REVISTA CAMINHOS DE GEOGRAFIA **ISSN 1678-6343**
http://www.seer.ufu.br/index.php/caminhosdegeografia/ DOI: http://doi.org/10.14393/RCG238859039

TENDENTIAL MODELING OF DEFORESTATION IN CAATINGA BIOME IN PIAUÍ STATE, BRAZIL

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ABSTRACT

The work aims to simulate the deforestation dynamics in the area covering the Caatinga biome in Piauí State, Brazil, for the next five decades. Dinamica EGO software was used in the aforementioned simulation, in association with 2002 and 2008 deforestation data and explanatory variables concerning deforestation in the investigated area. Five steps were performed in methodology: calculating transition matrices, determining weights of evidence, adjusting, validating and projecting the model in the trend scenario. Transition rates recorded for total and annual deforestation were 4.6% and 0.8%, respectively. Weights of evidence have shown that distances up to 600 m from deforested areas influence the transition process to deforestation. Variables presenting the highest weights comprised altitude up to 100 m; areas closer to urban patch and sustainable-use conservation units, in addition to land use and cover classes: urban influence, agriculture and livestock. Simulated images enabled seeing reduction in forest remnants of Caatinga area in the state, from 69% in 2008 to 43% in 2070. These results work as warning to the public authorities and the population. The herein proposed methodology can be applied to other Brazilian biomes.

Keywords: Spatial-temporal dynamics. Deforestation rate. Simulation.

MODELAGEM TENDENCIAL DE DESMATAMENTO NO BIOMA CAATINGA NO ESTADO DO PIAUÍ, BRASIL

RESUMO

O trabalho visa simular a dinâmica do desmatamento na área que abrange o bioma Caatinga no estado do Piauí, Brasil, para as próximas cinco décadas. O software Dinamica EGO foi utilizada na simulação supracitada, em associação com os dados de desmatamento de 2002 e 2008 e variáveis explicativas do desmatamento na área investigada. Cinco etapas foram realizadas na metodologia: cálculo das matrizes de transição, determinação dos pesos de evidência, ajuste, validação e projeção do modelo no cenário tendencial. As taxas de transição registradas para o desmatamento total e anual foram de 4,6% e 0,8%, respectivamente. Pesos de evidência mostraram que distâncias de até 600 m de áreas desmatadas influenciam o processo de transição para o desmatamento. As variáveis que apresentaram maiores pesos compreenderam altitude, até 100 m; áreas mais próximas à mancha urbana e unidades de conservação de uso sustentável, além das classes de cobertura e uso do solo: influência urbana, agricultura e pecuária. As imagens simuladas permitiram observar a redução dos remanescentes florestais da área de Caatinga no estado, de 69% em 2008 para 43% em 2070. Estes resultados servem como alerta ao poder público e população. A metodologia aqui proposta pode ser aplicada a outros biomas brasileiros.

Palavras-chave: Dinâmica espaço-temporal. Taxa de desmatamento. Simulação.

INTRODUCTION

Brazil has always been acknowledged for its extensive territorial space, which hosts a wide diversity of faunal and floral species distributed in six different biomes, namely: Amazon Forest, Caatinga, Savannah Forest, Atlantic Rainforest, Pampa and Pantanal – each of these biomes has its own phytophysiognomy, and edaphoclimatic condition. However, the country is also acknowledged for its significantly high deforestation rates, mainly in the Amazonian region, which hosts the largest tropical forest in the world, a fact that has been worrying not only Brazilian citizens but the whole world.

Natural forests have been mainly reduced due to illegal fire, tree cutting for commercial purposes, deforestation for agricultural and livestock production purposes, or even to natural phenomena (ARRAES; MARIANO; SIMONASSI, 2012). In addition, activities such as building roads, increasing urban areas, among others, also contribute to this issue.

Savanna and Caatinga come right after the Amazon Forest as the biomes mostly altered in Brazil. Caatinga, for example, was treated as non-priority region for conservation purposes for many years; however, the inappropriate use and predatory exploitation of its natural resources, mainly of its soil, has put it in the second position in the ranking of biomes mostly altered by man in the country (ICMBIO, 2013).

Remote sensing is increasingly consolidated as important environmental monitoring tool applied to Brazilian biomes. It is so, because it enables acquiring historical series of spatial data about deforested areas by surveying vegetation land cover and use, in order to help taking measures focused on the conservation of natural forests based on result-monitoring.

In addition, it is essential highlighting the importance of dynamic landscape modeling, which has gained room in recent decades due to the wide availability of remote sensing data, as well as to the development and popularization of geoprocessing platforms (LIMA et al, 2013).

Modeling enables analyzing how the dynamics of environmental phenomena, such as deforestation and changes (overtime) due to several environmental, economic, political and social factors (SOARES FILHO; RODRIGUES; COSTA, 2009). Dinamica EGO software is one example of the aforementioned environmental modeling platforms; it enables simulating land use and cover change (LUCC) models.

Dinamica EGO is a free platform available at the website of Federal University of Minas Gerais. It is used to develop from simple to complex spatial models in different environmental studies (SOARES FILHO; RODRIGUES; COSTA, 2009), such as the one focused on investigating deforestation dynamics in agricultural frontiers (MATRICARDI et al, 2018), and future projections on deforestation (CRUZ; BLANCO; OLIVEIRA JUNIOR, 2021), as well as on performing biodiversity and biogeography analyses (OLIVEIRA et al., 2019), analysis of areas susceptible to floods (RIEGEL et al, 2021), of fire incidence likelihood (SAHAGUN-SÁNCHEZ, 2021) and of urban water demand scenarios (ALMINO; RUFINO, 2021), among others.

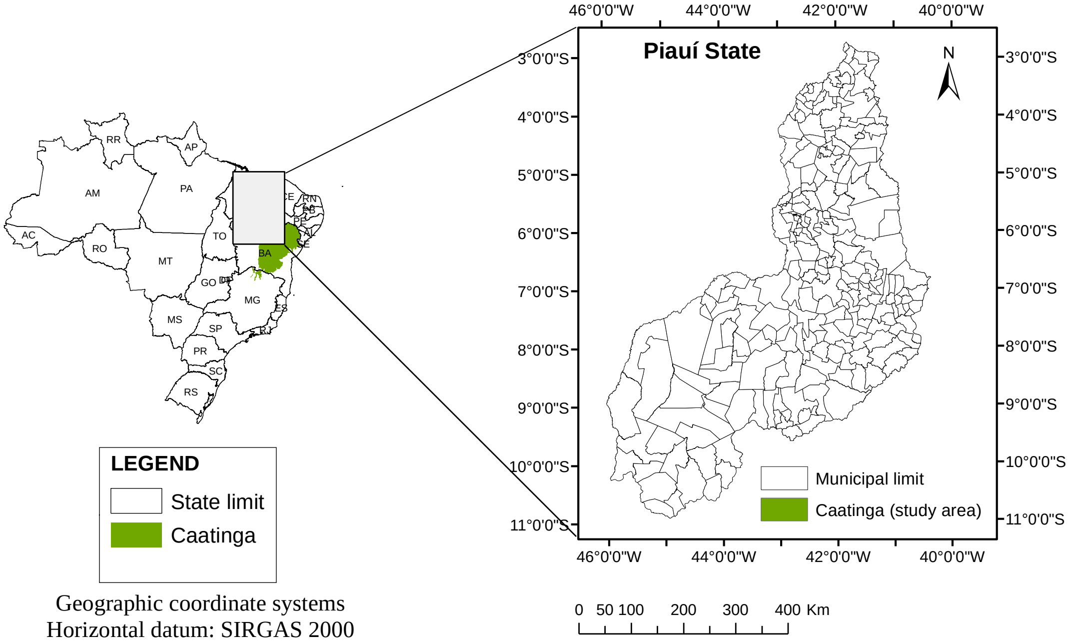
Thus, the aim of the current study was to simulate the spatial-temporal dynamics of deforestation in the area covering the Caatinga biome in Piauí State, for the next five decades.

METHODOLOGY

Study area

The study area comprises the entire Caatinga biome of Piauí (Figure 1), which covers an area of 158,518.59 km² in the State, Northeastern Brazil, between latitude coordinates 2º 44,82' and 10º 55,08' South; and longitude coordinates 40º 22,20' and 45° 59,70' West (CEPRO, 2013).

Figure 1 - Study area location.



Database set

In total, 11 variables were determined at the time to develop the deforestation simulation model (Table 1). They corresponded to environmental, social and topographic data about Piauí State, which may be associated with deforestation in the study area. The entire database was acquired at the website of different government institutions, such as National Institute for Space Research (INPE), National Institute of Colonization and Agrarian Reform (INCRA), Brazilian Institute of Geography and Statistics (IBGE), Satellite-Based Brazilian Biome-Deforestation Monitoring Project (PMDBBS), National Water Agency (ANA), Brazilian Agricultural Research Corporation (Embrapa), Chico Mendes Institute for Biodiversity Conservation (ICMBio).

Table 1 - Geospatial data collected to be used in the simulation model.

Variables	Source	Type	Year *
Altitude	INPE	Raster	-
Rural settlements	INCRA	Vector	2009
Land cover and use	IBGE	Vector	2018
Deforestation	PMDBBS	Vector	2009
Railways	MapBiomas	Vector	2017
Urban patches	IBGE	Vector	2010
Main rivers	ANA	Vector	2016
Highways	MapBiomas	Vector	2017
Census sectors	IBGE	Vector	2010
Soil types	EMBRAPA	Vector	2011
Federal Conservation Units	ICMBio	Vector	2016

* data publication year.

Deforestation data were collected through the Satellite-Based Brazilian Biome-Deforestation Monitoring Project – PMDBBS (MMA; IBAMA, 2010). They were used to generated the initial landscape map (2002), which comprised deforestation data recorded until 2002, as well as the final landscape map (2008), which comprised deforestation data recorded until 2008.

Euclidean distance maps comprising spatial information about settlements, railways, urban areas, main rivers, highways (state and federal) and federal conservation units were plotted. Each pixel in the map represented a specific value that described the distance from a given place to the reference element (AGUIAR, 2016). Integral protection conservation and sustainable use conservation units were shown in different maps due to their categories of use.

The generated deforestation maps were classified as deforested (1) and non-deforested (2) areas. They corresponded to all other areas rather than just to the forested ones. This procedure was required by the software for performing the transition rate procedures (2 to 1) based on codes introduced in each map, which identified each class.

All data were adjusted to the same cartographic projection (UTM zone 24 South) and horizontal datum (SIRGAS 2000) system, before they were inserted in the deforestation simulation model, in the Dinamica EGO Software. Finally, they were converted to matrix data, with the same size and spatial resolution (200x200 m).

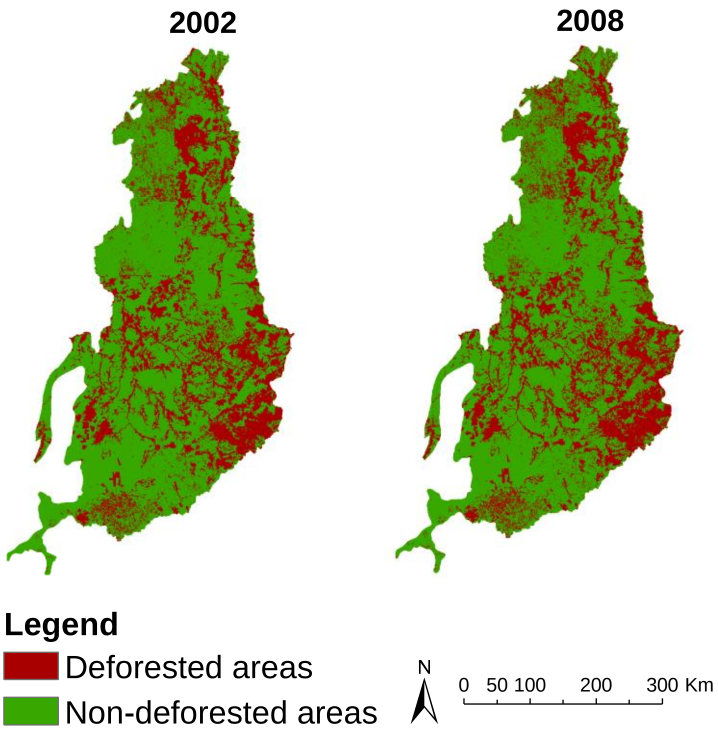
Maps of the model's explanatory variables

Explanatory variables were classified as categorical and continuous. Land use/cover and soil types were used as categorical variables; whereas altitude, slope and Euclidean distance maps (settlements, railways, urban areas, main rivers, highways, conservation units), were adopted as continuous variables.

Deforestation maps

Deforestation maps comprised the initial and final landscapes required by the model, as input maps, at all modeling stages (Figure 2).

Figure 2 - Initial (2002) and final (2008) landscape maps.



Study area regionalization

Dinamica EGO software was used to set the deforestation simulation model, which included sub-regions. In order to do so, it used a set of operations to divide the map into parts or regions in order to process the dataset collected for each sub-region, in separate and, then, to combine the results (SOARES FILHO; RODRIGUES; COSTA, 2009).

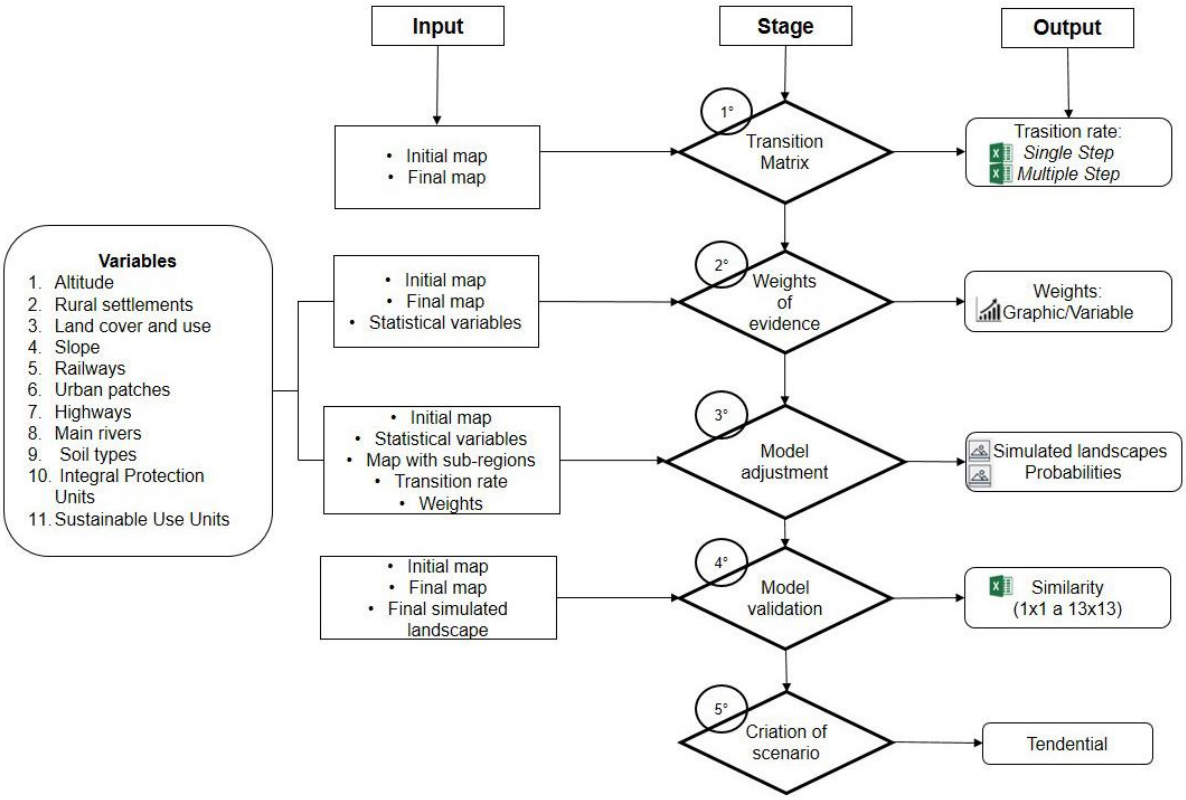
The herein selected sub-regions comprised census sectors in Piauí State, which correspond to the smallest territorial units established by IBGE for data control purposes. These sub-regions represent the more accurate landscape deforestation dynamics .

Deforestation simulation model

Land use and cover change (LUCC) models were used in Dinamica EGO software to simulate Caatinga biome deforestation; i.e., change from “non-deforested” to “deforested area”.

The aim of this simulation was to calibrate, conduct and validate the LUCC model as deforestation simulation model. It was done by following five different steps that were carried out in separate models, in Dinamica EGO software, in order to make the procedure easier. The aforementioned steps are shown in Figure 3.

Figure 3 - Flowchart with the main steps performed in Dinamica EGO.



1st Stage: Calculating the transition matrices

The transition matrix uses transition rates to show changes taking place in a given area, at certain time intervals. The transition rates of the generated matrix correspond to the percentage of changes - also known as net rates - taking place from one condition (forest) to another (deforestation) in the time range of input maps called initial landscape map (2002) and final landscape map (2008). This matrix was generated based on using the “Determine Transition Matrix” function, which determines the single step and multiple-step transition matrices that, in their turn, refer to the matrix set for a single time interval and to the one set for time units (year, month, among others), respectively (SOARES FILHO; RODRIGUES; COSTA, 2009).

2nd Stage: Calculating the evidence coefficient weights

According to Soares Filho, Rodrigues and Costa (2009), the only assumption necessary for the evidence weights' method is that input maps must be spatially independent; therefore, it is necessary applying tests, such as Cramer and Joint Information Uncertainty, to test pairs of maps in order to check the assumption of independence of variable maps by analyzing the overlaped area.

Results can range from 0 to 1; one of the variables is disregarded whenever values recorded for map pairs are higher than 0.5. On the other hand, they are taken into consideration whenever these values are lower than 0.5 (MOREIRA, 2014).

The weights of evidence (Bayesian method) calculates the effect or influence of a given variable on spatial deforestation likelihood. They are only applied to categorical data; thus, it was necessary categorizingthe maps of continuous variables (i.e., altitude, slope and Euclidean distance maps) (SOARES FILHO; RODRIGUES; COSTA, 2009).

Data on land cover/use and soil type were treated as categorical variables; therefore, only altitude, slope and Euclidean distance maps were categorized to establish the minimum-increment parameters, which corresponded to the minimum buffer increment in map units; the maximum / minimum delta, which represented intervals on the Y axis of graphs; and the tolerance angle, which measured a the straight line-deviation angle (SOARES FILHO; RODRIGUES; COSTA, 2009).

With respect to the minimum increment parameter, 100 m was used for altitude variable, 1° was used for slope; 200 m was used for the Euclidean distance maps, as suggested by the software. Minimum/maximum delta (1/50000) and tolerance angle (5°) values suggested in the manual for the "Determine Weights Of Evidence Ranges" tool were used in the model (SOARES FILHO; RODRIGUES; COSTA, 2009).

Thus, the function of "Determine Weights Of Evidence Coefficients" was used to set the weights of evidence; this function allows generating graphs capable of showing the weights of evidence calculated for each variable to enable seeing how deforestation behaves, based on different categories of the assessed variable.

3rd Stage: Adjusting the simulation model

Initial deforestation map, statistical variables, limit map ofcensus sectors, calculated weights of evidence and multiple-step transition matrix were introduced as input in the simulation model adjustment process.

Two products were generated at this stage, namely:

1) Probability maps, which represent the areas showing the highest and lowest likelihood of having certain cells transitioning to another condition; such a process will depend on a set of deforestation-related variables.

2) Simulated images showing simulations of areas that will be deforested in the future, based on the actual deforestation data introduced in the model. This simulation is performed through two functions ("Expander" and "Patcher") that account for enabling cells' transition from one state to another. "Expander" accounts for expanding the already existing deforestation patches, wheres "Patcher" accounts for forming new deforestation patches (SOARES FILHO; RODRIGUES; COSTA, 2009).

The model requires a value that refers to the percentage of cells that will undergo changes in each analyzed period-of-time (based on "Expander") through function "Modulate Change Matrix". The rate established for "Expander" was 50%; it was obtained through attempts carried out until reaching significant result for the similarity between the simulated deforestation area and the study area.

With respect to the formation of transition areas in the simulated maps, it was necessary adjusting the values of the parameters such as mean patch size, patch size variance and patch isometry to enable the formation of sizes and shapes different from those of patches referring to transition areas. The patch isometry parameter accepts values ranging from 0 to 2; the closer to 2, the greater the patch isometry.

After the entries (initial deforestation map, statistical variables, map showing census sectors' limits, calculated weights of evidence and multiple-step transition matrix) and the aforementioned parameters were inserted in the model, it was executed to generate the final simulated deforestation and probability maps for 2008 . It was done to use the 2008 simulated map as reference in the model validation process (next step).

4th Stage: Validating the simulation

The fuzzy similarity method was applied to validate the simulated model; according to this method, the similarity between the observed deforestation map (final landscape map) and the simulated deforestation one was analyzed based on an exponential decay function that uses window size ranging from 1x1 to 13x13.

Both the observed and simulated deforestation maps for 2008 were herein used as input to analyze the similarity. In addition, window size ranging from 1 to 13 was defined in the "For" functor, at 2-point increments; in other words, the window size would range from 1x1, 3x3, 5x5, 7x7, 9x9, 11x11 to 13x 13 pixels, whenever it was composed of even numbers.

When the 5x5 window size reached the highest minimum similarity value among the attempts, parameters such as mean, variance and patch isometry, which had been determined in the previous step to form the simulated image, were admitted.

5th Stage: Creating and simulating the scenario

The software used for dynamic simulation modeling enables understanding patterns and trends in landscape changes, as well as prospecting future scenarios.

According to Kawashima et al. (2016), scenarios are alternative images of the future that help decision-making processes, as well as outline political-economic, socio-demographic, legal, institutional, environmental and technological conjectures, among others, that enable viewing multiple future deforestation trajectories.

The herein created simulation model was the trend scenario, which took into consideration the current deforestation patterns. It used the mean annual rate of the historical deforestation series observed between 2002 and 2008 in order to calibrate the weights of evidence.

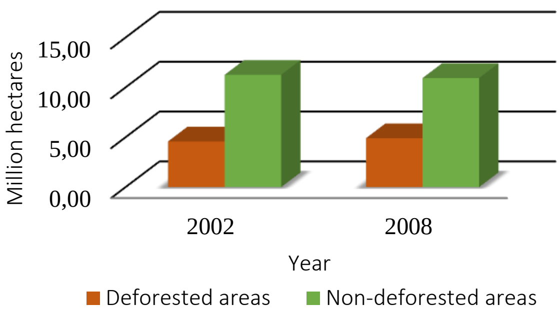
After parameters such as mean patch size, patch size variance and patch isometry were defined, and after the entries were inserted in the model, it was conducted to generate the final simulated annual deforestation maps.

RESULTS AND DISCUSSION

Transition matrix

According to PMDBBS data, the total Caatinga area deforested in Piauí State until 2002 comprised 4,579,276 hectares, against 11,255,892 hectares of non-deforested areas (all other areas); until 2008, the deforested area comprised 4,903,704 hectares against 10,932,160 hectares of non-deforested area. Thus, there was increase by 324,428 hectares in deforested areas during this time interval (2002-2008) (Figure 4).

Figure 4 - Data on deforested area until 2002 and 2008, according to PMDBBS.



The single-step and multiple-step transition matrices resulted in total and annual transition rates equal to 4.6% and 0.8%, respectively. These rates referred to deforestation data input in the model, from 2002 to 2008.

According to MMA and IBAMA (2010), Piauí State is the 3rd state in the ranking of highest loss of *Caatinga* vegetation. From 2002 to 2008, the Caatinga biome recorded annual deforestation rate of 0.33%; it was lower than the annual rate herein observed for Piaui State in the same period (0.8%). Oliveira; Santos; Ferreira (2019) have found annual deforestation rate of 1% to the South of Western Amazon State, whereas Aguiar (2016) recorded absolute deforestation rate of 7.9% and annual deforestation rate of 1.3% in MATOPIBA region (Savannah Forest) during the same period-of-time (2002-2008).

Weights of evidence

Map correlation analysis has shown that all variables were spatially independent, since no pair of variables presented correlation index higher than 0.5 (reference value) in the Cramer and Join Information tests.

Results of evidence weights of explanatory variables are often generated in the form of graphs and tables (Figure 5). Weight values can be positive, and it indicates classes and / or distances from the variable favorable to deforestation, or they can be negative, which indicates classes and / or distances that hinder the herein described transition (forest areas in deforested areas).

According to Silva et al. (2017), the weights-of-evidence analysis helps identifying potential state-changing areas at each transition, which can be checked in the transition probability map.

Figure 5 - Weights of evidence for spatial variables.

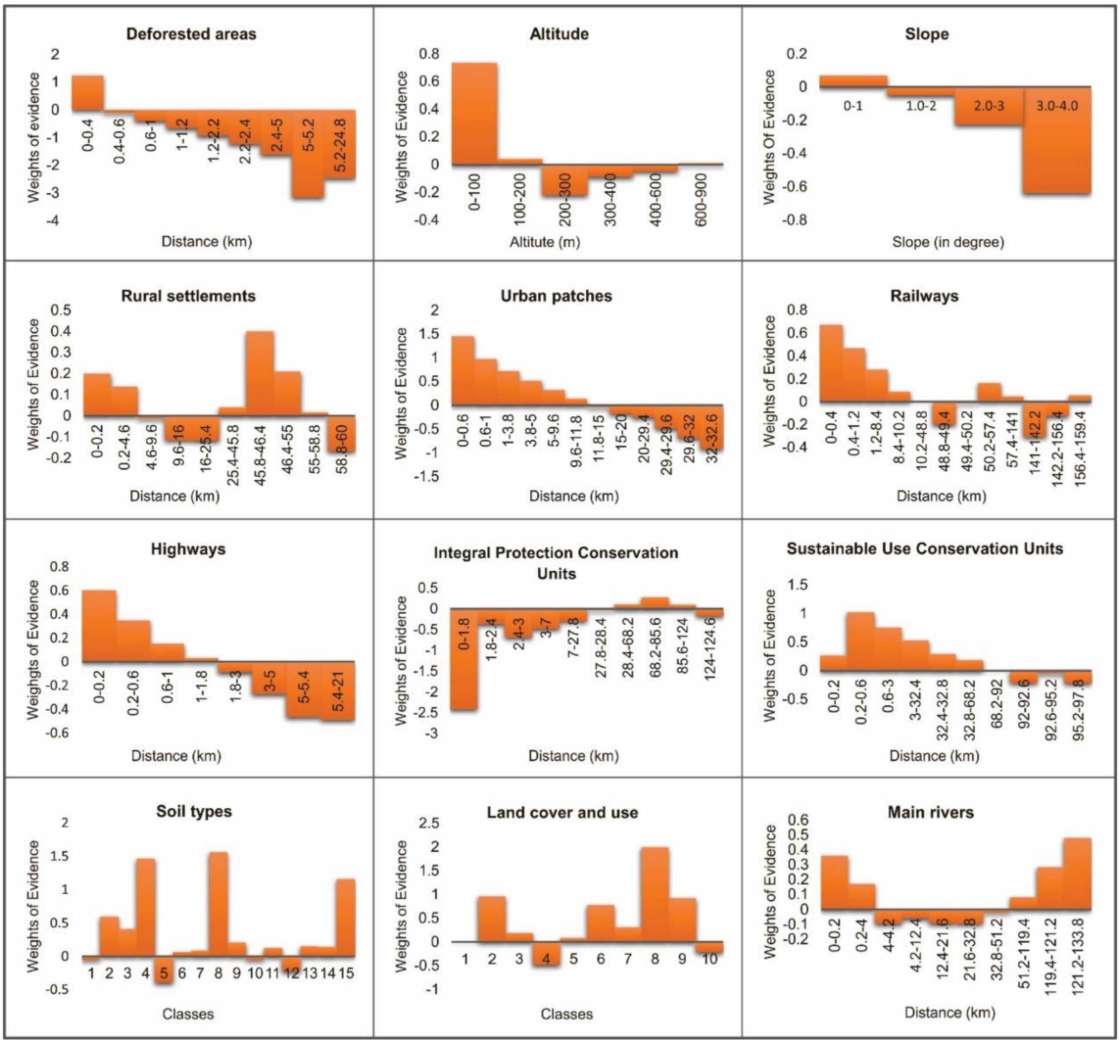


Figure 5 shows the behavior of each variable in deforestation processes. Based on categorical soil and vegetation maps, the influence is determined by soil class, as well as by land use and cover, respectively. On the other hand, based on Euclidean distance maps, the influence is defined by the distance from the object of interest (settlements, railways, urban areas, rivers, highways and conservation units). A different influence is noticeable as the slope and altitude increase or decrease - in m and degrees (°), respectively.

It was observed that distances up to 0.6 km from the deforested points can influence, or contribute to, the transition from deforested to non-deforested area (Figure 5). These distances were used by the model as reference in the simulation process.

With respect to deforested areas, the influence of variables taken into consideration in the model may be even higher depending on environmental, economic, political and social factors of the investigatedarea. Moreira (2014) conducted a study in the Amazon Forest and found positive influence over a distance range up to 2.2 km; this value was much higher than that found in the current study.

Variable altitude, ranging from 0 to 100 m, had positive influence on deforestation. Altitude higher than 100m had negative or null influence on transition areas. These results were similar to the ones observed by Aguiar (2016) and different from those found by Brochado (2014) (from 290 to 430 m). Low and medium altitude flat areas are more favorable to agricultural practices, since their soil is often more fertile and makes the use of agricultural machinery easier.

Variable slope has shown similar influence on deforestation since higher slopes had positive, although small, influence on it. On the other hand, lower slopes had negative or null influence. Silveira; Silva (2010) observed higher deforestation rates in Atlantic Rainforest areas presenting small declivity (up to 20%). This outcome was also reported by Macedo et al. (2013), who explained that it is more likely to happen in flat locations due to agricultural pressure.

The weight of evidence recorded for variables such as Euclidean distance vary a lot at different distance intervals. The closest distances to settlements favor deforestation, whereas further distances from them do not favor it. These findings corroborate results reported by Silva et al. (2017), according to whom, rural populations influence the forest / agriculture or pasture transition, mainly due to increase in credit lines. It is important highlighting that the use of traditional techniques and family labor for agricultural production purposes often prevails in rural settlements that use smaller areas than those used by large agricultural enterprises.

The same phenomenon is observed for highways. Fearnside et al. (2009), reported deforestation expansion along BR-319 highway, as well as along the neighboring roads associated with it. These findings corroborate the current results, as well as the ones reported by Santos Junior et al. (2018), according to whom, proximity to roads increases the likelihood of forest cells to undergo deforestation.

Oscillation in the weights of variables urban patches and railways was noticeable at different distances; shorter distances had noticeably positive influence on deforestation.

The farther the distance from the integral protection conservation units, the higher the influence on deforestation. On the other hand, the closer to the sustainable use conservation units, the higher the influence on deforestation.

The current results have indicated that areas surrounding integral protection conservation units are likely more effective in reducing deforestation than those surrounding sustainable use conservation units. It is so, because areas close to the conservation units presented positive weights of evidence. This finding can be justified by different use-related restrictions established for each unit.

Therefore, the of deforestation around sustainable use conservation units is a threat, since there is high risk of expanding deforestation inside them. According to Moretti et al. (2020), conservation units are easy targets for illegal activities, since they host species of high commercial value that attract lumbermen to illegally cut and trade them.

Soil types 8, 4, 15, 2 and 3 (Palic Chromic Luvisols, Sodic Salic Gleysols, Orthic Ebanic Vertisols, Eutrophic Red-Yellow Argisols and Orthic Argiluvial Chernozemic soils) presented higher weights, respectively. With respect to land cover and use types, classes 8, 2, 9, 6 and 7 (urban influence, agriculture, livestock, pioneer formation, forest) have shown higher weights of evidence, respectively (Figure 5).

Soil types mostly influencing deforestation depend on their suitability for agriculture and on their occupation area in the region. Thus, Brochado (2014) has crossed information about soil classes with greater influence on deforestation in areas suitable for agriculture at the studied site and deforestation information. His results enabled identifying soils favoring deforestation because they occupied few areas that were not yet deforested in flat relief regions.

With respect to land cover and use, classes such as Urban Influence, Agriculture, and Livestock presented the greatest weights of evidence and were consistent with the reality, according to which, population growth, agriculture and livestock are the main causes of deforestation, as pointed out by Arraes, Mariano and Simonassi (2012), Sano et al. (2019) and Cruz, Blanco and Oliveira Junior (2021).

As for the main rivers, longer distances have shown positive influence, since Law n. 12,651/12 (Brazilian Forest Law) has classified strips along rivers or along any watercourse as permanent protection units, as well as has established minimum protection widths depending on watercourse width. However, distances close to rivers had small influence on deforestation, as also observed by Macedo et al. (2013) - this factor may be associated with agriculture.

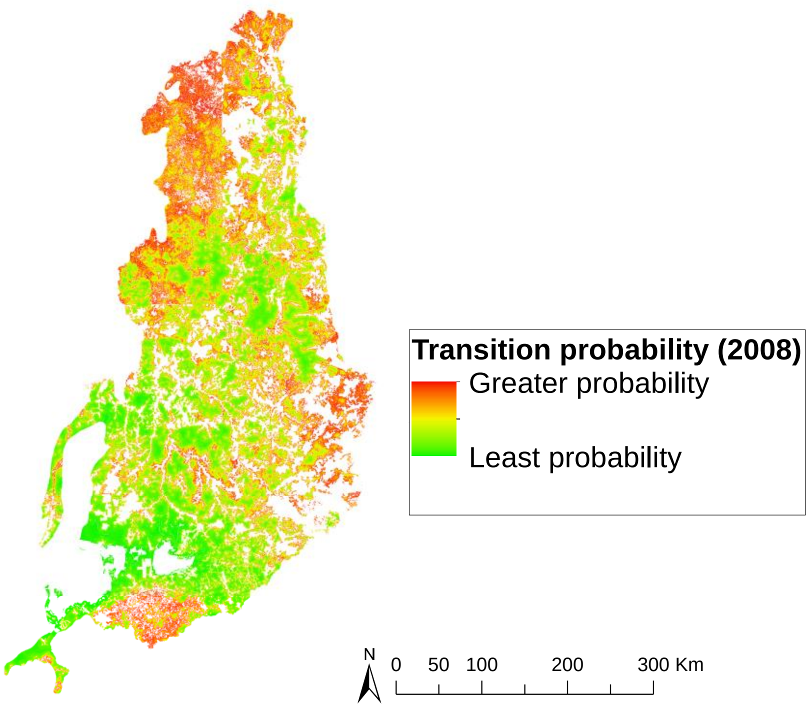
Model adjustment

Parameters such as mean patch size, patch size variance and patch isometry were adjusted to 4 ha, 8 ha and 0.5, respectively, at model adjustment time. Since cell size was 4 ha (200 x 200 m), patches formed in it had 1 cell, on average, as well as variance of 2 cells and low isometry. Deforestation probability (Figure 6) and simulation (Figure 7) maps were plotted at this stage.

Similar values for model adjustment parameters were found by Moreira (2014), who adopted mean patch size of 4.5 ha, variance of 9.0 ha and patch isometry of 1.5. These values were very close to the ones used in the model adopted in the current study. Piontekowski et al. (2019) have found mean patch size of 8 ha, variance of 16 ha and isometry of 1.5.

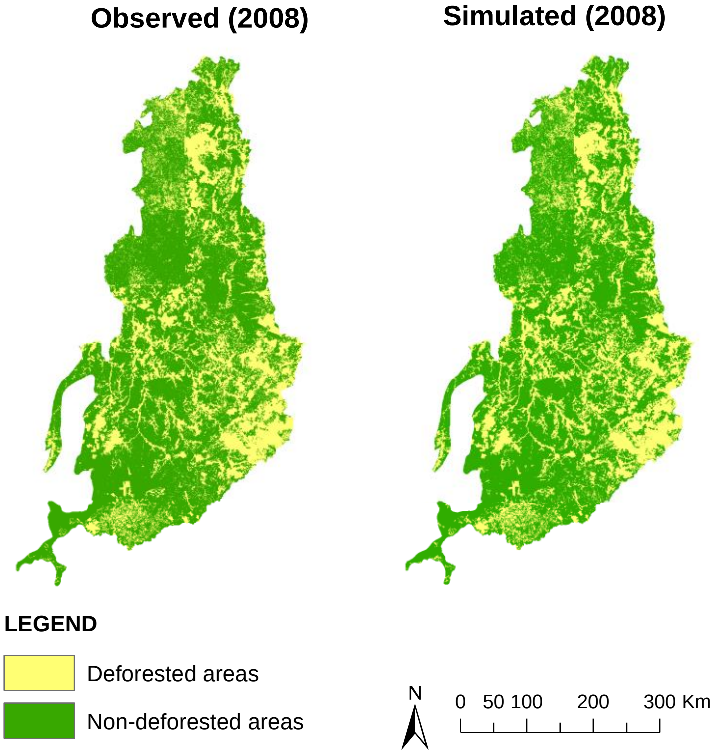
Based on the probability map (Figure 6), it is possible seeing red cells indicating the highest deforestation likelihood throughout the area, according to the generated weights of evidence. The map also presents green cells, which identify the areas showing the lowest probability of undergoing deforestation, which directly reflects deforestation areas in the simulated image (Figure 6).

Figure 6 - Transition probability map generated by the 2008 model.



Moreover, the white color on the map, Figure 6, highlights areas where there is no statistically significant probability of transition from native vegetation to deforestation. Overall, previously deforested cells are represented by the white color, which defines them as areas with no probability of being reclassified as deforestation to the time they are in that condition.

Figure 7 - Observed (2008) and simulated deforestation (2008) maps.



Based on Figure 7, it is possible seeing similarity in the distribution of deforested patches between the actual deforestation data recorded for 2008 (observed map) and data simulated for that very same year (simulated map).

Simulation validation

The similarity index enabled evaluating how the model fits the observed transitions, by comparing changes that took place between the observed deforestation map until 2008 and the map simulated by the model for that very same year (Figure 7) - it indicated the following minimum and maximum similarities (Table 2) at different window sizes.

Table 2 - Similarity values generated by the model for different window sizes.

Window size	Minimal similarity	Maximum similarity
1x1	0.10	0.15
3x3	0.21	0.39
5x5	0.31	0.61
7x7	0.40	0.76
9x9	0.47	0.84
11x11	0.53	0.89
13x13	0.58	0.92

According to Barni (2009) apud Brochado (2014), similarity value higher than 50%, in 5x5 cell windows, indicates satisfactory result. In addition, according to the aforementioned author, there must be similarity between spatial distribution patterns of the investigated phenomenon, as shown in Figure 6.

Oliveira; Santos; Ferreira (2019) conducted dynamic deforestation modeling studies in to the South of Western Amazon and recorded values 44% and 81% for observed and simulated deforestation maps, respectively; whereas Silva et al. (2017) found value of 62% in areas in Campanha Ocidental Region-RS.

It was possible seeing that similarity adjustment values tend to increase as image pixel dimensions increase (Table 2). Maximum similarity ranged from 15% to 92%, from the 1x1 cell window to the 13x13 cell window, respectively.

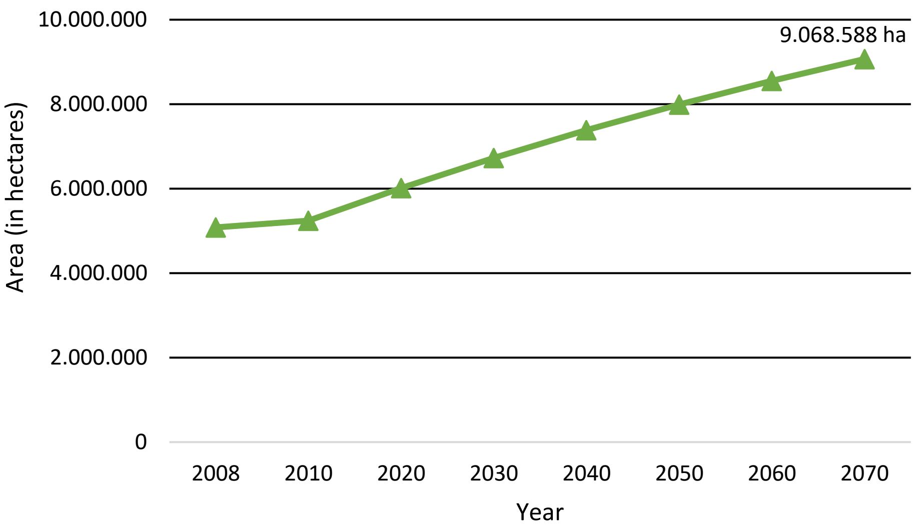
Fuzzy similarity index results have indicated 31% minimum similarity and 61% maximum similarity, in the 5x5 window taken into consideration for simulation validation purposes.

In addition, the deforested area size in the simulated (5,083,084 ha) and observed maps (4,903,704 ha) plotted for 2008 was analyzed. Results have shown 3.6% difference in total deforested areas between maps.

Trend scenario projection

The model was adjusted to perform interaction cycles at annual transition rate of 0.8% (obtained in the transition matrix); consequently, it has generated a set of deforestation maps, which were simulated on a yearly basis, from 2002 to 2070. Based on these maps, it was possible analyzing the evolution of deforestation in the Caatinga biome typical of Piauí State, on a decade-by-decade basis (Figure 8).

Figure 8 - Temporal evolution of deforestation in the study area.

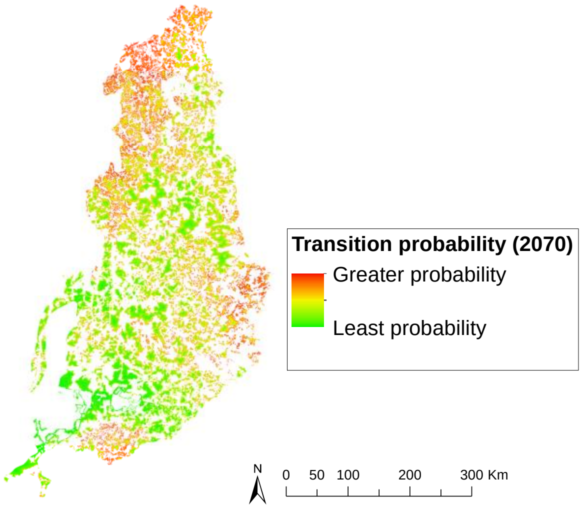


Results have suggested gradual increase in deforestation levels in the Caatinga biome throughout decades, as well as reduction by 3,985,504 ha in forest remnants (Figure 8).

According to MMA; IBAMA (2010), Piauí was the second state with the largest Caatinga remnant (10,944,600 ha) in 2008; 69% of the total area was taken by this biome in the state (15,798,500 ha). However, based on the deforestation rate recorded between 2002 and 2008, this biome can be reduced to less than 50% of its current size, by 2070. This process would leave only 6,759,592 ha of this biome, which represents 43% of the total Caatinga area in the state.

It is possible seeing the projection of deforestation processes likely to take place across the state until 2070 (Figure 9), with emphasis on its Northern and Eastern regions. The main factors possibly associated with deforestation in these regions comprise high urbanization level and, consequently, population growth, as well as agricultural activity in areas planted with sugarcane, corn and cashew. According to data pointed out by CEPRO (2013), these activities are developed in the same areas that show the highest probability of transition.

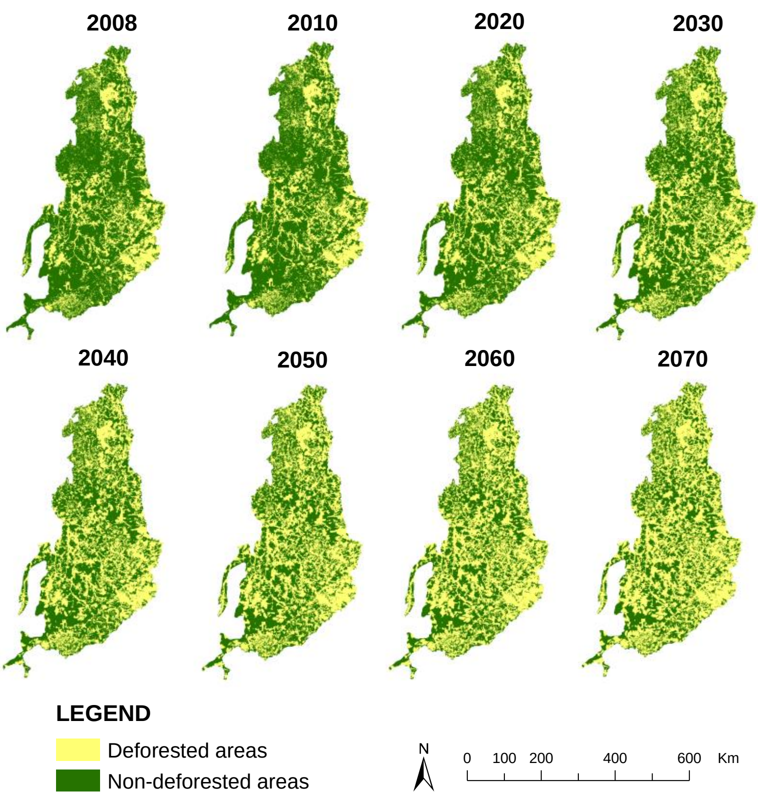
Figure 9 - Deforestation probability map (2070).



According to ICMBIO (2013), deforestation, mainly for energy production and agricultural purposes, is the main process accounting for changes taking place in the Caatinga biome; according to estimates, 42.3% of its original vegetation cover has already undergone some type of change and 52% of this biome suffers from degradation issues. These changes in landscape can lead to significant biodiversity loss and climate change, as well as to changes in hydrological cycles, as observed by Souza et al. (2019) and Cohen et al. (2007), who described changes in the hydrological cycle in the Amazon Forest due to deforestation dynamics.

Thus, with respect to the trend scenario, simulated deforestation represented the continuation of the forest degradation observed in the simulated maps (Figure 10), which will bring severe consequences such as Caatinga remnants' reduction, soil erosion, biodiversity loss, climate change, among others.

Figure 10 - Projection of the deforestation process from 2008 to 2070.



Assessing the direct impacts of this change is of interest to both regional planners and scientists, since, according to Fearnside (2006), deforestation impacts comprise loss of opportunities for sustainable forest use, such as forest management for timber and non-timber products. This process hinders the opportunity to capture the value of environmental services provided by forests.

Therefore, spatial dynamics modeling is an essential tool to help better understanding the future path of deforestation in the investigated area, as well as to help developing public policies focused on controlling deforestation processes that may take place in different ways, in different micro-regions of the Piauí state, based on areas most likely to transition. In addition, this modeling type can be applied in studies conducted in other Brazilian biomes, based on different approaches.

FINAL CONSIDERATIONS

Total and annual transition rates have shown worrying trend to deforestation in the Caatinga biome, in Piauí State.

Land cover and use classes such as Urban Influence, Agriculture and Livestock, have shown higher association with deforestation than that of other variables. Such a finding was confirmed by the weights of evidence, as well as by the proximity to urban patch areas presenting higher weight in the first distance ranges. Unlike sustainable-use conservation units, integral protection conservation units have shown lesser influence from the deforestation around them.

The projected scenario has indicated significant increase in deforestation by 2070, which will increase the total deforested area in the investigated biome to 9,068,588 ha. Consequently, it will reduce the remaining Caatinga biome in the state from 69% (2008) to 43% by 2070. The current study has shown the relevance of understanding future deforestation processes about to take place in Piauí State, and it can be used as basis for other studies conducted in the Caatinga biome or in other Brazilian biomes, based on different approaches.

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Recebido em: 26/01/2021
Aceito para publicação em: 20/04/2022