On the Map

GREENHOUSE GASES SCIENCE AND TECHNOLOGY

Spatial influence evaluation research of economic growth on greenhouse gas emissions in Brazil

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Abstract: Given the large contribution of rural activities to the Brazilian economy and the vast contribution of these agricultural activities to the emission of pollutant gases, this paper aims to analyze the impact of economic growth on greenhouse gas emissions related to the urban and rural areas of Brazil. Data from 2004 to 2014 were used and the environmental Kuznets curve equation for Brazilian states was estimated via a spatial econometric method for panel data. Thus, two effects have been demonstrated for both urban and rural areas. First, rising economic growth increases short-term pollutant emissions. Second, in the long run, maintaining the rise in economic growth levels leads to a reduction in greenhouse gas emissions. Finally, the estimation results showed the need to implement pollutant removal policies, especially in the rural areas of Brazilian states. © 2019 Society of Chemical Industry and John Wiley & Sons, Ltd.

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Introduction

Environmental questions related to economic growth have been discussed over the last few decades, and gained prominence in the late 1990s and early 2000s. In this context, some studies need to be highlighted.[1–3]

In Brazil, data from the greenhouse gas emission and removal estimates system SEEG (*Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa*) indicate that the levels of greenhouse gas emissions displayed heterogeneous behaviors over the last three decades. In relation to the emissions of carbon dioxide (CO_2), there was an increasing trend from 1990 to 2000. Furthermore, these data show an increase in Brazilian (CO_2) emissions from 1990 to 2000, at an average rate of 0.034% per year. But from 2000 to 2014, this rate was 0.0424%, indicating that on average, the (CO_2) emissions decreased by 0.04% each year.[4]

Because of the use of fossil fuel–based fertilizers, the use of agricultural machinery, and biomass burning,

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agricultural activities are the world's second largest emitters of greenhouse gases. SEEG data[4] indicate that in Brazil, the contribution of agricultural activities to greenhouse gas emissions has been showing a growing trend. In 1990, for example, 16.06% of CO_2 emissions came from agriculture. In the early 2000s, this value became 18.39%, reaching 23.28% in 2014.

Emissions generated by energy consumption, which can be used as an approximation for greenhouse gas emissions in urban areas, have increasing stakes, but lower than the holdings of the agricultural sector in total pollutant emissions in Brazil. SEEG data[4] from 1990 indicate that the emissions generated by this sector accounted for only 9.16% of the total CO_2 emissions. In the early 2000s, this value became 13.80%, reaching 22.95% in 2014.

In view of these considerations, the present work aims to answer the following question: what are the impacts of the increase in economic growth rates on CO_2 emissions in urban and rural areas from Brazil? Thus, the work aims to analyze the influence of economic growth on CO_2 emissions related to the urban and rural areas of Brazilian states. In addition to that, this research aims to contribute to the literature that studies the environmental Kuznets curve (EKC) and to verify relations between economic growth and greenhouse gas emissions in different areas of Brazil.

Many studies have analyzed the relationship between economic growth and pollutant emissions; however, only a few have done this analysis for Brazil and often disregard spatial characteristics in the analysis. Besides contributing to the literature on pollutant emissions, the main contribution of this study is the use of Brazilian states as a sample and the use of a spatial econometric methodology to find the EKC format.

To answer these questions, the present work has five sections, including this introduction; in the next section, the theoretical and literary arguments related to EKC research will be demonstrated; in the third section, there are demonstrations of the data and methods that were used; the fourth section presents the results and discussions; and the conclusions are presented in the fifth section.

Methodology

Spatial effect evaluation method

For spatial analysis, it is necessary to obtain characteristics of the data distribution in the studied space. The exploratory analysis of spatial data has been used for this. This methodological approach consists of a set of techniques that allow the identification of the best technique to be used to explain the phenomena studied, including the proximity characteristics in the data distribution.[5,6]

Spatial autocorrelation is measured by calculating general and local indicators, in which the first approach outlines the autocorrelation using a single value for all the spatial units verified.[7] Local indicators indicate a specific value for each locality, enabling the identification of clusters or outliers.

In this article, global spatial autocorrelation is verified by the calculation of the Moran Global index.[8]

$$I = \frac{\sum_i \sum_j W_{ij} \left(Z_i - \bar{Z}\right)\left(Z_j - \bar{Z}\right)}{\sum_i^n \left(Z_i - \bar{Z}\right)^2} \tag{1}$$

where n represents the number of regions studied, Z_i is the value of the studied variable in area i, $\bar{Z}$ is the average value of the variable in a given area, and W_{ij} represents the values indicated by the spatial proximity matrix. Positive values indicate that the variables in neighboring regions are changed to be in the same direction as the variables that were changed in a given region. The opposite is valid for negative values. The null hypothesis of this indicator (H0) is the absence of spatial autocorrelation. The neighborhood matrix has the following structure:

$$W_{ij} = \begin{cases} 1 \text{ if } i \text{ and } j \quad \text{are neighbors} \\ 0 \text{ if } i \text{ and } j \text{ not are neighbors} \end{cases} \tag{2}$$

Spatial panel data econometric model

Initially, the conventional model of fixed effects is considered, given by:

$$\ln\left(\frac{E_t}{p_t}\right) = \alpha_t + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 + \beta_3 \ln(G) + \beta_4 \ln(Est) + \varepsilon_t \tag{3}$$

where $\{\alpha_1, \ldots, \alpha_n\}$ is a vector of fixed effects, p is the state population, $(\frac{E_t}{p_t})$ is the per capita emissions of CO_2,[1] y is the annual family income per capita,[2] G is

[1] For the urban environment, the sum of emissions from waste and energy production was considered. Some articles use the emissions of the industrial sector. It is noteworthy that this variable was not included, due to the unavailability of data for some of the Brazilian states. For the rural environment, emissions from agriculture were taken into account.

[2] For urban areas, the per capita urban income was considered and, similarly, the per capita rural income was considered for the estimations referring to the rural areas.

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the income inequality measured by the Gini index and *Est* is the average schooling.

To verify whether the 'U' shape also exists in the long term, it will be inserted in the estimates made, with an additional term referring to the cube of the natural logarithm of growth. Thus, the delimitation considered in Eqn (3) will have the following form:

$$\ln\left(\frac{E_t}{p_t}\right) = \alpha_t + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 + \beta_3 \ln(y_t)^3 + \beta_4 \ln(G) + \beta_5 \ln(Est) + \varepsilon_t \quad (4)$$

Inserting spatial effects, we obtain a general model of fixed effects that considers spatial dependence, including spatial lags to control the spatial autocorrelation,[9] being given by:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \alpha + \rho W_1\left[\ln\left(\tfrac{E_t}{p_t}\right)\right] + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 \\ &\quad + \beta_3 \ln(y_t)^3 + \beta_4 \ln(G) + \beta_5 \ln(Est) \\ &\quad + W_1\left[\ln(y_t) + \ln(y_t)^2 + \ln(y_t)^3 + \ln(G) \right. \\ &\quad \left. + \ln(Est)\right]\tau + \xi_t \\ &\quad \text{with} \quad \xi_t = \lambda W_2 \xi_t + \varepsilon_t \end{aligned} \quad (5)$$

where $W_1[\ln(\frac{E_t}{p_t})]$ is the spatially lagged dependent variable, $W_2\xi_t$ are the spatially lagged errors, W is the neighborhood matrix, λ and ρ are the scalar spatial parameters, and τ is a vector of spatial coefficients.

The general model of random effects with spatial dependence is given by[7]:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \rho W\left[\ln\left(\tfrac{E_t}{p_t}\right)\right] + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 \\ &\quad + \beta_3 \ln(y_t)^3 + \beta_4 \ln(G) + \beta_5 \ln(Est) \\ &\quad + W\left[\ln(y_t) + \ln(y_t)^2 + \ln(y_t)^3 + \ln(G) \right. \\ &\quad \left. + \ln(Est)\right]\tau + \xi_t \\ &\quad \text{with} \quad \xi_t = \alpha + \lambda W \xi_t + \varepsilon_t \end{aligned} \quad (6)$$

Inserting the restrictions $\rho \neq 0$, $\tau = 0$ and $\lambda = 0$ in Eqn (5), a spatial lag model with fixed effects is obtained. This model is given by:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \alpha + \rho\left[\ln\left(\tfrac{E_t}{p_t}\right)\right] + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 \\ &\quad + \beta_3 \ln(y_t)^3 + \beta_4 \ln(G) + \beta_5 \ln(Est) + \xi_t \end{aligned} \quad (7)$$

Inserting the restrictions $\rho \neq 0$, $\tau = 0$ and $\lambda = 0$ in Eqn (6), a spatial lag model with random effects is obtained. This model is given by:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \rho W\left[\ln\left(\tfrac{E_t}{p_t}\right)\right] + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 \\ &\quad + \beta_3 \ln(G) + \beta_4 \ln(Est) + \xi_t \\ &\quad \text{with} \quad \xi_t = \alpha + \varepsilon_t \end{aligned} \quad (8)$$

Inserting the restrictions $\rho = 0$, $\tau = 0$ and $\lambda \neq 0$ in Eqn (5), a spatial error model with fixed effects is obtained. This model is given by:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \alpha + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 + \beta_3 \ln(y_t)^3 \\ &\quad + \beta_4 \ln(G) + \beta_5 \ln(Est) + \xi_t \\ &\quad \text{with} \quad \xi_t = \lambda W \xi_t + \varepsilon_t \end{aligned} \quad (9)$$

For the spatial error model with random effects, the restrictions $\rho = 0$, $\tau = 0$ e $\lambda \neq 0$ are considered in Eqn (6), so:

$$\begin{aligned}\ln\left(\tfrac{E_t}{p_t}\right) &= \alpha + \beta_1 \ln(y_t) + \beta_2 \ln(y_t)^2 + \beta_3 \ln(y_t)^3 \\ &\quad + \beta_4 \ln(G) + \beta_5 \ln(Est) + \xi_t \\ &\quad \text{with} \quad \xi_t = \alpha + \lambda W \xi_t + \varepsilon_t \end{aligned} \quad (10)$$

The choice of the best model among the estimates will be made by the criteria indicated in the spatial econometric literature.[7]

For each sample, the Wald test was used to test the null hypothesis that the coefficients of spatial autocorrelation are statistically equal to zero. The likelihood ratio test (LR) was used to test the null hypothesis that there are no significant differences between the models with spatial specification and the normal model for panel data. In addition to that, the Lagrange Multiplier test (LM) was used to test the null hypothesis that the model without spatial specification is maximizing the likelihood of estimation.

Data and variables

Information on greenhouse gas emissions (CO_2) was collected from the SEEG.[4] Data were collected for the 26 Brazilian states and the Federal District for the period from 2004 to 2014.

Information on economic growth, income inequality, and average schooling in urban and rural areas in Brazil was extracted from the Annual Brazilian Household Survey, PNAD (*Pesquisa Nacional por Amostra de Domicílios*), made available annually by the Brazilian Statistical Institute, IBGE (*Instituto Brasileiro de Geografia e Estatística*).[10] The per capita monthly family income of residents of urban areas was considered as a representation of the economic growth of urban areas. Similarly, for calculating the economic growth of rural areas, the monthly family income per capita of residents in rural areas of Brazilian states was considered. All monetary values were updated as per the value of R$ in 2015 by the price index IPCI (*Índice Nacional de preços ao consumidor*).

The average years of schooling for each state were used to represent average schooling. Income inequality was measured by the Gini index for the household income per capita average, and both variables were obtained from PNAD.

The population of each state was extracted from population estimates made available by IBGE. The average schooling and income inequality were obtained for urban and rural areas.

Results

Robustness tests

If the variables are distributed over time, it is necessary to perform some tests in relation to the temporal data characteristics. A co-integration test was performed to test the null hypothesis that the data are not co-integrated.[11] The results[3] show that the null hypothesis was rejected for three test statistics, indicating that the statistical estimations do not require additional treatment for the data used.

To decide which estimator should be considered in the analysis of environmental Kuznets curve (EKC), an F test was used to verify the possibility of estimating the models by ordinary least squares. This procedure rejected the null hypothesis, indicating that there were no significant effects, and that an estimation considering the effects of time is more appropriate for these data.

After making the estimates, a checking of whether the effects should be treated as fixed or random needs to be done. To do so, the Hausman test was applied. From this procedure, it was found that the random effects are invalid for all estimations, and the fixed effects models should be considered.

Two approaches were used—the first one sought to verify the inverted 'U' hypothesis and the second one considered the long-term effects of emissions to test the hypothesis of an 'N' form in the EKC. The results of the first approach are shown in Table 2 and the results of the second approach are shown in Table 3.

For estimations that do not include the cubic term, the results of the Wald test show that the coefficients of spatial autocorrelation are statistically different from zero, indicating that a model with spatial specification is preferable to the normal model with panel data. The results of the LM test demonstrate that models without spatial specification do not maximize likelihood when compared with models with spatial specification. In addition to that, the results of the LR test show that there are statistically significant differences between the normal model with panel data and the models with spatial specification.

Estimation

To choose the model that best explains the problem of the work, a procedure indicated in the literautre[7,12] was used: (i) it was verified whether the unobserved effects should be included in the estimations; (ii) the best model with no observed effects was chosen; (iii) the best model with no effects observed was estimated; (iv) the spatial dependence of the residues was verified; (v) given the existence of spatial autocorrelation in the residues of the unobserved effects model, the panel data model with individual and timing fixed effects was estimated, considering the spatial autocorrelation; and (vi) the model that did not present spatial autocorrelation in the residues and showed the lowest information criterion was chosen.

Main results

To calculate the Moran Global index, a K-neighbors[4] proximity matrix was used, considering $K = 2$. The criteria used to choose the most appropriate proximity matrix consists of estimating the model without spatial effects, obtaining the model residues, and verifying the spatial autocorrelation of the residues through the Moran Global index, using a set of proximity matrices. The chosen matrix will be the one that gives the highest statistically significant value for the Global Moran index applied to the residue of the model without spatial effects.[13]

The results of the global spatial autocorrelation index are shown in Table 1. The results indicated that the Moran Global index obtained a positive signal and was statistically significant in all the years considered. This result shows that the per capita emissions of CO_2 are

[3]See Table 4.

[4]In addition to this matrix, the matrices of type Queen, Rook, and K neighbors with $K = 1$, $K = 3$, $K = 4$, $K = 5$, and $K = 10$ were tested.

Table 1. Spatial autocorrelation of CO_2 emissions in urban and rural areas of Brazilian states.

Year	$\ln(\frac{E_t}{p_t})$ (rural)	$\ln(\frac{E_t}{p_t})$ (urban)
2004	0.5552*	0.4286*
2005	0.4416*	0.4613*
2006	0.5835*	0.4624*
2007	0.6123*	0.4440*
2008	0.1641*	0.3903*
2009	0.6336*	0.3292*
2010	0.5953*	0.3182*
2011	0.5755*	0.2849*
2012	0.3394*	0.3080*
2013	0.7109*	0.3305*
2014	0.6328*	0.3169*

Source: elaborated by the authors.
*Statistical significance at 1%.

Table 2. EKC estimation (excluding the cubic term).

	Rural areas		Urban areas	
	Spatial lag	Spatial error	Spatial lag	Spatial error
Fixed effects				
Constant	-	-	-	-
$\ln(y)$	23.5189**	23.6807**	7.1965***	7.1340***
$\ln(y)^2$	−1.9021**	−1.8949**	−0.5711***	−0.5742***
$\ln(G)$	−1.3205	−1.5090	0.6424**	0.8094***
$\ln(Est)$	−0.4888	−1.2136	−0.0442	−0.0379
ρ	0.1980**	-	0.0087***	-
λ	-	0.1982**	-	0.0090***
Akaike	1497.236	1497.434	−548.0145	−541.5343
Wald	-	3.24*	48.55*	107.09*
LM	1.89	2.84*	39.50*	66.75*
LR	-	3.19*	44.13*	87.52
Random effects				
Constant	−76.6142**	−75.2658**	−25.3598***	−25.6516***
$\ln(y)$	24.5538**	24.0908**	7.0627***	7.0116***
$\ln(y)^2$	−1.9042**	−1.8574**	−0.5600***	−0.5633***
$\ln(G)$	1.1774	0.9736	0.6582***	0.8202***
$\ln(Est)$	−1.6030	−2.0619	−0.0552	−0.0488
ρ	0.1633**	-	0.1847***	-
λ	-	0.1730**	-	0.1345*
Akaike	1538.098	1537.76	−346.6926	−341.253
Wald	-	5.57*	48.90*	93.32*
LM	3.05	3.17*	28.43*	60.60*
LR	-	4.89*	47.19*	81.48*
Hausman	11.2000**	11.19**	26.77***	25.46***

Source: elaborated by the authors.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

spatially correlated in the urban areas and rural regions of Brazilian states, indicating that there are spatial agglomerations of high or low emission levels.

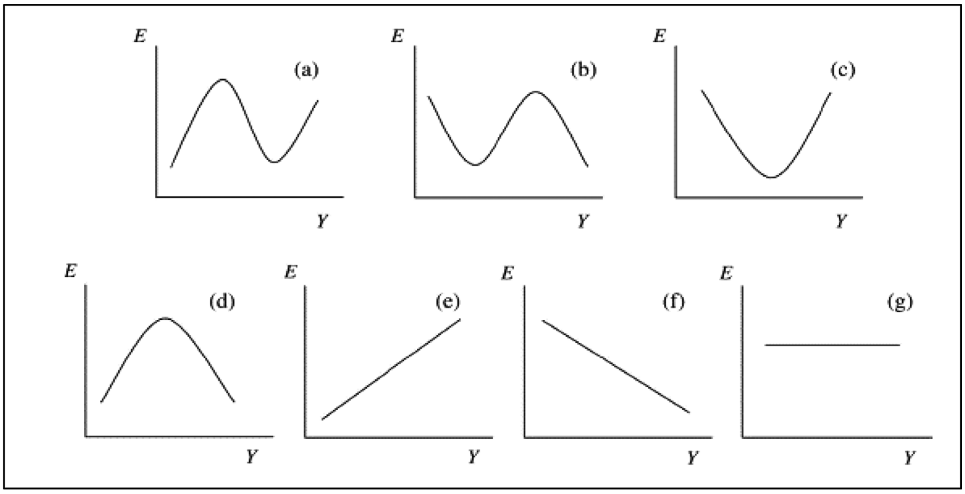
In relation to Table 2, a functional form that best explains the environmental hypothesis of Kuznets is the spatial lag model for urban and rural areas. The results show that for both the census situations studied, the inverted U hypothesis was confirmed for a short-term scenario. The exclusion of the cubic term of income implies that $\beta_1 > 0$ e $\beta_2 < 0$, confirming the functional form indicated in Fig. 1(d).

The results indicate the existence of a quadratic function of downward concavity, as shown in Fig. 2. This result shows that CO_2 emissions rise as economic growth increases, but after a certain point, the increase in growth levels would cause a decrease in CO_2 emissions in urban areas and in rural regions.

For the estimations that include the cubic term, robustness tests present the same results found in estimates without the cubic term, indicating that the models with spatial specification better explain the problem in question when compared to a normal model for panel data. For these estimates, the models chosen are the spatial error model for rural areas and the spatial lag model for urban areas, according to the specification indicated in the literature.[7] The results of these procedures are shown in Table 3.

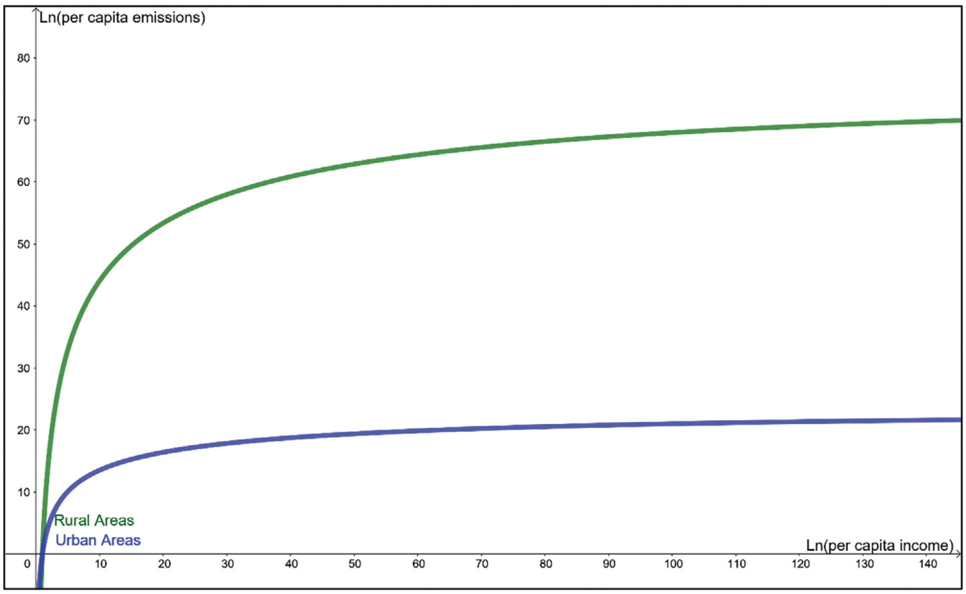
For rural areas, the signs of the coefficients obtained indicate that $\beta_1 > 0,\ \beta_2 < 0$ e $\beta_3 > 0$. This result shows the existence of an EKC in the form of 'N', as specified in Fig. 1(a), confirming the hypothesis presented in previous papers[14] and indicating that the EKC does not hold up in the short term, so that the inverted U would only be an initial step. Over time, a new inflection point is found, causing the trajectory to rise again, generating a curve in the form of an N.

In urban areas, the positive and statistically significant value of ρ indicates that CO_2 emissions are spatially



Source: Elaborated by the authors.
Note: E = Emissions, Y = Growth.

Figure 1. Graphical representations of the environmental Kuznets curve. Source: elaborated by the authors. Note: E = Emissions, Y = Growth.



Source: Elaborated by the authors.
Note: Natural logarithm of per capita income in x axis and natural logarithm of per capita emissions in y axis.

Figure 2. Graphic representation of the EKC (excluding the cubic term), based on the results in Table 2. Source: elaborated by the authors. Note: natural logarithm of per capita income on the x-axis and natural logarithm of per capita emissions on the y-axis.

overflowing among Brazilian states, so that changes in CO_2 emissions in a given state can also cause changes in the emissions from neighboring states.

The signal and statistical significance of the coefficients indicate that $\beta_1 < 0$, $\beta_2 > 0$ e $\beta_3 < 0$, representing an inverted N-shaped EKC, as shown in Fig. 1(b). The inverted N form indicates that increased growth reduces environmental impacts in the short run, reaching an inflection point where increasing levels of growth would create an increase in environmental impacts. However, over time, the curve would have a new inflection point, which would make the trajectory descending, giving the EKC an inverted N-shape.

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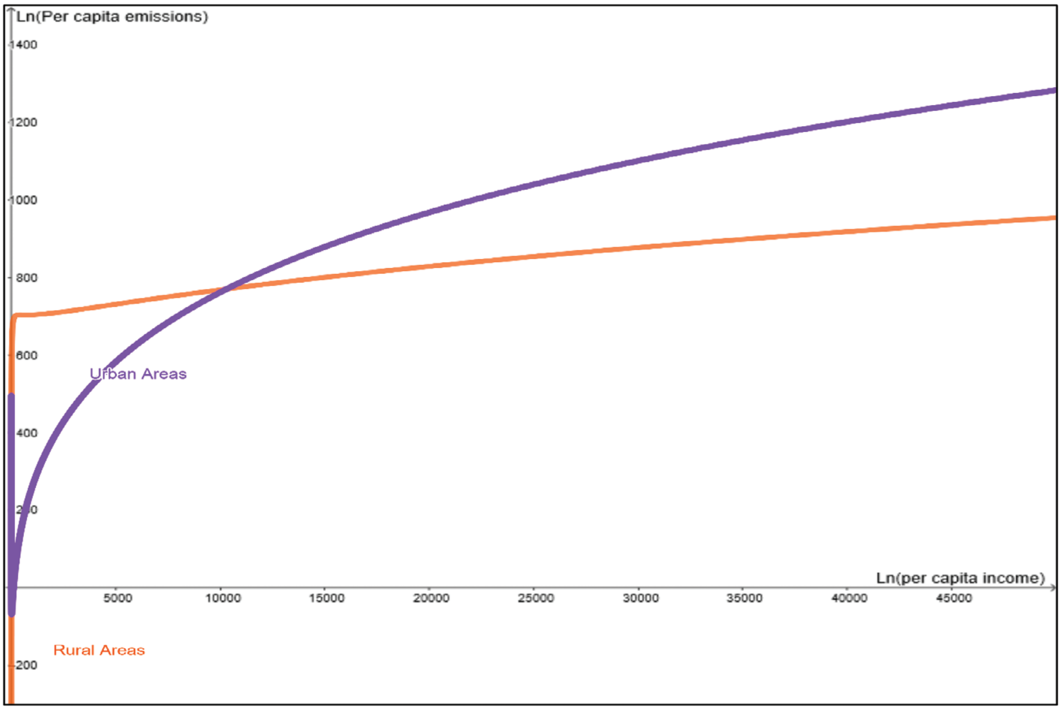

Source: Elaborated by the authors.
Note: Natural logarithm of per capita income in x axis and natural logarithm of per capita emissions in y axis.

Figure 3. Graphic representation of the EKC (including the cubic term) based on the results in Table 4. Source: elaborated by the authors. Note: natural logarithm of per capita income on the x-axis and natural logarithm of per capita emissions on the y-axis.

The graphic representations of the curves obtained in Table 3 are shown in Fig. 3. For rural areas, the N-shape is well defined. In this case, CO_2 emissions increase as economic growth increases. After a certain period, an inflection point is reached where increasing growth levels generate a reduction in emissions. Over time, the curve gets another inflection point, where highs of economic growth begin to increase environmental impacts again.

For urban regions, the curve has an inverted N format. In this case, increasing growth levels initially result in a reduction in emissions. This situation reverses after the curve reaches an inflection point, obtaining a form in which the growth increase leads to an increase in emissions.

The formats of the curves obtained in Fig. 3 may indicate that probably, the economic agents of the urban environment have greater incentives to reduce their CO_2 emissions, because much of the sample used is in the downstream part of the urban EKC. In rural areas, it is possible to observe that a large part of the sample is located in the ascending parts of the curve.

This result leads to the conclusion that production in rural areas needs more attention in relation to CO_2 emissions. Similarly, the results point to the need to apply measures that try to reduce CO_2 emissions in the rural regions of Brazilian states.

Conclusions

This paper verifies the effects of economic growth on greenhouse gas emissions in urban and rural areas in Brazilian states. To do so, a spatial econometric methodology capable of considering the phenomena of time and space was used.

Through the calculation of the Global Moran index applied to the per capita CO_2 emissions, it was observed that the emissions in urban and rural areas of Brazilian states have a spatial dependence, indicating that states with large emission levels have neighbors with this same characteristic. The reciprocal is true for small emission levels.

The results show that the relationships between economic growth and greenhouse gas emissions are

Table 3. EKC estimation (including the cubic term).

	Rural areas		Urban areas	
	Spatial lag	Spatial error	Spatial lag	Spatial error
Fixed effects				
Constant	-	-	-	-
ln(y)	321.4579**	336.0175**	−52.2403**	−51.3179**
ln (y)^2	−50.9804**	−53.2888**	8.1681**	8.0179**
ln (y)^3	2.6836**	2.8083**	−0.4274***	−0.4201***
ln(G)	−1.6433	−1.9462**	0.7045***	0.8870***
ln(Est)	−0.9331	−1.9984	0.0212	0.0334
ρ	0.2017**	-	0.2041**	-
λ	-	0.2052**	-	0.1469*
Akaike	1497.582	1497.501	−562.2975	−555.5988
Random effects				
Constant	−354.2692	−408.8936	109.3302**	107.0944**
ln(y)	162.2531	189.4096	−52.4868**	−51.6855**
ln (y)^2	−24.5823	−29.0642	8.1956**	8.0649***
ln (y)^3	1.2470	1.4877	−0.4282***	−0.4219***
ln(G)	1.1308	0.8641	0.7213***	0.8980***
ln(Est)	−1.6783	−2.2027	0.0112	0.0240
ρ	0.1647**	-	0.1969**	-
λ	-	0.1768	-	0.1564*
Akaike	1539.686	1539.15	−359.8332	−354.0508
Hausman	12.57**	12.29**	31.23***	26.83***

Source: elaborated by the authors.
*Statistical significance at 10%.
**Statistical significance at 5%.
***Statistical significance at 1%.

Table 4. Co-integration test according to Pedroni.[11]

	t	P-value
Urban areas		
Phillips–Perron	0.9405	0.1735
Modified Phillips–Perron	5.8511	0.1050
Augmented Dickey–Fuller	2.1477	0.1590
Rural areas		
Phillips–Perron	0.3333	0.3694
Modified Phillips–Perron	5.4743	0.0915
Augmented Dickey–Fuller	1.0238	0.1530

Source: elaborated by the authors.

different between urban and rural areas. Thus, the studies show that policy makers seeking to reduce pollutant emissions should form policies that are appropriate for each type of census situation.

In addition to that, the results show that economic agents have greater incentives to emit pollutants in rural areas, indicating that environmental education and policies to restrict greenhouse gases emission should be implemented with greater Intensity in rural areas.

Another result that should be considered is that the relationships between economic growth and greenhouse gas emissions may be different in the short and long term. Based on this result, it is possible to affirm that during the creation of policies to reduce emissions of pollutants in Brazil, their temporal effects on economic growth in Brazilian states should be considered, since the restriction of emissions of pollutants in the short term can impair economic growth; but this relationship may not be true in the long term.

The paper concludes that the format of the EKC obtained for urban areas provides evidence that the economic agents of the urban regions of Brazilian states have greater incentives to reduce their greenhouse gas emissions. For rural areas, the EKC format indicates that economic agents may be more encouraged to raise CO_2 emissions. Thus, we emphasize the need to implement public policies to support reduction in greenhouse gas emissions through rural activities in Brazilian states.

Finally, it is concluded that the effects of growth on pollutant emissions in Brazil vary widely between urban and rural areas, indicating that efficient reduction of greenhouse gas emissions depends on the application of public policies aimed at the removal of pollutants in each economic sector.

References

1. Carvalho TS and Almeida E, A hipótese da curva de Kuznets ambiental global: uma perspectiva econométrico-espacial. *Estud Econ* **40**(3):587–615 (2010).
2. Rocha LA, Khan AS and Lima PVPSN, Nível tecnológico e emissão de poluentes: uma análise empírica a partir da curva de Kuznets ambiental. *Econ Apl* **71**(1):21–47 (2013).
3. Ávila ES and Diniz EM, Evidências sobre curva ambiental de Kuznets e convergências das emissões. *Estud Econ* **45**(1):97–126 (2015).
4. SEEG, Sistema de Estimativas de Emissões e Remoções de Gases de Efeito Estufa. [Online]. Available: http://seeg.eco.br [11 February 2017].

  Greenhouse Gas Sci Technol. **0**:1–9 (2019); DOI: 10.1002/ghg.1936

5. Cancian V, Vidigal VG and Vidigal BR, Pobreza e desigualdade de renda nos municípios da Região Sul do Brasil: uma análise espacial. *Encontro de Economia da Região Sul* **16** (2013).
6. Gonçalves E, O padrão espacial da atividade inovadora brasileira: uma análise exploratória. *Estud Econ* **37**(2):405–433 (2007).
7. Almeida ES, Econometria espacial aplicada, Editora Alínea ed. (2012).
8. Anselin L, Exploratory spatial data analysis and geographic information systems. *New T Spat Anal* **17**:45–54 (1994).
9. Elhorst JP, Applied spatial econometrics: raising the bar. *Spat Econ Anal* **5**(1):9–28 (2010).
10. IBGE, Pesquisa Nacional por Amostra de domicílios. [Online]. Available: http://www.ibge.gov.br/home/estatistica/populacao/trabalhoerendimento/pnad2015/microdados.shtm [11 February 2010].
11. Pedroni P, Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford B Econ Stat* **61**:653–670 (1999).
12. Elhorst JP, *Spatial Econometrics: From Cross-Sectional Data to Spatial Panels*. Springer ed., Heidelberg (2014).
13. Baumont C, Spatial effects in housing price models: do housing prices capitalize urban development policies in the agglomeration of Dijon (1999)? Working papers hal-01525664, HAL (2004).
14. de Bruyn SM, van den Bergh JCJM and Opschoor JB, Economic growth and emissions: reconsidering the empirical basis of environmental Kuznets curves. *Ecol Econ* **25**(2):161–175 (1998).

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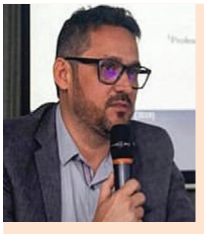

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