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FORESTRY SCIENCE

Spatial pattern analysis of deforestation in the northeast of Minas Gerais State, Brazil

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Abstract: Understanding the spatial pattern of a particular geographic phenomenon such as deforestation is a key issue to establish monitoring programs to prevent the depletion of natural resources. Thus, the goal of this study was to assess the spatial pattern of deforested areas in the Pardo and Jequitinhonha River basins using Ripley's K function. First, we mapped all deforested areas in these basins using Landsat multispectral imagery from 2007 to 2015. Then, we used the Ripley's K function to test for spatial interactions between deforestation events. Our results showed that deforestations predominantly occur in a clustering spatial pattern in these basins. Spatial statistical analyses as Ripley's K function may provide a baseline for deforestation monitoring, as well as allowing us to understand the spatial pattern of deforestation in different natural ecosystems, especially in countries like Brazil, where the territorial dimension presents a great difficulty for the effectiveness of deforestation monitoring.

Key words: spatial point patters, Ripley's K-function, remote sensing, deforestation.

INTRODUCTION

Biodiversity loss and climate changes are major concerns regarding the increasing rates of deforestation in natural ecosystems (Vié et al. 2008, Françoso et al. 2015). It is well documented that deforestation affects soil nutrient dynamics, species diversity, vegetation composition, and results in warmer, drier conditions at the local scale, whereas it increases the atmospheric carbon dioxide levels and affects the temperature and rainfall patterns at the global scale (Lawrence & Vandecar 2015, Kamlun et al. 2016).

Despite the development of advanced techniques concerning land use/land cover change detection, deforestation in tropical regions has expanded continuously. The rate of global forest loss has hit 13 million ha per annum (World Bank 2009, Hansen et al. 2013) with major forest cover losses occurring in South America and Africa countries (FAO 2010). This is particularly true in Brazil, where most of the deforested areas are caused by anthropogenic activities such as agriculture and cattle ranching (Miles et al. 2006, Jusys 2016).

Several studies have shown that the deforestation in the Amazon Biome has increased in the last years (Ferreira Filho & Horridge 2017). In 2018, there was an increase of 13.7% of the deforestation in the Legal Amazon (a political-administrative area located within the limits of the Amazon River Basin) in relation to 2017, which corresponds to an area of 7,900 km² (INPE 2018). Following the same tendency concern the rates of deforestation, the Cerrado biome reached a peak of 0.75 Mha deforested in 2012, which was higher than the annual deforested area in the Amazon biome for the same period, which was equal 0.43 Mha (Ferreira Filho & Horridge 2017).

Monitoring forest cover changes is essential to track ecosystem dynamics and to provide basis for reducing deforestation and forest degradation (Wulder et al. 2012, Kamlun et al. 2016). Understanding the impact of deforestation requires detailed knowledge about where these events occur, which can be detected using remotely-sensed imagery. In fact, satellite remote sensing technologies along with Geographic Information Systems (GIS) have been increasingly used for mapping and monitoring deforestation (Reddy et al. 2016, Grecchi et al. 2017, Taubert et al. 2018).

Recently, efforts have been placed to integrate spatial statistical analysis with remotely-sensed data to improve deforestation detection and monitoring (Anwar & Stein 2015, Hamunyela et al. 2016). In general, spatial analysis is a technique of geographic data analysis based on the spatial distribution of a geographic phenomenon (Druck et al. 2004, Pereira et al. 2013). Since most of the deforested areas identified using remotely-sensed imagery are quantified in the form of event data, spatial point pattern analysis has a great potential to be used to identify deforestation patterns (Anwar & Stein 2015).

Ripley's K function (Ripley 1977) is a spatial distance-based statistical approach used to investigate pairwise interactions between events at different spatial scales (Fuentes-Santos et al. 2013), providing great flexibility over other methods of spatial analysis (Ripley 1977, Rode & Filho 2010, Machado et al. 2012). This function evaluates the second-order property of point patterns by taking into account the number and the distance between point events over a given area of interest (Hohl et al. 2017). Moreover, the Ripley's K function allows for quantitatively evaluating how much the observed point pattern deviates from randomness at multiple spatial scales (Ripley 1977).

The Ripley's K function has been used for analysing spatial patterns of a range of phenomena such as tree species distribution (Lv et al. 2019, Scalon et al. 2012), sprinkler irrigation system (Zeilhofer & Mara 2011), forest mortality (Hatala et al. 2010). In the study of Pu & Bell (2017), Ripley's K function was applied to investigate the spatial distribution of submerged aquatic vegetation. Pereira et al. (2013) used the Ripley's K function to analyse the spatial distribution of burned areas, and found that the spatial pattern of burned areas is affected by its area extent.

Thus, the goal of this study was to test for spatial interactions between deforestation events in the Pardo and Jequitinhonha River basins, Minas Gerais State, Brazil, using Ripley's K function.

MATERIALS AND METHODS

Study area

The Pardo and Jequitinhonha River basins are located in the northeast of Minas Gerais State, Brazil (Figure 1). The Pardo River basin is located in both Minas Gerais (12,729.55 km²) and Bahia (19,738.53 km²) States, whereas the Jequitinhonha River basin covers a large part of the northeast of Minas Gerais State (65,660 km²) and a small part of southeastern of Bahia State (4,655 km²), totalling an area of 70,315 km². Both basins are located at the transition between Atlantic Forest and Brazilian savanna (known as Cerrado) biomes (Scolforo & Carvalho 2006).

Change detection

Landsat 5 TM (Thematic Mapper) and Landsat 8 OLI (Operational Land Imager) multispectral imagery were acquired for the agricultural years (from July to June) 2007-2008, 2008-2009, 2009-2010, 2010-2011 and 2014-2015.

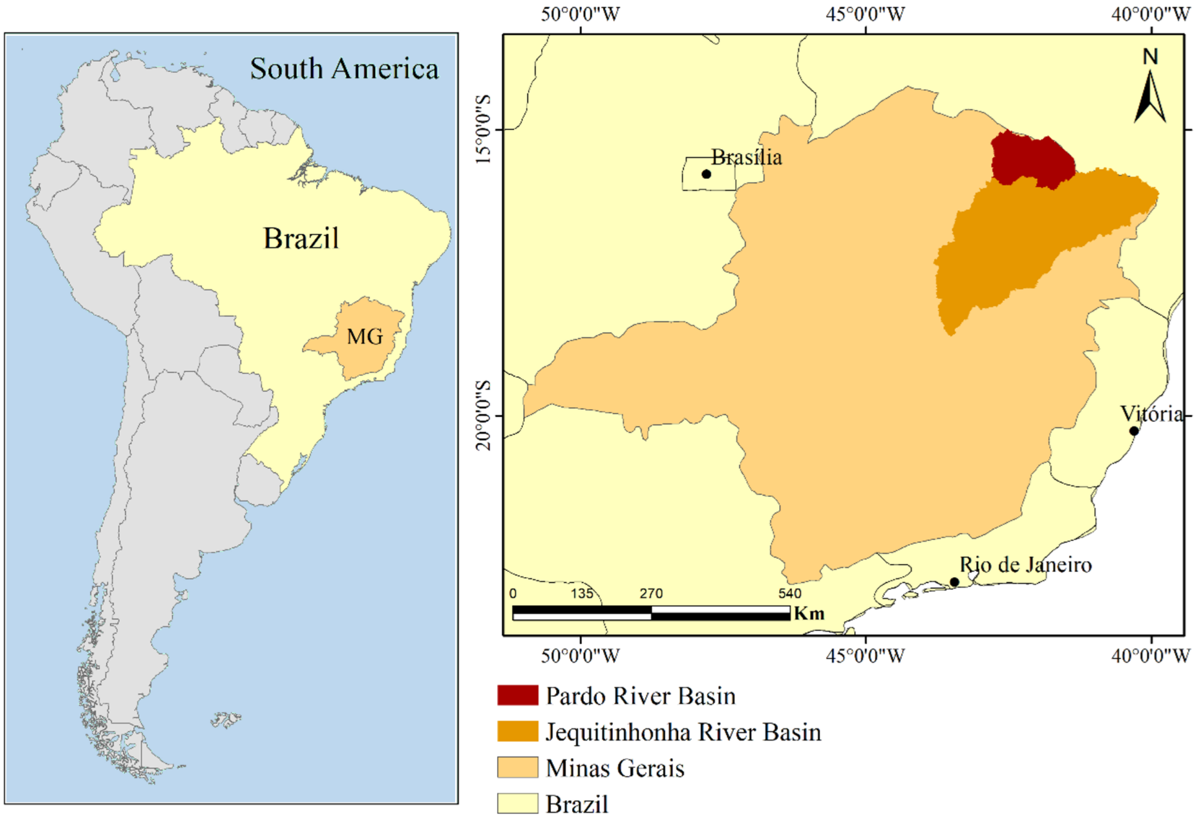

Figure 1. Location of the Pardo and Jequitinhonha River basins in Minas Gerais State, Brazil.

Landsat 5 TM scenes were obtained from the INPE (Instituto Nacional De Pesquisas Espaciais) database (available at: http://www.inpe.br), whereas Landsat 8 OLI scenes were obtained from the USGS (United States Geological Survey) database (available at: https://earthexplorer.usgs.gov/) as Level 1 Terrain Corrected (L1T) product.

The NDVI (Normalized Difference Vegetation Index) image differencing was applied to detect land cover changes for all Landsat imagery over the years. NDVI differencing is a useful method to detect the changes occurring in vegetated areas (Acerbi Júnior et al. 2015, Silveira et al. 2017). In this study, only deforested areas larger than 1 hectare were considered as deforestation events. For each of these events, we calculated the centroid of the deforested area to be used as inputs in the following spatial interactions analysis. The change detection analyses were carried out using the softwares ENVI Version 4.7 (Exelis Visual Information Solutions 2015), and ArcGis version 10.1 (Esri 2010).

Ripley's K function analysis

A spatial point process is a particular kind of stochastic process in which the realizations consist in countable sets of point in the plane (Ripley 1977). Spatial point pattern is defined as a particular realization of such a process, and the point locations are generally referred to as events of the process or pattern (Diggle 1983). A spatial point process may be homogeneous and inhomogeneous. In a homogeneous spatial point process, the point events are uniformly distributed in the study area. Therefore, the first- order intensity (the number of points per unit area) is constant. On the other hand, in an inhomogeneous spatial point process, the point events are not uniformly distributed in the study area and are distributed according to the intensity function of the process.

The first step in analysing a spatial point pattern is to test the complete spatial randomness (CSR) hypothesis. This hypothesis indicates that is equally likely that an event will happen anywhere within the study area (Diggle 2003). The homogeneous and inhomogeneous K-functions (Ripley 1977, Baddeley et al. 2000) may be used to analyse the CSR hypothesis. These functions analyse and describe the spatial structure of a point process (the second order property) and are based on the analysis of pair of points.

In this study, the deforestation events identified in the Pardo and Jequitinhonha River basins can be seen as a realization of a spatial point process. First, we estimated the intensity (λ) of the deforestation events using the kernel smoothed estimator of intensity, and the edge correction described by Jones (1993) and Diggle (2010) (Equation 1). The kernel estimator allows the spatial distribution characterization of the events under study (Fuentes-Santos et al. 2020).

$$\hat{\lambda}\left(x\right)=\sum_{i=1}^{n}k_{\tau}\ (x-x_i)w_i e\left(x_i\right) \tag{1}$$

Where k is the Gaussian smoothing kernel, $e(x_i)$ is an edge correction factor and w_i are the geographical weights of the i^{th} observations.

The kernel estimator was generated using the *density.ppp* function in the *spatstat* package in R (Baddeley & Turner 2005). To select the smoothing bandwidth (τ) for the kernel k, we used a cross-validation method using the *bw.diggle* function. This function minimizes the mean-square error criterion defined by Diggle (1983). The kernel weights (w_i) are determined by the Euclidian distance from x_i, with the weight reducing as the distances increases. The edge correction described by Jones (1993) and Diggle (2010) was applied to avoid edge-effect bias, considering the study region D (Equation 2).

$$\frac{1}{e(x_i)}=\int_D k\left(x-x_i\right)dx \tag{2}$$

To test the CSR hypothesis, both the homogeneous and the inhomogeneous K function may be applied. When the events are uniformly and independently distributed in the study area, its first-order intensity is constant, and the spatial point process is homogeneous. In this case, the homogeneous K function is used. The homogeneous K- function with an edge correction can be estimated as in Equation 3, where r is the distance between the events.

$$\hat{K}\left(r\right)=\frac{\left|A\right|}{n^2}\sum_{i}^{n}\sum_{j,\,i\neq j}^{n}\frac{I_r(d_{ij})}{w_{ij}} \tag{3}$$

Where $|A|$ is the area of the observation domain; n is the number of observed events; dij is the Euclidian distance between points i and j, $i \neq j$; $I_r(d_{ij})$ is an indicator function whose value is equal to 1 if $(d_{ij}) \leq r$ and equal to 0 if $(d_{ij}) \geq r$ and wij is an edge corrector factor that represents the proportion of the circumference around an event i, passing over the event j that is within $|A|$.

When the first-order intensity is not constant, the homogeneous K-function can overstate the departure from CSR. In this case, the inhomogeneous K-function (Baddeley et al. 2000) is used to overcome this difficulty (Equation 4)

$$\hat{K}_{in\hom}\left(r\right)=\frac{1}{A}\sum_{i}\sum_{j,i\neq j}\frac{1\left\{d_{ij}\leq r\right\}e\left(x_i,x_j,r\right)}{\lambda\left(x_i\right)\lambda\left(x_j\right)} \tag{4}$$

Where A is the area of the observation domain, that represents the area, d_{ij} is the distance between points i and j, $i \neq j$, $e(x_i, x_j,$

r) is an edge corrector factor (Equation 5), λ is the estimated intensity obtained by the kernel smoothed estimator.

$$e\left(x_i, x_j, r\right) = \frac{1\left(b_i > r\right)}{\sum_j 1\left(b_j > r\right) / \lambda\left(x_j\right)} \tag{5}$$

Where b_i and b_j are the distance from x_i and x_j to the boundary of the window, respectively.

The homogeneous and inhomogeneous K-functions can be transformed to an L- function to directly compare with distance x in a linear manner (Equation 6).

$$\hat{L}(r) = \sqrt{\frac{\hat{K}(r)}{\pi}} \text{ and } \hat{L}_{in\hom}(r) = \sqrt{\frac{\hat{K}_{in\hom}(r)}{\pi}} \tag{6}$$

In this study, the Monte Carlo test envelops were obtained for either the homogeneous or inhomogeneous L-functions from s − 1 = 99 simulations under the corresponding null hypothesis. In this case, if the observed values (L (r)) are within the limits of the reliable envelops, the spatial pattern is classified as random, whereas values below or above this threshold indicate regular and clustering patterns between events at distance r, respectively.

Data analysis for this study was performed using the *spatstat* package in R (R Core Team 2016) (Baddeley & Turner 2005).

RESULTS

The number of deforestations and their respective areas detected in the Pardo and Jequitinhonha Rivers basins, for each agricultural year during the period between 2007 and 2015 are shown in Table I. Figure 2(a to e) shows the spatial distribution of the deforested areas in the study region, between 2007 to 2015. We could not identify the deforested areas in a small part of the northeast of Jequitinhonha River basin due to the lack of cloud-free images for this basin region for all the analysed years.

Table I. Deforested areas detected in Pardo and Jequitinhonha Rivers basins, Minas Gerais State, Brazil, for each agricultural year during the period between 2007 and 2015.

Agricultural Year	N° of deforestations	Deforested area (ha)
2007-2008	661	17,096.83
2008-2009	132	9,808.47
2009-2010	426	12,590.81
2010-2011	369	13,723.14
2014-2015	1,788	9,922.09
Total	**3,376**	**63,141.34**

The kernel estimates of the first-order intensity (Figure 3) indicated distinct spatial patterns in the study region in all analysed years. The hotspots show regions with high intensity of deforestation events. Therefore, the presence of hotspots in our study area is an indicative that the first-order intensity is not constant, and deforestation occurrence is dependent on the spatial location.

In addition, we noticed that the intensity of the events increased over the years, with more hotspots observed in different locations within the basins. The 2007-2008 agricultural year shows that the deforestation events occurred with an intensity higher than 8 x 10^{-7} deforestations/m² in the hotspots. In 2008-2009, the intensity of the events was lower than in 2007-2008, with 1.5 x 10^{-8} deforestations/m² in the hotspots. Visually, the 2014-2015 agricultural year presented the highest number of deforestation hotspots in the Pardo and Jequitinhonha Rivers basins.

Since the kernel estimates of the first order intensity shows that the intensity of the deforestation events is not constant, we applied the Monte Carlo test envelops under the inhomogeneous hypothesis to check the second-order structure of the deforestation events (Figure 4).

The inhomogeneous L-function provide evidence of clustering, randomness, and regular

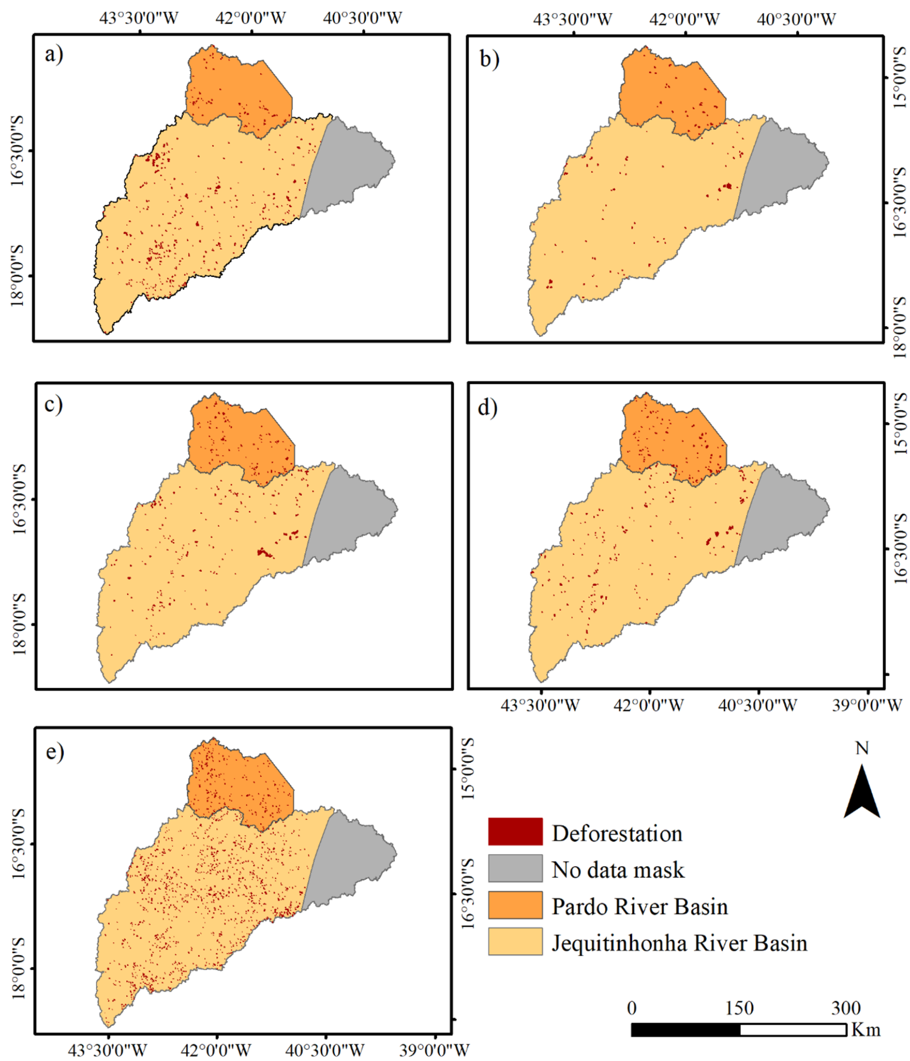

Figure 2. Deforested areas mapped in Pardo and Jequitinhonha Rivers basins, Minas Gerais State, Brazil, for each agricultural year during the period between 2007 and 2015: a) 2007-2008, b) 2008-2009, c) 2009-2010, d) 2010-2011, and e) 2014-2015.

spatial patters during the analysed periods. In the agricultural year 2007-2008, this function detected clustering with an interaction radius close to 50 km and randomness between 50 km and 70 km. The agricultural year 2008-2009 showed a clustering patter up to 65 km, after that, a randomness patter was observed.

We observed a pattern of clustering, randomness, and regularity in sequence for the agricultural years of 2009-2010, 2010-2011, 2014-2015, and for all deforestation events occurred between 2007 and 2015, again with some variation between the distance limit of spatial patterns.

Although the inhomogeneous L-function have identified patterns of regularity for large distances, these results should be interpreted carefully since the variability of the empirical estimator of the K and L-functions increases in large distances.

DISCUSSION

In this study, we applied the spatial point process analyses for an improved understanding of the spatial pattern of the deforested areas in Pardo and Jequitinhonha Rivers basins, located in Minas Gerais State, Brazil, during the period

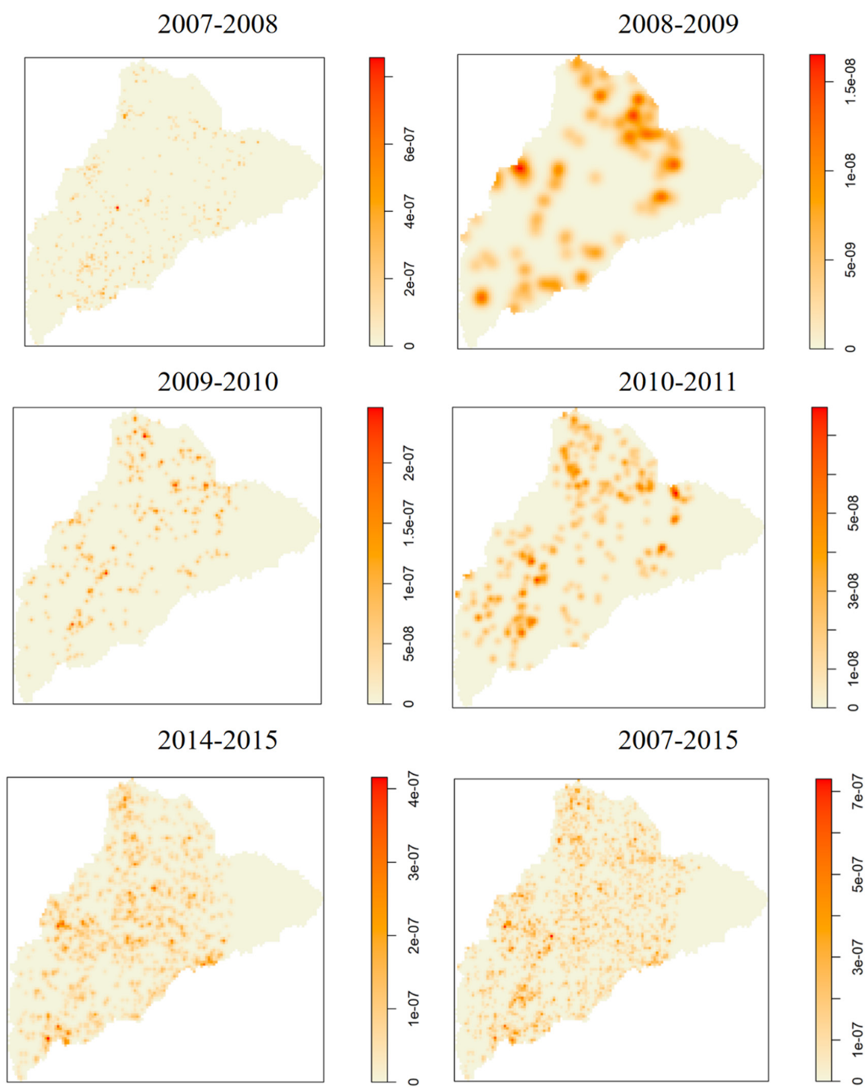

Figure 3. Kernel estimates of the deforestation event intensity in Pardo and Jequitinhonha Rivers basins, for each agricultural year during the period between 2007 and 2015.

between 2007 and 2015. Our study demonstrates that the Ripley's K function was successfully able to determine the spatial pattern of deforested areas at different scales in the study region.

The inhomogeneous K-function identify the clustering pattern around small distances from a given event. However, at large scales, the behaviour of inhomogeneous K-function indicates that the point process is closer to CSR and regularity. This behaviour was also observed by Hering et al. (2009) analysing the spatio-temporal wildfire ignition point patterns.

From 2007 to 2015, the agricultural year 2008-2009 showed the lowest number of deforested areas identified in our study. For this same year, Chen et al. (2015) observed that the deforestation rate fell drastically in the Amazon basin. The authors considered the 2008 global economic crisis, that affected many economic activities such as wood production and logging (Canova & Hickey 2012), as one of the major causes of the deforestation decline in this year. Besides that, they also considered as another cause of this decline the enforcement of the Brazilian Law of Environmental Crimes that began in July 2008 and aim to protect wildlife and plants from environmental crimes (Brazil 2008).

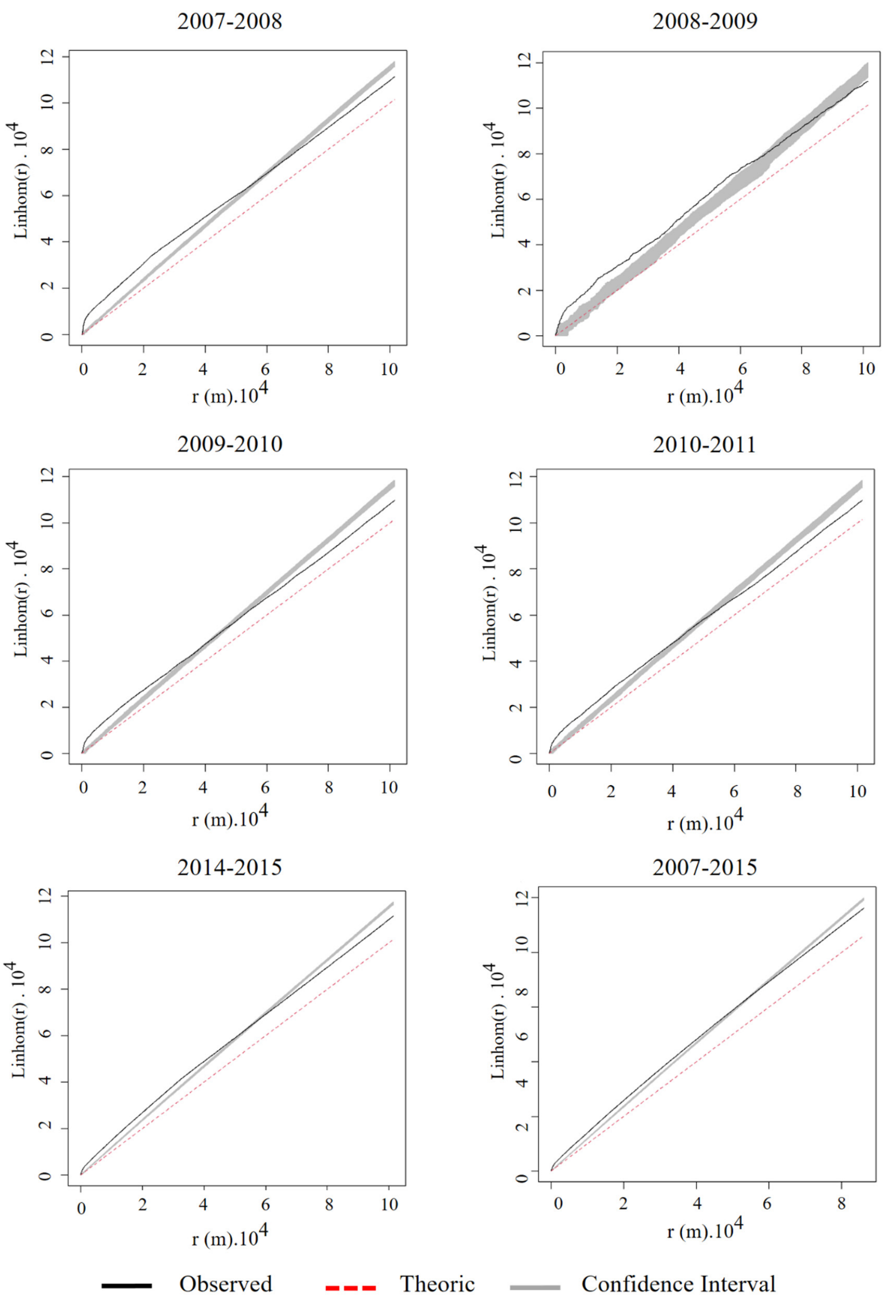

Figure 4. Inhomogeneous K-function transformed to the L-function for the deforestation events in each agricultural year during the period between 2007 and 2015.

The clustering spatial pattern observed for small scales may be related to small deforested areas, especially for the agricultural year 2014-2015. In this agricultural year, we observed an increase in the number of deforested area (Table I and Figure 2). In 2012, the Brazilian Forest Code (BFC) was modified by Brazilian government. This new code resulted in a weaker protection for natural vegetation and less requirement for restoration (Soares-Filho et al. 2014). Besides that, the BFC granted amnesty for small farmers that have deforested their lands, and consequently have insufficient Legal Reserve areas in their farms, providing them the exemption from having to perform restoration (Sparovek et al. 2015). Legal Reserve is the percentage of the farm total area which need to be preserved, and now with BFC modifications, the farmers do not have to perform restoration of those areas, resulting in increased vulnerability of the remaining vegetation to agriculture expansion (Rajão & Soares-Filho 2015). Thus, the increase in the number of deforested areas in the agricultural year 2014-2015 observed in this study may be related to BFC modification.

Deforestation causes can be direct or indirect and can be due to natural events or human interference (Geist & Lambin 2001). The direct causes are related to land use and land cover changes, where forest areas are replaced mainly by agriculture and livestock expansion (Reddy et al. 2016), whereas the indirect causes are related to social processes, where population dynamics and various other technological, economic, and political factors influence practices such as deforestation (Geist & Lambin 2002).

Furthermore, deforestation pattern can be compared to fire pattern, mainly due to the fact that in many regions, fires are associated with initial land clearance (Aragão & Shimabukuro 2010). Both fires and deforestation occur in specific areas, related to factors such as region characteristics, prevention practices, and management of native vegetation areas, which make their spatial distribution difficult to be random (Fuentes-Santos et al. 2013, Mateus et al. 2014). Pereira et al. (2013) analysed the spatial pattern of fires in protected areas and verified that the spatial pattern may be related to the use of fire in soil management, which explain the clustering pattern in some regions. In addition, in many regions, soil management is carried out with deforestation practices followed by fires, corroborating the association between fires and deforested areas.

Zeilhofer & Klemp (2011) observed a clustering spatial pattern for sprinkler irrigation (an agricultural production system) in the upper Rio das Mortes basin, located in Mato Grosso State, using the Ripley's K function. In the Amazon forest, Anwar & Stein (2012) used the distance-based G-function to analyse selective logging detected using Landsat imagery and observed that this process also have a clustering spatial pattern. Both sprinkler irrigation and selective logging are process that can be related to deforestation process.

Besides that, deforestation process also is related to fragmentation process. Landscape modification and habitat fragmentation are key drivers of global species loss (Lindenmayer & Fischer 2006). Habitat fragmentation implies a loss of habitat, reduced patch size, and an increasing distance between patches, but also an increase of new habitats (Haddad et al. 2015). Moreover, according to Lawrence & Vandecar (2015), the pattern of deforestation can also influence how regional climate is modified. These authors also observed that the impacts of deforestation vary by region and depend on the use of converted forests.

Considering the increased rate of deforestation around the world, it seems sensible to invest in further studies that focus on more techniques to determine deforestation patterns in different natural ecosystem. Our methodology presents a quantitative method which has a great potential to analyse deforestation patterns at multiple scales and it is indispensable for analysing and interpreting deforestation patterns in terms of multi-date detection in an effective manner. Further studies could also investigate the influence of geographic and socioeconomic factors on the distribution of deforested areas in the study region.

CONCLUSIONS

The methodology presented in this study provides a useful tool for identifying the spatial interactions between deforestation events in the Pardo and Jequitinhonha Rivers basins. The combination of remote sensing techniques and spatial statistics is a promising way ahead for better understanding of and possibly reducing deforestation in native vegetation.

The clustering spatial pattern was the predominant spatial pattern of deforested areas in Pardo and Jequitinhonha Rivers basins during the period from 2007 to 2015, mainly in small distances. Spatial statistical analyses as first and second-order estimation are useful tools to decisions makers and may provide a baseline for deforestation monitoring. Furthermore, these tools allow us to understand the spatial pattern of deforestation events in different natural ecosystems, especially in countries like Brazil, where the territorial dimension presents a great difficulty for the effectiveness of deforestation monitoring.

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Juliana Maria Ferreira de Souza Diniz: conception and design of the study, data collection, data analysis, data interpretation and writing of the manuscript. Aliny Aparecida dos Reis: contributed to statistical analyses, actively participated in the discussions and interpretation of the results, writing of the manuscript, reviewed and approved the final version of the article. Fausto Weimar Acerbi Junior: supervised the research project, provided ongoing guidance and support throughout the process, reviewed and approved the final version of the article.