Analyzing the Spatial Dynamics of Deforestation in Brazilian Amazon

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Abstract

Historically, development in Brazilian Amazon was promoted by permits of deforestation under soft territory control or supervision. However, due to the importance of this biome for biodiversity and ecosystem balance in a global perspective, Brazilian`s government has tighten deforestation control. This work investigates the spatial pattern of deforestation in a cross-section and time perspective using global and local spatial data analysis. Global results indicate the existence of high spatial correlation and that deforestation holds concentrated across space, despite the efficacy of policy mechanisms adopted for controlling and reducing the level of deforestation in Legal Amazon. Furthermore, local results support the hypothesis of high spillover effects. Considering the spatial analysis results, we highlight some implications for policy design aiming deforestation control.

Introduction

Deforestation in Brazilian Amazon has been discussed in different areas with many approaches, mainly because of Amazon importance for biodiversity and ecosystem balance in a global perspective (Fearnside 2008; Nepstad et al. 2009; Souza et al. 2013). The significance of rainforest has made Brazilian government take explicit political actions since 2004 to control the deforestation in Legal Amazon Region (May et al. 2011). Many papers have dedicated attention for modeling the deforestation causes, but few studies took into account an explicit spatial approach to investigate the spatial pattern of deforestation process in Brazilian Amazon (Hargrave and Kis-Katos 2013), although spatial dependence seems to play an important role in deforestation (Robalino and Pfaff 2012).

According to Haining (2003), there are four types of spatial processes that operate in the geographic space: diffusion, dispersion, exchange and rate transfer, and interaction. The diffusion process occurs

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when some attribute is acquired by a population and, at some point of time, it is possible to identify those individuals (or areas) that own the attribute. Contrary to diffusion, when an attribute spreads, the dispersal process consists of population movement. The third process, exchange and rate transfer, refers to expenditure among regions and products flow. The last one - interaction process - takes place when the outcome of one location influences and is influenced by the outcome of another. In light of this, literature concerning deforestation dynamics points out evidences for the existence of spatial process in deforestation (Robalino and Pfaff 2012; Aguiar et al. 2007).

The competition between forest land and alternative land uses is one of the main drivers of deforestation, conditioned by both opportunity costs and net benefit maximization (Barbier and Burgess 1997; Barbier et al. 2010). From another point of view, Piazza and Roy (2015) characterize the economic and ecological conditions under which deforestation may occur, considering the relationship of benefits brought by standing forests or by alternative uses of land.

Fearnside (2008), assuming that there the property definition of public land is weak, points out three phases for the land transaction process. During the first phase, colonists and settlers clear forest areas to determine ownership. Throughout the second phase, ranchers acquire the deforested lands and decide about land use based on products and land prices. The third phase is characterized by the transaction of land property from ranchers to capitalized farmers. As a complement, Souza et al*.* (2013) show evidences of higher deforestation in areas with higher density of farmlands (private properties).

In summary, we have empirical reasons to believe that the deforestation mechanism sustains a spatial process. As an example, the description in Fearniside (2008) shows evidence of diffusion process. Further, the works of Robalino and Pfaff (2012) and Hargrave and Kis-Katos (2013) showed significant spatial coefficients for deforestation, both covering rainforest areas.

This study aims to investigate the spatial dynamic of deforestation process in Brazilian Amazon in the context of the policies adopted over the last decade aiming to control or reduce deforestation. First, we present a brief description on the deforestation policies built by Brazilian authorities followed by a description of the database, variables, and the spatial techniques used in this analysis. The results provide information about the dynamics of global and local spatial dependence of deforestation. Finally, the implications of this spatial analysis for deforestation policies are discussed.

Overview of deforestation policy in Brazilian Amazon

Historically, the development in Brazilian rainforest occurred based on permissions for conversion of forestry land into agriculture or pasture, tax incentives for agriculture development, and forest-selective cut (Dennis et al. 2011). The National Institute of Spatial Research (INPE) has published data about annual deforested area in Brazilian Amazon since 1988, which allows monitoring the evolution of deforestation process. Since 2004, the Brazilian government has announced legal mechanisms for controlling deforestation (May et al. 2011) and deforested area in Legal Amazon has been decreasing annually (INPE, 2015). Based on policy instruments, we highlight 2004 and 2008 as key years for deforestation reduction, the same considered by Assunção et al. (2012).

In 2004, the Brazilian government launched a national plan, known as PPCDAm[1], for preventing and controlling deforestation in Brazilian Amazon. This plan puts responsibilities to federal, state, and municipal governments as well as private agents. Concisely, the main strategies of PPCDAm are based on planning land use, monitoring and controlling deforestation, and favoring sustainable production. Owing to changes in deforestation dynamics, PPCDAm has passed through three phases since 2004. The first phase (2004-2008) focused on planning land use by creating conservation unities (250 thousand km²) and indigenous territories (100 thousand km²). The second phase initiated in 2009 and lasted till 2011. Within this period, the DETER[2] project, which provides daily information about deforestation in favor of better supervising, permitted an integrated action between the IBAMA[3], federal police, highway federal police, National Force, and Brazilian army for command and control mechanisms. The third phase has been planned for 2012-2015 and aims to expand sustainable production (Ministério do Meio Ambiente, 2013).

[1] Action Plan for the Prevention and Control of Deforestation in the Legal Amazon
[2] Real Time System for Detection of Deforestation
[3] Brazilian Institute for the Environment and Renewable Natural Resources

Moreover, the presidential decree nº 6321, approved in 2007, assigns to the Ministry of the Environment the responsibility of formulating an annual list containing risky municipalities, based on municipal deforestation indicators, which should be monitored closely. The resolution of National Monetary Council nº 3545, established in 2008, restrains properties without proof of environmental regularity from receiving financial aid to invest in agriculture or cattle. Also in 2008, by approving the National Law of Climate Change, the Brazilian government committed to reduce its projected emissions of greenhouse gases (GHG) by 36.1% or 38.9% until 2022. For this purpose, two funds that finance environmental projects were created: the Climate Fund and the Amazon Fund. Since its creation, Amazon Fund has financed 28 projects statewide and 37 projects that focus on specific municipalities.

The policies implemented until 2006 were horizontal, affecting all economic agents in Brazilian Amazon area, and proved successful for achieving a systematic reduction in the deforested total area, despite some years of transitory inflection in the declining tendency. The new policy mechanisms has raised the importance of vertical actions, putting in evidence the need for incorporating spatial analysis into the formulation and execution of deforestation policies.

Data and methods

Brazilian government established Legal Amazon in 1959 covering approximately 5 million hectares across nine Brazilian`s states: Acre, Amapá, Amazonas, Mato Grosso, Rondônia, Roraima, Pará, Tocantins, and most of Maranhão[4]. For the last decades, the main pressure for converting forestry areas has concentrated the in arc of deforestation, which extends from southeast of Maranhão, passing by Tocantins, Pará, Mato Grosso, and Rondônia, and finish in southeast of Acre. Deforested areas are mainly used for cattle production (May et al. 2011).

[4] To the west of meridian 44° west.

Figure 1. Brazilian Amazon and the arc of deforestation.

The Brazilian National Institute of Spatial Research (INPE) provides annual deforested area by municipality estimated by using satellite images. Because of weather conditions, the deforestation rate is calculated as the difference between deforested areas in July of year *t* and august of year *t-1*. There is no differentiation between legal and illegal deforestation in the satellite images data.

We considered the period between 2002 and 2013. The total sample covers 760 municipalities. However, from these, we removed the sample municipalities, which are covered with tropical savanna (Cerrado)[5] and municipalities that did not present any forest area after 2002. Finally, we ended up with 686 municipalities, which were used for applying the spatial analysis techniques.

Variables

Searching to assess the spatial dynamics of deforestation, we used three variables. The first one represents the annual deforested area (y_{it}) measured in squared kilometers, commonly used for evaluating the level of deforestation and for defining the arc of deforestation. In addition, we use two relative indexes for deforestation, which allow assessing the intensity of the deforestation process over the space. These relative indexes were calculated as follows:

[5] Deforestation in Cerrado areas is not reported by INPE.

$$\varphi_{it} = \frac{y_{it}}{s_i} \tag{1}$$

where y_{it} is the annual deforested area and s_i is the total municipal area, both in squared kilometers, and φ_{it} provides the annual rate of deforestation. The second index is determined as:

$$\zeta_{it} = \frac{\sum_{t=1}^{T} y_{it}}{s_i} \tag{2}$$

where $\sum_{t=1}^{T} y_{it}$ is the cumulative deforested area between t and T for each municipality and thus ζ_{it} provide the annual cumulative rate of deforestation.

The motivation for using these three variables is to capture different aspects to discuss policy implications. On the one hand, the annual deforested area indicates regions that most contribute to aggregate deforestation. On the other hand, the relative indexes indicate regions that suffered higher environmental degradation – in forest area conversion terms. Moreover, when compared with the first index (equation 1), the second one (equation 2) tries to capture a maximizing behavior of alternative land uses. We expect that this index presents a positive growth rate and, as deforestation occurs and forest areas become scarcer, the growth rate decreases and the index value nears its maximum, i.e., whether there is no more forests or the only forest areas remaining must be protected by law and any deforestation is illegal.

Fig. 2 reports the mean and standard deviation of each variable calculated based on the municipalities data. The systematic reduction observed in the mean and standard deviation for variables y and φ shows the efficacy of horizontal deforestation policies and suggests convergence dynamic in deforestation among municipalities. As expected, ζ presents a concave behavior suggesting that the cumulative deforestation rate could achieve a maximum value.

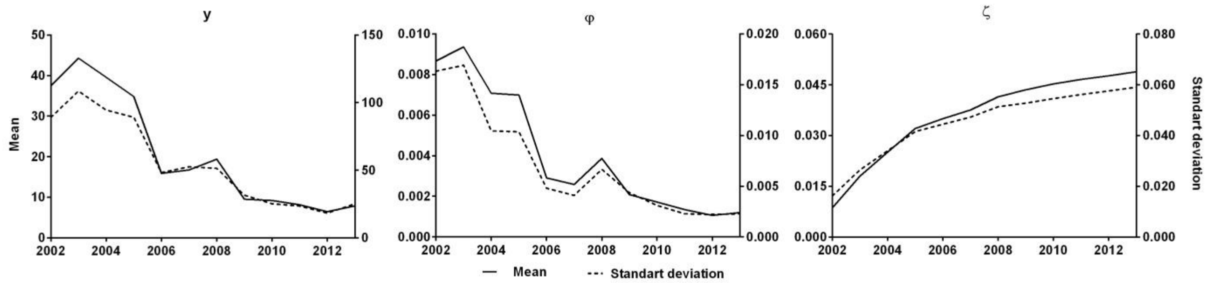

Figure 2. Mean and standard deviation of the deforestation and the two indexes.

Methods

The spatial dynamics of deforestation process is evaluated by using the global and local measures of spatial dependence. First, we calculate the Moran's I for each variable, described as follows:

$$\Lambda = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{\sum_{j=1}^{n}(y_i-\bar{y})^2} \qquad (3)$$

where y is the variable of interest in deviations from the mean and w_{ij} represents the spatial weights. Moran's I informs about the existence and degree of spatial concentration and calculating by each year provides dynamic information at least in the global perspective.

The local dynamic is evaluated by using the Local Indicator of Spatial Association (LISA) statistics, which represents the local decomposition of Moran's I. Following Anselin (1995), LISA statistics is represented as follows:

$$L = z_i \sum_{j=1}^{j} w_{ij} z_j \qquad (4)$$

where z_i and z_j are the variables of interest in deviation from the mean. As is well known, by incorporating neighboring behavior, LISA statistics allow identifying four types of clusters to the deforestation process: high-high (HH), low-low (LL), high-low (HL), and low-high (LH). Applying this technique on the variables for each year allows investigating the extent to which the spatial pattern of deforestation in terms of homogeneity and heterogeneity remains constant or changes over time.

Spatial weight matrix

The selection of *W* can be broad and is critical for spatial analysis, varying among a contingency matrix, distance-based or k-nearest neighborhoods. As described previously, the original sample provided by INPE covers 760 municipalities and was reduced to 686 municipalities. Such an aspect of the database implies that some locations became “islands” in the sense that the municipality does not present any physical border with its neighbors. Given this condition, we employed the procedure used by Carvalho and Almeida (2010) for choosing W. The structure of W was defined based on a k-nearest matrix with three neighborhoods, which maximized the Moran’s I statistic after testing for higher-order k neighborhoods.

Results

Global analysis

Moran`s I results show the presence of spatial correlation for the three variables and the degree of spatial correlation is higher for the relative indexes when compared with the deforested area (Fig. 3). Initially, the concentration of locations that most contribute to aggregate deforestation, represented by *y*, presents the same behavior of average deforestation by municipality with a peak in 2003 and with a second in 2008. However, rather than a decrease after 2008, Λ value has increased until 2013 (Λ = 0.385), *i.e.*, regions that most contribute to aggregate deforestation in Legal Amazon are more concentrated in recent years, with values similar to Moran`s I in 2002 .

Results for deforestation controlled by municipal area (*φ*) show that when average municipal deforestation presents peaks (2003 and 2008), the spatial correlation of *φ* decreases when compared with the previous year. Considering that the average municipal area of our sample is 6,368 km^2 (standard deviation 13,512), with a maximum and minimum of 159,540 km^2 (municipality Altamira - PA) and 64 km^2 (municipality Raposa - MA), respectively, peaks in total deforestation may occur together with an increase in deforestation of large municipalities. Therefore, relative deforestation becomes less concentrated. Comparing 2002 and 2013, Moran`s I for *y* increased 3% and for *φ* decreased 9%.

As ζ is a cumulative measure, the expected result was a positive variation. As seen in Fig. 2, from 2004 to 2013, Moran`s I results are flat. The behavior of spatial correlation for ζ shows that municipalities with high deforested area were concentrated and, since the relative rate of deforestation decreased in Brazilian Amazon since 2002 (see Fig. 1), less municipalities detach from others because of relative high deforestation, maintaining Λ at the same level.

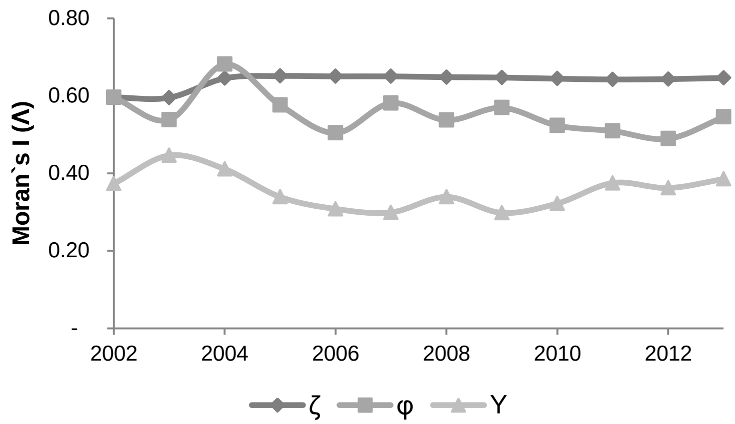

Figure 3. Moran`s I statistics for municipal deforestation in Brazilian Legal Amazon.

Motel et al*.* (2009) divide the causes of deforestation into two categories: structural and political. Structural causes are related to local infrastructure and market factors. Political causes are related to government instruments that result in higher deforestation (incentives to agroindustry for example) or instruments that control deforestation. The presence of spatial correlation reinforces that deforestation is related to local characteristics, *i.e.*, there are near regions where deforestation occurs with higher frequency. Additionally, the spatial correlation holds despite the decrease in deforested area during the period. One implication is that policy instruments are not acting to fragment locations with high deforestation.

Local analysis

For LISA estimation, we used the same k-nearest matrix with three neighborhoods with 0.05% of significance and results were submitted to a 10,000 permutation for robustness check. Deforestation clusters are revealed in Fig. 4-Fig. 6. Red polygons correspond to high-high (HH) clusters and blue polygons to low-low (LL) clusters, and these are hot-spot polygons. Yet, polygons with low deforestation surrounded by polygons with high deforestation (LH) and polygons with high deforestation surrounded by polygons with low deforestation (HL) are colored in purple and yellow, respectively. Gray polygons indicate municipalities with no forest since 2002 and, consequently, are excluded from estimation.

The low frequency of HL and LH clusters supports the argument that deforestation is a border phenomenon and related with regional features, i.e., there are regions more likely of being deforested and once deforestation becomes infeasible, agents move towards nearest regions to expand their activities.

Considering the annual deforested area (Fig. 4), the location of low-low (LL) clusters holds from south to northeast borders. From 2002 to 2013, the high-high (HH) cluster shifted to north and no longer covers the north region of Mato Grosso. In 2002, the state of Amazonas had only 1 municipality as an HH region, but in 2013, 6 municipalities were located in this cluster. In Rondônia, the same pattern occurred: in 2002, there were 2 municipalities in HH cluster, and in 2013, there were 9. On the other hand, the state of Mato Grosso presented 29 municipalities in HH clusters and 8 municipalities remained as HH cluster at the end of the period. Initially, there were 44 municipalities in high-high clusters and 121 in low-low clusters. In 2013, these numbers were 34 and 139, respectively.

The production of soy and maize in Mato Grosso has increased since 2002, mainly in the center of the state according to the Municipal Agricultural Survey, elaborated by the Brazilian Institute of Geography and Statistics (IBGE). Hence, the movement of the high-high cluster towards north may be indicative of a new agriculture frontier.

The occurrence of HH cluster reduces when we control deforestation by municipal area (Fig. 5). In 2002, HH clusters covered 43 municipalities and in 2013, this number dropped to 34. Similar to the annual deforested area results (Fig. 4), the area of the cluster in central Mato Grosso decreases. Furthermore, the HH cluster in the border of Pará and Maranhão defragmented after 2009. The only HH cluster in 2013 was located in the border of the north of Rondônia connected with the south of Amazonas.

Lastly, Fig. 5 shows ζ results. As for global spatial analysis (Fig. 3), since 2004 the pattern of spatial distribution holds. From 2002 to 2004, the number of municipalities in-hot spots increased: HH clusters had 43 municipalities in 2002 and 74 in 2004; LL clusters had 117 municipalities in 2002 and 129 in 2004.

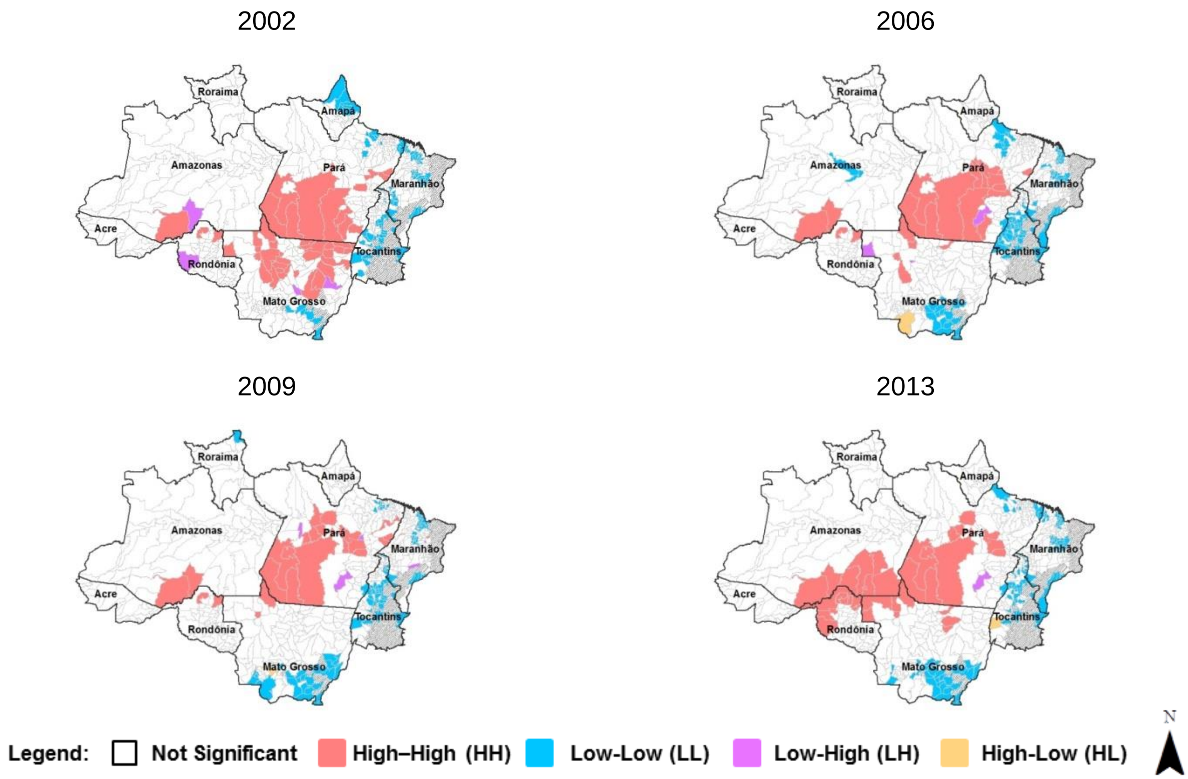

Figure 4. LISA analysis for annual deforested area (y)

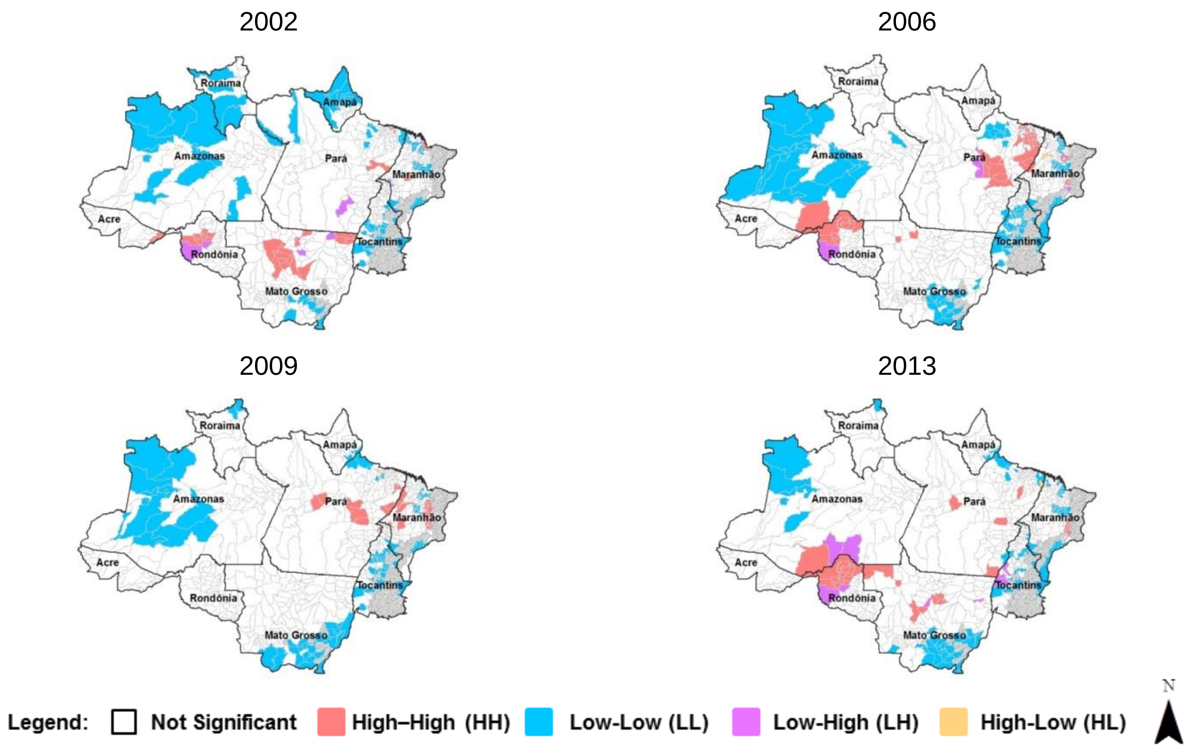

Figure 5. LISA analysis for annual relative deforestation index (φ)

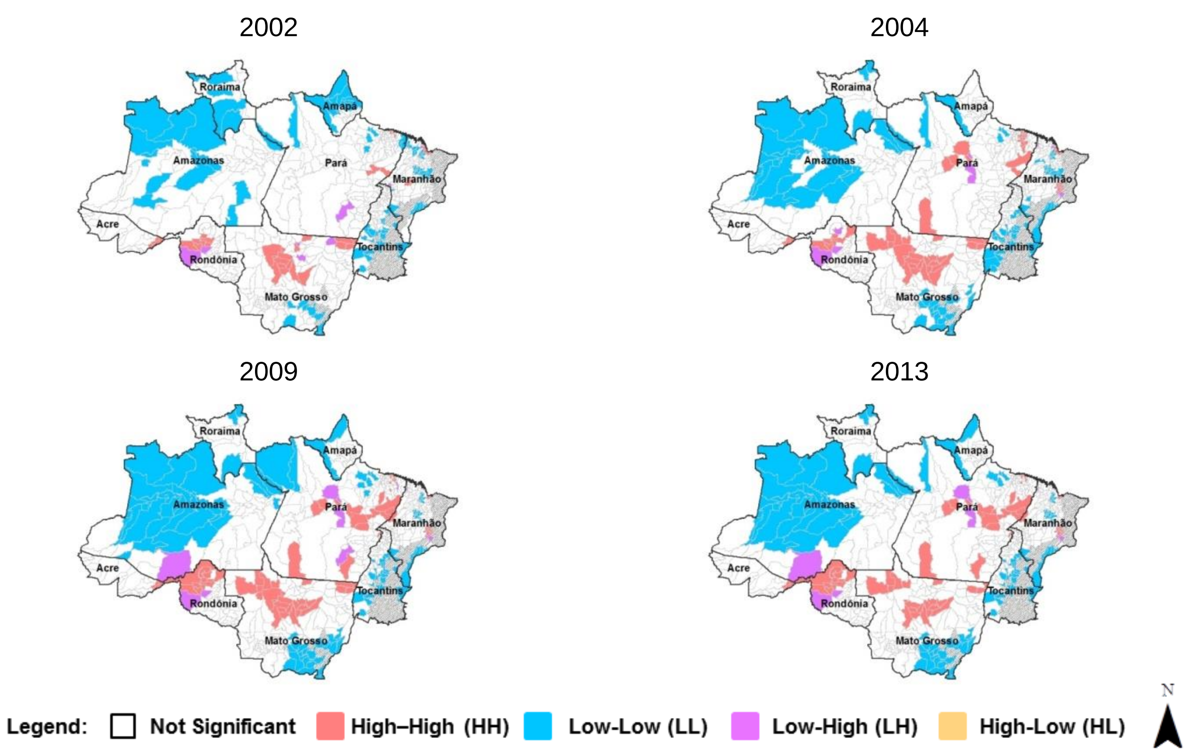

Figure 6. LISA analysis for annual cumulative deforestation index (ζ)

Discussion and conclusion

We refer to policy instruments that cover all Legal Amazon territory as horizontal. For example, the second phase of PPCDAm was a horizontal mechanism being focused in command and control mechanisms by enhancing deforestation monitoring. Another example is projects financed by Amazon Fund that cover all states of Legal Amazon. From 2009 to 2013, the Amazon Fund financed 63 projects in Legal Amazon region, among which 29 are statewide (Fundo Amazônia 2015). The creation of Conservation Unities can also be considered as a horizontal instrument, except when the assumptions for creation are based on regional aspects, as for creating green barriers for deforestation.

The expected result of effective horizontal policy instruments is the decrease of annual deforested area in Legal Amazon. Data published by INPE show evidences of effective results due to lower levels in historical deforested area after 2004. Moreover, Hargrave and Kis-Katos (2013) show that fines disobeying environmental laws intensity have a significant effect on deforestation reduction. However, our results show that spatial correlation holds despite the reduction in total deforested area, as seen by Moran`s I results.

From another perspective, vertical policy instruments are concerned about region-specific deforestation. The presidential decree n^{o} 6321 and the resolution n^{o} 3545 of Monetary Council affect municipalities, which are considered as key locations for decreasing deforestation. Also, 34 projects financed by Amazon Fund cover specific municipalities. The expected effect of vertical policy is the decrease of deforestation in municipalities where deforestation highlights. In this context, the results of Assunção et al. (2013) show that the credit constraint policy (resolution n^{o} 3545) led to a reduction in deforestation levels.

The spatial interpretation of vertical policy effectiveness would be less frequency or smaller area of high-high clusters. LISA results of municipal deforestation controlled by municipal area (φ) show that HH clusters are decreasing and we could interpret this fact as an evidence of the vertical policy efficacy. However, the results of LISA estimated for annual deforested area show persistence of concentrated regions with high deforestation. We point out two hypotheses for these results. The first one is that deforestation in municipalities that are perceived as critical and suffer deforestation control returns to its original relative levels after the implementation of policy instruments ceases. The second is that when deforestation in critical municipalities is controlled, deforestation in other regions grows as if they were scape areas, as seen by the shift of HH clusters to north when considering the annual deforested area.

Together with deforestation regulation, initiatives to recover environmental degradation are important for Amazon ecosystem balance. Since 2009, Amazon Fund has financed 20 projects that aimed to recover deforested areas. LISA maps for ζ, the cumulative index, show regions that historically detach because of higher deforestation and, consequently, suffered higher environmental degradation. Therefore, LISA maps for ζ indicate regions that mostly demand environmental degradation recovery actions.

From another perspective, actions that increase the value of forest land and sustainable production should contribute to decrease in deforestation, assuming that these actions reduce the attractiveness of alternative land uses (Barbier et al*.* 2010). The objectives of the third phase of PPCDAm are aligned with this strategy because of focus in promotion of sustainable production. Considering the index ζ, municipalities in high-high clusters suffered higher relative deforestation and are more likely to present deforestation in newly grown forest areas because of infrastructure or territory composition and are potential targets for policy instruments for sustainable production and increase in forest value.

In conclusion, deforestation is spatially correlated and spillover effects must be considered when planning policies for deforestation reduction. Further, spatial correlation supports the necessity of territory planning in Brazilian Amazon to achieve sustainable development.

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