Dynamical spatial modeling to simulate the forest scenario in Brazilian dry forest landscapes

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ABSTRACT

Caatinga is a biome located in Brazilian northeast region well known by the dry forest vegetation. The analyzed area called charcoaling zone has a great suppression of native vegetation to supply the charcoal market. Through the images from the Operational Linescan System sensor of LANDSAT 8, this paper demonstrates, in a spatial-temporal way, the degradation in landscapes of the Caatinga biome and the evaluation of the forest scenario. Thus, it has been possible to evaluate the changes experienced by the vegetation (2013–2016) and to identify the land use patterns and coverage and to quantify them according to the obtained satellite images. Agriculture and the exposed soil represent about 70% of the area, considering the growing of the anthropic area and consequently the emergence of several exposed soil areas. The simulation of the future scenarios was used by modeling with the application DINAMICA EGO, generating projections of the region of the coal for the year of 2019. In addition, the assessment of the forest effacement demonstrates decreased development of the forest and increased levels of exposed soil.

1. Introduction

The Caatinga biome (dry forest) is a predominant vegetation in the northeast region, covering 54.53% of the 1,548,672 km² of the total area, occupying 83% of the state of Pernambuco (IBGE, 2008).

The semi-arid zone is an area where anthropogenic action occurs with great intensity on forest resources, indicating a need for strategic planning to contain the devastation of its vegetation. The strategic planning for the application includes the application of sustainable forest management planning techniques, remote sensing, and geoprocessing (CPRM, 2005).

These techniques increase the understanding of the behavior of the Caatinga biome (dry forest) and its aspects related to geographic, agricultural, geopolitical, and environmental parameters (Silva, 2015).

Thus, monitoring and planning for the sustainable use of natural resources are necessary in all areas of societies associated with their management through agricultural, forestry, and urban development. In this context, it is necessary to know the importance of land cover and land use, seeking to identify, in landscapes, subsidies to understand the physical, economic, and social aspects in the global-scale levels (Pereira, 2008).

Wood and coal are the main products from the Caatinga, but obtaining these energy sources is far from sustainable. Deforestation originates around 80% of these forest products in the northeast (Gariglio, 2010).

In this context, this study establishes and identifies a possible relationship between the use of land cover and the increase or decrease in the areas established as agriculture, bare soil, water, and forest cover. The field surveys and remote-sensing technique data are used in the landscape modeling, and such information is relevant to the diffusion of forest management in Pernambuco. Contributing to the sustainability of the micro-region called the “Zona de Carvoeijamento” (charcoaling zone) bound by Sá (2003), the field surveys and remote-sensing technique data constitute important tools for the formulation of more effective public and environmental policies in this region (Silva, 2015).

This study aims to create a model to simulate future forest scenarios of the Caatinga biome (dry forests) in relation to changes in time and influence of economic, social, and environmental variables. Also, this study further projects and evaluates the changes suffered over the years, through the demonstration of the dynamic mode representing changes in areas of forest cover and identifies which factors that could influence such changes.

2. Methodology

First, prior to forming the geographic database for the study, the search periods were defined according to their availability and image quality. For the
execution of this work, four scenes from different dates of the LANDSAT 8 satellite OLS (Operational Linescan System) sensor were used. The four scenes were acquired in the format “.geotiff” free of charges from the United States Geological Survey (www.earthexplorer.usgs.gov). The scenes covered the entire study area from 2013 to 2016 (Table 1). Previously georeferenced metadata of the images was imported into the image manipulation software.

The mosaic of the images was completed and later cut within the limits of the study area defined by Sá (2003) (Figure 1). Linear contrast was used to improve the image quality. From then on, the acquisition of land cover and land use samples was carried out which defined the classes of forest, exposed soil, agriculture, and water. Also, static maps were created, and a wide range of variables was utilized that included cattle, sloping roads, logging, hydrography, hypsometry (Shuttle Radar Topography Mission (National Aeronautics and Space Administration (NASA), 2012)), Human Development Index, urban cores, Gross Domestic Project, and population.

The methodology was the same as used by Silva (2015) and Tramontina (2016), being considered and adopted as the basic methodologies in this research.

The steps to land cover and land use modeling start after the analysis of the evolution caused by the land use and land cover and their transitions. The projection into the future scenarios (2019) used maps of land use and the cover model (2013 and 2016), which are continuous variables, in the DINAMICA EGO application. The final results also visually compared with the land use and coverage map for 2016 (Silva, 2015). The maps used to demonstrate static variables were determined by Evidence Weights (W+), the transition probabilities of land cover and land use classes. As you process the data, other files will be generated, and these will be utilized in the following steps (Tramontina, 2016).

The first step is the calculation of transition matrices. According to Silva (2015), the “categorical maps” set functors to calculate the transition matrix

| Scene | Orbit | Point | Year 2013 | Year 2016 |
|-------|-------|-------|-----------|-----------|
| 1     | 216   | 65    | 30/10     | 23/11     |
| 2     | 216   | 66    | 30/10     | 23/11     |
| 3     | 215   | 65    | 10/12     | 02/12     |
| 4     | 215   | 66    | 10/12     | 02/12     |

Figure 1. Studied area (Carvoeijamento area/coaling zone) defined by Sá (2003).
for the initial and final maps of the analyzed periods. Making a link with these data sets in the matrix “functor,” with the time differences between the initial map and the final map. The maps were from 2013 to 2016, and the time window was 3 years. The results of the matrix calculation were interconnected with two single-step and multiple-step output “functors.” The first matrix involves the transitions that occur from year to year, and the second matrix involves the transitions that occur throughout the analysis period. The results are saved in a Comma-Separated Values (CSV) file.

The second step is the calculation of intervals for categorization of continuous variables. In this step, “the calculation of evidence weights,” it was necessary to group the static variables into a single file called “Cube.” This is used to facilitate the insertion into the program of the maps that used to calculate the continuous variables.

The third step is the calculation of Weights of Evidence coefficients. After calculations that define the ranges of distances, the coefficients of the evidence weights were used to select the variables that influence the dynamics of transitions from land cover and land use, creating local probabilities of differences. It requires: Input parameters (the initial and final maps and the cube with static maps; the sliced file “Skeleton,” created in the previous step); the functor “Determine Weights of Evidence Coefficients”; and as an output parameter saving the file of Weights of Evidence coefficients.

The fourth step is the calculation of correlations between variables. At this stage of modeling, the spatially independent variables are observed that include the spatial association between two variables, eliminating from the model to those who were strongly correlated with each other. The variables should consider the evaluation of the independence between these to and explain the same transition of land use and land cover.

The parameters used to obtain the “correlation maps” are the Cramer (V) and Joint Information Uncertainty (U) indexes that helped to decide which variables should be kept in the model. The Cramer Index (V) is defined by Zuquette (2017) and Bonham Carter (1994) by Equation (1):

\[ V = \sqrt{\frac{\chi^2}{T \cdot M}} \tag{1} \]

where
- \( T \) = marginal totals of the cross-tabulation matrix between two maps A and B;
- \( \chi^2 \) = chi-square statistics; and
- \( M \) = minimum of \((n-1, m-1)\), where \( n \) is equal to the number of rows and \( m \) is the number of columns of the crosstab matrix between maps A and B.

Thus, the “Uncertainty of Joint Information” of A and B, \( U(A, B) \), can be used as a measure of association, being defined by Equation (2):

\[ U(A, B) = 2 \frac{H(A) + H(B) - H(A,B)}{H(A) + H(B)} \tag{2} \]

According to Almeida (2003), the U index varies between 0 and 1, and when the two maps are completely independent, \( H(A, B) = H(A) + H(B) \) and \( U(A, B) = 0 \) (zero), and when the two maps are completely dependent, \( H(A) = H(B) = H(A, B) = 1 \) and \( U(A, B) = 1 \) (one). Values that are less than 0.5, for both U and V, have a lower association and values above 0.5 show a high correlation.

Ferrari (2008) emphasizes that the above formula is indispensable, given that the Evidence Weights method is based on Bayes’ conditional probability theorem. According to this theorem, the selection of variables for modeling analysis should consider the evaluation of the independence between pairs of explanatory variables selected to explain the same type of transition of land cover and land use (Silva, 2015).

We used the initial land use and land cover (use) map, the cube of static variables, the Weights of Evidence file, and the “Determine Weights of Evidence Correlation” functor. These, along with the calculation of the distance map, the class numbers, and a functor, were generated into a table in the CSV format for further analysis.

The fifth step is running the simulation model. After the correlation step of the variables, we used the functors with the use of the initial map, the cube of variables, the transition matrix (from one year to another), and the file of Weights of Evidence. A container called “Repeat” was added, which has the function of executing the operations during the time intervals, for example, between 2016 and 2019, the parameter used for 3 years.

In this container, were inserted functors to carry out the model process as follows:
- “Mux Categorical Map” which is used to re-inject the maps produced from one interaction to another and allows the feedback of the maps;
- “Calc Distance” which is used to calculate the distance maps;
- “Modulate Change Matrix” it when the transitions have been defined in percent change rates;
- “Expander” is used in the process for expansion or contraction of spots that were already of a certain class;
- “Patche” has the function of generating or forming new spots through the sowing mechanism, that is, looking for cells around the chosen location for a joint transition;
“Calc W. OF. E. Probability Map” was entered to calculate a transition probability map for each transition specified by adding the Evidence Weights.

Finally, the exit parameters were inserted, one with the generation of the landscape of the annual maps and the other with the generation of probability maps of changes in the annual landscape. In this way, the simulated maps were obtained for the final years and the same as the real maps (Figure 2).

After the validation of the model, the scenario simulation procedure was carried out for 2019, and the maps created were quantified in terms of land use and land cover. The calculation of the transitions matrices for the years 2016–2019 was also carried out in order to observe the trends of the changes from year to year and of the total changes in the period of 3 years.

3. Results and discussion

The land cover and land use mapping is based on the classification of images of LANDSAT 8. It was possible to quantify the coverage and use of the Carvojamento area (coal area) defined by Sá (2003), in a satisfactory way. These indicate the decrease of the vegetation to the detriment of the increase in the agricultural and cattle raising, which is predominant in the central region to the west. These practices may be more common due to incentives for families and subsidies for agricultural growth from the federal and state governments.

The progress of the thematic classes analyzed during the two years, specifically in the agriculture and exposed soil, were the highest values in hectares and consequently in percentage; that is, they were the predominant classes in the region of study (Silva, 2015). This relationship is biased due to increased production, and a balance is needed between the demand for agricultural production and environmental preservation. It can be observed in Figure 3.

In Figure 3, it is also noted that there is a greater predominance of the agricultural and livestock class and exposed soil where the largest cattle-producing municipalities in the region are found. This region is characterized by areas of higher altitudes, which may hinder the introduction of new agricultural areas.

When considering future simulation analysis and scenarios according to Benedetti (2010), the simulation of maps through DINAMICA EGO is valid when done under a calibrated model. In fact, this model adequately represents the transition processes that have elapsed in the time interval considered, according to the result obtained in the validation.

Upon obtaining the simulation performed in the application (Figure 4), the visual comparison is used between the classified map of 2016 and the simulated map of that year to observe the model’s condition. The simulated map bears similarity to the real map optically, but the future studies may corroborate the quality of the simulated maps precision, in relation to the real maps obtained through a set of procedures and methods of digital image processing.

Observing the simulation data for the year 2019 (Table 2) (Figures 5 and 6), the forest areas will be on the decline, given the increase in the exposed soil variable areas. This is due to the intense use and extraction of wood in areas that do not have an adequate supervision or monitoring or a sustainable forest management plan. A management plan in the local forests would allow for well thought out and conscious consumption of the forest areas. If the logging continues, statistically, in 2025, the forest class will correspond to 10.36% of the area, which would be equivalent to the
Catimbau National Park. This park is the only preserved park in the area which is considered a national conservation unit and has management plan.

4. Conclusion

In this study, it is possible to find the geoprocessing capacity for forest-related studies on its development and use in the Charcoaling Zone, using Landsat 8 Sensor OLS, with images of 2013 and 2017, respectively, to create models that proved to be efficient tools in monitoring the transition processes of the forest cover while incorporating important variables in the zone of coaling.

The decrease in the forest class was determined to be detrimental, and the increase of the exposed soil class showed an alarming result that prompted the following proposals of intervention: zoning; creation of studies for the implementation of a management plan (for the coaling zone); implementation of ecological corridors; and also a massive plan of environmental education, enabling a gradual cultural change that would reduce the illegal logging in the study area.

Simulation of predictions for future scenarios will aid public policies to focus on the preservation of the forest cover in the region. The simulation provides determining factors that allow the expansion or retraction of these areas in the studied area. It is evident, therefore, that it is necessary to monitor the
Comparison of land use and land cover in 2013, 2016 and 2019.

|          | 2013 (hectare) | 2016 (hectare) | 2019 (hectare) |
|----------|----------------|----------------|----------------|
| Water    | 17216.46       | 12886.29       | 9865.41        |
| Bare Soil| 361850.22      | 546161.22      | 689836.19      |
| Farming  | 729356.85      | 726882.93      | 678521.68      |
| Forest   | 634755.96      | 457249.05      | 364956.20      |

**Figure 5.** Graph of comparison of land use and land cover in 2013, 2016, and 2019. The agricultural class remains at the same level as observed in Figure 5.

**Figure 6.** Simulated model for the year 2019.
area for the maintenance of the natural ecosystem and, thus, guiding other work both in the area of forest protection and its dynamism as well as in the area of geospatial monitoring.

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