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SIMULATED DEFORESTATION VERSUS SATELLITE DATA IN RORAIMA, NORTHERN AMAZONIA

Resumo

Analises de cenários de mudança de uso e cobertura da terra na Amazônia são passos necessários para subsidiar decisões que podem evitar a emissão de milhões de toneladas de CO_2 para a atmosfera. Portanto, é importante avaliar modelos que visem a simulação de cenários futuros. O atual estudo avaliou cenários simulados no período 2011-2017, em Roraima, situado na porção norte da Amazônia brasileira. Comparou-se o desmatamento simulado com os dados de satélite do PRODES. O mapeamento para as avaliações compreendeu (***i***) uma Área de Uso Silvo-pastoril – AUS (excluindo terras indígenas, unidades de conservação e não floresta) intersectada com (***ii***) uma grade de 09 (nove) sub-áreas de 10.000 km^2 (100 × 100 km). O cenário de 2013 apresentou a maior similaridade (55,2%) com o mapa correspondente do PRODES. Apesar das divergências entre o desmatamento simulado nos cenários e o desmatamento oficial, no geral, as avaliações demonstraram a validade do modelo e a sua habilidade para gerar cenários que representam, de forma realística, o desmatamento ocorrido em Roraima no período analisado.

Palavras-chave: Mudança de uso da terra, Modelagem ambiental, Sensoriamento remoto, Amazônia, Brasil.

Abstract

Scenario analyses of land-use and land-cover change in the Amazon are necessary steps to support decisions that can avoid the emission of millions of tons of CO_2 into the atmosphere. It is important to evaluate models that aim to simulate future scenarios. The present study evaluated scenarios generated for the 2011-2017 period in Roraima state, in northern Amazonia. Simulated deforestation was compared to PRODES satellite data. The mapping for the evaluations comprised (***i***) a “silvopastoral use area” (excluding indigenous lands, conservation units and non-forest areas) intersected with (***ii***) a grid of nine (9) 10,000-km^2 (100 × 100-km) sub-areas. The 2013 scenario had the greatest similarity (55.2%) with the corresponding PRODES map. Despite divergences between simulated deforestation in the scenarios and PRODES deforestation, the evaluations generally demonstrated the model’s validity and its ability to produce scenarios that realistically represent the deforestation that occurred in Roraima state during the analyzed period.

Keywords: Land-use change, Environmental modeling, Remote sensing, Amazon, Brazil.

1. INTRODUCTION

Deforestation actors and motives

Actors

Deforestation is done by a wide variety of actors for a wide variety of reasons. Roraima, located in the northern portion of Brazil's Amazon region, has almost all of the actors and processes that are present in other parts of the region, although the relative importance of each varies greatly in different parts of Amazonia and in different parts of the state of Roraima. Actors include migrants, that is, family farmers (small farmers) who come from other states to settle in Roraima. These are mostly individual migrants, although Roraima has had some activity by organized groups ("*sem-terras*"). Many of these actors obtain lots in government "settlement projects" of different types (YANAI et al. 2017). However, deforestation expands further when squatters illegally occupy land beyond the settlement boundaries, often resulting in endogenous roads extending from the access roads (*vicinais*) in the official settlement projects. An example is an illegal road extending from access road No. 7 in the Jatapú Settlement project in Roraima's municipality of Caroebe (BARNI et al. 2012). Also important are actors with more wealth than the small farmers for whom settlement projects are created. These include an Amazon-wide pattern of wealthy newcomers purchasing multiple lots in a settlement project and operating them as a single medium or large landholding (FEARNSIDE 1986, 1989; CARRERO et al. 2011; YANAI et al. 2020).

Roraima also has its share or "*grileiros*," or "land grabbers," who illegally appropriate government land and usually later subdivide it for sale to others. *Grileiros* often use violence and threats of violence to remove other claimants, and can obtain official recognition of their claims through corrupt means (FEARNSIDE 2008a; TORRES et al. 2017). A series of recent laws now facilitates land grabbing, for example the limit on the area that can be "legalized" per claimant was increased from 100 ha to 1500 ha in 2009 by Law No. 11,952 (PR 2009), and in 2017 Law No. 13,465 increased this area to 2500 ha (PR 2017). Land grabbing is now further facilitated by a provisional measure

(MP910) signed by President Bolsonaro on 10 December 2019 allowing legalization of land claims through a mere "self-declaration" of ownership (PR 2019). The provisional measure has the force of law for 120 days after it was signed by the president and can be made permanent if approved by the National Congress, as is expected (see: BRANFORD and BORGES 2019). In addition, a wide-ranging dismantling of Brazil's environmental agencies and policies under the presidential administration that took office on 1 January 2019 means that regulations restricting deforestation and logging are often not enforced (FERRANTE and FEARNSIDE 2019).

An important group of deforestation actors is made up of mostly urban individuals who invest money from other sources in purchasing rural properties and in deforestation, mostly for pasture. The funds may be from legal sources, such as pharmacies, gas stations and other businesses, or from illegal sources such as trafficking in drugs, arms or people, or from government corruption, truck hijacking and tax evasion (FEARNSIDE 2005, 2008a). In Roraima funds from illegal gold mining in indigenous lands can be invested this way, both by wealthy patrons of this activity and by individual "*garimpeiros*" ("wildcat" miners) (e.g., MACMILLAN 1995).

Actors on the other side – those who try to slow and contain deforestation – include environmental agencies such as the federal government's IBAMA (*Instituto Brasileiro do Meio Ambiente e dos Recursos Naturais Renováveis*) and the state government's FEMARH (Fundação Estadual do Meio Ambiente e Recursos Hídricos). The Federal Public Ministry (MPF), a public prosecutor's office created by Brazil's 1988 constitution, also has an important role through its ability to threaten punishment for the heads of the federal and state environmental agencies when they fail to enforce regulations governing deforestation. Other actors include associations of producers of present or likely future crops, such as soy and palm oil (e.g., NEPSTAD et al. 2014). Non-governmental organizations at the local, national and international level are also actors that can press for deforestation control (e.g., FEARNSIDE 2017). Governments and consumers in other parts of the world also influence Brazilian policies affecting deforestation through the threat of boycotts of Brazil's agricultural exports and through contribution of funds that assist in Brazil's deforestation control efforts (e.g., WEST et al.

2019). The effectiveness of these different actors is, of course, highly varied. Roraima has long been notorious for having a state government with environmentally destructive policies and an aversion to environmental protection; Roraima was one of the three states in Brazil's nine-state Legal Amazonia region that was informally classified by the World Bank as a "red" state to indicate this pattern (FEARNSIDE 2016).

Motives

The different actors have different motives, and often there are more than one factor that contribute to a decision to deforest. One often hears statements emphasizing deforestation for subsistence, that is, for farmers to feed their families directly from the crops they harvest. However, this represents a minimal contribution to the total. A much larger fraction comes from agriculture and cattle ranching activities that generate products for sale. This applies both to small farmers and to larger landholders. However, this "normal" economic logic is only part of the motivation for deforestation. Profits in deforested areas can be boosted by various kinds of government subsidies, such as loans at interest below market rates and "amnesties" forgiving or indefinitely postponing loan debts whenever crops fail or other adversities appear (FEARNSIDE 2001, 2020). In Roraima subsidies currently include support for biofuel production (FERRANTE and FEARNSIDE 2020). Profits from timber also motivate clearing, both from the sale of wood from trees felled in the areas that are cleared and by the licenses permitting the clearing being used to give an appearance of legality to wood cut in unauthorized selective logging being carried out either in the same property or elsewhere. This practice is widespread in Amazonia (BRANCALION et al. 2018).

A major motivation for deforestation in Amazonia is to establish and maintain land tenure (FEARNSIDE 1979). Before a land title is obtained, deforestation is regarded as an "improvement" proving "productive use" of the land, which is a requirement for official recognition (e.g., INCRA 2019). After official recognition is obtained, deforestation is still motivated by land-tenure concerns (especially for large landholders) as a means of guaranteeing that the land will not be invaded by squatters (especially organized "*sem-terras*"), and that it will not be considered "unproductive" and therefore confiscated by the government for agrarian reform.

The importance of simulation models

Future scenarios of land-use and land-cover change in the Amazon are important tools for regional analyses in space and time. They anticipate possible deforestation trajectories and offer valuable inputs for decision making to protect the forest and its environmental services, preventing, for example, millions of tons of CO_2 from being released into the atmosphere (FEARNSIDE 2008b; IPCC 2013; LE CLEC`H et al. 2019; SIIKAMÄKI et al. 2019; SOARES-FILHO et al. 2010).

A catastrophic forecast generated by a simulation model can mobilize organized society and the media to fight against a possible future and prevent it from actually happening (SOARES-FILHO et al. 2006). However, it is impossible to measure the extent to which catastrophic scenarios, like the BAU (Business As Usual) scenario of Soares-Filho et al. (2006), have contributed to the reduction of deforestation in the Amazon and the emission of carbon into the atmosphere. Although the importance of scenarios cannot be denied, they are only rudimentary simplifications of reality. Notable cases include "The Limits to Growth" (MEADOWS et al. 1973) and the "Brundtland Report" (CMMAD 1988), both of which spurred discussions on the environment at the global level and influenced conservation policies worldwide (OLIVEIRA 2012; FEARNSIDE 2019).

Few environmental-modeling studies have had as much repercussion as that of Soares-Filho et al. (2006), which was carried out in the mid-2000s and foresaw the destruction of the eastern half of the Amazon rainforest by 2050 (BAU scenario). The importance of these scenarios lies precisely in their "non-effectiveness." In other words, the fact that the scenario does not entirely match what has happened in reality may be its greatest merit.

The great Roraima fire during the El Niño of 1997/98 was an event of enormous national and international repercussion (BARBOSA and FEARNSIDE 1999; MARTINS et al. 2012; XAUD et al. 2013). This event can be considered as a catastrophic scenario, and it motivated the beginning of discussions that culminated in the creation of public policies for preventing and fighting fires in the state (BARBOSA et al. 2003; FONSECA-MORELLO et al. 2017). The great advantage of creating computer simulations, unlike the real event, is that they can be manipulated in terms of their spatial reach (e.g., the affected area), the intensity of the events (e.g., tree mortality) and their timing (e.g., their relation to the frequency of climatic events). They can also generate public policies that ensure the conservation of forest carbon stocks without the need to burn or damage a single tree.

Despite the importance of land-use models, there are few studies in the literature that seek to demonstrate their validity or effectiveness by comparing the simulated results with the real phenomenon after the event in question has occurred. This step is generally used for the calibration of simulation models in the training phase (e.g., ROSA et al. 2015). In calibrating these models, known data from a short historical time period is used for calibration, and the model is expected to reproduce the same patterns based, for example, on weights-of-evidence or on a Markov chain. After the training or calibration rounds of the modeling, the simulated scenario is validated by comparison with the “real” scenario that occurred in a “validation period” subsequent to that used in the calibration, thus ensuring independence (SOARES FILHO et al. 2013).

The present study aimed to evaluate scenarios that had been generated to predict the deforestation that would occur between 2011 and 2017 in the state of Roraima. We sought to evaluate the model’s efficiency in representing future deforestation by comparing the deforestation simulated by the model with what actually occurred in the region. For this we used official deforestation data from the Project for Monitoring Deforestation in Amazonia by Satellite (PRODES) (INPE 2018). The following variables were used as criteria for evaluating the scenarios in the comparison: annual occurrence of deforestation (km^2, ha); frequency (n); polygon size (ha) and; similarity (%) between the generated maps.

The scenarios were simulated between 2011 and 2050 and modeled using Dinamica-EGO 2.4.1 software (https://csr.ufmg.br/dinamica/) considering the MT-GOV scenario simulated by BARNI et al. (2015a). In this governance scenario it was assumed that deforestation would be controlled in the state only beginning in 2020, in line with the commitment voluntarily made by Brazil under the Paris Agreement at COP-

15 of the United Nations Framework Convention on Climate Change (GONÇALVES et al. 2009). In the period prior to 2020 (2011 to 2019), deforestation was assumed to continue in accord with the trends observed between 2005 and 2010.

The state of Roraima can be considered to represent the most recent large agricultural frontier in the Brazilian Amazon. This condition still exists due to Roraima's isolation from most of the rest of the Brazilian Amazon (BARNI et al. 2015b). In the near future one can expect the creation of new municipalities and settlement projects, the implementation of major infrastructure projects including reconstruction of Highway BR-319 (Manaus - Porto Velho) and building the Bem Querer hydroelectric dam on the Rio Branco. These developments would attract migrants to Roraima and intensify disorderly land occupation, in addition to increasing emissions of greenhouse gases.

2. MATERIALS AND METHODS

Study area

The study area covered the entire state of Roraima, with the exception of protected areas, which are defined here as indigenous lands and conservation units (both national and state). Also excluded were the savanna areas (locally called *lavrado*) in the northeastern portion of the state and areas of oligotrophic ecosystems (locally known as *campinas*) that are characterized by sparse vegetation on seasonally flooded sandy soils, which are located in the central and southwestern portions of the state. The remaining area, after exclusion of the "silvo-pastoral use area" (SAU) (65,150.0 km^2: BARNI et al. 2016), is a strip of land along federal highways BR-174 and BR-210 and state highway RR-070. All of these highways are associated with secondary roads that provide access to the farm lots in settlement projects.

In order to better understand the assessment of the scenarios, the SAU was overlaid with a grid of nine "sub-areas" (SUBs). This set of sub-areas totaled 53,871.4 km^2 (82.7% of the SAU), but it did not exclude any of the deforestation that had occurred in the SAU during the period (Figure 1).

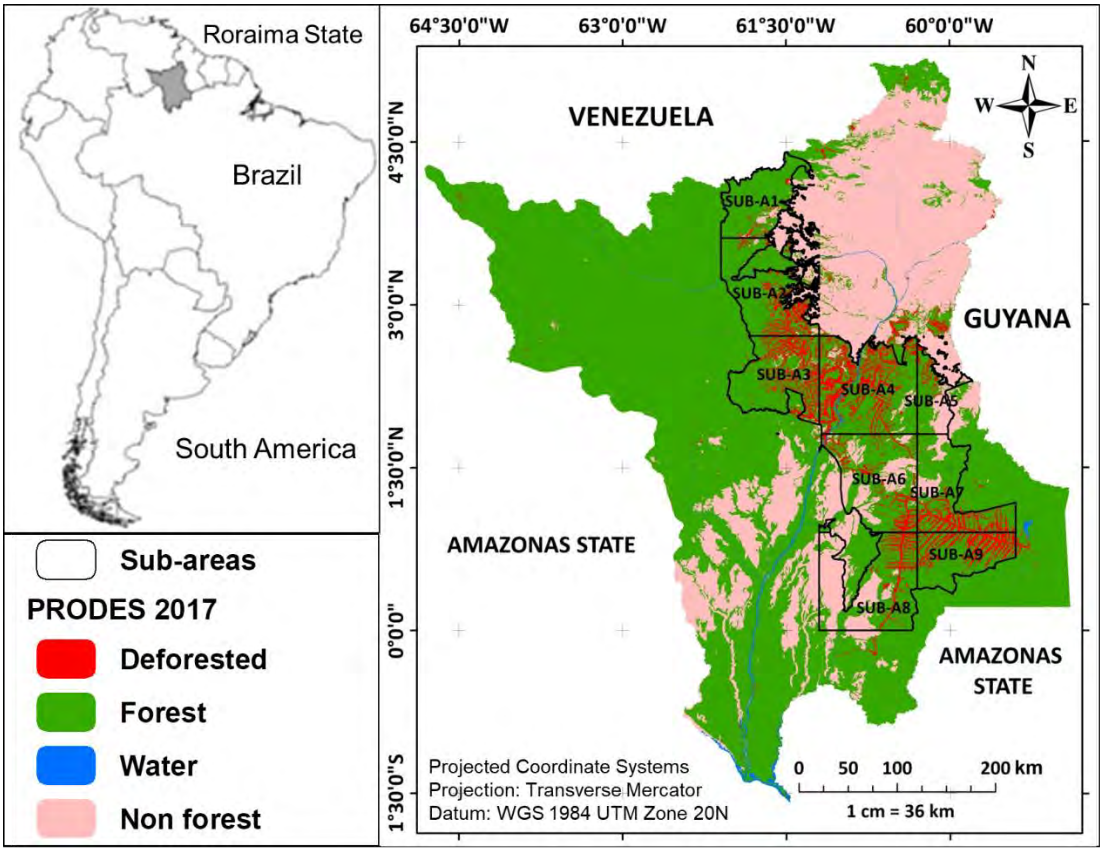

Figure 1. Study area comprising the “silvo-pastoral use area” (SUA) and the grid of nine sub-areas.

Database

The simulation output for the interval between 2011 and 2017, with 1-ha (100 × 100-m) spatial resolution (BARNI et al. 2015a), was used for comparison with deforestation data for the same period from the PRODES deforestation-monitoring program of the National Institute for Space Research (INPE) (INPE 2018). The PRODES data represent the “real” or official deforestation in the state during the analyzed period. Figure 2 presents a simplified flowchart of the methodology.

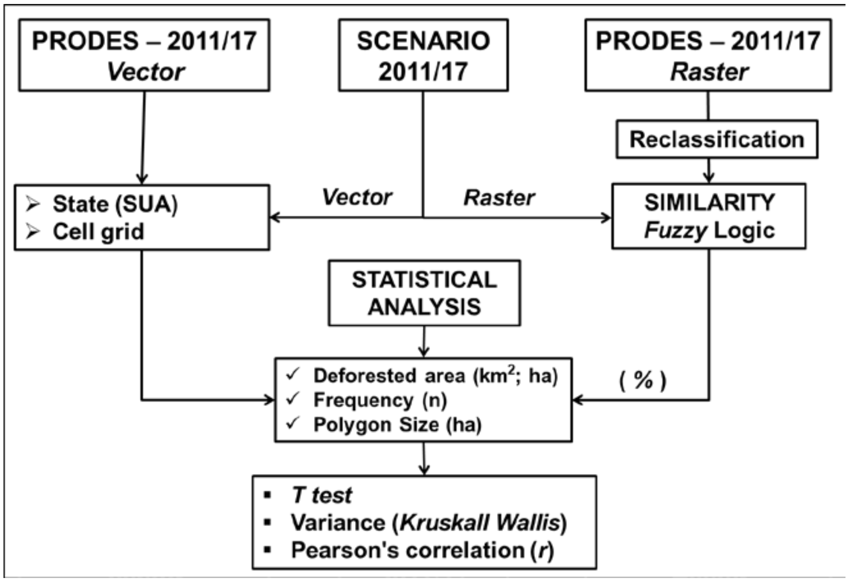

Figure 2. Flowchart of the methods applied in the systematic evaluation of the simulated scenarios and the PRODES data. “SUA” is the acronym for “silvo-pastoral use area.”

The areas (km^2) as of 2017 of the land-cover classes that are included in the attribute table of the PRODES vector file (Mainclass) were tabulated and are available in the Supplementary Material. This represents the SAU landscape. Data manipulation (mapping) was performed using QGIS 2.18.1 “Las Palmas” software (https://www.qgis.org/pt_BR/site/) and Dinamica-EGO.

Method

To assess the scenarios, simulated annual deforestation and PRODES annual deforestation were both vectorized and were evaluated considering only the SAU. Then the SAU was intersected with the grid of nine sub-areas, each sub-area originally measuring 10,000 km^2 (100 × 100 km). However, when crossing the vector layers (Intersection of the SAU with the grid), all sub-areas, without exception, lost part of their original area (Supplementary Material, Appendix 1).

The simulation model was calibrated using one of the nine sub-areas, which was chosen at random during the training phase. This approach can be considered to be an independent alternative to using either ecological-climatic criteria (e.g., BARNI et al. 2015c) or municipal boundaries (e.g., SOARES-FILHO et al. 2008) to subdivide the study area. This follows the example of Soares-Filho et al. (2013), who used 12 sub-areas, each corresponding to a Landsat-TM scene, to evaluate methods for calibrating land-use models in the Amazon.

Similarity analysis

For this procedure, the 2017 PRODES map in raster format was first degraded from 30-m to 100-m spatial resolution in order to be compatible with the resolution of the scenarios, after which it was reclassified in the years of the analysis to represent the areas of the classes (1) (deforestation) and (2) (forest). To make the 2011 map, for example, the deforested areas of the subsequent years (2012 to 2017) had to be reclassified to the value (2) (forest) because these areas had not yet been deforested in 2011. The "non-forest" and "water" classes were reclassified as "no data;" "cloud" areas were reclassified as "forest" and residual areas for each year and were assigned to class (1) (deforestation) in their respective years of deforestation. This procedure was carried out for all years after 2011.

Subsequently, the similarity between the simulated maps and the reclassified PRODES annual deforestation maps was evaluated using the reciprocal similarity comparison technique developed by Soares-Filho et al. (2008) as a modification of the fuzzy-similarity method (HAGEN, 2003). This method employs multiple "windows" of increasing numbers of cells. The simulated annual maps and the annual PRODES maps were subdivided into these windows and compared in a sub-model that is included in the Dinamica-EGO software. For this assessment, the windows were matrices of cells ranging from 3 x 3 cells (300 x 300 m) to 39 x 39 cells (3900 x 3900 m).

The method considers the central cell of each window and the states of the cells in its neighborhood as parameters for comparison between the maps. It is important to highlight that the comparison is made only on the map of the change of interest, that is, on annual deforestation, without considering the cumulative deforestation in the landscape. In this approach, a similarity index value between maps equal to or greater than 50% is considered to be reasonable for validation of a simulation model.

The same decision criteria were used to determine whether the simulated and "real" maps were similar or not in given years and locations. This approach was used to assess both the similarity between the annual scenarios, considering the SAU as a whole, and the similarity within each sub-area.

Statistical analysis

Statistical analysis was carried out using R 3.1.1 software (https://www.r-project.org/). The evaluations consisted of analysis of variance and the "t" test, using the raw data obtained from the crossing of vector maps with the SAU and the grid of sub-areas. Tests were made for differences in "deforested area" (ha: "t" test), "Frequency" (n) and "Polygon size" (ha) (non-parametric: Kruskal-Wallis). Pearson's correlation (r) was applied to test whether the percentage values (%) obtained from the reciprocal-similarity test in a 3900 × 3900-m window in each scenario from 2011 to 2017 and in each sub-area in the grid are correlated with the values of the variables considered above. The following criteria were considered in interpreting the results: values between 0.10 and 0.29 = low correlation; between 0.30 and 0.49 = medium correlation and; between 0.50 and 1.00 = high correlation (COHEN 1988).

3. RESULTS AND DISCUSSION

Comparing simulated deforestation (total in the analyzed period = 949.9 km^2: annual mean = 135.7 ± 28.7 km^2) and real deforestation detected by PRODES (total in the analyzed period = 1144.0 km^2: annual mean = 163.4 ± 33.2 km^2), there was no significant difference ($t = 2.1788$; $p = 0.1474$; $\alpha = 0.05$) between the means (Figure 3). The real deforestation rates in this period were 41.1% lower than the historical average (277.0 km^2) computed for the state up to 2010 (BARBOSA et al. 2008; BARNI et al. 2015c). Despite the significant decrease in deforestation rates in Roraima, this decrease was 20% less than the 61.8% decrease in deforestation observed for the Amazon as a whole in the same period.

The more modest decline in deforestation rates in Roraima up to 2010 may be related to the state's own deforestation dynamics, which, on average, seem to be disconnected from the deforestation dynamics in the rest of the Amazon (e.g., RODRIGUES et al. 2009; FEARNSIDE 2017; FONSECA-MORELLO et al. 2017). This was not considered by the model. In fact, one would expect Roraima's deforestation to be restrained by the lack of road connection with most of the rest of the country and by the low rural population in the state, which was 23.4% of the state's total population in the last census (IBGE 2019). However, this expected brake on deforestation was not seen in practice (e.g., BARNI et al. 2012, 2015c). The lower deforestation rate (~17.0%) in the analysis interval shown in the simulated scenarios to the PRODES data as compared was due to the presumption of a decrease in deforestation rates such that consequent CO_2 emissions in the state would be consistent with what was voluntarily proposed by the Brazil at COP 15 for the entire Brazilian Amazon (GONÇALVES et al. 2009; BARNI et al. 2015a).

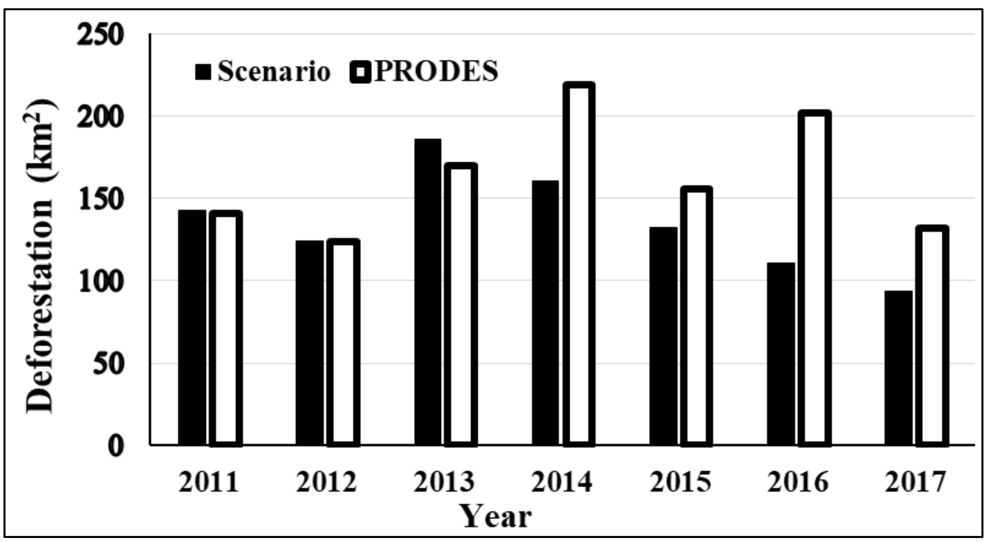

Figure 3. Comparison between simulated (Scenario) and "real" (PRODES) deforestation.

Considering the annual deforestation in the nine sub-areas (covering 82.7% of the 65,150-km^2 SAU), modeled deforestation (period total = 851.2 km^2: annual mean = 121.6 ± 27.2 km^2), representing 89.7% of the total simulated deforestation in the SAU, it also did not differ from the real deforestation (period total = 987.3 km^2: annual mean = 141.0 ± 43.5 km^2), representing 86.3% of the deforestation recorded in the SAU between 2011 and 2017 ($t = 2.23$; $p = 0.34$; $\alpha = 0.05$). However, there were some divergences in the total area deforested (ha) and in the frequency (n) when considering the annual deforestation computed by the model as compared to that found by PRODES within each sub-area individually. For example, there was a significant difference (Kruskal-Wallis) between the means for deforested area within the SUB-A4 sub-area (Difference between polygons = 39.3; p = 0.04) and SUB-A8 (Difference between polygons = 39.9; p = 0.04), while the frequency of polygons was significantly different only in SUB-A4 (p = 0.02) (Table 1; Figure 4).

Table 1. Deforested area (ha) in the scenarios computed by the model (SUB-An-Sc) and detected by PRODES (SUB-An-P) within each sub-area throughout the analysis period.

	2011	2012	2013	2014	2015	2016	2017	Total
SUB-A1-Sc	277.5	256.5	324.6	345.0	10.1	58.2	23.5	1,295.3
SUB-A1-P	540.9	307.1	314.2	586.6	756.4	444.5	529.8	3,479.5
SUB-A2-Sc	1,880.3	1,368.3	2,137.4	1,982.8	1,247.3	749.4	692.0	10,057.5
SUB-A2-P	142.0	928.8	2,842.0	2,064.3	1,522.8	3,588.3	588.1	11,676.3
SUB-A3-Sc	2,128.3	1,759.6	3,323.4	2,407.9	1,414.4	1,054.8	828.8	12,917.2
SUB-A3-P	1,894.7	1,537.9	3,821.9	5,198.5	1,814.2	4,887.6	1,675.9	20,830.6
SUB-A4-Sc	3,291.8	2,773.3	4,051.0	4,093.1	4,363.7	3,589.9	3,576.5	**25,739.3**[a]
SUB-A4-P	1,053.2	1,703.2	1,096.5	2,923.9	2,947.9	2,365.9	909.8	**13,000.4**[b]
SUB-A5-Sc	399.4	499.1	800.2	580.3	225.4	211.5	281.3	2,997.2
SUB-A5-P	357.3	95.3	139.8	145.9	963.9	558.2	586.1	2,846.5
SUB-A6-Sc	1,137.5	1,179.6	1,496.1	1,373.2	1,331.9	1,056.7	859.9	8,434.9
SUB-A6-P	1,622.3	1,782.9	1,222.8	2,299.2	1,446.7	3,319.1	1,641.5	13,334.5
SUB-A7-Sc	1,079.1	1,134.2	1,318.2	1,005.6	1,365.3	1,250.5	1,110.4	8,263.3
SUB-A7-P	1,812.1	1,164.6	805.7	1,991.0	1,470.6	2,214.7	1,182.5	10,641.2
SUB-A8-Sc	1,416.6	927.7	1,189.2	1,089.2	697.5	774.0	422.2	**6,516.4**[a]
SUB-A8-P	699.2	1,203.3	1,998.4	1,566.4	2,002.5	1,896.3	3,051.5	**12,417.5**[b]
SUB-A9-Sc	1,222.2	1,105.9	1,894.4	1,469.6	1,378.2	1,165.0	660.3	8,895.6
SUB-A9-P	1,350.0	1,180.3	1,688.1	1,276.6	1,447.3	2,095.9	1,460.5	10,498.7
Total-A-Sc	**12,832.6**	**11,004.1**	**16,534.5**	**14,346.6**	**12,033.8**	**9,910.0**	**8,454.9**	**85,116.6**
Mean-A-Sc	**1,425.8**	**1,222.7**	**1,837.2**	**1,594.1**	**1,337.1**	**1,101.1**	**939.4**	**9,457.4**
Total-A-P	**9,471.7**	**9,903.3**	**13,929.3**	**18,052.4**	**14,372.1**	**21,370.6**	**11,625.7**	**98,725.1**
Mean-A-P	**1,052.4**	**1,100.4**	**1,547.7**	**2,005.8**	**1,596.9**	**2,374.5**	**1,291.7**	**10,969.5**

***The letters "a" and "b" under bold values in the "Total" column highlight significant differences between the means at the 95% confidence level (*Kruskal-Wallis*: α = 0.05).**

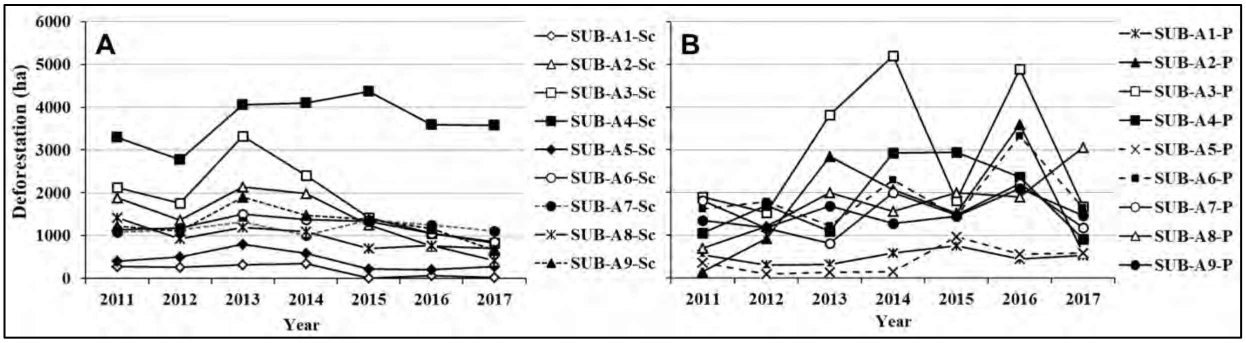

Figure 4. Variation in deforested area (ha) in the scenarios computed by the model (**A**: SUB-Ax-Sc) and detected by PRODES (**B**: SUB-Ax-P) within each sub-area throughout the analysis period.

These inconsistencies are explained by the large deforestation seen in these sub-areas both before and during the analysis period. This made it difficult for the model to “capture” the dynamics of deforestation, sometimes deforesting “too much” (SUB-A4) and sometimes deforesting “too little” (SUB-A8) based on the comparison with PRODES. SUB-A4, for example, is a region that historically has had greater deforestation pressure due to its proximity to the state’s capital city of Boa Vista (BARNI et al. 2015b); this sub-area covers part of the municipalities of Mucajaí, Iracema (right bank of the Rio Branco, cut by BR-174), Cantá (left bank and cut by RR-070) and Caracaraí (both banks and cut by both highways) (Figure 5a).

In 2009, for example, the municipality of Mucajaí was on the “black list” of the municipalities that most deforested in Brazil’s Amazon region (PR 2007). Currently Mucajaí leads the ranking of municipalities in the state in terms of the absolute area deforested (1898.2 km^2), followed by Cantá (1583.0 km^2) and Rorainópolis (1235.8 km^2) (INPE 2019), the latter being covered by SUB-A8.

Considering the municipalities of Cantá and Caracaraí, it is expected that there will be greater growth in deforestation rates in the coming years due to the paving of Highway RR-070, which bisects these municipalities from south to north beginning at km 500 of Highway BR-174 in Novo Paraíso, in the municipality of Caracaraí. The paving is in its final phase, and it is expected that the highway will act as a “magnet” attracting immigrants to the region (SOARES-FILHO et al. 2004; BARNI et al. 2018a).

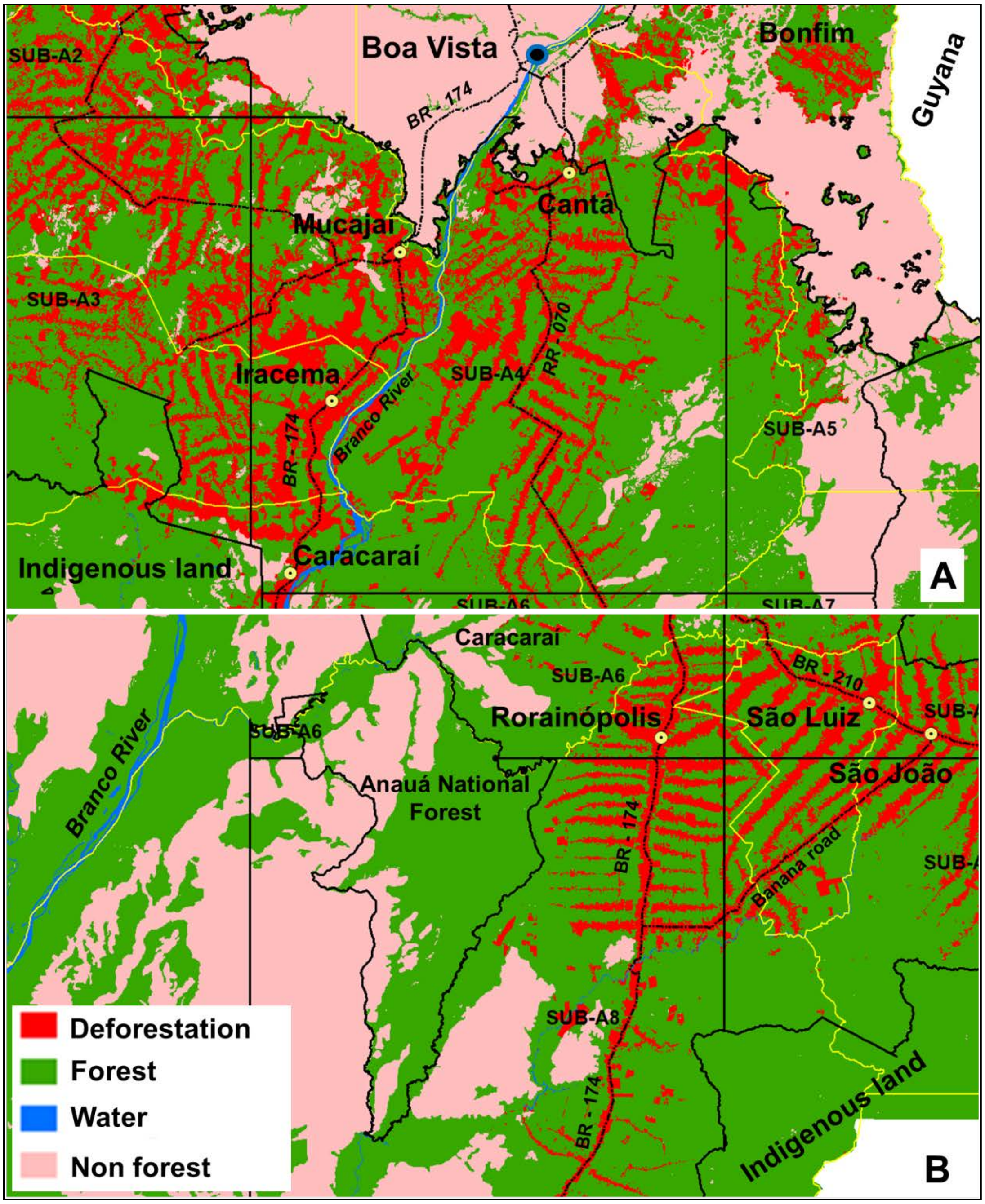

Figure 5. In (**A**), location of subarea four (SUB-A4) between subareas three (SUB-A3) and five (SUB-A5); and in (**B**), subarea eight (SUB-A8) to the left of subarea nine (SUB-A9). The black lines represent the outlines of the grid sub-areas and the yellow lines represent the borders of the municipalities.

All these considerations concerning SUB-A4 are even more worrying due to the fragility of the ecotone forests (contact zone between ombrophilous forest and the savannas) that characterize this sub-area. Due to their proximity to the savanna (locally called the "*lavrado*"), these forests have repeatedly been affected by major forest fires, especially in El Niño years (BARBOSA and FEARNSIDE 1999; BARNI et al. 2015c; FONSECA et al. 2017).

Contrary to what was seen in sub-area SUB-A4, where our model had its worst performance, SOARES-FILHO et al. (2013) reported that their models performed best (with highest accuracy) for deforestation frontiers that were already consolidated, as is the case in SUB-A4. SOARES-FILHO et al. (2013) found that the worst performances were for recent deforestation frontiers and for those that were in transition, with multiple actors present and where changes in the deforestation processes were underway. This is the case in sub-area SUB-A8, which covers a large part of the municipality of Rorainópolis and, as mentioned above, contains both a large consolidated deforested area close to the municipal seat and other deforestation frontiers in different stages of consolidation, ranging from frontiers that have begun to be occupied only recently (2014-2015), are in transition (2008-2009) and are already consolidated (1985-2002) (BARNI et al. 2012, 2018a; MOURÃO 2011). All of these processes are related to the creation of settlement projects (YANAI et al. 2017) and to the invasion of public lands that lack any protection status (FEARNSIDE 2017).

In SUB-A8, deforestation has been speeded by the role that authorizations granted for the use of wood in areas approved for “clearcutting” (deforestation) plays in laundering wood from illegal selective logging (CONDÉ et al. 2019). The clearcutting projects are licensed by the State Foundation for the Environment and Water Resources (FEMARH) upon the written request of the land owner.

The vast majority of the vegetation in the study area is dense ombrophilous forest (BARNI et al. 2016; NOGUEIRA et al. 2015). Due to the high humidity of the forest understory, this type of vegetation is normally resistant to the spread of fire. However, during the 2015/16 El Niño event, about 1800 km^2 of forests burned in the southern portion of Roraima (BARNI et al. 2018b). It is suspected that selective logging, along with fire from new deforestation and from management of existing pastures and agricultural fields, is responsible for much of the spread of fire in the region (e.g., BRANDO et al. 2014; FONSECA-MORELLO et al. 2017).

Considering the average polygon size simulated annually by the model (9.7 ± 12.5 ha) and the average polygon size detected by PRODES (12.6 ± 17.6 ha) within the grid of sub-areas ($n = 9$), a significant difference was observed only in sub-area SUB-A6 ($p < 0.01$). In this sub-area, the average size of the simulated polygons was 9.6 ± 2.5 ha, while the average size of polygons detected by PRODES was 18.9 ± 5.6 ha, or almost twice as large as the simulated polygons. Sub-area SUB-A6 includes a new settlement project (~700 km^2) that was in the process of opening lots (SOARES-FILHO et al. 2013) via clearcutting authorizations. This settlement had unusually large lots, and, because FEMARH releases up to 20% of the lot area to be felled, it is likely that this factor contributed to the occurrence of larger deforestation polygons, and therefore to the fact that they were detected by the PRODES system in this sub-area.

The settlement in question with lots of 500 to 1000 ha was created to meet the demands of logging entrepreneurs and other business owners living in the municipal seat of Rorainópolis (BARNI et al. 2018a, p. 168). This contrasts with other settlement projects in the southern portion of Roraima where, in general, lot sizes have ranged from 50 to 100 ha, and the lots were distributed to landless farmers (BARNI et al. 2012; YANAI et al. 2017).

The sizes of the deforested polygons that were simulated by the model and that are registered in the PRODES data were evaluated separately for each year ($n = 7$) in each sub-area ($n = 9$). In this case, a significant difference between the deforestation polygons was only observed in 2017 (Difference between polygons = 66.8; $p = 0.0001$); in 2017 the average polygon size was 6.5 ± 2.4 ha for simulated deforestation and 14.7 ± 5.6 ha for polygons detected by PRODES (Figure 6).

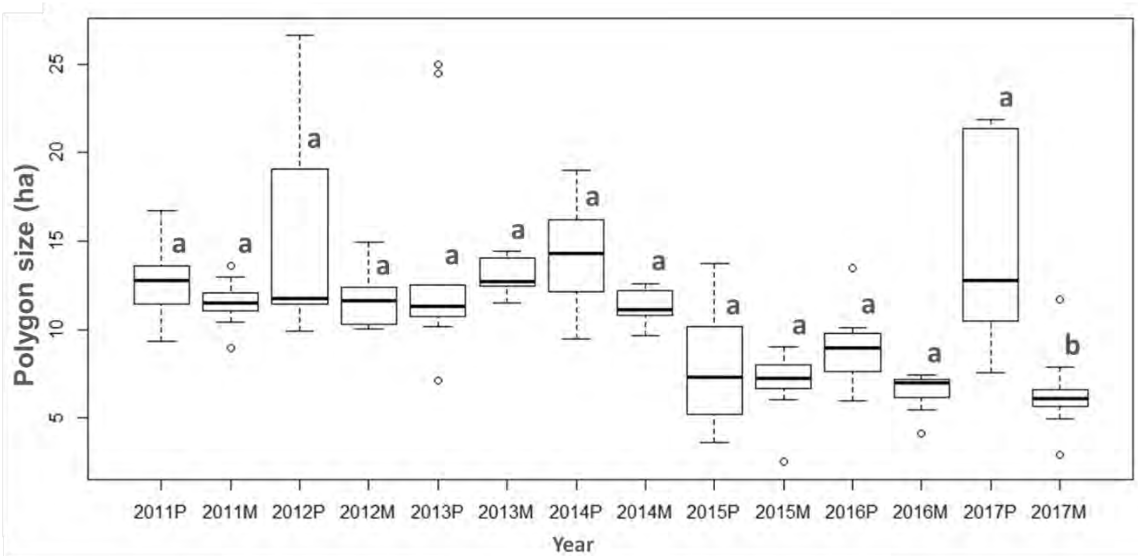

Figure 6. Comparison of polygon sizes (ha) within the grid of sub-areas in each year evaluated.

In other words, the real polygons of deforestation were 2.3 times larger than the simulated ones, thus corroborating the conclusion that deforestation in this sub-area (SUB-A8) was being carried out in larger polygons due to the state government's release of clearcutting projects to facilitate selective logging (e.g., ROSA et al. 2012). However, part of the explanation for having larger polygons in the PRODES data than in simulated data is due to the fact that PRODES only considers polygons ≥ 6.25 ha in area, while the simulation considered polygons ≥ 1 ha in area.

Figure 7 exemplifies the situation discussed above, showing deforestation in 2017 in a settlement project that had been recently opened to meet the demands of businesspeople in Rorainópolis (BARNI et al. 2018a). Note that the size of the deforestation polygons detected by the PRODES system far exceeds the area of the polygons simulated by the model.

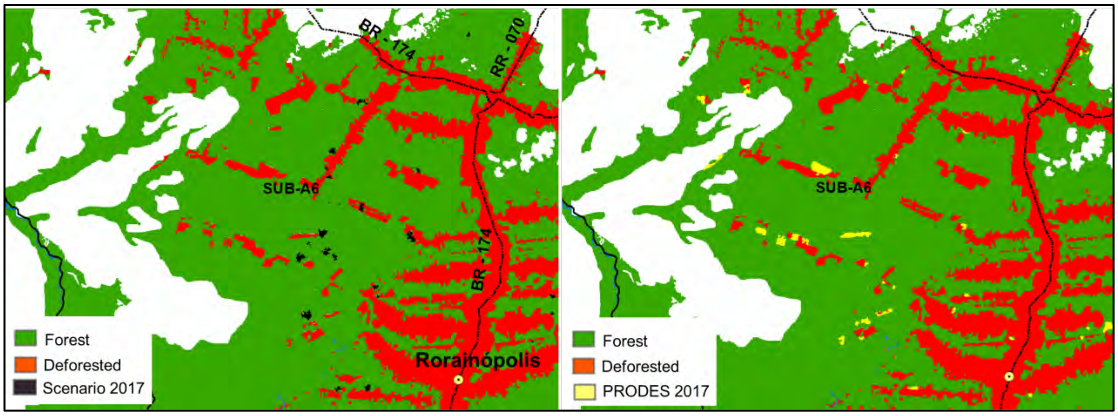

Figure 7. Visual comparison between simulated deforestation polygons (black) and observed in 2017 (yellow) by PRODES in a part of the SUB-A6 sub-area where a settlement project with unusually large lots had been recently opened.

Similarity assessment in the SAU

The results of the similarity tests (%) between the annual deforestation scenarios and the PRODES data for the SAU registered the overall mean of 46.4% in a 3900 x 3900-m window (39 x 39 cells). The annual scenario that showed the greatest similarity with the PRODES data was that of 2013 with 55.2%, and the lowest was that of 2017, with 24.0% similarity in a 3900 x 3900-m window (Figure 8).

The result for 2017 positively influenced the mean similarity of the scenarios below the limit value of 50.0%, together with the years 2012 (42.3%), 2016 (48.0%) and 2015 (49.0%), while the years 2013, 2011 (54.5%) and 2014 (52.0%) registered values above this value. With the exception of 2012 and the inversion observed between the values for 2013 and 2011, the results agree with the data of Rosa et al. (2015). Studying the calibration / validation response (accuracy of predictions) of land-use change models according to the choice of the time period used in this phase, these authors observed that the closer or shorter the interval used for the calibration / validation of models the better was their performance. In other words, the longer the interval used, the less accurate the models were in predicting future deforestation.

Although the reciprocal similarity comparison test in our study was truncated in a 39 x 39-cell window, in contrast to the 19 x 19-cell window used in the Soares-Filho et al. (2013) study, we can consider that our results were similar to these. This is due to the spatial resolution used by the two studies. The study by Soares-Filho et al. (2013) used a 250-m spatial resolution, making the area of their cells 6.25 ha, or 6.25 times larger than those in our study. The 250-m spatial resolution in the Soares-Filho et al. (2013) study meant that their 19 x 19-cell window measured 4750 x 4750 m, or 2256 ha, which is 48.3% larger than the 1521-ha (3900 x 3900-m) window in our study.

However, a factor that must be considered and that does not allow valid comparisons of similarity between the models is the fact that the results of Soares-Filho et al. (2013) were based on the comparison of simulated scenarios in just three iterations in the training or calibration / validation phase (e.g., ROSA et al. 2015). While the scenarios evaluated in our study were taken from the results of the simulation itself, after the calibration / validation phase. In other words, the 2017 scenario, for example, was "far" from 2010, the year that was used in the calibration of our model (ROSA et al. 2015).

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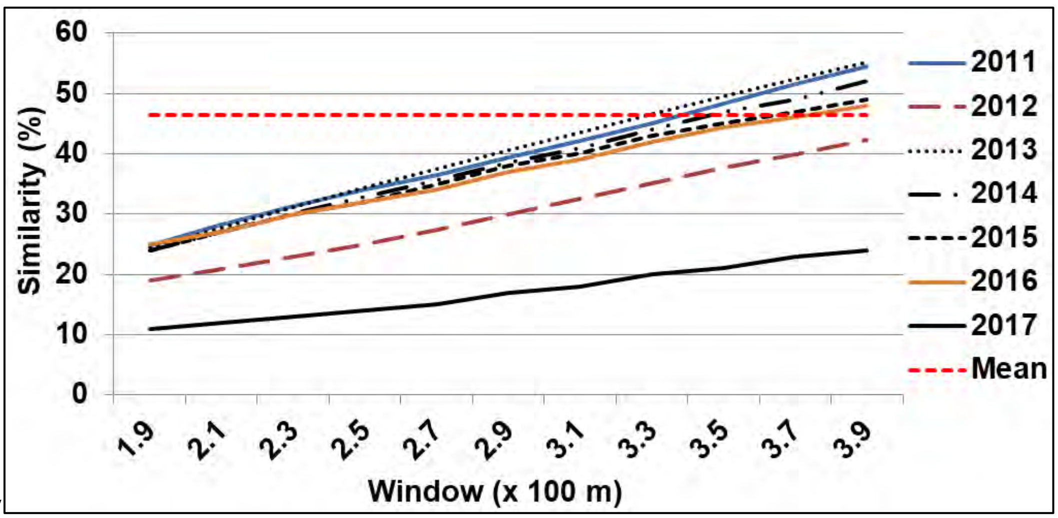

Figure 8. Similarity test between scenarios for the SUA and PRODES data.

The overall mean similarity achieved by each annual scenario, within each sub-area in a 3900 x 3900-m window, was 48.9%. The lowest similarity recorded was 4.0%, which was in sub-area SUB-A1 in 2017, and the highest (91.9%) was in e SUB-A5 in 2014. SUB-A1 showed the greatest variability in the annual scenarios (SD = 26.7%), followed by SUB-A5 (SD = 26.3%), with the least variability being found in SUB-A7 (SD = 7.1%). The mean variability was 16.1% (Table 2; Figure 9).

Table 2. Similarity values (%) achieved by each scenario in each sub-area with a 3900 × 3900-m window. SD is the standard deviation of the sample (%).

Area/Year	2011	2012	2013	2014	2015	2016	2017	Mean	SD
SUB-A1	44.3	37.1	68.2	47.0	25.0	85.0	4.0	**44.4**	**26.7**
SUB-A2	68.9	39.4	60.0	67.9	57.8	41.9	14.3	**50.0**	**19.5**
SUB-A3	41.3	44.5	61.4	61.1	33.8	56.3	17.9	**45.2**	**16.0**
SUB-A4	63.8	54.2	56.0	49.0	44.0	46.6	23.8	**48.2**	**12.6**
SUB-A5	47.5	6.0	52.9	91.9	48.9	41.2	26.5	**45.0**	**26.3**
SUB-A6	48.4	31.0	47.4	48.6	64.5	53.7	43.8	**48.2**	**10.1**
SUB-A7	70.1	58.2	51.3	51.9	54.1	55.3	48.2	**55.6**	**7.1**
SUB-A8	68.3	25.2	37.3	54.5	66.9	68.9	57.3	**54.1**	**16.9**
SUB-A9	44.4	53.4	54.9	45.1	45.0	65.2	36.5	**49.2**	**9.4**
Mean	**55.2**	**38.8**	**54.4**	**57.4**	**48.9**	**57.1**	**30.3**	**48.9**	**16.1**
SD	**12.2**	**16.5**	**8.9**	**14.8**	**13.7**	**14.1**	**17.4**	**-**	**14.0**

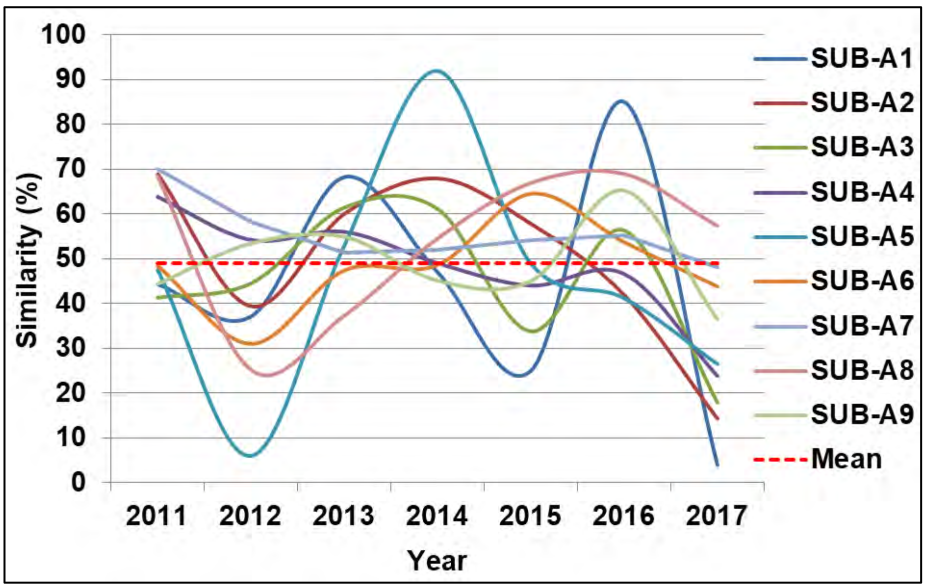

Figure 9. Similarity behavior in the annual scenarios in each sub-area.

When the data matrix is inverted (Table 2), the 2017 scenario shows the greatest variability (SD = 17.4%), followed by the 2012 scenario (SD = 16.5%). The mean deviation was 14.0% considering all scenarios (Figure 10).

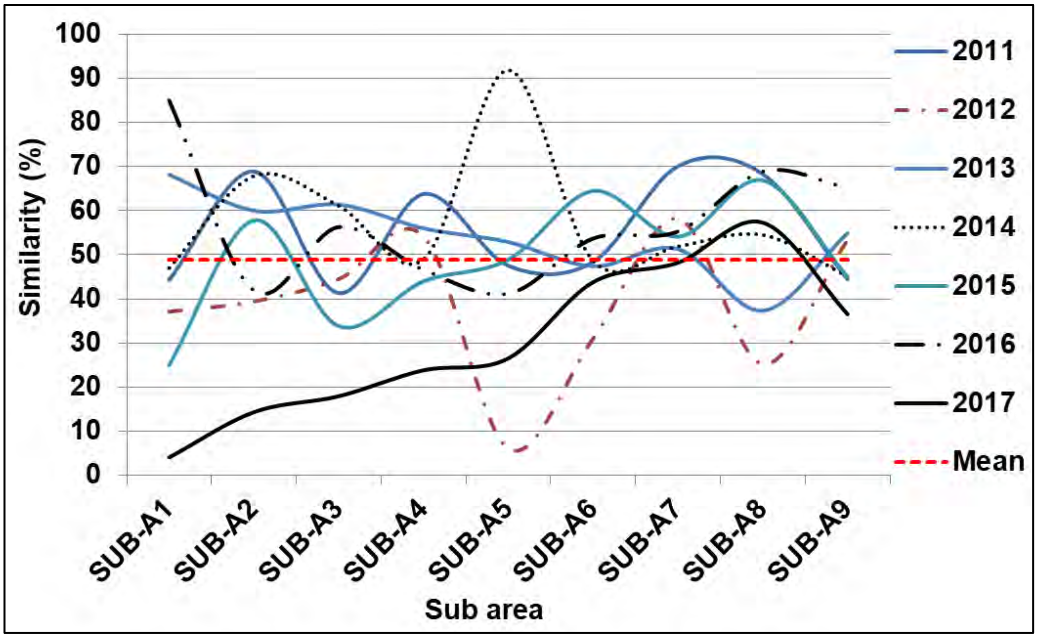

Figure 10. Similarity behavior of the sub-areas in each annual scenario.

In Figure 10 it can be seen that the 2017 scenario increases the similarity starting from the north (SUB-A1) to the south (SUB-A8). The opposite behavior can be seen in the 2013 scenario, in which the similarity decreases considering the same direction of growth as in the 2017 scenario.

Correlation analysis

Correlation analysis was used to test whether the deforested area (ha), the frequency of polygons (n) and the size of the average polygon (ha) deforested in each sub-area influenced the similarity in each scenario within the sub-areas (Table 3).

Table 3. Result of the correlation analysis applied between the similarity values (%) and the values for "deforested area" (ha), "frequency" (n) and "polygon size" (ha).

SUB-AREA	Deforestation (ha)		Frequency (n)		Polygon size (ha)	
	Scenario	PRODES	Scenario	PRODES	Scenario	PRODES
SUB-A1-SIM	**0.5557**	-0.3283	**0.5355**	**-0.6315**	**0.5561**	0.2266
SUB-A2-SIM	**0.8002**	0.1076	**0.8370**	**0.6227**	**0.6498**	0.0997
SUB-A3-SIM	**0.7072**	**0.7236**	**0.8472**	**0.8050**	0.4930	-0.4451
SUB-A4-SIM	-0.1546	0.1914	**-0.6379**	0.0856	**0.6478**	0.0564
SUB-A5-SIM	0.0239	0.2991	0.1753	0.3246	-0.1897	-0.3319
SUB-A6-SIM	0.2087	0.0556	**0.6702**	**0.5431**	-0.3644	**-0.8640**
SUB-A7-SIM	-0.1998	0.3601	-0.4276	0.2472	0.4250	0.2358
SUB-A8-SIM	-0.1801	0.0703	**0.7512**	**0.6253**	-0.4817	**-0.7318**
SUB-A9-SIM	**0.5008**	**0.5637**	0.2839	**0.7619**	0.3257	**-0.8020**

*** Values in bold indicate high correlation (r> 0.4900) between the variables analyzed.**

The results indicate that the frequency or number of polygons provided by the simulation of the scenarios and also from the PRODES data, in the sub-areas, contributed more strongly to the similarity than did the other variables. Even so, the variable "deforested area," for example, showed a strong correlation with similarity in sub-areas SUB-A1, SUB-A2, SUB-A3 and SUB-A9.

Most of the results showed a strong positive correlation of the variables with the similarity observed in the sub-areas. However, five cases of strong negative correlation were observed for the "frequency" variable (2 cases: SUB-A1 and SUB-A4) and the "polygon size" variable (3 cases: SUB-A6, SUB-A8 and SUB-A9).

Considering the "frequency" variable, the strong inverse correlation observed in SUB-A4 is explained by the large number of polygons (n = 435) generated by the simulation model compared to the low frequency of polygons (n = 213) detected by PRODES. The same occurred in SUB-A1, but the reverse occurred in SUB-A4, the PRODES detection frequency (n = 346) being higher than the frequency generated by the model (n = 137). Therefore, in these two cases, the results indicate that the number of polygons negatively influenced the similarity between the simulated maps and the maps of actual deforestation.

Considering the variable “polygon size,” the highest mean sizes of the deforestation polygons detected by PRODES in 2014 (14.3 ha) and 2017 (14.7 ha) versus the smaller mean sizes of simulated polygons in the scenarios (11.6 ha for 2014 and 6.5 ha for 2017) may have inversely influenced the similarity in the sub-areas. In this case, the larger size of the polygons detected by the PRODES system in these years implied less similarity between the simulated scenarios and the real data in sub-areas SUB-A6, SUB-A8 and SUB-A9.

4. FINAL CONSIDERATIONS

The lessons learned from the approach applied in our study suggest that the behavior of deforestation is not linear and that it can change depending on time (from one year to the next) and space (from one location to another). This is consistent with the idea that the occurrence of deforestation in different parts of the study area in the period was favored by road construction, creation of settlement projects, cumulative previous deforestation close to roads and proximity to urban consumer centers (SOARES-FILHO et al. 2004; BARNI et al. 2015b; ROSA et al. 2015).

The problem of divergence between the simulated deforestation results and the real or official deforestation that occurred in some sub-areas of the study area, shown by the similarity tests, does not jeopardize the validity of the scenario analysis. These divergences are difficult to predict and can often be related to the origin and culture of the landholders, who base their decision to deforest or not to deforest an area on the basis of market behavior (RODRIGUES et al. 2009; FEARNSIDE 2017).

Considering these issues, the probability of deforestation in our study area was increased by the creation of settlement projects for large landholders and by invasions of public lands (government areas “without destination”). The creation of settlement projects for large landholders and the action of land grabbers (*grileiros*), for example, opened thousands of hectares of untouched forests as areas for speculation in the real estate market, then to the selective logging market and finally to the meat market ending (FEARNSIDE 2017). This process may take several years to stabilize the cumulative deforested area in the properties, which, by law, can deforest a maximum of

20% of the lot area. During this time the area is transformed into a zone “producing” deforestation. The process can be accelerated with the arrival of loggers who open roads for landholders in exchange for permission to remove timber from the lots.

Despite the divergences pointed out above between deforestation simulated in the scenarios and official PRODES deforestation, in general the evaluations demonstrated the validity of the model and the ability of future scenarios to realistically represent the deforestation that occurred in the study area, considering the clearing from 2011 to 2017. The correlation analysis, for example, offered excellent inputs for the simulation model calibration phase. Prioritizing the frequency (n) and the mean polygon size (ha) of deforestation during the calibration phase of a simulation model can substantially improve the model’s performance.

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Supplementary material

SIMULATED DEFORESTATION VERSUS SATELLITE DATA IN RORAIMA, NORTHERN AMAZONIA

Appendix 1. Sub-areas in the SAU grid with areas (km^2) for each PRODES land-cover class (*Mainclass*) up to 2017.

	SUB-A1	SUB-A2	SUB-A3	SUB-A4	SUB-A5	SUB-A6	SUB-A7	SUB-A8	SUB-A9	Total	%
Original area	4,502.7	6,026.6	5,990.0	9,086.0	2,436.6	7,782.7	5,644.0	7,925.8	4,477.1	**53,871.4**	**100.0**
%	45.0	60.3	59.9	90.9	24.4	77.8	56.4	79.3	44.8	**-**	**-**
Forest	3,589.7	3,419.7	2,904.1	3,956.6	1,304.5	4,311.0	3,692.0	3,744.7	2,752.4	**29,674.7**	**55.1**
%	79.7	56.7	48.5	43.5	53.5	55.4	65.4	47.2	61.5	**-**	**-**
Water	0.0	34.3	1.9	137.3	0.0	27.6	0.0	19.4	9.3	**229.7**	**0.4**
%	0.0	0.6	0.0	1.5	0.0	0.4	0.0	0.2	0.2	**-**	**-**
Non-forest	262.8	206.8	93.6	385.0	821.1	2,178.9	681.5	3,009.7	0.0	**7,639.4**	**14.2**
%	5.8	3.4	1.6	4.2	33.7	28.0	12.1	38.0	0.0	**-**	**-**
Deforestation	171.9	1,050.6	1,428.9	2,526.5	222.4	942.8	1,032.9	782.4	1,244.7	**9,403.2**	**17.5**
%	3.8	17.4	23.9	27.8	9.1	12.1	18.3	9.9	27.8	**-**	**-**
Cloud	422.4	1,297.0	1,543.4	2,060.7	80.8	310.4	232.7	360.3	457.4	**6,765.1**	**12.6**
%	9.4	21.5	25.8	22.7	3.3	4.0	4.1	4.5	10.2	**-**	**-**
Residual	3.3	18.2	17.9	19.9	3.0	12.0	4.8	9.3	13.3	**101.8**	**0.2**
%	0.1	0.3	0.3	0.2	0.1	0.2	0.1	0.1	0.3	**-**	**-**
Total in vectorized dataset	**4,450.1**	**6,026.6**	**5,989.9**	**9,086.0**	**2,431.8**	**7,782.6**	**5,644.0**	**7,925.7**	**4,477.1**	**53,813.8**	**99.9**
Difference*	**52,5**	**0,1**	**0,0**	**0,0**	**4,8**	**0,0**	**0,1**	**0,0**	**0,0**	**57,6**	**0,1**

* Area lost in crossing the vector layers (Intersection of the SAU with the grid)