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DEFORESTATION IN THE BRAZILIAN AMAZONIA AND SPATIAL HETEROGENEITY: A LOCAL ENVIRONMENTAL KUZNETS CURVE APPROACH

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Abstract

There is a concern about the increasing pressure over the forest as economic growth increases. As for the Brazilian Amazon deforestation, there are noticeable intra-regional differences due to its occupation history, extensive area, economic structure and geographical aspects, inducing a strong spatial heterogeneity in this environmental phenomenon. This paper investigates locally the Environmental Kuznets Curve (EKC) hypothesis applied to the Brazilian Amazon region - whether there is an inverted "U" relation between a deforested area and economic growth for each municipality in Brazilian Amazonia from 2001 to 2006. Some other variables were considered in explaining deforestation: the amount of cattle, soybean and sugar cane plantations, vegetal extraction and forestry products, population density, rural credit, and previous forested area. The local econometric model was estimated using geographically weighted regressions (GWR). The results show different local relations between deforestation and GDP *per capita* at the municipal level, and also different local relation between deforestation and additional variables.

Key words: Amazonia, deforestation, local environmental Kuznets curve, spatial heterogeneity, geographically weighted regressions (GWR).

1. Introduction

Economic growth is often related to environmental degradation. When a region's income per capita is increasing, various indicators are expected to show environmental degradation: concentration of air and water pollutants tends to increase, dischargeable solid residues tends to be higher, and natural land cover is liable to be modified so as to give place to new economic activities. The Environmental Kuznets Curve (EKC) describes a hypothesized inverted U-shape relation between an environmental degradation indicator and income per capita. This means that degradation increases in the early stages of economic growth, but environmental impact tends to diminish at higher income levels, due to technological changes, scale effects and institutional advances (Stern, 2004).

Tropical deforestation is a main concern in the climate change issue, due to that CO_2 emissions are engendered when a forest is cleared by burning. Tropical natural forests are liable to be cleared with no replacement in low-income regions, but when income rises, economic structure can change producing a lower impact on the forest. Therefore, as stated by EKC hypothesis, there seems to be a relation between deforestation and income level. However, empirical studies are controversial about an EKC hypothesis as far as deforestation is concerned (Battharai and Hammig, 2004).

The Brazilian Amazonia, as defined by law,[1] comprises the states of Acre, Amapá, Amazonas, Mato Grosso, Rondônia, Roraima, Tocantins, Pará and part of Maranhão (Figure 1). Until the 1980s, the history of deforestation in the Amazon region was linked to government actions for the occupation and development of the territory, by opening roads and encouraging population migration (Salati and Ferreira, 2005; Becker, 2005). Until this decade, deforestation in the Amazon region reached about 300 thousand square kilometers, equivalent to 6% of total area, according to the *Plano Amazônia Sustentável* (Sustainable Amazonia Plan). From 1980 to 2007, more than 432,000 km² were cleared, corresponding to almost 15%

of the Amazon region (Brazil, 2008). Recent conditions of deforestation, however, point to expanding agricultural activities according to economic considerations (Margulis, 2003).

Figure 1 – Brazilian Amazonia

Source: FAO (available at: http://www.fao.org/docrep/009/j5416e/J5416E2.gif.)

Besides Margulis (2003), other authors have investigated the causes of recent deforestation. Miragaya (2008) reinforces that the demand for beef is by far the most important factor of deforestation in the region, even more than the expansion of grain production, especially soybeans, which has also been cited as a factor pushing the agricultural frontier toward forested areas (Brown et al., 2005; Vera-Diaz et al., 2008). Silva (2006) argues that most of the Amazon deforestation by 1997 occurred on land with higher agricultural potential, which is consistent with the work of Chomitz and Thomas (2003), which verifies that the conversion of land for agricultural use decreases substantially as levels of rainfall increase, making wetter areas less interesting economically and therefore less subject to deforestation advance. According to Aguiar et al. (2007), the area converted into pasture is about 70% of total deforested area, and the areas converted into temporary and permanent crops account for 13% and 3% of total deforested area, respectively.

Such deforestation is characterized by being spatially heterogeneous due to intra-regional differences related to its historic occupation and the territory's huge size. The *Plano Amazônia Sustentável* (Sustainable Amazonia Plan) Report points out that differences among its productive systems are a consequence of the natural, social and cultural diversity of the region (Brazil, 2008). The spatial heterogeneity and its consequences to deforestation are stressed in some studies (Prates, 2008; Aguiar et al., 2007).

As deforestation, especially in the Amazonia, occurs unevenly in space, it seems that

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[1] This is because this region is officially termed *Amazônia Legal* (Legal Amazonia).

that a single model for the entire region would not be the most appropriate approach to study it. Rather, a possible unstable relation in this case should be considered and it is advisable to investigate whether there are local responses to the phenomenon under study. The Geographically Weighted Regression Method (GWR), developed by Fotheringham, Brunsdon and Charlton (2002), is possibly an appropriate tool to estimate local coefficients of the regression model.

Within this context, this paper is aimed at identifying a relation between economic growth and deforestation in the Amazonia, as suggested by the Environmental Kuznets Curve, by considering spatial dependence and spatial heterogeneity, and adding additional explanatory variables as determinants of deforestation, according to the literature. This paper also adopts controls for observable and non-observable spatial heterogeneity. Estimating EKC for the Amazon region, with emphasis on its uneven spatial deforestation, would require estimating a model of local coefficients using geographically weighted regressions (GWR) in order to control observable spatial heterogeneity. The data on annual deforested area of 782 municipalities in the region over the period 2001-2006 come from the PRODES System[2]. A fixed effect model is implemented using the GWR methodology in order to control for non-observable spatial heterogeneity.

This paper consists of four sections. The next section presents a review of previous studies which address to the relation between deforestation of tropical forests and economic growth based on the EKC approach, and the factors that affect deforestation in the Brazilian Amazonia. Section 3 describes the methods used for the model, considering aspects of the spatial heterogeneity. Section 4 reports and discusses the results. The final section summarizes the main findings and presents concluding remarks.

2. Literature Review

[2] This system encompasses the Program for Assessment of Deforestation in the Amazonia (Prodes) from Instituto Nacional de Pesquisas Espaciais – INPE (national institute for spatial research).

The search for the answer whether or not economic growth brings environmental degradation multiplied the amount of EKC papers. The hypothesis of the Environmental Kuznets Curve has been extensively tested for various indicators of environmental degradation at different temporal and spatial contexts. Besides pollutant emissions, an EKC hypothesis may also include deforestation as an indicator of environmental degradation. The geographic range for which the EKC is investigated is also quite diverse: multi-country, national and regional analysis can be found in empirical work. Stern (2004) reviews main theoretical and empirical papers, as well as a critical approach pointing out their methodological flaws. Maddison (2006) tests the EKC hypothesis to several indicators, incorporating aspects of spatial dependence. Ciriaci and Palma (2009) investigated the EKC as a local phenomenon, using geographically weighted regressions.

The traditional specification of the EKC model includes income per capita and its quadratic term (Barbier and Burgess, 2002). Some studies also include the logarithm and cubic shape (Gomes and Braga, 2008; Santos et al., 2008). Thus the general specification is given by the following expression:

$$DEFOREST = \alpha_1 + \alpha_2 Y_i + \alpha_3 Y_i^2 + \alpha_4 Y_i^3 + \sum_k \beta_k Z_{ki} + \varepsilon_i \qquad (1)$$

where *DEFOREST* is the dependent variable, Y represents income per capita, Y^2 denotes the squared income per capita and Y^3 stands for cubic income per capita. In turn, Z_k is a set of other explanatory variables affecting deforestation (population, institutional variables, etc.), ε is the random error term and α_i and β (k x 1 vector) are parameters.

The coefficients α_2, α_3 and α_4 determine the shape of the curve relating degradation and income (De Bruyn et al., 1998). Figure 2 illustrates the different shapes for such relation, adapted for the case of deforestation as an indicator of environmental degradation. There may be a linear monotonic increasing function, indicating that the increase in income is associated with higher levels of deforestation (Figure 2.a) or, conversely, there may be a linear monotonic decreasing function, indicating that the increase in income is associated with decreased levels of deforestation (Figure 2.b). The inverted "U" shaped curve of traditional EKC is observed when there is a quadratic relation, indicating that the increase in income is associated with higher deforestation in the initial levels, reversing the process at some point (Figure 2.c). Or, again, the relation between deforestation and income can assume an "N" shape, i.e., a cubic relation, denoting that the increase in income would cause increasing levels of deforestation following a stage of deforestation decrease (Figure 2.e). Other ways to represent the relation between degradation and income, as for example, an inverted "N" shaped curve (Figure 2.f), are also found in the literature (Carvalho, 2008; Ciriaci and Palma, 2009).

Figure 2- The relation between Environmental Degradation and Income

Source: adapted from Carvalho (2008).

In the international real scenario, Latin America shows the greatest loss of tropical forests in terms of cleared area, while Asia shows the highest growth rates of deforestation. Economic studies relate deforestation to economic growth, mainly through expanding agriculture. Many studies have been conducted seeking to identify factors that lead to the decline of tropical forests. Some these factors can be cited as follows: income, population density, population growth, agricultural prices, agricultural production, agricultural exports, roads, scale factors, and institutional factors such as political stability, property rights, etc. (Barbier and Burgess, 2002). Based on a compilation of 152 empirical studies, Geist and Lambin (2002) investigated the causes of deforestation of tropical forests. These authors suggest interpreting the major forces for this as follows: proximate driving forces, i.e., those human activities causing immediate impact on the local level, and underlying driving forces, those actions taken at the national level. Such proximate driving forces would be, for example, infrastructure extension, agriculture expansion and timber extraction. On the other hand, underlying driving forces would be explained by demographic, economic, technological, cultural, institutional and political factors. Other forces, such as soil, topography, etc., would be predisposing environmental factors. The authors conclude that there is no single pattern causing such situation and that forest loss is a combination of proximate and underlying driving forces that vary in terms of a historical and geographical context. In a comprehensive review of studies on deforestation, Kaimowitz and Angelsen (1998) point out the regional approach as the most promising and conceptually more interesting, because it is possible to include – in the models - spatial elements, which affect the decision of microeconomic agents and have consequences at the regional level.

Numerous studies address the determinants of deforestation in the Brazilian Amazonia, such as environment (soil quality, rainfall, temperature, etc.), socioeconomic status (urban and rural population, education, income, agricultural production, agricultural products prices, characteristics of farms, etc.) and accessibility (paved and unpaved roads, distance from local and national markets, etc.). As to environmental variables, rainfall is considered the most relevant one (Margulis, 2003; Igliori, 2006; Caldas et al., 2003; Chomitz and Thomas, 2003). With respect to ease of access, all studies investigating this variable found it relevant somehow (Pfaff, 1999; Reis and Guzmán, 1993, Aguiar et al., 2007). Margulis (2003), however, did not get to a conclusive result in this respect.

Among socioeconomic factors, population is considered relevant and it follows a nonlinear pattern, by increasing at first and then decreasing (Igliori, 2006; Pfaff, 1999). The income variable is regarded as significant in all studies, although less intensively. The EKC hypothesis applied to the Amazonia deforestation was found in the studies of Gomes and Braga (2008) and Araújo et al. (2009) carried out at the state level. The EKC hypothesis was also corroborated by Santos et al. (2008) and Prates (2008) using official municipal data and

Caldas et al. (2003) using data collected locally. All such studies find a higher or lower relation between agricultural activities and deforestation.

In general, empirical studies have used traditional econometric models. Angelo and Pereira de Sá (2007) and Ewers et al. (2008) adopted time series methodology to address the issue. Gomes and Braga (2008), Santos et al. (2008), and Prates (2008) utilized econometric models for panel data. Reis and Guzmán (1993), Chomitz and Thomas (2003), Aguiar et al (2007) and Caldas et al (2003) implemented regressions with cross-sectional units (states, municipalities, census tracts or grids).

Deforestation has a strong spatial component because an area containing forest cover is converted into another type of land use for activities observed in neighboring deforested areas. Based on this idea, some studies used models that considered spatial effects of deforestation. Among them, we highlight the work of Reis and Guzmán (1993), Caldas et al. (2003), Igliori (2006), Aguiar et al. (2007). As a matter of fact, Reis and Guzmán (1993) used data collected at the municipal level: Caldas et al. (2003) adopted data from small farms in Uruará in the state of Pará; Igliori (2006), data from 257 minimum comparable areas, while Aguiar et al. (2007) related to deforestation and environmental factors using a spatial econometric model with spatial units based on 25 km squared grids. All these studies have found significant spatial dependence on deforestation, by using cross-sectional data. Even without using a spatial econometric model, Pfaff (1999) investigated deforestation causes through data with spatial characteristics (distances and densities) at the municipal level. The justification for the inclusion of this kind of variables is given by Alves (apud Margulis, 2003): Deforestation is a process of spatial interaction in which the deforested areas are adjacent to previously deforested areas. So the control for spatial autocorrelation is an important issue.

Qualitatively speaking, Becker (2005) and Ferreira and Salati (2005) point to intra-regional differences. Given the historical process of occupation and the vastness of its territory, the Amazon region presents intra-regional differences affecting the process of deforestation. Spatial heterogeneity affecting deforestation was quantitatively observed and highlighted by Prates (2008) and Aguiar et al. (2007). In the latter study, the region has been studied comprehensively and also partitioned into three zones termed "Macrozones", namely, Densely Populated Arch, Central Amazonia and Western Amazonia. The spatial econometric models for the three regions show different patterns of spatial autocorrelation, and reinforce the importance of considering the heterogeneity of the region. Prates (2008) found econometric models to describe the process of deforestation for each Amazonian state. These authors concluded that the subdivision of the Amazon region is very relevant in order to understand the organization of their production systems, given its spatial heterogeneity.

Table 1 reports some aspects about studies on the Brazilian Amazon deforestation. These aspects are directly linked to identification issues. In order to have a well-identified EKC relation, it is necessary to control spatial autocorrelation and observable and non-observable spatial heterogeneity. It is noteworthy that none of the previously mentioned studies was able to control all of these potential bias sources in the regression estimates.

In this context, this paper seeks to identify any relation between economic growth and deforestation in the Amazonia, as suggested by the Environmental Kuznets Curve hypothesis, taking into account spatial dependence and extreme spatial heterogeneity. In addition, it seeks to control additional explanatory variables, as reported in the literature as determinants of deforestation. Taking heterogeneous characteristics in space, by using Geographically Weighted Regressions (GWR), makes it possible to verify the relation between deforestation and economic growth with different coefficients and even with different functional forms. As long as we know, this kind of investigation has no counterpart in previous studies on deforestation (see Table 1).

[Table 1]

3. Methods

The classical linear regression model assumes global parameters that represent the mean responses of independent variables to a particular phenomenon. However, the phenomena may have different responses depending on the region studied, i.e., the theoretical relation can vary across space. This structural instability is not captured by the classical linear regression model; therefore, studying localized relations requires an alternative methodology.

The observable spatial heterogeneity of parameters is referred to as changes in the relations of variables over space. These different relations are expressed by different regression coefficients. In the extreme case, there is a regression for each spatial unit considered. The methodology known as Geographically Weighted Regression (GWR), developed by Brunsdon, Fotheringham and Charlton, in 1996, allows estimating linear regressions found for each spatial unit by using a subsample weighted by distance. The idea of assigning weights to individual observations from a calibration point embeds the concept that their relative importance decreases with distance from the analyzed point. In other words, subsets of data are created around specific points where the influence of observations is reduced as these points become more distant from the calibration point (Fotheringham et al., 2002).

In sum, the GWR model produces a sequence of linear regressions estimated for each point located in space using a data subsample, with the neighboring observations. Thus the local EKC model for the Amazon deforestation is specified as follows:

$$DEFOREST = \alpha_1(u_i,v_i) + \alpha_2(u_i,v_i)Y_{\mathrm{i}} + \alpha_3(u_i,v_i)\, Y_{\mathrm{i}}^2 + \alpha_4(u_i,v_i)Y_{\mathrm{i}}^3 + \sum_k \beta_k(u_i,v_i)\, Z_{\mathrm{ki}} + \varepsilon_{\mathrm{I}} \qquad (2)$$

where (u_i,v_i) represents the coordinates of point i in space, and $\alpha_h(u_i,v_i)$ and $\beta_k(u_i,v_i)$ stands for the value of local estimates of EKC and control variables, respectively.

The estimation of $\alpha_h(u_i,v_i)$ and $\beta_k(u_i,v_i)$ is done by weighted least squares where the weights are modified under the influence of proximity to the point of regression i, and are defined by the function $W(u_i, v_i)$, or "spatial kernel ". Matrix $W(u_i,v_i)$ represents the weights w_{ij} based on the distance between the observation point i and the other observations in the subsample selected by the "moving window", and defined by the spatial kernel function. There are several ways to define the weighting matrix $W(u_i,v_i)$ as the distance from observation point j with respect to regression point i (d_{ij}), as illustrated in Table 2. Figures 3.a and 3.b display the types of fixed and adaptive kernel.

The optimal choice of bandwidth involves a trade-off between bias and variance: a very small bandwidth leads to a great variance in local estimates; a very wide band brings bias to local estimates. The amount of bandwidth can also be chosen based on the use of the Akaike information criterion (AIC) to compare the regressions obtained with different values of bandwidth.

The fitness of GWR model can be compared to the classical linear regression model by means of an ANOVA test. The null hypothesis of ANOVA test is that the GWR model does not improve the results of classical linear regression model, and is measured by the F statistic.

[Table 2]

Figure 3 – Types of spatial kernel: a) Kernel with Gaussian weights and fixed bandwidth; b) Adaptative Kernel. Source: Fotheringham et al. (2002).

Additionally, the local coefficients estimated for an explanatory variable can be evaluated by a significance test of Monte Carlo: if there is a significant spatial variability, the null hypothesis of spatial structural stability does not hold. The standard deviation of local coefficients is used to compute the test statistic. The observed standard deviation is compared with simulated values of standard deviation obtained by m successive random reallocations of observations in the regions under study. The values obtained (simulated and observed) are classified in rank, and position occupied by the standard deviation observed is used to calculate the p-value:

$$p\text{-}value = 1 - rank/m, \qquad \text{where } m \text{ is the number of simulations} \qquad (3)$$

In summary, by allowing estimation of parameters, considering its spatial variability, the GWR methodology solves an important source of misspecification. In addition, the effects of spatial dependence can be considered locally, if an evaluation of residuals of the GWR model shows the presence of spatial autocorrelation.

The software GWR 3.0 is used to estimate geographically weighted regressions for a cross-section. In the GWR methodology, it is not available to incorporate the temporal dimension in the estimation. So, in order to remove non-observable effects, the data was differenced over the period of 2001-2006.

As the Amazon municipalities present different spatial dimensions, the northern, central and western portions of the region show a lower data density, while a higher concentration of data can be seen in the eastern and southern portions. In order to deal with such diversity, an adaptive kernel with a bi-squared shape was chosen to carry out the regressions. The bandwidth is chosen considering the results for the AIC minimization. All regressions points are used for the estimation.

The environmental degradation indicator for this EKC study is the annual increment of deforested area, available for 782 municipalities of the Brazilian Amazon region, given by the PRODES System of the *Instituto Nacional de Pesquisa Espacial* – INPE (national space research center). Its explanatory variables correspond to income per capita, quadratic and cubic forms, and an additional set of variables reported in the literature, particularly related to the tropical deforestation. Income per capita is represented by the municipal GDP per capita. Other variables that are considered relevant in the literature on deforestation are also included, as follows: amount of cattle, soybean and sugar cane plantations, vegetal extraction and forestry products, population density, rural credit, and previous forested area. The analysis period covers the years from 2001-2006, with data being processed for the difference over the period 2001- 2006.

The income Y is represented by the municipal GDP per capita at constant 2000 prices, obtained from the database of the System of National Accounts of IBGE.[3] The squared GDP per capita is included in order to test the hypothesis that deforestation grows at decreasing rates for lower levels of income and, from a given point, reduces, as income increases. The term cubic in GDP per capita is included to test whether EKC follows a form of "N", i.e. after deforestation is reduced and increased again with the level of income. The set of variables taken into account in the empirical model are detailed in Table 3. Table 4, in turn, reports descriptive statistical data.

The Exploratory Spatial Data Analysis shows a concentration pattern for the global spatial autocorrelation. There are also clusters in a High-High pattern in part of the Densely Populated Arch and Central Amazonia, which means that there are groups of municipalities with high values for deforested area near other municipalities with high deforestation too (Figure 4).

[Table 3]

[Table 4]

Figure 4 – Clusters Map for Deforested Areas in Amazonia, 2006

Source: authors' elaboration.

4. Results and Discussion

In the global model with differenced data, the relation between deforestation and GDP per capita (*Y*, *Y2*, *Y3*) is not significant, and thereby the EKC hypothesis is not corroborated. The amount of cattle (*CATTLE*), soybean acreage (*SOY*) and extraction of timber products

(*TIMBER*) are positively related to deforestation, while the other variables (sugar cane acreage, extraction of non-timber products, forestry, population density and rural credit) do not significantly affect the variation in the annual increment of deforested area.[4] Using the Moran's *I* test, there is evidence that global model's residuals are spatially autocorrelated. The procedure based on Lagrange multiplier tests has been performed in order to specify the spatial parameters of the model (Anselin, 2005). The model indicated by this procedure is the spatial error model (SEM).

The GWR model fits these data better as compared to the global model, since the latter has the Akaike value information criterion higher than the former one (34,682 against 5,838, respectively). Furthermore, to ascertain whether the GWR model represents an improvement over the global model, the ANOVA test shows a value of F statistic of 83.72.

The ANOVA test shows a value of F statistic of 75.25, indicating that the GWR model with the spatial error term represents an improvement over the corresponding global model. The Akaike criterion for the GWR model with spatial correction is less than the GWR model without correction for spatial dependence, which indicates that the inclusion of spatial error term in the specification of the model generates a better fit to this data. Finally, the spatial autocorrelation of the residuals was checked by means of Moran's *I* and there was no evidence of remaining spatial autocorrelation.

For an indication of spatial structural instability, the results of Monte-Carlo test are presented in the first column of Table 5. There is evidence in favor of variables related to GDP per capita (*Y*, *Y2*, *Y3*), amount of cattle (*CATTLE*), soybean acreage (*SOY*) and sugar cane acreage (*CANE*), extraction of non-timber products (*NON_TIMBER*) and existing forested area (*FOR*), which actually vary over space. The parameter (λ) of the error term has no spatial variability, according to the Monte Carlo test.

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[3] IBGE is the Brazilian agency for statistical and geographical information.
[4] See the Appendix for EKC model global estimates.

[Table 5]

The GWR model local parameters estimated are mapped due to so many results found. The color shading of all maps indicates the standard deviation distribution in which only the significant parameters at 5% level are highlighted. The blank shade indicates those municipalities whose parameters have not significant values.

The increased amount of cattle is positively correlated with the variation of the increment of the cleared area in Pará, Amapá, Maranhão and Tocantins, as can be seen in Figure 5. The amount of cattle contributes more heavily to increased deforested land in Pará, especially that close to the border with the state of Maranhão. In some municipal districts of the state of Roraima the relation between the amount of cattle and deforestation is slightly negative.

Figure 6 shows that the variation of the soybean cultivated area is related to the variation of deforestation in the southwestern Amazonia, an area covering the state of Rondônia, part of Acre and southern Amazonas. Such relation also occurs in northeastern Pará, where deforestation is associated with a reduced growth of the area cultivated with soybean. In the other regions this relation is not significant. The incremental variation sugar cane cultivated area affects deforestation in Pará, Amapá and Maranhão, but it is not important in other regions, as shown in Figure 7. This relation is always positive and becomes more intensive in the northeastern portion of Pará.

Figure 5 – Map of local coefficients: Amount of cattle

Source: authors' elaboration.

Figure 6 – Map of local coefficients: Soy acreage

Source: authors' elaboration.

Figure 7 – Map of local coefficients: Sugar cane acreage

Source: authors' elaboration.

The increased extraction of non-timber products is negatively related to the deforestation variation in a band stretching from southern Mato Grosso to the center of the Amazonia. In this region, the lowest deforestation is associated with a greater presence of this type of harvest activity. The increment of deforested areas is related to previously existing forests in almost all regions (except for the western portion of the whole Amazonia, where the forest is still more preserved), and it becomes more important in the eastern part of Amazonia, mainly in the state of Maranhão. In all these regions, deforestation is observed near clearable areas, where less deforestation is associated with smaller areas of the remaining forest. This result suggests an effect of forest scarcity, because this usually occurs in smaller areas with remaining forest, but not where the forest is the dominant landscape.

Results for individual parameters suggest that the increased deforested area is due to causes unevenly distributed in space. This reinforces the idea that this fact should be taken into account in specifying a more adequate model for analyzing deforestation in the region. In addition, this idea is in consonance with the conclusion that the GWR model is a better fit in this case in contrast to the global model, as indicated by the Akaike information criterion and the ANOVA test. The EKC relation between deforestation and GDP per capita, using data on differences is not significant for the most part of Amazonia, as it can be seen in Figure 5. In this figure, the final ascending EKCs mean the following functions: U-shaped curve, N--shaped curve, and monotonically increasing function. In turn, the final descending EKCs encompass the inverted U-shaped curve, inverted N-shaped curve and monotonically decreasing function.

The municipalities where this relation is significant are concentrated in the central and northeast regions. However, several forms of the relation between deforestation and GDP per capita can be observed in Figure 8. On the border between Pará and Amazonas, the monotonically increasing relation prevails, in which the N-shaped curve is prevalent in cities around this border, where only few municipalities show the traditional form of inverted U-shaped curve. So, as it can be seen in Figure 9, in this region – which is an important forest frontier - the EKC shapes found for the municipalities tend to have a final ascending form. This result points out an undesirable aspect of growth: the forest cover removal as a consequence of growth, which is not sustainable over time.

In the northeastern region of Amazonia, it is possible to find a monotonically decreasing relation in much of Maranhão and Pará and part of Amapá, where there are also forms of U- and inverted N-shaped curves. Next to these areas, an N-shaped curve is also found in Pará. Figure 9 shows this portion with the EKC shapes having mainly the final descending form (an inverted U-, N- and monotonically decreasing shapes). This result suggests that a sustainable development can be achieved in this region.

Nevertheless, when calculating the turning points for local curves (considering the estimated local coefficients), it is possible to find out on what portion of the curve regions lie. For example, if the current value for an increment of the municipal GDP per capita is on the left of the turning point for a traditional inverted U-shaped curve, this means that the municipality is in such a situation that the relation between growth and deforestation is increasing. The same happens to the interval between the minimum and maximum of an inverted N curve. Conversely, if current value lies on the interval between the maximum and minimum points of an N-shaped curve, deforestation is expected to decrease as income increment grows. Figure 9 illustrates the situation of municipalities based on current values of the relation between growth and deforestation, allowing us to know whether these municipalities are located on increasing or decreasing portions of the local CKA. Thereby, it is possible to indicate which municipalities deserve more attention as to the fact that increased income increments provoke increased deforestation increments. Public policies should mostly focus on preventing the advance of deforestation in these municipalities.

The endogeneity problem or “reverse causality”, which is liable to exist between deforestation and income, is an issue not addressed in the EKC literature. The point is that, in addition to the fact that higher income would enhance deforestation, a highly deforested region would lead to higher income. To check whether such endogeneity issue exists the Durbin-Wu-Hausman test[5] for these variables was carried out. The null hypothesis of exogeneity was not rejected at the 5% level.

Figure 8 – Map of Local EKC

Source: authors’ elaboration.

Figure 9 – Map of Local Relations between Growth and Deforestation: current values on EKC

Source: authors’ elaboration.

5. Conclusions

The GWR methodology provides the possibility to estimate local coefficients in order to capture the extreme spatial heterogeneity that is manifested in the deforestation phenomenon. With differenced data in order to remove the time invariant individual effects, the results of the GWR estimation show that this model is more adequate than the classical model of linear regression used for estimating global coefficients. The diagnosis of spatial dependence indicates the spatial error model for treating spatial autocorrelation. Therefore, the final GWR model was estimated with including the spatially lagged error term. The analysis of residuals indicates the removal of spatial autocorrelation. Thus, the GWR model with spatial error is capable of solving problems of misspecification, namely, spatial dependence and spatial heterogeneity in their extreme form.

The findings reveal that all shapes of the relation between deforestation and economic growth can be found in the Amazon region: monotonically increasing function, monotonically decreasing function, U-shaped curve, inverted U-shaped curve, N-shaped curve and inverted N-shaped curve. These results reinforce the idea that the relation between deforestation and economic growth is primarily a local phenomenon. With regard to other explanatory deforestation variables, the results show that there is spatial variability of parameters for amount of cattle, soy and sugar cane, extraction of timber products, and existing previously forested area.

In conclusion, this paper attempted to understand deforestation in the Amazonia as a spatially heterogeneous process. Its relation to development is unevenly distributed in the region, expressed by the different shapes found for the relation between deforestation and economic growth at the municipal level, based on local coefficient estimates. The causes of deforestation also exhibit a spatial variability. The GWR method was especially suited to capture the spatial aspects involved in deforestation. Finally, it is worth noting that public policies should take into account these intraregional differences. For instance, in those regions where there is evidence that deforestation takes place as economic growth increases, it is necessary to think of public policies when implementing alternative development drives in favor of fostering activities that both generate income and preserve the tropical forest.

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[5] The table reporting the Durbin-Wu-Hausman tests is in the appendix B of this paper.

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APPENDIX A

Table A.1 – Global Coefficients of the Regression

Coefficient	Global model	Global spatial error model
Constant	-15.9429	-17.1945
Y	-0.0073	-0.0062
*Y2(*10^{-6})*	0.3141	0.2678
*Y3(*10^{-6})*	-0.0053	-0.0047
CATTLE	0.0012***	0.0013***
SOY	0.0018***	0.0019***
CANE	0.0064	0.0059
TIMBER	0.0011***	0.0011***
NON_TIMBER	0.0008	0.0015
FORESTRY	0.0002	0.0001
CREDIT	0.0000	0.0000
POPDENS	-0.0024	-0.0390
FOR	0.3124***	0.3255***
λ		0.6998***
AIC	35682	33200

*** significant at 0.1%.

APPENDIX B

Table B.1. Durbin-Wu-Hausman test

Test of exogeneity for income			
Coefficient	2.37	*p*-value	0.12

Source: authors´ elaboration.

Note: The instruments for income were WY_{t-1}, WY^2_{t-1}, WY^3_{t-1}.

Table 1 – Studies on Brazilian Amazon Deforestation

Author	Type of data	EKC	Non-observable heterogeneity	Spatial dependence	Observable heterogeneity
Gomes and Braga (2008)	Panel	√	√	-	-
Araújo et al. (2008)	Panel	√	√	-	-
Igliori (2006)	Differenced data	-	√	√	-
Reis and Guzmán (1993)	Cross-section	-	-	√	-
Santos et al. (2008)	Panel	√	√	-	-
Pfaff (1999)	Pooled data	-	-	√	-
Prates (2008)	Panel	√	√	-	√
Chomitz and Thomas (2003)	Cross-section	-	-	√	-
Aguiar et al. (2007)	Cross-section	-	-	√	√
Caldas et al. (2003)	Cross-section	√	-	√	-

Source: authors' elaboration.

Table 2 – Types of spatial kernel for GWR models

Type of kernel	Function	Observations
Cylindrical, fixed width	$w_{ij} = 1$, if $d_{ij} < d$ $w_{ij} = 0$, otherwise	Disadvantage: local coefficients are very sensitive to change the point of regression, since all observations within the kernel has equal weight.
Continuous, fixed width	$w_{ij} = \exp(-d_{ij}^2/b^2)$	Disadvantages: - If there are few observations in the window, the inefficiency of the local estimates for the coefficients will be generated. - If there is a high density of data in some regions, certain subsamples may become redundant, resulting in bias in the estimation of local coefficients
Adaptative	$w_{ij} = [1-(d_{ij}/b)^2]^2$, if $d_{ij} < d$ $w_{ij} = 0$, otherwise	
Adaptative	$\Sigma_j\, w_{ij} = C$	where C is a constant.

Source: authors' elaboration.

Table 3 – Variables Used in the Local EKC Model for Brazilian Amazon Deforestation

	Variable	Description	Unit	Expected signal	Source of data
Dependent variable	*DEFOREST*	Annual increment of deforested area	km^2	-	PRODES/INPE
Explanatory variables (EKC)	*Y*	GDP *per capita*	2000 R$ (reais)	Positive	IBGE
	Y2	Squared GDP *per capita*	2000 R$	Negative	Calculated from Y
	Y3	Cubic GDP *per capita*	2000 R$	Positive or zero	Calculated from Y
Additional explanatory variables (**z**)	*CATTLE*	Amount of cattle	Units (head of cattle)	Positive	IBGE
	SOY	Soybean acreage	Hectare	Positive	IBGE
	CANE	Sugar cane acreage	Hectare	Positive	IBGE
	TIMBER	Extraction of timber (charcoal, firewood and logs)	m^3	Positive	IBGE
	NON_TIMBER	Extraction of plant non-timber products	Tons	Negative	IBGE
	FORESTRY	Forestry (timber)	m^3	Negative	IBGE
	POPDENS	Population density	number of inhabitants/ km^2	Positive	IBGE
	CREDIT	Rural credit	2000 R$	Positive	Brazilian Central Bank
	FOR	Forested area in (t-1)	km^2		PRODES/INPE

Source: authors' elaboration.

Table 4 – Descriptive Statistics

Variable	Average	Standard deviation	Minimum	Maximum
DEFOREST	40.47	137.28	0.00	4673.20
Y	3665.34	5116.78	579.91	84496.32
Y2	3.96E+07	2.63E+08	3.36E+05	7.14E+09
Y3	1.33E+12	1.72E+13	1.95E+08	6.03E+14
CATTLE	83340.74	124998.20	0.00	1596411.00
SOY	6698.75	35279.23	0.00	596658.00
CANE	296.68	2316.42	0.00	42452.00
TIMBER	40769.77	119464.60	0.00	2988000.00
NON_TIMBER	354.65	1419.75	0.00	32039.00
FORESTRY	2671.30	47852.79	0.00	1825789.00
POPDENS	21.54	115.87	0.11	2692.41
CREDIT	3.55E+06	9.96E+06	0.00	1.51E+08
FOR	4335.08	12691.78	0.00	152235.10

Source: Authors' elaboration.

Table 5 –Test for Spatial Variability using Monte-Carlo Significance Test

Coefficient	*p*-value	
Constant	0.6500	n/s
Y	0.0000	***
Y2	0.0000	***
Y3	0.0000	***
CATTLE	0.0000	***
SOY	0.0000	***
CANE	0.0100	**
TIMBER	0.9900	n/s
NON_TIMBER	0.0000	***
FORESTRY	0.7100	n/s
POPDENS	0.3500	n/s
CREDIT	0.2700	n/s
FOR	0.0000	***
λ	0.6600	n/s

*** significant at 0.1%; n/s: not significant.