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FORESTRY SCIENCE

Environmental vulnerability evolution in the Brazilian Amazon

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Abstract: Decision making and environmental policies are mainly based on propensity level to impact in the area. The propensity level can be determined through artificial intelligence techniques included in geotechnological universe. Thus, this study aimed to determine the areas of greatest vulnerability to human activities, in Amazon biome, through MODIS images of Land use and land cover (LULC) from the 2001 and 2013. Remote sensing, Euclidean distance, Fuzzy logic, AHP method and analysis of net variations were applied to specialize the classes of vulnerability in the states belonging to the Amazon Biome. From the results, it can be seen that the class that most evolved in a positive net gain during the evaluated period was "very high" and the one that most reduced was "high", showing that there was a transition from "high" to "very high" risk areas. The states with the largest areas under "very high" risk class were Mato Grosso (101,100.10 km^2) and Pará (81,010.30 km^2). It is concluded that the application of remote sensing techniques allows the determination and assessment of the environmental vulnerability evolution. Mitigation measures urgently need to be implemented in the Amazon biome. The methodology can be extended to any other area of the planet.

Key words: Geographic Information Systems, artificial intelligence techniques, anthropism, environmental evolution, MODIS.

INTRODUCTION

An inherent challenge to the contemporary society is to face climate change due to modifications in the environment. This fact is widely disseminated once it directly and indirectly interfere in the world socioeconomic and environmental systems (Perez & Selvaraj 2019). According to Homer et al. (2020), conversions in Land use and land cover are of most importance among environmental changes, as they can alter surface biophysics, intensify climatic variations, land degradation, and affect biodiversity. In Brazil, for instance, the Amazon biome has undergone significant changes in Land use and land cover.

The Amazon stands out as the largest tropical forest in the world and the largest biome in Brazil, with an area of 4,196,943 km^2, hosting great biodiversity and influencing climate in global scale (Pieniz 2011). Despite its ecological importance, deforestation has been intense in this biome, leading to loss of important ecosystem services (Mello & Artaxo 2017). This biome has been increasingly studied in order to assess its behavior in face of the most diverse types of disturbances. In this way, the agriculture expansion (Batista et al. 2018), logging (Michele & Alcantara 2016), forest fires and urbanization (Silva et al. 2020), are the main factors responsible for deforestation in the biome.

Anthropogenic actions, mainly changes in Land use and land cover, have generated great environmental vulnerability, threatening the natural resources of the Amazon biome. Environmental vulnerability is defined by Moser (1998) as a situation in which the ecosystem is exposed to risk, has an inability to react and difficulty adapting. In other words, the susceptibility of a system to environmental degradation, considering the exposure and the sensitivity of the system to anthropogenic pressures, assessed by the use of indicators which show the characteristics of the physical and biotic environment characteristic of a region (Figueirêdo et al. 2007). The greater the exposure to pressures, the greater the sensitivity and the less responsiveness of a system, and therefore the greater its environmental vulnerability.

Aiming plans capable of protecting and restoring this biome, it is essential to understand and quantify the susceptibility to environmental vulnerability, mapping its spatial distribution concerning anthropic or natural sources. In this case, geotechnologies stand out as an essential tool to study Land use and land cover changes, as well as their interaction with the ecosystem's environmental vulnerability (Maggiore et al. 2019). Artificial intelligence (AI) techniques present in the universe of geotechnologies are linked to the innovative development of several computational mechanisms, in addition to a huge range of spatial geographic data (Valle et al. 2016). There is no scientific unanimity regarding a definition of the term "Artificial Intelligence". However, its objective seems very clear and helps to understand this term: development of paradigms or algorithms based on the use of machines in the performance of cognitive activities, which are commonly performed by humans (Franco 2014, Medeiros 2018).

Fuzzy logic used in this study stands out among the most widespread AI techniques in environmental and forestry studies, which according to (Ramalho et al. 2021) can be defined as a Multicriteria Analysis technique that seeks to solve world problems by converting subjective qualitative information, such as that found in nature, into numerical language, varying in an interval of 0 to 1, where the closer to 1 the greater the representativeness within the proposed model.

Through digital images and AI technics, geotechnologies allow the acquisition of information about the spatial distribution of Land use and land cover patterns, in addition to structural characteristics of vegetation, enabling quick, cost effective and efficient monitoring of large areas (Zhu & Liu 2015). Remote sensing for very large areas, normally works with information acquired at orbital level, through sensors carried by artificial satellites that orbit the planet (Shimabukuro et al. 2009). MODIS sensor stands out when it comes to acquiring images of Land use and land cover (LULC).

The MODIS MCD12Q1 product addresses 17 classes of land use and land cover and includes five types of classification (Schulz et al. 2017). This sensor has a high periodicity on a global scale, presenting atmospheric and geometric correction, which facilitates the applicability of the data and increases the reliability of the results. The option to use the MODIS sensor is often based on some particular characteristics, such as the distribution of products already corrected geographically and radiometrically, which results in a reduction in the influence of clouds and aerosols and consequently improves information visualization (Rosendo & Rosa 2005), in addition to the variety of spatial resolution options (moderate to global) and the free distribution of these products or images over the internet (Anjos et al. 2013).

The importance and justification for conducting this study are related to the location and global importance of the Amazon biome, the quality of remote sensing information, the relevance of determining environmental vulnerability in the face of threatening human actions, and because this is one of the most important areas studied in the world. In this sense, the need for studies to assess the environmental risks to which the biome is subjected to is clearly evidenced through supporting scientific evidence (Verburg et al. 2014a, Fagundes et al. 2018, de Souza 2020, Valente et al. 2021).

In this context, the hypothesis that guides the present study is that, through the application of remote sensing techniques, it is possible to evaluate the evolution of environmental vulnerability in the Amazon biome. Therefore, the aim of this research was to analyze the evolution of environmental vulnerability in the Brazilian Amazon through MODIS images of Land use and land cover, between years 2001 and 2013.

MATERIALS AND METHODS

Study area

The study area corresponds to the Brazilian part of the Amazon Biome, comprising a total of 4,196,943 km² (Pieniz 2011). It is located between meridians 45º00'00" and 73º00'00" west of Greenwich and parallels 5º20'00" north and 16º20'00" south (Figure 1).

The Amazon biome is composed by a mosaic of ecosystems linked to a range of topographic (relief) and meteorological characteristics (climate, hydrological cycle, rainfall, sunshine and humidity). According to Köppen classification, the Amazonian biome falls under the climates type Af (rainy Equatorial), Am (tropical monsoon) and Aw (dry and humid tropical) (Alvares et al. 2014).

Database development

The Amazon Biome mask, obtained from Instituto Brasileiro de Geografia e Estatística (IBGE), was used to clip the MODIS images to the study area boundary. The used Land use and land cover images correspond to MCD12Q1 product from MODIS sensor, 500-meter spatial resolution, onboard Terra satellite, referring to the period between years 2001 and 2013. This period was selected due to the fact that the images of this product began to be made available for free on the NASA website based on data from the year 2000. Therefore, it was decided to use this period (2001 to 2013) to evaluate a representative series.

The most complete classification of MCD12Q1 product is type 1, established by the International Biosphere and Geosphere Program (IGBP), was used in this study. According to Menashe & Friedl (2018), it has the following classes: water; coniferous forest; dense rain forest; deciduous coniferous forest; deciduous seasonal forest; mixed forest; closed bush vegetation; open shrub vegetation; woody savanna; savanna; grasses; permanently flooded areas; agricultural predominance; urban areas; mosaic of agricultural areas/vegetation; ice/snow; and exposed soil or sparse vegetation.

The classes of anthropic actions in the Amazon Biome were defined as: urban areas, exposed soil, grasses, agricultural areas and mosaic of agriculture and vegetation.

Methodological steps

Initially, MODIS Land use and land cover images were pre-processed with temporal, spatial and thematic analysis of Land use and land cover corresponding to their respective years (2001 and 2013). For this purpose, the Land Change Modeler (LCM) was employed, which takes previous and posterior maps from a processing year as initial data.

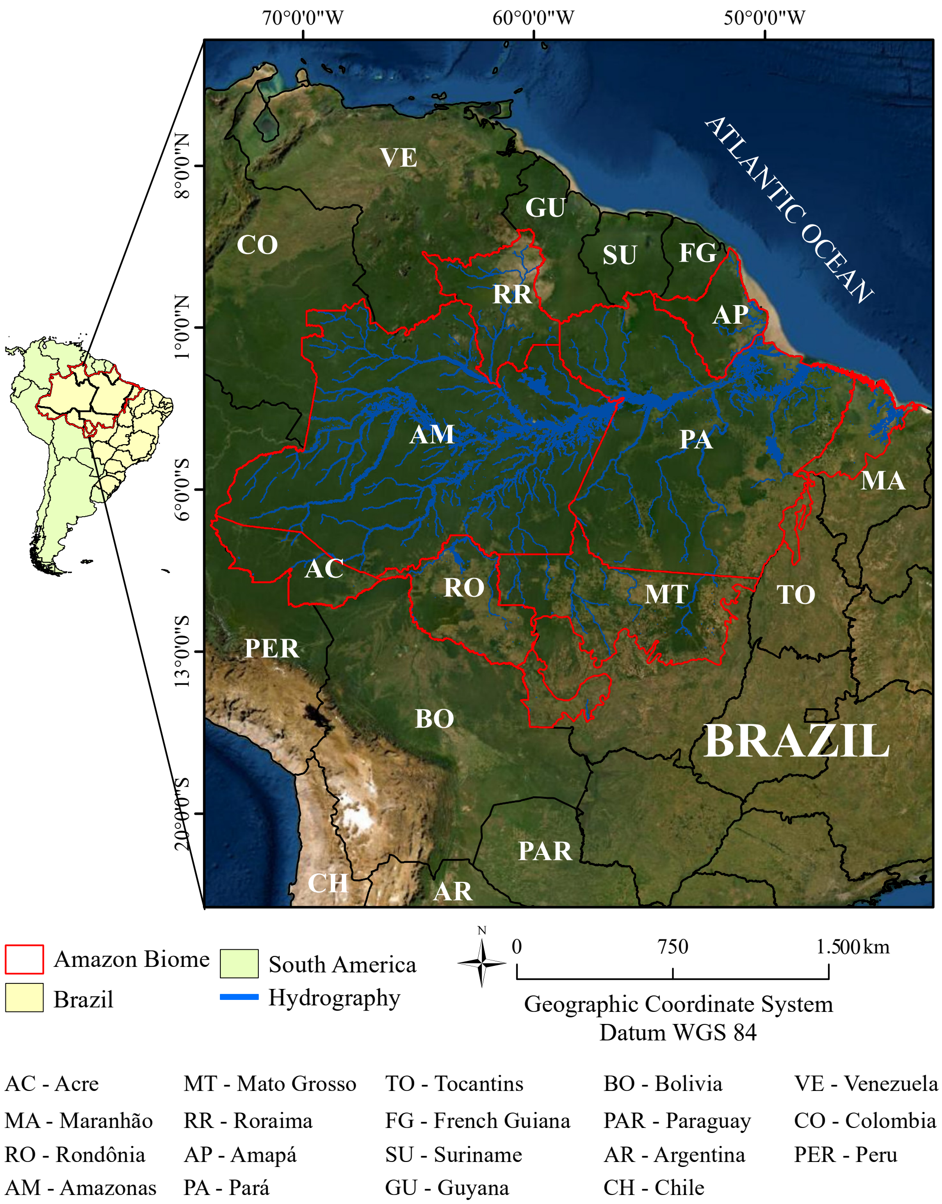

Figure 1. Geographic location of the Amazon Biome.

During pre-processing, the images were set to the proper spatial reference system and have their format suitable to ArcGIS 10.3® software. Images were downloaded and converted using MODISsp application.

After extracting by mask, the 2001 and 2013 images were loaded in LCM module from TERRSET software, to obtain the global graphical and tabular analysis of comparison. In this way, it was analyzed how much each class gained and lost area, in square kilometers. The net graphic analysis was performed comparing both years, that is, the balance between losses and gains and also how much each anthropic class lost or gained area in comparison to the others.

The second step proceeded with the conversion of Land use and land cover images to polygons. The flowchart with necessary steps to elaborate the second step of the proposed methodology is shown in Figure 2.

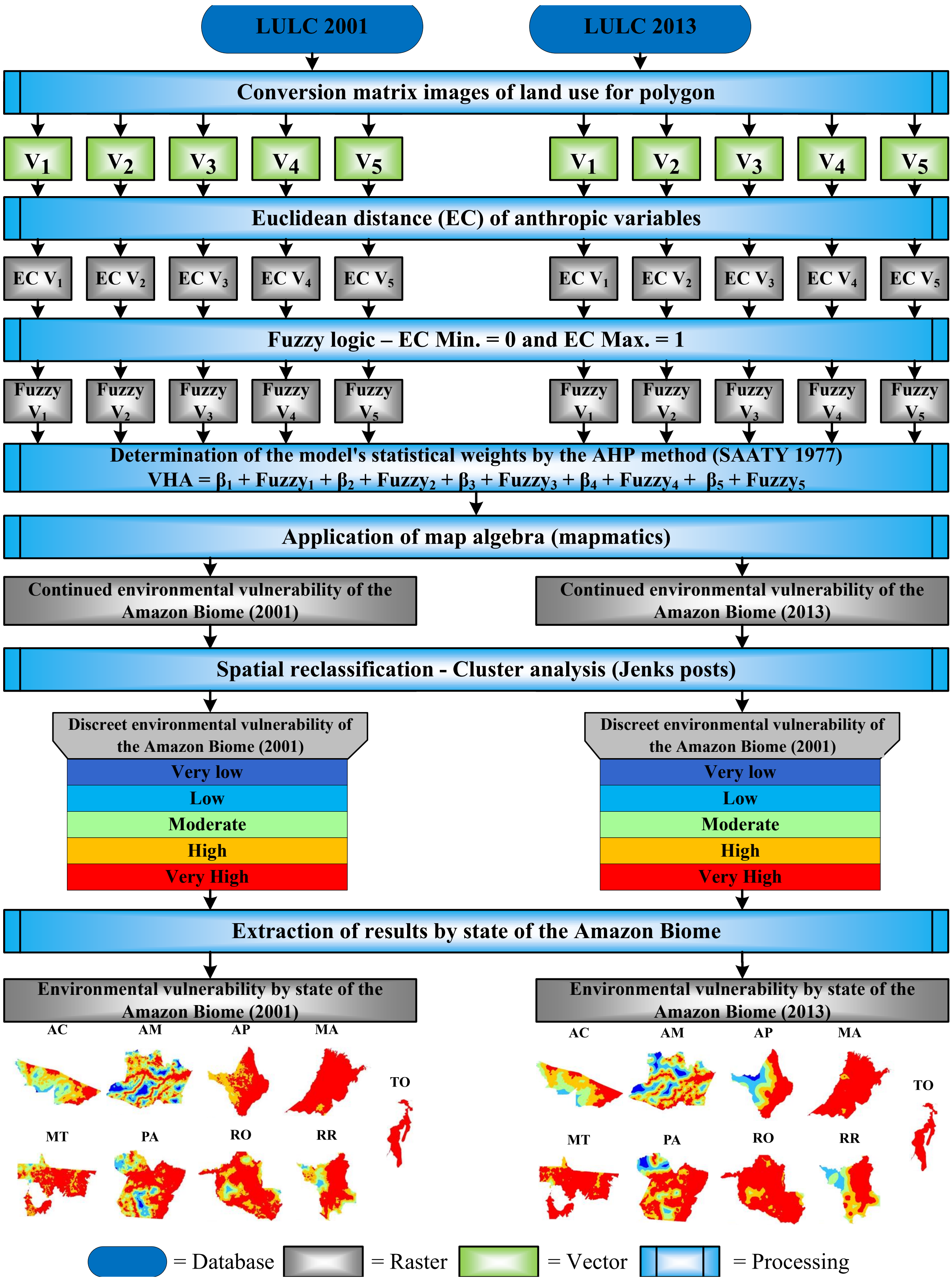

Figure 2. Methodological flowchart.

The influence of anthropic classes was defined from Euclidean distance with the aid ArcGIS 10.3® computational application. This measure refers to the distance, in a straight line, between the centers of two cells. The Euclidean distance between two points D_{AB} (X_A, Y_A) e (X_B, Y_B) in a plan is calculated through the Pythagorean Theorem.

To standardize the images, fuzzy logic was applied under a linear relevance function. Fuzzy logic allows to translate a qualitative attribute into a numeric value, concerning an interval between 0 and 1 (Gaglione et al. 2019). In this case, the closer to 1, the lesser the environmental vulnerability for the anthropic action. The choice for the linear membership function is due to lack of a maximum distance of influence for each class.

The mathematical weights were defined based on the methodology proposed by Saaty (1977), aiming to generate maps with values suitable to reality. Once the used AHP method takes into account variables in importance levels, an importance table was defined (Table SI).

Based on the proposed classification (Supplementary Material - Table SI), a comparison matrix among variables was elaborated, according to Table I.

It was necessary to confirm if the calculated weights were real. For this purpose, the Consistency Ratio (RC) (Equation 1) (Saaty 1980) was employed. Consistent weights present RC value lower than 0.10.

$$CR = \frac{CI}{\boldsymbol{RI}} \tag{1}$$

where, CR is the consistency ratio; RI is the random index (Table II); and CI corresponds to consistency index (Equation 2) (Saaty 2004).

$$IC = \frac{(\lambda_{max} - n)}{(n - 1)} \tag{2}$$

where, n is the number of tested variables, which correspond to the number of rows and columns in Table I; and λ_{max} is the eigenvector calculated by Equation 3 (Saaty 2008).

$$\lambda_{max} = \frac{1}{n} \sum_{i=0}^{n} \frac{\{Aw\}i}{w} \tag{3}$$

where, {Aw}i corresponds to resulting matrix from the product of paired comparison matrix (Table I) by calculated weights (w).

The calculus of vulnerability to anthropic actions was performed using Equation 4.

$$VHA = \beta_1 \times Fuzzy_1 + \beta_2 \times Fuzzy_2 + \beta_3 \times Fuzzy_3 + \beta_4 \times Fuzzy_4 + \beta_5 \times Fuzzy_5 \tag{4}$$

where, VHA is the Vulnerability to human actions; β_1, β_2, β_3, β_4 and β_5 correspond to the weights defined by the AHP model for each respective variable; fuzzy 1, 2, 3, 4 and 5 refer to the fuzzy maps of the respective variables.

For the generation of 2001 and 2013 vulnerability maps, map algebra (“mapmatics”) was applied to 2001 and 2013 Fuzzy logic maps, through ArcGis software 10.4®. The resulting maps were reclassified into 5 categories of vulnerability (low-very low, low, medium, high and very high) defined through Jenks posts.

Subsequently, for a more detailed analysis, results were extracted through the clipping mask of each state. Afterwards, the area of each vulnerability class was calculated by state.

Table I. Comparison matrix.

Factors	V_5	V_4	V_3	V_2	V_1
V_5	1	1/3	1/5	1/7	1/9
V_4	3	1	1/3	1/5	1/7
V_3	5	3	1	1/3	1/5
V_2	7	5	3	1	1/3
V_1	9	7	5	3	1
Σ	25	16.33	9.40	4.68	1.79

To obtain the weights for each variable, each element of Table I was divided by the sum of the elements of its corresponding column and, later, the arithmetic mean of the values belonging to each line was calculated.

Table II. RI values for square matrices of order n.

n	2	3	4	5	6	7
RI	0	0.58	0.9	1.12	1.24	1.32

Source: Adapted from Saaty (2004).

Table III. Losses, gains and liquid variation by LULC class between 2001 and 2013, in square kilometers.

Class	Losses (km^2)	Gains (km^2)	Liquid variation (km^2)
Water	-6,385.36	8,366.19	1,980.83
Coniferous forest	-1,513.45	1,869.91	356.46
Dense ombrophilous forest	-209,650.15	148,691.80	-60,958.35
Deciduous coniferous forest	-228.01	135.41	-92.60
Deciduous forest	-4,953.56	1,626.56	-3,327.00
Mixed forest	-13,608.10	6,209.32	-7,398.78
Closed bush vegetation	-6,746.20	745.97	-6,000.23
Open shrub vegetation	-3,161.32	371.59	-2,789.73
Woody savanna	-42,964.83	18,287.84	-24,676.99
Savanna	-184,666.16	191,730.11	7,063.95
Grasses	-32,388.01	23,569.18	-8,818.83
Permanent wetlands	-38,406.76	58,062.28	19,655.52
Agricultural areas	-8,469.14	21,635.75	13,166.61
Urban areas	-602.59	587.06	-15.53
Agriculture/vegetation mosaic	-120,954.66	112,932.18	-8,022.48
Others	-33.65	98.77	65.12
Exposed soil	-954.27	766.28	-187.99

RESULTS

Analysis of Land use and land cover change

Table III presents the global graphic analysis results, that is, a comparison between 2001 and 2013 years, with gains, losses and net balance in square kilometers, for each class of Land use and land cover generated from MCD12Q1 product.

Figure 3 illustrates the contribution of classes considered as anthropic actions in the Amazon Biome, showing the conversion of Ombrophilous Dense Forest to Agricultural Areas and the conversion of Grasses and Mosaic agriculture/vegetation to Savannah, again justifying the process of "Savanization", which is characterized by both the degradation of the environment and the combination of degradation with climate change on the planet.

Euclidean distance

The Euclidean distances of the classes belonging to anthropic actions, for years 2001 and 2013, are shown in Figure 4. Regions in red correspond to center of the pixel and regions in blue refer to regions where there is no vulnerability to anthropic action, with the pixel size equal to 500 m.

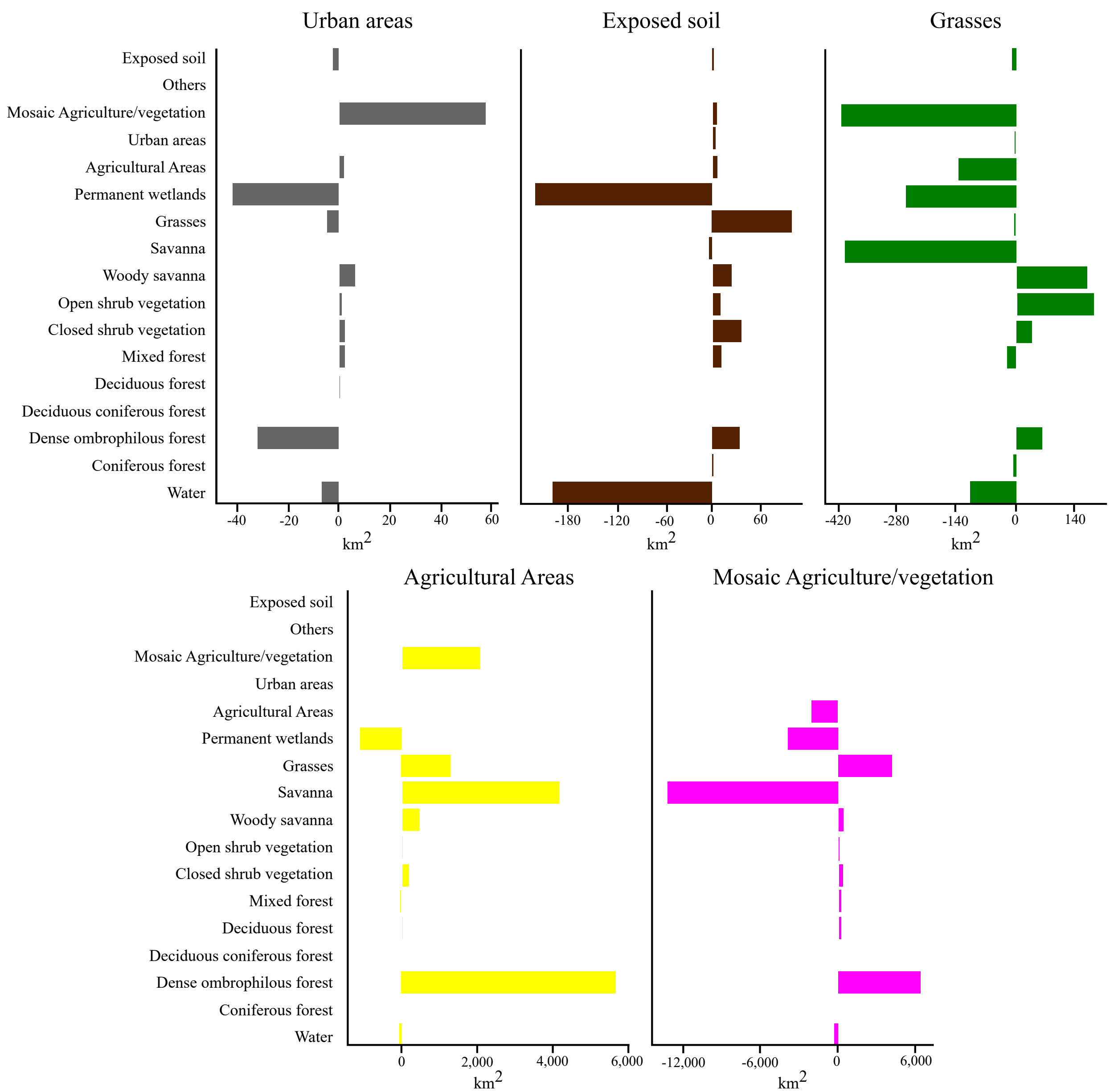

Figure 3. Contribution of classes considered as anthropic actions in the Amazon Biome.

Fuzzy Logic

The fuzzy logic results concerning the anthropic actions classes are shown in Figure 5. For standardization of the legend, where 0 = the greatest environmental vulnerability, that is, the pixel center of the class (red) and 1 = the least vulnerability, therefore, the furthest point from the pixel center (blue).

The classes weights according to AHP model were: V1 = 0.5128; V2 = 0.2615; V3 = 0.1290; V4 = 0.0634; and V5 = 0.0333.

The calculated Consistency Ratio was 0.05, being within the suitable limit (smaller than 0.10, or 10.00%). Therefore, the equation for environmental vulnerability is acceptable. Thus, the adjusted equation for Environmental Vulnerability to human actions (VHA) in the Amazon Biome is presented (Equation 5):

$$VHA = 0.5128 \times FuzzyVAR01 + 0.2615 \times FuzzyVAR02 + 0.1290 \times FuzzyVAR03 + 0.0634 \times FuzzyVAR04 + 0.0333 \times FuzzyVAR05 \quad (5)$$

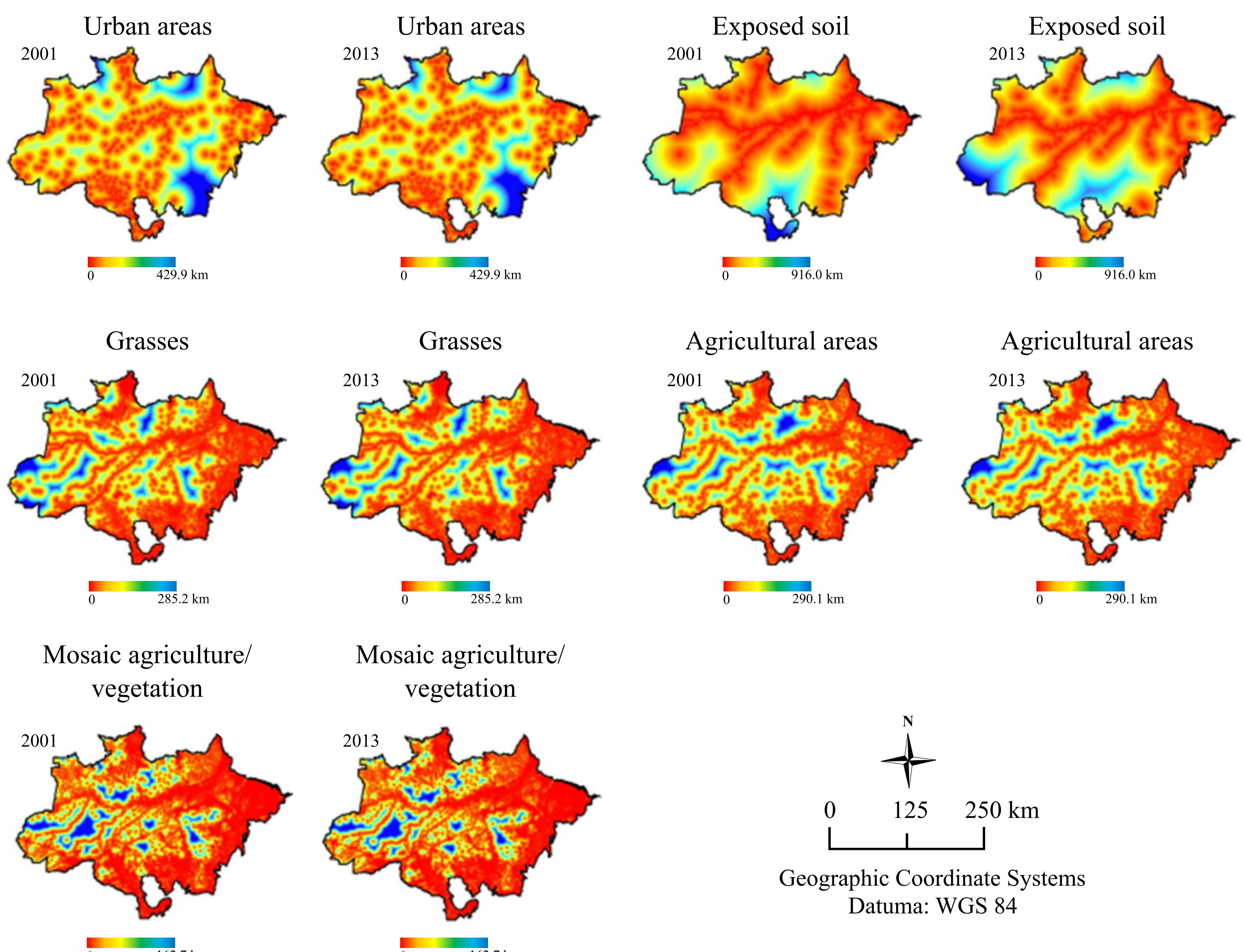

Figure 4. Euclidean distances of the classes belonging to anthropic actions, for years 2001 and 2013. Anthropic actions refer to the following classes: Urban Areas, Exposed Soil, Grasses, Agricultural Areas and Mosaic of agriculture and vegetation.

The map of environmental vulnerability to human actions in the Amazon Biome, generated through Equation 5 for years 2001 and 2013, is shown in Figure 6.

The evolution of environmental vulnerability by state is shown in Table IV.

The net variations of each class for each state, between years 2001 and 2013, can be seen in Table V.

DISCUSSION

Environmental vulnerability of the Amazon biome and its interactions with the planet

Environmental vulnerability is defined as the susceptibility of a community, structure, service or geographical area to suffer damage due to the impact of a given risk (Jordão & Moretto 2015). Thus, urban expansion combined with human activities can directly increase environmental vulnerability (Nguyen et al. 2016).

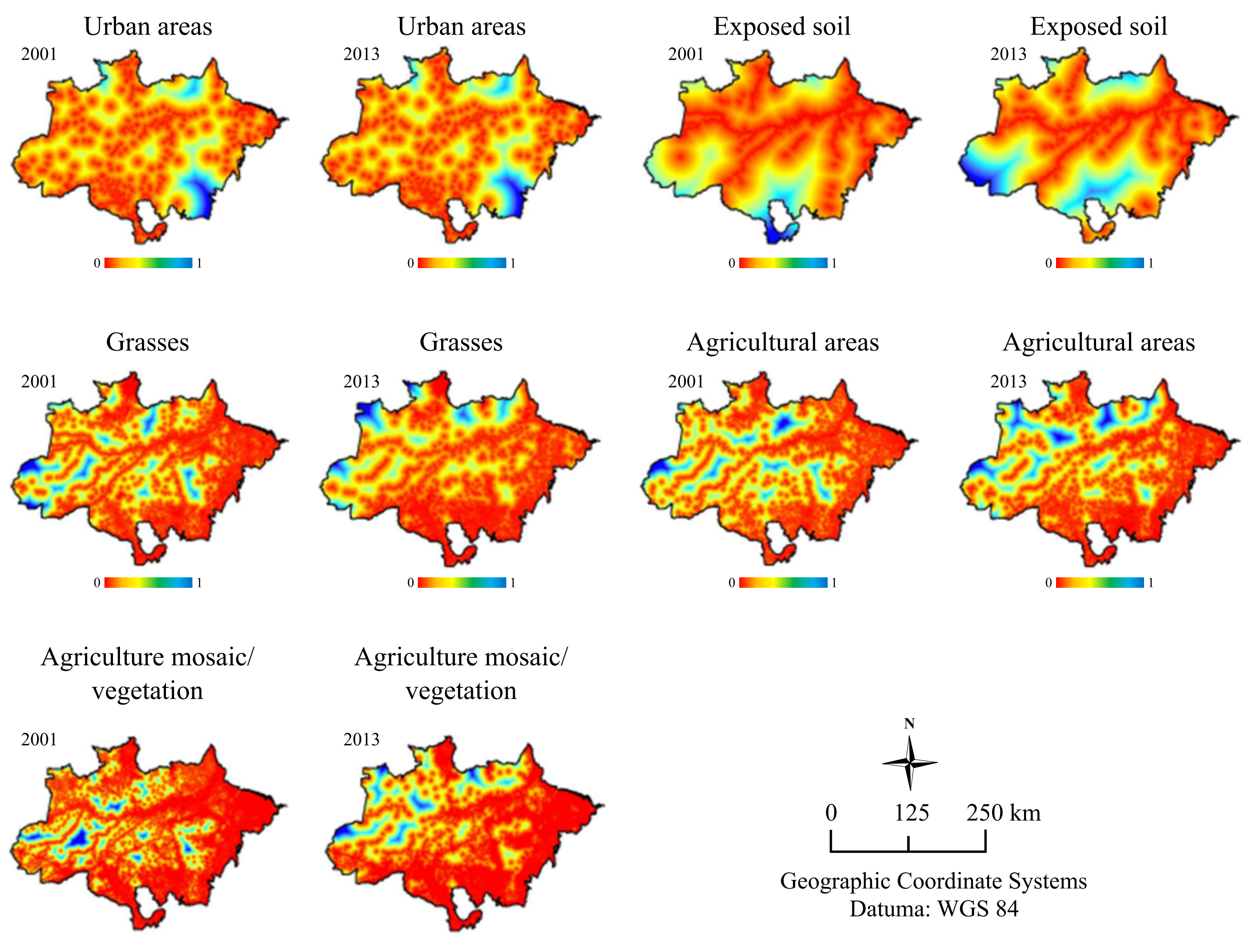

Figure 5. Fuzzy logic classes belonging to anthropic actions, for years 2001 and 2013. Anthropic actions refer to the following classes: Urban Areas, Exposed Soil, Grasses, Agricultural Areas and Mosaic of agriculture and vegetation.

Table IV. Percentage evolution of environmental vulnerability in the states between 2001 and 2013.

States	2001					2013				
	Very High (%)	High (%)	Medium (%)	Low (%)	Very Low (%)	Very High (%)	High (%)	Medium (%)	Low (%)	Very Low (%)
AC	22.60	35.77	33.39	8.04	0.20	27.99	40.57	26.36	4.98	0.10
AM	20.21	29.92	25.91	16.44	7.52	20.68	30.39	25.72	16.75	6.46
AP	68.51	31.11	0.38	0.00	0.00	46.10	15.83	15.56	19.33	3.18
MA	97.88	2.12	0.00	0.00	0.00	97.78	2.22	0.00	0.00	0.00
MT	67.79	24.66	6.87	0.68	0.00	88.87	10.25	0.88	0.00	0.00
PA	52.28	23.98	13.98	8.83	0.93	58.79	21.64	10.63	6.23	2.71
RO	67.32	25.01	6.52	1.15	0.00	88.82	10.51	0.67	0.00	0.00
RR	58.45	25.22	13.38	2.95	0.00	48.79	25.38	14.74	11.06	0.03
TO	100	0.00	0.00	0.00	0.00	100	0.00	0.00	0.00	0.00

Where: AC = Acre; AM = Amazonas; AP = Amapá; MA = Maranhão; MT = Mato Grosso; PA = Pará; RO = Rondônia; RR = Roraima; and TO = Tocantins.

Table V. Liquid variations for the states of the Amazon between 2001 and 2013 in km².

States	Classes (km^2)				
	Very High	High	Medium	Low	Very Low
AC	8,149.90	7,724.70	-10,796.20	-4,788.20	-290.20
AM	7,299.10	7,281.30	-3,015.40	4,880.20	-16,445.20
AP	-31,787.50	-21,674.40	21,535.90	27,409.90	4,516.10
MA	-118.10	118.10	-	-	-
MT	101,100.10	-69,090.10	-28,730.20	-3,279.90	-
PA	81,010.30	-29,098.30	-41,587.90	-32,318.30	21,994.20
RO	50,747.80	-34,231.50	-13,798.50	-2,717.90	-
RR	-21,550.90	358,40	3,036,70	18,099,30	56.50

Where: AC = Acre; AM = Amazonas; AP = Amapá; MA = Maranhão; MT = Mato Grosso; PA = Pará; RO = Rondônia; and RR = Roraima.

When analyzing the environmental vulnerability of a biome as a whole, it is possible to identify several points of worldwide interest, especially when that biome is the Amazon, which is one of the most important ecological systems in the world (Foley et al. 2007). According to Luo et al. (2021), the evolution of vulnerability caused by anthropic actions can result in severe impacts on the environment which lead to the loss of important ecosystem services of immeasurable value, both local and global, such as the maintenance of biodiversity, the climatic, hydrological and carbon stock balance in forest biomass and soil (Foley et al. 2007).

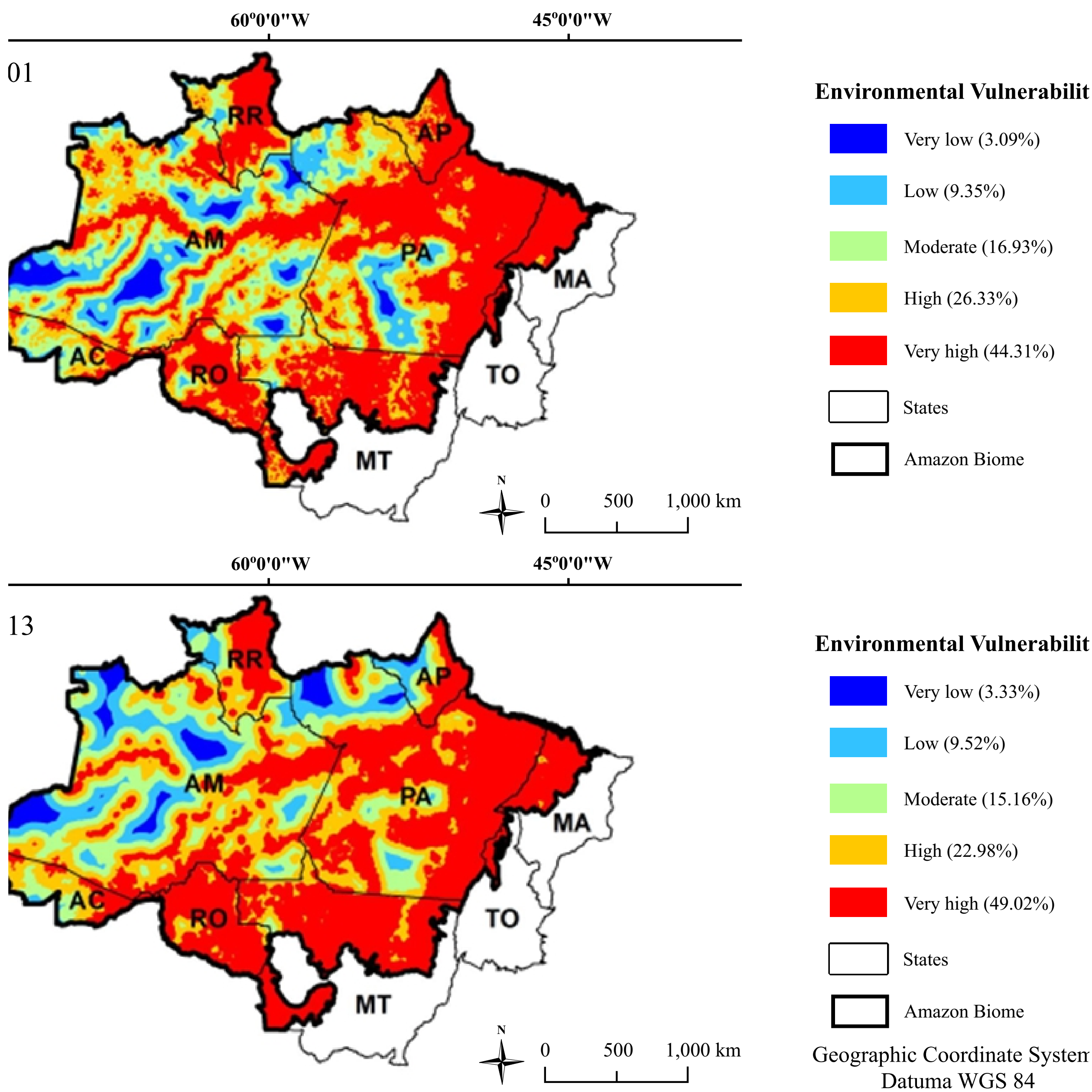

Figure 6. Environmental vulnerability to anthropic actions in the Amazon Biome, for years 2001 and 2013.

Several vectors of environmental changes on a macro scale have been simultaneously occurring with non-linear behavior in the Amazon biome, such as changes in land use and climatic variations, mainly influenced by anthropization and the effects of global warming (Ellwanger et al. 2020). These environmental changes are responsible for the increase in the frequency of extreme weather events and forest fires, which in turn are constantly influenced by the global economy and the inefficient use of resources to meet demands (Nobre et al. 2016).

An example which corroborates the aforementioned information is proposed by Cavalcante & Santos (2012) and Chen et al. (2015); according to the authors, the rural development technique based on the replacement of forests by agriculture, livestock and hydroelectric power generation on a large scale used in the Amazon is extremely inefficient for several social, environmental and economic reasons. The Brazilian agricultural sector is influenced by about 14.5% by Amazon production, which uses about 750,000 km^2 to achieve this result (Nobre et al. 2016). On the other hand, the state of São Paulo, in the southeastern region of Brazil, is responsible for 11.3% of this sector, using 193,000 km^2 (Nobre et al. 2016), which demonstrates the sector's lag in the Amazon compared to the other regions in the country.

In contrast, the events that took place in the Amazon biome also influence the quality of life in the rest of the world. This fact happens because when forested areas converted to anthropized areas becomes more severe, it results in a drastic reduction in the conversion of carbon dioxide into oxygen by photosynthetic processes (Mello & Artaxo 2017). The decrease in photosynthetic processes leads to CO_2 becoming more abundant in the atmosphere and in turn results in an intensification of the greenhouse effect, and an increase in the average temperature of the planet, which is called global warming (Amazonas 2009).

Assessment of the environmental vulnerability of the Amazon biome

The urban area class obtained the greatest weight among all variables (0.5128) due to the high intensity of human activities. The reduction of vegetation cover (Nguyen et al. 2016), expansion of impermeable surfaces (Fan et al. 2019), deforestation (Huang et al. 2019) and pollution of water resources (Vianna 2015) are examples of activities that increase the environmental vulnerability in urban areas.

In addition to urban areas, exposed soil class also had a high mathematical weight (0.2615), being classified as the second most influencing class to the evolution of environmental vulnerability in the biome states. Exposed soils become more vulnerable to erosive processes, leaching, surface runoff and, consequently, contribute to water courses silting up while lose their surface layer (de Almeida et al. 2016, Falcão & Falcão Sobrinho 2019 , Vianna 2015). It is worth noticing that the Amazon surface layer is the most fertile in comparison to other biomes.

Grasses, in turn, obtained the third most influential weight classification on environmental vulnerability (0.1290). Soils from the Amazonian biome are mainly characterized by nutrient poverty, requiring intense nutrient cycling, which is provided by the presence of native vegetation. Consequently, chemical-physical properties of soils tend to worsen while the propensity to vulnerability increases due to impoverishment of nutrient cycling that occurs in grass areas.

The least influential classes, with respective weights, correspond to agricultural areas (0.0634) and mosaic of agriculture areas/vegetation (0.0333). According to Souza et al. (2018), soil is enriched with manure and fertilizers used in production most of the time. In addition, due to nearby native vegetation, nutrient cycling has a certain effectiveness.

By comparing the data for the years of study (2001 and 2013), through Land Change Modeler, a better understanding of spatial and temporal land use change in the Amazon Biome was possible. Thus, from results (Table III), it was noticed that the classes that suffered the most area losses were, respectively, dense ombrophilous forest (209,650.15 km^2) and savannah (184,666.16 km^2), while those with least reductions were others (33.65 km^2) and deciduous coniferous forest (228.01 km^2). Savannas, classified as having anthropic influence, were largely replaced by mosaic of agriculture/vegetation (Figure 3).

Savanna (191,730.11 km^2) and dense rain forest (148,691.80 km^2) suffered the most changes regarding area gains, while were others (98.77 km^2) and deciduous coniferous forest (135.41 km^2) were the classes with least expansions. Dense ombrophilous forest, the class with most net variation, presented a reduction of 60,958.35 km^2 in 2013 when compared with its area in 2001. Urban areas, which suffered the least change during the study period, had a negative net balance of 15.53 km^2 in 2013.

Urban areas class was expected to gain territory over the years due to population growth and anthropic occupation. According to The World Bank (2020), between 2000 and 2013, the Brazilian population increased by around 26 million people in its total population. However, based on data of the present research, this class lost territory concerning the Amazon region.

From Figure 3, it can be seen that urban areas were mainly replaced by permanently flooded areas and dense rain forest during the study period. It is also possible to see that the class that suffered the most reduction in relation to urban areas was the mosaic of agriculture/vegetation.

The agricultural areas also presented expressive results in relation to net variation, showing a positive balance of 13,166.61 km^2 (Table III). The increase in agriculture areas, according to Çolak & Sunar (2020), reflects in higher propensity for forest fires. In addition, the authors Verburg et al. (2014b), affirm that Mato Grosso and Pará States, both constituents of the Amazon biome, were facing deforestation at the period of study, due to common conflicts with agricultural expansion caused by increased international demand for commodities.

Agricultural areas had a significant part of their increase over places previously covered by dense rain forest, savanna, grasses and mosaic of agriculture/vegetation. However, some permanently flooded areas replaced in 2013 areas that were previously used for agriculture (Figure 3).

It is also important highlight that exposed soil areas presented a reduction of 187.99 km^2, contributing to runoff reduction. These areas were mainly replaced by water classes, permanently flooded and grasses (Figure 3).

Another class considered as a result of anthropic actions by the present research, correspond to grasses. According to Table III, this class reduced its area by, approximately, 8,800 km2 during the evaluated period. Figure 3 clarifies that mosaic of agriculture/vegetation, agricultural areas, savannah, permanently flooded areas and places with water presence were the ones that most influenced this significant reduction. In addition, another important data is that woody savanna and open shrub vegetation have replaced part of the area previously covered by grasses.

The Euclidean distance corresponds to the distance from anthropic action pixel to pixels where there is no vulnerability to it. The regions in red correspond to pixel centers while blue refer to regions where there is no vulnerability to anthropic action, considering a pixel size equal to 500 m (Figure 4).

It can be seen (Figure 4) that, for year 2001, the maximum Euclidean distance was 492.2 km for Urban Areas class, 916 km for Exposed Soil, 285.2 km for grasses class, 290.1 km for Agricultural Areas and 162.7 km for Mosaic of agriculture/vegetation. The greater the maximum Euclidean distance, the class will have more areas without the influence of this class for the vulnerability to human actions by it. Thus, we can conclude that exposed soil class is the less influencing one.

In 2013 (Figure 4), Urban Areas class presented the maximum Euclidean distance of 492.8 km, Exposed soil, 756.1 km, and grasses class, 449.9 km. The Agricultural Areas and Mosaic of agriculture/ vegetation presented a distance of 290.7 and 274.5 km, respectively. Similarly, to 2001, the class with least influence in 2013 was also exposed soil.

The maps generated by application of linear membership functions (Supplementary Material - Figure S1) on variables resulting from anthropic actions are shown in Figure 5, while the respective pixel frequencies are shown in Fig. S2. The fuzzy results show that in 2001, the classes that had the highest number of pixels under range of greatest influence for environmental vulnerability (0.00 - 0.25) were, respectively, agriculture/vegetation mosaic (87.00%), grasses (82.90%), agricultural areas (79.60%), urban areas (75.30%) and exposed soil (74.10%) (Fig. S2).

The values remained similar in 2013, however grasses become the class with the largest amount of pixels (85.40%) under 0.00 - 0.25 range, followed by mosaic agriculture/vegetation (83.10%), urban areas (75.30%), agricultural areas (74.20%) and exposed soil (63.90%) (Fig. S2).

These values elucidate that in 2001 all classes presented pixel frequency greater than 70.00% for the most vulnerable points of the Amazon Biome (0.0 - 0.25 range). This means that more than 70.00% of the Biome's territory was very vulnerable to human actions in 2001. In 2013, the pixels frequency for 0.00 - 0.25 range increased for Grass class, that is, areas where there is degraded pasture, and decreased for Exposed Soil, Agricultural areas and Mosaic of agriculture /vegetation. This fact is justified once agricultural areas might have been extensively used until became pasture with degrade rated characteristics.

Areas that do not suffer with anthropic actions (0.76 - 1.00) have not exceed 1.20% in any class during 2001 or 2013. Therefore, it can be said that the Amazon Biome has been constantly exposed to environmental vulnerability during the studied period.

According to AHP method, the classes' weights must add up 100.00% (that is 1), which was observed.

According to Figure 5, in 2001, the very high-high environmental vulnerability class was mainly concentrated in the surroundings of water courses in Amazonas (AM) and Acre (AC) States, as well as on east side of Amapá (AP), Pará (PA) and Mato Grosso (MT) States and, in practically, 100% of the biome area belonging to Tocantins (TO) and Maranhão (MA) States. In addition, there was a strong influence on Roraima (RR) and Rondônia (RO) States. Together, areas belonging to high-high and very high classes represented, in 2001, 70.64% of Amazon biome area.

In 2013, the spatial distribution pattern of vulnerability was maintained. However, there was an increase of 1.36% in the area under influence of high-high and very high classes, corresponding to 72.00% of the biome area. This result indicates the evolution of environmental vulnerability in the Amazon biome, highlighting the need for mitigation measures in order to prevent more worrying levels and their negatives consequences.

From Figure 5, it can be seen that "very high" vulnerability class evolved from 44.31% of the Amazon biome territory in 2001, to 49.02% of the territory in 2013. This class occurs mainly along rivers. This is justified according to National Department of Transport Infrastructure, once waterway transportation, in the northern region of Brazil, is the main transport type, accounting for about 65.00% of the total transported cargo flow (DNIT 2018).

This result shows an increase in the biome environmental vulnerability that is mainly fostered by states of Mato Grosso, Pará and Rondônia, which presented a positive balance of the “very high” class of, respectively, 101,100.10 km^2, 81,010.30 km² and 50,747.80 km² during study period (Table V). According to Table IV, these values correspond to a percentage increase of 21.09% (MT), 6.52% (PA) and 21.50% (RO). This fact can be explained once these three states are part of the “Arc of deforestation”, which according to Macedo et al. (2012), already accounted for 85.00% of deforestation in the Amazon.

Castro (2005) validates these results when he affirms that over the last decades, there has been a continuous loss of forest cover in the Amazon biome, especially in Maranhão, Mato Grosso, Pará and Rondônia States, mainly due to agroforestry cultivation practiced by social groups in family production units. Macedo et al. (2012) conducted a study on deforestation and soy production in southern Amazonia, between 2001 and 2009, founding that there was a change in forest cover for soy cultivation and livestock production in Mato Grosso State.

It is also noticed that “low” and “very low” classes also underwent an evolution in relation to their areas of influence, presenting a respective jump from 3.09% and 9.35% in 2001 to 3.33% and 9.52% in 2013 (Figure 5). This result is interesting, given that, despite the significant increase in “very high” class, there were states that managed to reverse part of the vulnerability process in their areas. Thus, it was observed a joint increase of “very low” and “low” classes in Amapá (31,926.00 km^2) and Roraima (18,155.80 km^2) States (Table V). In percentage, these values correspond to a respective increase of 22.51% and 8.15% between 2001 and 2013 (Table IV).

The “middle” and “upper” classes, however, underwent an involution process during the studied period. Middle class decreased from 16.93% in 2001 to 15.16% in 2013 (Figure 5), mainly in Pará (-41,587.90 km^2) and Mato Grosso (-28,730.20 km^2) States (Table V). Upper, on the other hand, reduced its area of influence from 26.33% to 22.98% (Figure 5), mainly in Mato Grosso (-69,090.10 km^2) and Rondônia (-34,231.50 km^2) states.

These results are of paramount importance, considering that the Amazon extension covers 9 countries (Brazil, Bolivia, Colombia, Ecuador, Venezuela, Guyana, French Guiana, Peru, Suriname). Thus, this research identify, quantify and map the environmental vulnerability that influenced the Amazon biome between 2001 and 2013. Given that environmental vulnerability is expected to continue, new studies are needed to develop mitigation measures that integrate all biome border holders, among Brazilian states and nearby countries.

CONCLUSIONS

The application of remote sensing techniques allows to determine and assess the evolution of environmental vulnerability with precision and reliability in the Amazon biome, as well as any other area of the planet. Based on the vulnerability analysis, it is possible to conclude that mitigation measures need to be implemented with some urgency, given that “very high” risk class showed significant changes towards positive balance in five out of the 9 states that compose the Amazon biome.

The presence of highly vulnerable areas in the vicinity of water courses is mainly due to urban areas and agricultural crops. In the Amazon region, part of the cities are located in the rivers marginal regions due to ease transportation, while agriculture due to availability of water for cultivation.

Areas of exposed soil, which can be considered as sandbanks when close to rivers, were reduced in 2013 due to increase in the Water class. There was a rainfall increase in the Amazon region, which consequently increased the volume of water courses covering the sandbanks.

The States with greatest territorial extensions under “high-high” and “high” risk were Mato Grosso and Pará, however, it is important to clarify that, although relatively small, the Tocantins State area is completely taken by the class of greatest risk of environmental vulnerability since 2001. The Amapá State, on the other hand, was the most significant in relation to “low” and “very low” risk classes.

One of the main problems to be analyzed with caution is that a large part of the areas classified under “very high” risk class are found in the vicinity of water courses, highlighting the negative aspects of human presence and waterway transport in the biome.

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SUPPLEMENTARY MATERIAL

Figures S1, S2.
Table SI.

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