship between Economic Growth and Deforestation in Brazil: the role of Spatial Spillovers and Heterogeneity

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ABSTRAT: This paper estimates an Environmental Kuznets Curve (EKC) for deforestation in Brazil and access the role of both spatial spillovers and heterogeneity in the economic growth and forest clearings relationship, using models from spatial econometrics and a Geographically Weighted Regression with spatial lag (GWR-SL). The exploratory analysis pointed to spatial concentration of deforestation in agricultural frontier regions, especially Matopiba. We confirm the importance of spatial spillovers and heterogeneity and get a global and locals (for Legal Amazon) inverted-"U" format for the EKC, indicating that deforestation increases until a certain threshold, as the region develops, from which it begins to fall. The empirical evidences point to additional variables that also induced deforestation: (i) – Global: forest area and spatial spillovers from deforestation; (ii) – Local: soil suitability for farming and openness to trade both for Amazon and agricultural dependence in Matopiba and Northeast region. The inverted-"U" relationship for Brazil has the turning point occurring at R$26,220, demonstrating that deforestation increase until a certain threshold as the country develops, from which it begins to fall

Keywords: Deforestation; Environmental Kuznets Curve (EKC); Spatial Effects.

ABSTRAT: Este artigo estima uma Curva Ambiental de Kuznets (CKA) considerando o desmatamento no Brasil ao mesmo tempo que leva em considerações possíveis efeitos espaciais de transbordamento (*spillovers*) e de heterogeneidade, utilizando-se de modelos espaciais econometria espacial e uma Regressão Ponderada Geograficamente (RPG) com defasagem espacial. Uma análise exploratória preliminar apontou para uma concentração espacial do desmatamento em regiões de fronteira agrícola, especialmente no Matopiba. Em seguida, confirmamos a importância dos efeitos espaciais para a relação com a Amazônia Legal apresentando efeitos locais significativos – relação em "U" invertido para a CKA -, indicando que o desmatamento cresce até um certo patamar conforme a região se desenvolve, a partir do qual se reduz progressivamente. Além disso, as evidências empíricas demostraram a importância das seguintes variáveis para explicar o desmatamento: (i) – Globais: área florestas e transbordamentos espaciais do desmatamento; (ii) – Locais: qualidade do solo e abertura comercial na Amazônia Legal e dependência do setor agrícola no Matopiba e Nordeste. Por fim, a relação em "U" invertida para o Brasil apresentou um ponto de inflexão da ordem de R$26.220, demonstrando que o desmatamento cresce até esse patamar de renda conforme o país se desenvolve, a partir do qual apresenta tendência a decrescer.

Keywords: Desmatamento; Curva Ambiental de Kuznets (CKA); Efeitos Espaciais

Classificação JEL: Q01; Q56.

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1. INTRODUCTION

Brazil holds a considerable share of the planet's natural resources and play a key role in regulating the global climate. Nevertheless, the country's deforestation has caused concern worldwide due to irreparable loss of its natural wealth and biodiversity, along with greenhouse gas emissions that leads to climate change (Myers et al., 2000).

In fact, in tropical underdeveloped countries as Brazil, economic growth is largely associated with land use changes and deforestation (Igliori, 2006). However, it is worth mentioning that Grossman and Krueger (1995) propose an inverted-U relationship between economic growth and environmental degradation, known as the Environmental Kuznets Curve (EKC). In other words, the economic growth could reverse its negative impact on the Brazilian forests after reaching a certain threshold. In this context, this paper aims to check if there is an inverted-U relationship between economic growth and deforestation in Brazil and, then, estimate the tipping point for the EKC. There is no paper, to the best of our knowledge, that estimated an EKC for Brazil considering all biomes of the country, therefore, this is an important contribution to the literature.

However, for specific Brazilian biomes as Amazon and Cerrado, the empirical evidence is mixed, which varies according to the period, region and method used. In the Amazon, Gomes and Braga (2008), Prates (2008), Santos et al. (2008), Polomé and Trotignon (2016), Tritsch and Arvor (2016) found evidence of an inverted "U" relationship while Araújo et al. (2009), Jusys (2016) and Barros and Stege captured a "U". Oliveira et al. (2011) and Oliveira and Almeida (2011) identified a relationship in the "N" format. For the Cerrado biome, Stege and Barros (2019) support an inverted "U" relationship while for Matopiba region, the agricultural frontier of the Cerrado, Barros and Stege (2019) also found an inverted "U" relationship for the EKC. Therefore, the evidences are not conclusive, which reinforces the need for additional empirical efforts, the aim of this paper.

It is worth mentioning that there are several additional factors can also explain deforestation. Especially, we can mention the Brazilian agricultural frontier expansion at Arc of Deforestation and Matopiba[2], located in Amazon and Cerrado, respectively, since it increases the pressure for new agricultural areas, inducing land use changes and environmental degradation. The Amazon, for example, is the most active agricultural frontier in the world in terms of forest loss and CO_2 emissions (Assunção et al., 2015). In addition, activities related to cattle and crops that have gained market value, such as soybeans, maize and sugarcane (Godar et al.; 2012; Andrade de Sá et al., 2013; Assunção et al., 2015; Faria and Almeida, 2016; Jusys, 2016; Araújo et al., 2019). The infrastructure network also causes considerable direct and indirect damages by influencing the spatial patterns of land use and illegal activities (Pfaff et al., 2007; Jusys, 2016).

According to Maddison (2006) and Robalino and Pfaff (2012), spatial interactions are a common effect when considering forest conversion and land use changes, since both are affected by neighbors' decision and by spatially correlated unobservables. Deforestation is also heterogeneous, occurring mainly in agricultural frontier areas, which fails to produce robust estimates for EKC since each has its own turning point. In fact, the literature supports heterogeneous patterns and spatial spillovers in deforestation (Igliori, 2006; Oliveira and Almeida, 2011; Andrade de Sá et al., 2015; Jusys, 2016; Amin et al., 2019). In this context, spatial interactions and heterogeneous outcomes may change the relationship between economic growth and deforestation, therefore, to overcome this caveat, this paper aims to adopt complementary models that considered these spatial effects. First, we propose to estimate models from the spatial econometrics[3] to capture interactions and, then, we also proposed to

[2] Cerrado's agricultural frontier in Maranhão, Tocantins, Piauí and Bahia.
[3] Spatial Autorregresive Model (SAR), Spatial Lag of X (SLX) and Spatial Durbin Model (SDM).

estimate a local EKC with Geographically Weighted Regression with spatial lags (GWR-SL), calculating one coefficient for each region while controlling for both spatial heterogeneity and spillovers.

This paper is structured into four sections, including this one. In the second, we detail the framework while in the third we describe the methodology and the database. The results and discussions are in the fourth, followed by the final considerations.

2. THEORETICAL FRAMEWORK

Grossman and Krueger (1991), in a pioneering work, found an inverted U-relationship between economic growth and environmental impact, which became known as the Environmental Kuznets Curve, due to the North American Free Trade Agreement creation. In addition, the authors attempted to decompose the effects of this relationship: scale, composition, and technical. The scale effect occurs due to an increase in production, which causes a pressure on the environment, since greater natural resources use are needed. The composition effect is the change that occurs in the composition of goods and services (such as, for example, the displacement of industrial goods for services). Finally, the technical effect is related to technological advances that increase productivity and/or make production "cleaner"", generating less externalities. The composition and technical effects can be large enough to minimize the scale effect after a certain development threshold, which can reverse the negative impact from economic growth and then generate the descending part of the Environmental Kuznets Curve (Grossman and Krueger, 1991).

Several papers have attempted to broaden the understanding of the relationship between economic development and environmental degradation. Among them, we can mention Shafik and Bandyopadhyay (1992), Selden and Song (1994), Arrow et al. (1995), Stern et al. (1996), Suri and Chapman (1998), De Bruyn et al. (1998), Culas (2007). The environmental pressure, argues Selden and Song (1994), is due to growth in income and production, which lead to greater natural resources use. However, there are counter forces that may lead to an inverted U-relationship EKC: (i) a positive income elasticity for environmental quality; (ii) - changes in the economy composition; (iii) - technological innovations. Arrow et al. (1995) argue that the EKC occurs due to the nature of economic that shifts the productive activities from the agricultural sector to the industrial and, finally, to services, which is less harmful to the environment. Many researchers, however, argue that the EKC declining part occurs because the polluters move from developed countries to the underdeveloped ones, reflecting the sticker laws in richer countries, known in the literature as the Pollution Haven hypothesis (Suri and Chapman, 1998; Arrow et al., 1995; Stern et al., 1996).

On the other hand, De Bruyn et al. (1998) argue that the inverted U-shape is sustained only in the short term because there is another turning point in which per capita income growth leads once again to environmental degradation. Therefore, an "N" -shaped curve would better represent the relationship; and that other formats are possible, which require specific investigations.

Considering deforestation in the EKC approach, there is no consensus about the existence of an inverted "U" relationship. Shafik and Bandyopadhyay (1992), in a pioneering investigation, have not found statistically significant results while Cropper and Griffiths (1994), considering Africa, Latin America and Asia, confirmed the economic growth impact on deforestation for the first two. Bhattarai and Hammig (2001) conducting a similar empirical strategy also confirmed an inverted "U" relationship. The authors argue that underdeveloped areas have a demand structure, as the consumption of firewood, which causes deforestation, but as economic growth occurs, such demand tends to move goods, and especially services, that are less harmful to the environment. In addition, it also leads to restoration efforts, which ends up reversing the deforestation process. Koyuncu and Yilmaz (2009) supports that an increase in demand for arable land also has a significant impact on deforestation along economic growth.

2. METHODOLOGY

2.1 Exploratory Spatial Data Analysis (ESDA), Spatial Econometrics and the Geographically Weighted Regression with spatial lag (GWR-SL)

The ESDA capture effects of spatial dependence and heterogeneity, spatial clusters and distribution. To investigate spatial correlation, we use Moran's I,

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

n is the number of regions, S_0 is the sum of Welements, z is deforestation (normalized). For local spatial clusters, we use LISA statistic,

$$I_i = z_i \sum_{j-1}^{J} w_{ij} z_j \quad (2)$$

z_i and z_j represents deforestation in region i and j, respectively; w_{ij} is the spatial weighting element (W). The LISA capture four spatial clusters: High-High (AA), Low-Low (BB), High-Low (AB) and Low-High (BA). The most analyzed is the High-High cluster, which indicates that a region with a high value for the analyzed variable is surrounded by regions with similar values.

In an econometric model, it is possible to incorporate the spatial component through spatially lagged variables. It is possible to propose a general spatial model that, by imposing restrictions on the parameters, can achieve the desired specifications. Such a model is

$$y = \rho W y + X\beta + WX\tau + \varepsilon \quad (3)$$

where X is the matrix of explanatory variables; β is the vector $k \times 1$ of regression coefficients; ε is the error term with mean zero and constant variance. The Spatial Autoregressive Model (SAR) is obtained by imposing the following constraints on the model (16): $\rho \neq 0,\ \tau = 0$ and $\lambda = 0$. In this paper, the SAR model will seek to identify if the deforestation rate of a given municipality is influenced by the value of its neighbors, determined according to a spatial weight matrix. If $\rho > 0$ and significant, there is evidence of positive spatial autocorrelation, while a significant $\rho < 0$ indicates the presence of negative spatial autocorrelation. The above model will suffer from the problem of endogeneity of the lagged variable, then, it estimated through instrumental variables, which are the lagged explanatory variables (WX).

The Spatial Lag of X model (SLX) occurs when $\rho = 0,\ \tau \neq 0$ and $\lambda = 0$, it seeks to capture the presence of spatial spillover from the explanatory variables. The model does not present the problem of endogeneity, and it is therefore possible to estimate by Ordinary Least Squares. The Spatial Durbin Model (SDM) is a combination of the previous models, obtained with $\rho \neq 0,\ \tau \neq 0$ and $\lambda = 0$.

The Geographically Weighted Regression with spatial lag (GWR-SL), developed by Brundson, Fotheringham and Charlton (1996), estimates a coefficient for each region to control spatial heterogeneity while capturing spillovers from the dependent variable. It uses subsamples weighted by geographical distance,

$$y_i = \beta_0(u_i, v_i) + \rho(u_i, v_i)Wy_i + \sum_k \tau_k W\chi_{ik} + \sum_k \beta_k (u_i, v_i)\chi_{ik} + \varepsilon_i \quad (4)$$

Wy_i and $W\chi_{ik}$ are the dependent and independent spatially lagged variables with an spatial weights matrix W; ρ are τ capture spatial spillovers; (u_i, v_i) indicates the coordinates i; $\beta_k(u_i, v_i)$ is the local coefficient; χ_{ik} are the independent variables. The model suffers from endogeneity, requiring to estimate Wy_i with the instruments WWX. The estimation is based on the weighted least squares

$$\beta(u_i, v_i) = (X'W(u_i, v_i)X)^{-1}X'W(u_i, v_i)y \quad (5)$$

W is the adaptive weight matrix based on the distance between region i and j. The subsample is obtained from a spatial kernel function with bandwidth determined by the akaike criterion.

3.2 Database

The deforestation data comes from the *Mapbiomas Project* and we considered the proportion of forests and natural areas deforested. The database considers as a geographic cut all 558 microregions, which is a sub-state territorial entity in Brazil, for the year 2017, except for per capita income, forest area and agricultural GDP that is from 2016; road and rail network that is from 2014, necessary to avoid endogeneity problems. We include covariates to prevent poor specification and spurious regressions, following Stern (2017). Table 1 brings the variables description.

Table 1 – Variables description.

Abbreviation	Description	Unit	Source
Deforest	Normalized Deforestation	Unit	Mapbiomas
GDP	Per capita GDP	R$	IBGE
C.T Index*	Capital and Technology Index	Unit	Agricultural Census/IBGE
Rural Education	Proportion with Elementary School in Rural Areas	%	Agricultural Census/IBGE
Road Network	Roads (km)/Microregion (km²)	km/ km²	CSR/UFMG
Rail Network	Rail (km)/Microregion (km²)	km/ km²	CSR/UFMG
Rural Title	Rural Property title	%	Agricultural Census/IBGE
Open.Trade	(Export+Import)/GDP	R$	IPEA/IBGE
Agric.GDP	Agricultural GDP	%	IBGE
Pasture	Pasture (km²)/Microregion (km²)	%	Agricultural Census/IBGE
Crop	Crop (km²)/Microregion (km²)	%	Agricultural Census/IBGE
Protected Area	Protected Area (km2)/Microregion (km²)	%	CSR/UFMG
Soil	Soil suitability for farming	%	MMA/IBGE
Altitude	Altitude	m	IPEA
Rainfall	Annual precipitation	mm	CPRM
Temperature	Temperature	ºC	CSR/UFMG
Amazon	Dummy for Amazon	binary	-
Cerrado	Dummy for Cerrado	binary	-
Forest	Forest (km²)/Microregion (km²)	%	Mapbiomas

Source: research data. *Note:* *Constructed with: 1. Warehouse; 2.No-till farming; 3.Fertilizing; 4.Soil preparation; 5.Agricultural machinery; 6.Truck and utility vehicle.

We constructed the Capital and Technology Index with factorial analysis, which permits to model important influences that may correlated, helping prevent bias from poor specification and multicollinearity. First, we confirm the sample suitability with the *Kaiser-Meyer-Olkin*[4]. The factors were extracted using the Principal Component Method and the Index calculated with factorial loads.

We consider geographic and structural variables and used vectors data to construct, some of the controls, with the spatial joint tool in the GIS software (ArcMap 10.7), specifically to this empirical design: Road and Rail Networks, Protected Area, Soil, Temperature, Rainfall, Altitude. It is worth mentioning that we check for correlation and notice no values (Appendix F) that could compromise the estimations.

3.3 Empirical Design

Forest conversion and land use changes may present spatial interactions that result in significant spillovers, influencing the economic agent's decision. This spatial externality usually occurs in the presence of centripetal forces, generated by productivity and transport costs differences, which attracts productive activities (Maddison, 2006; Wenhold and Reis, 2008; Robalino and Pfaff, 2012). On other words, this externality may influence the agricultural frontier expansion, leading to deforestation, which we try to capture with the model

$$Deforest_i = \beta_0 + \beta_1 GDP_i + \beta_2 GDP^2{}_i + \beta_3 GDP^3{}_i + \beta_k Z_i + \rho WDeforest + \tau WS + \varepsilon_i \qquad (5)$$

Z is the matrix of k additional explanatory variables; S is a vector containing elements that represents the agricultural frontier expansion: pasture and crop, in other words, S is a subset of Z. The spatial matrix W represents the structural configuration between the regions and capture the spatial spillovers from deforestation (ρ) and from the agriculture frontier expansion (τ). In other words, the $WDeforest$ and WS are constructed by multiplying the deforestation variable and the vector for the agricultural frontier expansion, pasture and crop, respectively, with the spatial matrix W, which result in a measure that in practice capture the mean value for neighbors defined by the spatial matrix.

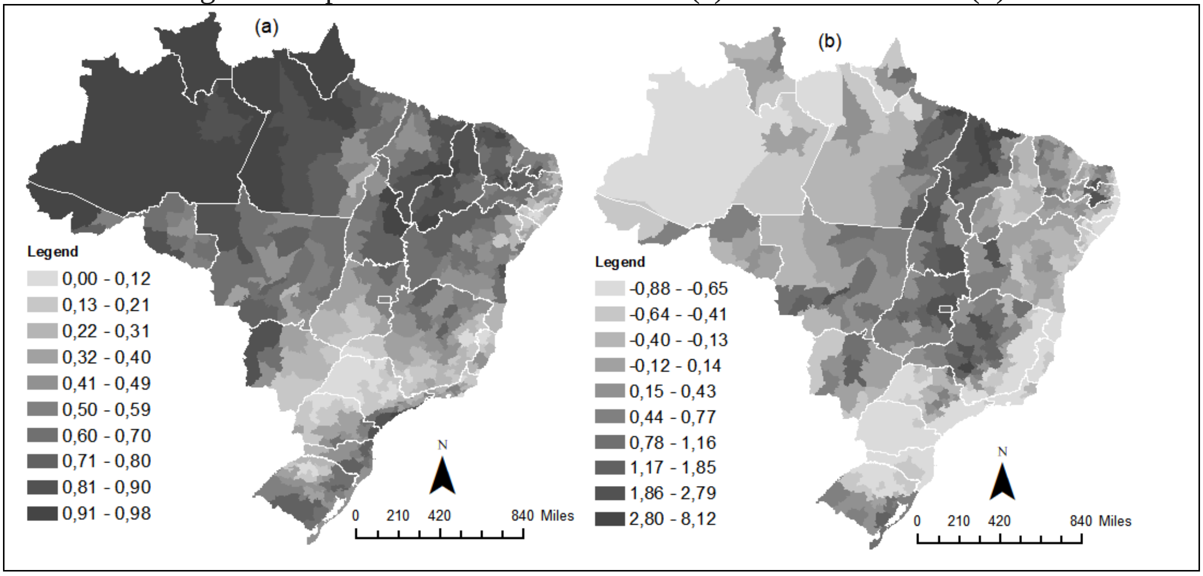
The EKC format reflects the statistical significance and signs of the coefficients β_1, β_2 and β_3. It is a sufficient condition to a linear format, a significant $\beta_1 > 0$ with β_2 and β_3 not significant. For an inverted "U" shape, it is sufficient that $\beta_1 > 0$, $\beta_2 < 0$ and that both are significant while β_3 is not. Finally, $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 > 0$, all statistically significant, is a necessary and sufficient condition for an "N" curve shape. According to Stern (2017), if the model presents a β_1 and β_2 statistically significant, it is possible the curve turning point with equation $\tau = -\frac{\beta_1}{2\beta_2}$.

4. RESULTS AND DISCUSSION

Deforestation in Brazil has significant negative impacts, potentially affecting the global climatic stability; therefore, the search for its causes is fundamental to developed inhibitory measures. Figure 1 shows the forest (a) and deforestation (b) spatial distribution in Brazil. We have a concentration for both variables with forest area (%) concentrated in Amazon and Matopiba while deforestation is spatially concentrated in Cerrado

[4] The test presented a value of 0,8189, indicating the suitability of the method for the database.

Figure 1 - Spatial Distribution of Forest (a) and Deforestation (b).



Source: research data.

The Moran's I (Table 2) ratify the spatial concentration hypothesis for forest and deforestation with positive and significant coefficients - independent of the convention matrix. This spatial concentration may result from interactions, which can reinforce it (Igliori, 2006; Pfaff et al., 2007; Oliveira and Almeida, 2011; Oliveira et al., 2011; Andrade de Sá et al., 2015; Jusys, 2016; Amin et al., 2019).

Table 2 - Moran's I for Forest and Deforestation.

	Weights Matrix					
	Queen	Rook	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
Forest	0.48*	**0.49***	0.40*	0.38*	0.35*	0.31*
Deforestation	0.71*	**0.72***	0.69*	0.68*	0.66*	0.60*

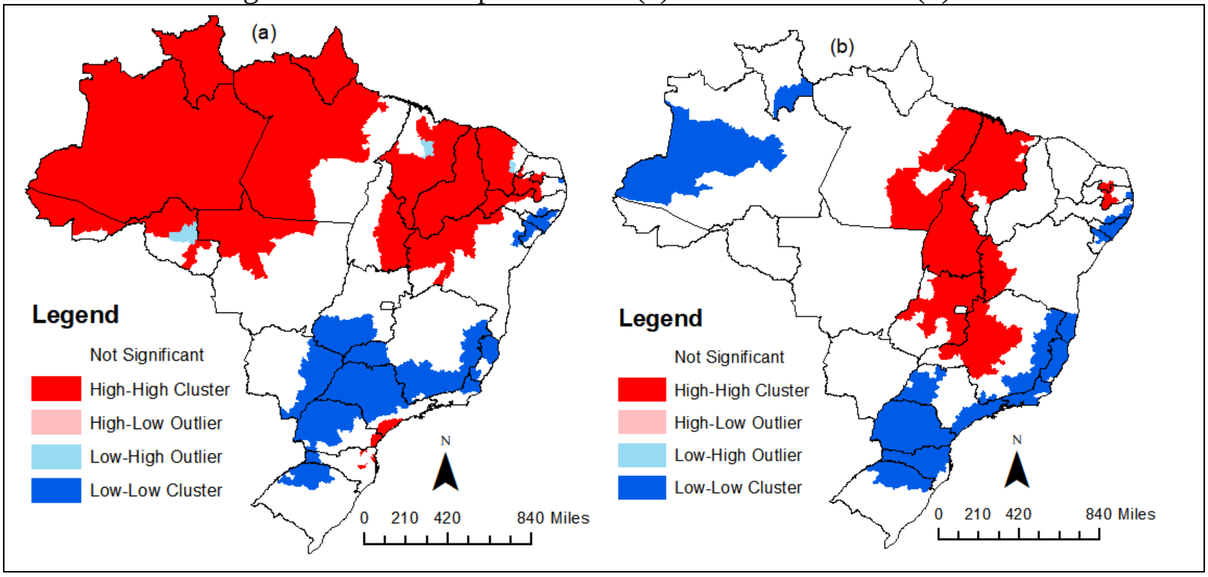
Source: research data. *Note*: * Level of significance of 1%.

Figure 2 confirms it with similar spatial configuration from Figure 1. We have a High-High cluster for forest in Amazon and Matopiba and for deforestation in Cerrado, including its agricultural frontier.

The next step is to model deforestation. First, we estimated the OLS and the spatial model's SAR, SLX and SDM[5] (Table 3), choosing the spatial matrix based on Moran's I from the OLS residuals (Appendix A). The Jarque-Bera rejected the residuals normality while Koenker-Bassett reject homoscedasticity. Therefore, we estimated the models with GMM and White's robust error. The SAR model minimize the Moran's I in the residuals and control the spatial autocorrelation problem (statistically insignificant) by including spillovers from deforestation. We confirmed an inverted-"U" relationship for Brazil with the turning point occurring at R$26,220, demonstrating that deforestation increase until a certain threshold as the country develops, from which it begins to fall[6]. Finally, we have statistical significance for: Soil, Rainfall, Amazon, Cerrado, Forest; and Spatial Spillovers (ρ) from deforestation.

[5] Spatial Autorregresive Model, Spatial Lag of X and Spatial Durbin Model, respectivly.
[6] We test the cubic model, but the coefficients was not significant.

Figure 2 – LISA Map for Forest (a) and Deforestation (b).



Source: research data.

Therefore, it confirmed the importance of spatial spillovers from deforestation, highlighting the importance of spatial interactions in forest conversion. In addition, the Forest significance indicates that higher clearing is associated with greater proportion of native forests while the Soil highlight concern since shows that deforestation is occurring in soils relatively unfit for farming, a fact that may result in lower productivity and profits in agricultural production. After controlling for covariates, the Amazon and Cerrado variables indicates that these biomes present a higher deforestation rate, especially the first.

Table 3 – Environmental Kuznets Curve.

	OLS	SLX	**SAR**	SDM
Constant	-0.0162	-0.1079	**-0.4245**	-0.5007
GDP	0.0006**	0.0006**	**0.0004****	0.0004**
GDP^2	-1.00E-07**	-1.00E-07**	**-1.00E-07****	-1.00E-07**
C.T Index	-0.6288	-0.6136	**-0.0644**	-0.0563
Rural Education	0.1284	0.0524	**0.0225**	-0.0071
Road Network	-2.1484**	-2.1256**	**-1.0735**	-0.9918
Rail Network	0.0697	0.2019	**0.2661**	0.3156
Rural Title	-0.3820	-0.3756	**-0.1770**	-0.2080
Open.Trade	-0.0735	-0.0989	**-0.1511**	-0.1519
Agric. GDP	0.0085	0.0080*	**0.0057**	0.0051
Pasture	0.0103**	0.0065	**0.0042**	0.0018
Crop	0.0039	0.0025	**0.0016**	-0.0013
Protected Area	4.00E-07	6.00E-07	**1.60E-06**	1.70E-06
Soil	-0.6827**	-0.6847**	**-0.4936****	-0.5198**
Altitude	0.0001	0.0001	**1.49E-05**	8.50E-06
Rainfall	-0.0004**	-0.0004**	**-0.0003****	-0.0003**
Temperature	-0.0256	-0.0242	**0.0105**	0.0139
Amazon	1.6186**	1.6342**	**0.8564****	0.8664**
Cerrado	0.6350**	0.6270**	**0.2252***	0.2119*
Forest	0.9721**	1.0036**	**0.4797***	0.4932*
ρ (Spillover)	-	-	**0.5988****	0.6200**
W_Pasture	-	0.0062	-	0.0031

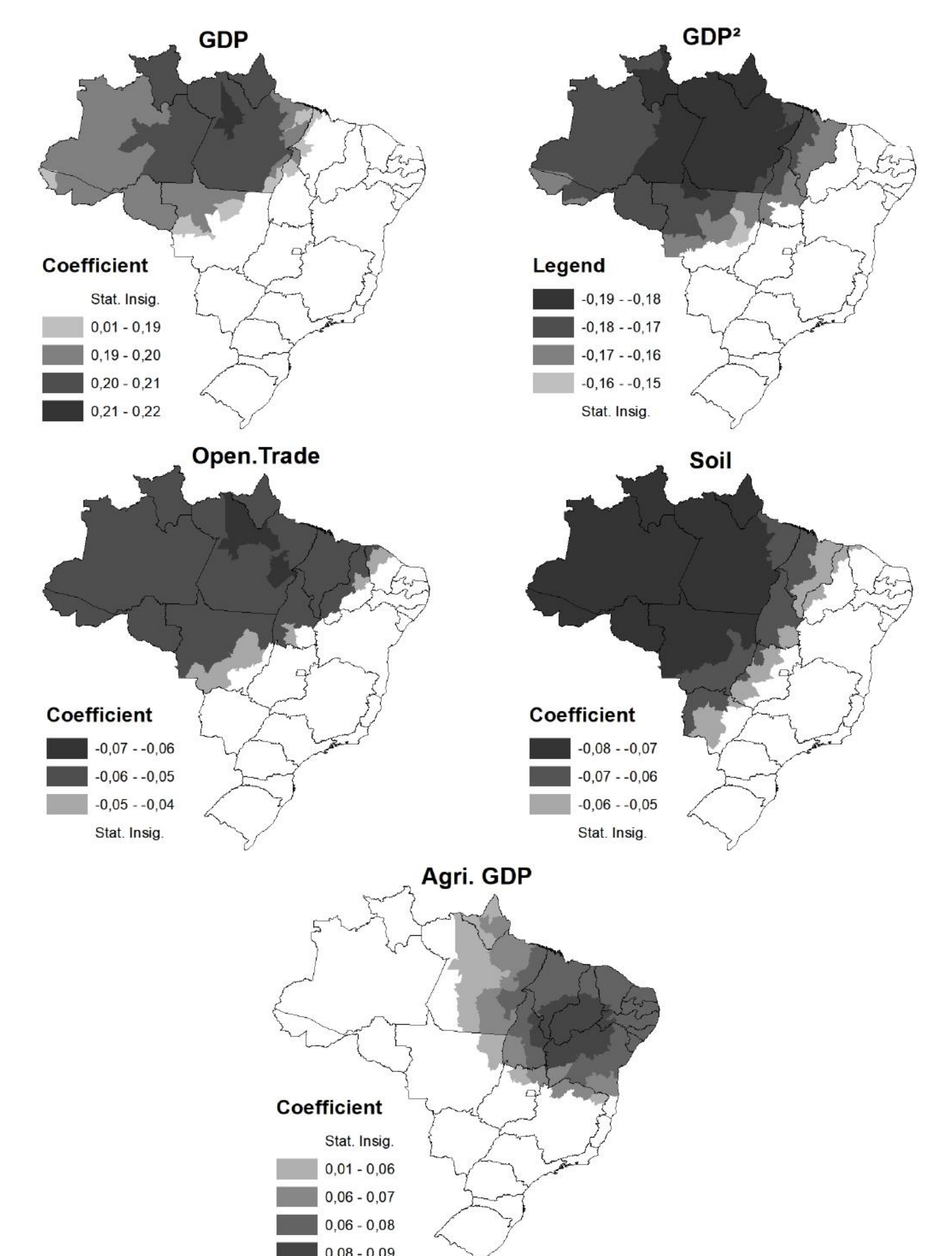
W_Crop	-	0.0022	**-**	0.0044
Jarque-Bera	4862.63			
Koenker-Bassett	62.559			
R-squared	0.5044	0.5046	**0.5158**	0.5112
Moran's I (Residual)	0.3451**	0.3452**	**-0.0290**	-0.386

Source: research results. *Note:* ** Significant at 1%; * Significant at 5%.

To confirm the spatial heterogeneity, we calculated the Monte Carlo Test for Spatial Variability (Appendix B), which was not statistically significant only for: Pasture, Altitude, Temperature, Forest, and Spatial Spillovers (ρ). In other words, these variables have a homogenous impact throughout the country while the others have heterogeneous effects. In this context, we estimated the GWR-SL to control heterogeneity. Despite many variables were significant in the Monte Carlo Test, only GDP, GDP², Open.Trade, Soil and Agric.GDP presented local coefficients statistically significant after the estimations (Figure 3).

The Moran's I of the GWR-SL residuals is also statistically insignificant, therefore it controlled both spatial dependence and heterogeneity. We got an inverted-"U" format for the EKC, mostly in Legal Amazon. Similarly, the Open. Trade and Soil variables have negative impact in Legal Amazon. Openness to trade, in line with Faria and Almeida (2016), inhibit deforestation while soil reflects the fact that deforesters are not clearing land specifically due to its greater agricultural potential, highlighting concerns with possible allocative inefficiencies. Finally, the agriculture dependence leads to deforestation in Matopiba, possibly reflecting the agriculture frontier expansion, and in Northeast.

Figure 3 – Spatial Distribution of local coefficients from the GWR-SL.



Source: research data. *Note:* Stat. Insig means that the coefficient is not statistically significant at 10%.

5. FINAL CONSIDERATIONS

This paper aimed to investigate the relationship between economic growth and deforestation in Brazil, using the Environmental Kuznets Curve hypothesis. The exploratory analysis pointed to spatial concentration for deforestation. Initially, we estimated the models using conventional and spatial econometrics techniques in order to control the spatial dependence in the residuals. The model that best captured the EKC relationship, according to the Moran's I in the spatial models' residuals and the Akaike Information Criterion, are the SDM model. We found an inverted "U" format to the EKC, corroborating the initial hypothesis between economic development and deforestation for Brazil. Therefore, economic development, although it initially leads to deforestation, it occurs until a certain level, from which the relationship reverses and induces a sustainable development.

However, we confirmed heterogeneity patterns for deforestation in Brazil. Investigating a Local Environmental Kuznets Curve, we confirmed: (i) spatial concentration and heterogeneity for forest and deforestation; (ii) - local (for Legal Amazon) inverted "U" relationship in the EKC. (iii) – GWR-SL control both spatial dependence and heterogeneity; (iv) – spatial spillovers and forest area are globally important for deforestation while agricultural dependence are locally in Matopiba and Northeast; (v) - openness to trade and soil suitability decreases it. Therefore, the results of this papers highlight the importance of consider heterogeneity patterns in deforestation and economic development as well as the presence of spatial spillovers and other factors that lead to forest clearings.

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Appendix

Appendix A - Moran's I for the OLS residuals - convention matrix decision.

	Weights Matrix					
	Queen	Rook	Three neigh.	Five neigh.	Seven neigh.	Ten neigh.
OLS	0.28*	**0.29***	0.27*	0.22*	0.22*	0.19*

Source: research data. *Note:* * Level of significance of 1%.

Appendix B - Monte Carlo Test for Spatial Variability.

Variable	p-value
Constant	0.121
GDP	0.075
GDP^2	0.066
Road Network	0.052
Open.Trade	0.083
Soil	0.053
Rail Network	0.028
Pasture	0.630
Crop	0.046
Altitude	0.253
Agric. GDP	0.043
Railfall	0.095
Temperature	0.256
Forest	0.286
Protected Area	0.470
Rural Title	0.077
Rural Education	0.078
C.T Index*	0.084
ρ (Spillover)	0.443

Source: research data.

Appendix C– Correlation Matrix

	GDP	Road	Op.Trade	Soil	Rail	Pasture	Crop	Altit	Ag. GDP	Rainfall	Temp	Forest	Prot Area	R Title	R Educ	C.T Index
GDP	1.0000															
Road Network	0.1986	1.0000														
Open.Trade	0.4074	-0.0493	1.0000													
Soil	0.2200	-0.2567	0.0528	1.0000												
Rail Network	0.2432	0.5199	0.0579	-0.0153	1.0000											
Pasture	0.0148	-0.0158	-0.0294	0.0226	-0.0503	1.0000										
Crop	0.3840	0.1333	0.0444	0.4053	0.0831	-0.1269	1.0000									
Altitude	0.2515	0.0659	0.0009	0.1135	0.0494	0.1068	0.2601	1.0000								
Agric. GDP	-0.0488	-0.3940	-0.0790	0.1324	-0.3069	0.0787	0.2430	0.0180	1.0000							
Rainfall	0.3285	-0.2381	0.1817	0.2013	-0.0157	-0.1553	0.1194	-0.0727	0.2946	1.0000						
Temperature	0.2275	0.2591	0.0881	0.0913	0.2611	0.0514	0.1912	0.4998	-0.2790	-0.0755	1.0000					
Forest	-0.3619	-0.3609	0.0074	-0.2425	-0.2550	-0.4502	-0.5191	-0.3849	0.0702	0.1144	-0.4610	1.0000				
Protected Area	-0.1130	-0.2827	-0.0498	0.0891	-0.1414	-0.1418	-0.1330	-0.2005	0.1939	0.3116	-0.1937	0.2726	1.0000			
Rural Title	-0.0590	-0.0721	-0.0377	-0.0402	-0.0324	-0.1663	-0.1739	-0.4011	-0.0509	0.1114	-0.2734	0.2877	0.1155	1.0000		
Rural Education	0.5861	0.0669	0.2007	0.3901	0.2260	0.3049	0.3538	0.3372	0.0098	0.2801	0.3273	-0.5113	-0.0974	-0.1110	1.0000	
C.T Index*	0.5160	0.0907	0.2102	0.3723	0.1659	-0.0254	0.5524	0.4203	0.1696	0.3299	0.3216	-0.4922	-0.1252	-0.2364	0.5495	1.0000

Source: research results.