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Modeling Dynamics in Land Use and Land Cover and Its Future Projection for the Amazon Biome

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Abstract: The objectives were to analyze the dynamics of land use and land cover of the Amazon biome over time through spatial modeling, and project its future scenario with the Land Change Modeler (LCM) module. This analysis was based on 1985, 2014 and 2017 land cover data from the MapBiomas project, which was associated with socioeconomic explanatory variables based on the Cramer-V test. Results showed that the Forest Formation class occupied 3,844,800.75 km^2 (91.20%) in 1985, and in 2014, there was a reduction to 3,452,129.25 km^2 (81.89%). The pasture class had an initial area of 71,046.50 km^2 (1.69%), and in 2014, there was an expressive increase to 437,670.00 km^2 (10.38%). The analysis made it possible to verify that Forest Formation and Pastures were the classes that suffered the most changes, followed by the Annual and Perennial Culture and Mosaic of Agriculture and Pasture. The projected land use and coverage for 2044 suggests that there will be a reduction in Forest Formation due to a significant increase in the Pasture class. The simulations foreseen in this work are an important tool that can provide subsidies for supporting territorial planning in the region, public policies, and encouragement of best practices with a reduced impact in pasture areas.

Keywords: land use; deforestation; rainforest; simulation

1. Introduction

The Amazon is the world's largest tropical rainforest, representing 35% of the total primary forest land. It provides a series of essential ecosystem services, making it extremely important to understand its behavior in the face of various disturbances. It not only stands out due to its great biodiversity but also influences regional and global climates [1,2].

The Amazon biome is located within the tropics and provides a wide range of essential ecosystem services such as biodiversity maintenance, storage and absorption of atmospheric carbon, transport of trace gas, aerosols, and water vapor to other regions of the country, and especially precipitation recycling [3,4].

Given the importance of this biome and its diverse environmental functions, the Amazon has been extensively studied to understand its behavior in the face of disturbances as well as its influence over climate.

Brazil has one of the largest areas of forest cover in the Amazon biome; however, there are extensive deforested areas due to fast-developing anthropic activities such as logging, livestock, burning, and urbanization that emit high amounts of gases and aerosols into the atmosphere. In addition, changes in land use are strongly influenced by the occurrence of devastating fires that have spread across the Brazilian Amazon in recent years. Such fires are strongly related to deforestation [5].

The rapid change in land use and land cover is considered one of the main factors that promote a decline in ecosystem and environmental conditions, generating several ecosystem disservices [6,7]. For instance, deforestation results in the loss of biodiversity [8], soil exposure to erosion [9], and loss of forest functions concerning water cycling and carbon storage [10]. In addition, changes in forest cover cause serious damage to the local and regional climate [11].

Thus, understanding the recent and anticipated structure and dynamics of land use becomes essential for landscape management and aids in the implementation of public policies and environmental prevention aimed at preserving and conserving the Amazon biome. In this context, geotechnologies serve as fundamental tools for this study [4,12–14]. The combined use of remote sensing techniques, geographic information systems (GIS), and terrestrial environment modeling allows for the analysis of changes in behavior as well as the simulation of future scenarios.

Modeling is considered one of the most used techniques for studying land cover dynamics [15] and can be performed through computational models of change detection such as Land Cover and Use Change (LUCC). These models seek to explain the causes of the changes and predict where, when, and how the changes will occur, assisting in establishing the factors associated with them and different scenarios of future projections [16,17].

In this sense, the search for low-cost, faster, and accurate techniques concerning the processing of large areas is essential for mapping and monitoring deforestation and agricultural crop expansion, which are the main factors responsible for the decrease of native forests.

Some studies in the literature in Brazil and in the world prove the importance and applicability of the study of soil dynamics and occupation. One can cite research in modeling the dynamics of land use and land cover change for the Amazon [11]; the assessment of land use and land cover change in Pakistan [18]; land use changes in the city of Lagos [19]; and characteristics of land use change in a temperate rainforest in Mexico [20]. Thus, one can see the potential and importance of modeling for land use and land cover studies, as it is a widely used technique.

This study differs from others with a similar theme in the sense that it presents a spatialized future scenario of land use and cover for the entire Amazon biome in the Brazilian portion, which was based on modeling land cover and use throughout a long period of time and with more recent dates using the MapBiomas product. In addition, it identifies how much each class gained or lost in area for other classes by mapping the losses and gains for each class, areas of change, areas of persistence, and specific transitions between coverage classes.

Given the above information, current and previous knowledge of land use and land cover dynamics becomes an essential tool for land use planning and assistance in implementing public policies and environmental interventions aimed at preserving and conserving the Amazon Biome. Therefore, the objective of this study was to analyze the dynamics of land use and cover over time through spatial modeling and project its future scenarios for the Amazon biome.

2. Materials and Methods

2.1. Study Area

The study area pertains to the Brazilian portion of the Amazon Biome (Figure 1). This is the largest biome in Brazil, covering an area of 4,196,943 km^2, which represents approximately 40% of the national territory and spans nine states: Amazonas, Pará, Mato Grosso, Acre, Rondônia, Roraima, Amapá, part of Tocantins, and part of Maranhão [21]. It is notable for its extensive plant and animal species diversity, with a wide and largely unknown genetic variety [22].

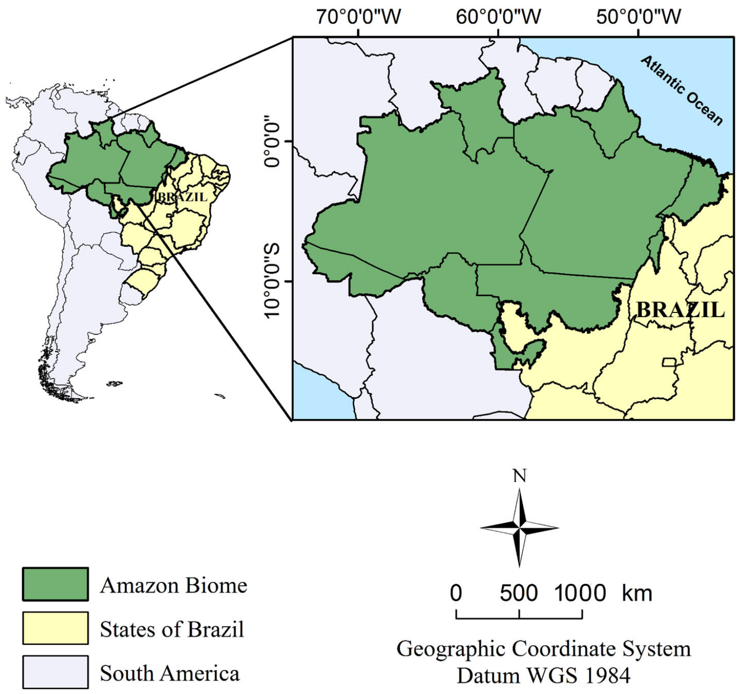

Figure 1. Corresponding portion of the Amazon Biome within the Brazilian territory.

The Amazon biome is composed of a mosaic of ecosystems conditioned by a great diversity of relief, climates, water cycles, rainfall, sunlight, and moisture [23]. According to Köppen's definitions [24], the climate in the region falls into three categories: (a) rainy equatorial (Af), (b) monsoon tropical (Am), and (c) dry and humid tropical (Aw) [25]. The predominant vegetation of the Amazon biome is the Dense Rainforest, which covers 41.67% of its area [26].

2.2. Database

2.2.1. Land Use and Land Cover

For the analysis of changes in land use and land cover, land use and land cover data from the MapBiomas Project—Collection 3.0 of the Annual Series of Land Cover and Land Use Maps of Brazil [27] were used. The data were collected for the years 1985, 2014, and 2017, and had a 30 m spatial resolution and annual temporal resolution. All MapBiomas coverage and land use maps are produced through the pixel-by-pixel classification of Landsat satellite images [28]. The classification process was carried out using extensive machine learning algorithms on the Google Earth Engine platform, which offers immense processing power in the cloud. To facilitate the parameterization of the algorithms and the organization of all processing steps, the platform used 5561 $\times$ 1.5° (latitude/longitude) charts from the IBGE [29,30]. This approach enabled the generation of annual mapping of land use and land cover for the Brazilian territory, from which the delimitation with classes defined for the biome was extracted. The images were exported from Google Earth Engine, a computing platform that allows users to perform geospatial analysis on Google's infrastructure cloud platform [31] and projected to the Albers Conical Equivalent projection system [32], using ArcGIS® software version 10.3 [33].

The year 1985 was chosen due to the characteristics of the satellite, as this was when the Landsat satellite began operating. The year 2014 was chosen because it was considered suitable to represent changes over a large part of the study period, and 2017 was chosen because it was the most current period studied. The decision to use the MapBiomas product was based on its availability and applicability, as it provides pre-classified data over long periods of time.

2.2.2. Highways

To represent the distance of a potential impact in the future scenario simulation, the explanatory variable "highways" (a variable that may encourage changes) was used. A 250 m buffer was applied to create a 500 m wide zone with the same pixel scale as the land use and land cover image.

2.2.3. Protected Areas

In order to incorporate restrictive variables into the modeling process, maps from the Instituto Chico Mendes de Conservação da Biodiversidade (ICMBIO) [34] that depict the locations of Federal Protected Areas were utilized.

2.2.4. Water Courses

The explanatory variable "Watercourses," which was obtained from the website of the Agência Nacional de Águas e Saneamento básico (ANA) [35], was used to inform the analysis of changes in the simulation of future scenarios.

2.2.5. Elevation and Slope Data

The Digital Elevation Model (DEM) was used to determine the altimetry and slope of the study area. The DEM was obtained from the Shuttle Radar Topography Mission (SRTM) [36] radar with a spatial resolution of 30 m. These raster images were adapted and provided by the GIS Laboratory of the Ecology Center of UFRGS [37].

2.2.6. Rainfall Images

Rainfall data for 2017 were obtained from the Modern-Era Retrospective analysis for Research and Applications project, Version 2 (MERRA-2) [38], which was made available through the National Aeronautics and Space Administration (NASA). The reanalysis resolution was $0.5° \times 0.625°$ in latitude and longitude, respectively, and the data were obtained in millimeters per month. Monthly images were used to create a single image of the annual precipitation for the year 2017.

The other explanatory variables used in the modeling process were obtained from the land use and land cover maps provided by the MapBiomas project [27].

2.3. Images Pre-Processing

All images used in the database were projected to the Tapered Equivalent Albers projection in order to preserve areas and reduce distortions. The images were then standardized and resampled to a spatial resolution of 500 m. This processing was carried out using the ArcGIS 10.3 computer application.

Before the images were inserted into the Land Change Modeler change analysis module (LCM) coupled with TerrSet version 18.0 software [39], they were converted to ".rst" format using the SAGA version 2.2.8 computer application [40].

The dynamics of changes in land use and land cover were generated through the LCM module, coupled with TerrSet 18.0 software. This enabled the creation of maps representing losses, gains, net changes, switching between classes, class persistence, and simulations of future scenarios.

2.4. Dynamics of Changes and Projection of Future Land Use and Cover

The analysis of land cover change was based on land use and cover maps for 1985 and 2014, which refer to the modeling calibration period. The "Trend Spatial" function was used to obtain the spatial trend from the change maps, which is based on a third-order polynomial parameter. The resulting interpolation values, whether lower or higher, indicate less or more change [41].

For the calibration and validation of the potential transition sub-model, transitions of interest were defined based on prior knowledge of the dynamics of the study area. These transitions included Forest Formation to Pasture, Forest Formation to Annual and Perennial Culture, Agriculture Mosaic or Pasture, Mosaic of Agriculture and Pasture to Annual and Perennial Culture, Another Non-Forest Natural Formation to Mosaic of Agriculture and Pasture, and Pasture to Annual and Perennial Culture.

These transitions were determined by analyzing and understanding the land cover changes in the study area between 1985 and 2014, with the help of the Change Analysis tool, which also identified the main cover classes.

After defining the transitions of interest, explanatory variables related to physical and socio-economic factors were tested and selected for entry and calibration of the potential transition sub-model (Table 1). These variables were derived from previous mappings and selected based on the history of the area's occupation and their potential to explain changes. The Distance tool was used to determine the distance of variables related to socioeconomic aspects. For this step, the Cramer-V test [42], made available by LCM, was used to relate categorical variables. Cramer-V is a number between 0 and 1 that indicates the strength of association between two categorical variables [43]. Only variables with Cramer-V values greater than 0.15 were selected, as a significant relationship between the change in coverage and the explanatory variable is usually only created from this value [44]. This processing was performed on the Potential Transition tab.

Table 1. Explanatory variables tested for validation and calibration of the potential transition sub-model.

Explanatory Variables	Units
Altitude	m
Slope	%
Annual Average Precipitation	mm
Distance from Highways	m
Distance from Water Courses	m
Distance from Urban Infrastructure	m
Distance from Pasture	m
Distance of Annual and Perennial Culture	m
Distance from Semi-Perennial Culture	m
Distance from Agriculture and Pasture Mosaic	m
Distance from Mining	m
Distance from Protected Areas	m
Distance from Change Areas	m

After selecting the transitions of interest and the explanatory variables, each transition was modeled using the Multilayer Perception Neural Network (MLPNN), in the LCM module, generating a potential map for each transition.

After this modeling, a potential transition map was generated, which represented the change probability for each cell of the transitions of interest, with values between 0 and 1, where values close to 0 represent a low probability of change while values close to 1 represent a greater potential of change. This probability was used to carry out the allocation of changes.

Next, the changes in land cover were modeled, which included a validation step. The validation of the land cover simulation was performed by comparing the mapped and simulated land cover maps for the year 2017. To validate, the Minus tool was used along with the Validate function from Terrset, which employed an additional measure according to the methodology proposed by Pontius Junior, Huffaker, and Denman [45] through the Validate tool.

According to Pontius Junior, Huffaker, and Denman [45], information is provided on how much a pair of maps coincides, in terms of the number of pixels and the location of pixels in each category [44], in which the following resulting indices were analyzed: quantity agreement—N (m), standard agreement—M (m) and adjusted location agreement—P (m), in addition to standard Kappa—Kstandard, Kappa for no information—Kno and Kappa for location—Klocation. A value equal to or greater than 0.80 is considered strong, and it is reasonable to make future projections plausible [46,47].

To simulate land cover changes and make future predictions, the Markov Chain prediction process was used to determine the amount of changes that occurred at a later date based on two maps of land cover—an older and a newer one.

The Markov Chain is a mathematical model that describes processes that move in a sequence of steps and through a finite number of discrete states. The probability of obtaining a given state at time t + 1 depends only on the state verified at time t. A Markov process is one in which the state of a system can be determined by knowing its previous state and the probability of transition from one state to another [48]. In LCM, the Markov Chain determines how many pixels are most likely to convert and will be considered for the change of use and cover of the studied land [49]. The model assumes transitions as stationary, which means that the statistics do not change over time [48,50–52]. Therefore, the transitions between a land use and land cover map of time 1 (t1) and time 2 (t2) are used as an example to predict the land cover of future time (t3) [53].

The Markov Chain enabled the quantification of changes in land use and cover based on the projection of future transition potentials, generating a transition probability file for each category [54]. Consequently, a land use and coverage model was obtained by comparing land cover between the years 1985 and 2014.

Based on this data, simulations were performed for the years 2017 and 2044. The simulation for the year 2017 was used for model calibration and validation, while the simulation for the year 2044 represents the next 30 years from 2014, after model calibration. It is important to note that the simulation of land use and cover was based on the assumption that the observed conditions of change in land use and land cover between 1985 and 2014 would remain unchanged.

The allocation phase for the 2017 change was conducted using the hard prediction option, which indicated the future land use and coverage for each cell. This simulation was based on the interaction between the transition matrix (obtained from the Markov chain) and the potential transitions mapped to each pixel (obtained from the potential transition sub-model). For the year 2044, two simulation options were utilized: hard prediction and soft prediction. The hard prediction method projects a specific scenario resulting in a land use and cover map with the same input categories [55]. In contrast, the soft prediction method characterizes each pixel based on the higher probability of change [44]. The resulting smoothed map represents the vulnerability to change, creating a classification of areas that are less prone to more prone to change, ranging from 0 to 100% on a scale (Table 2) [56].

Table 2. Classes of vulnerability to change.

Change Vulnerability Percentage	Vulnerability to Change
0%	There will be no change
0%–5%	Very low vulnerability to change
5%–15%	Low vulnerability to change
15%–50%	Medium vulnerability to change
50%–80%	High vulnerability to change
80%–100%	Very high vulnerability to change

Source: Adapted from Luiz (2014) [56].

Figure 2 simplifies the methodological steps needed to develop this research as described above.

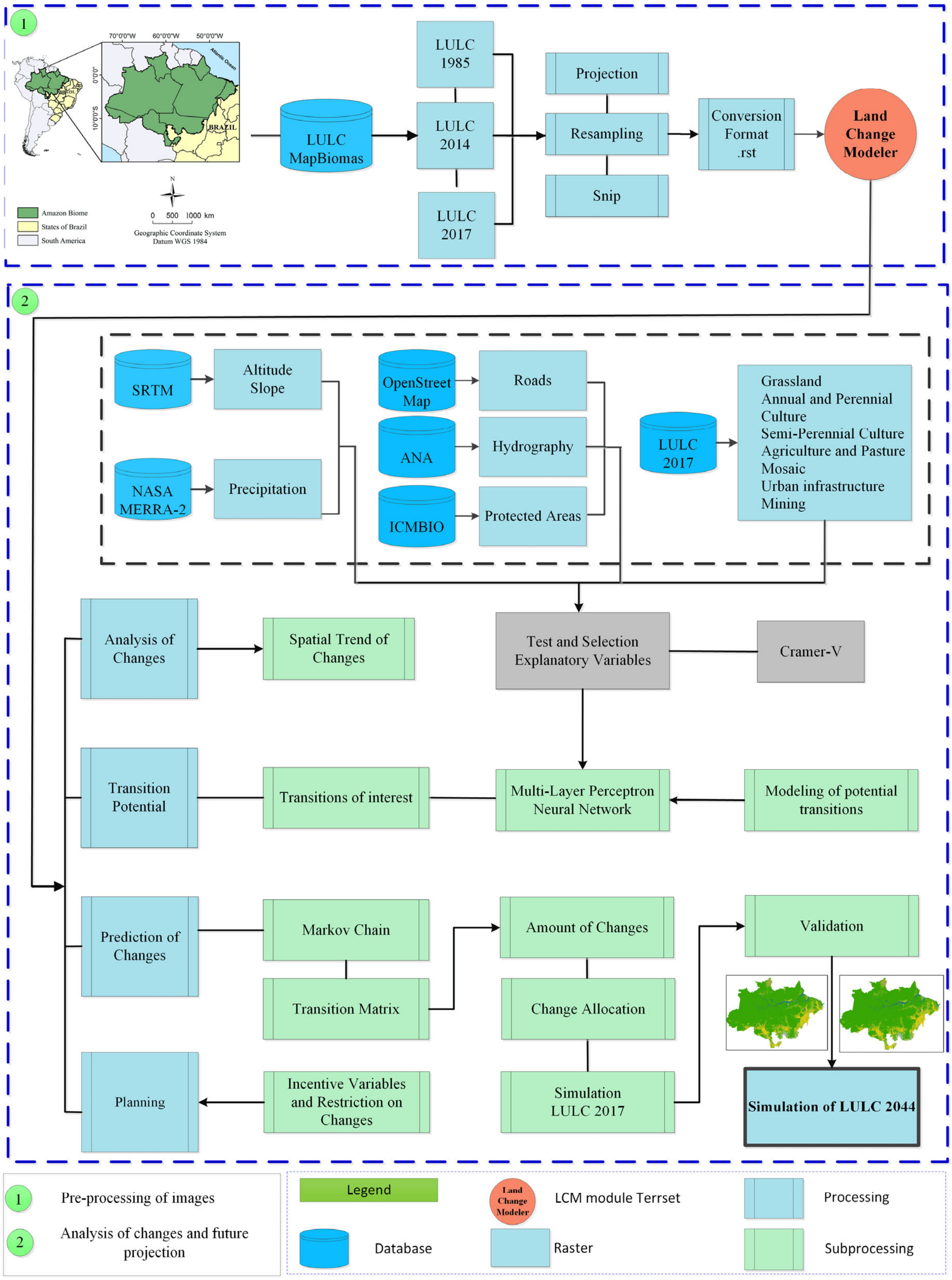

Figure 2. Simplified flowchart outlining the methodological steps of this research. Abbreviations used: LUO—Land Use and Land Cover; SRTM—Shuttle Radar Topography Mission; NASA—National Aeronautics and Space Administration; MERRA-2—Modern-Era Retrospective Analysis for Research and Applications, Version 2; ANA—National Water Agency; ICMBIO—Chico Mendes Institute for Biodiversity Conservation.

3. Results

3.1. Mapping Land Use and Land Cover among 1985, 2014, and 2017

The land use and land cover maps for the Amazon biome in 1985, 2014, and 2017 are presented in Figure 3. The quantification of classes in square kilometers and their percentage in relation to the study area are displayed in Table 3.

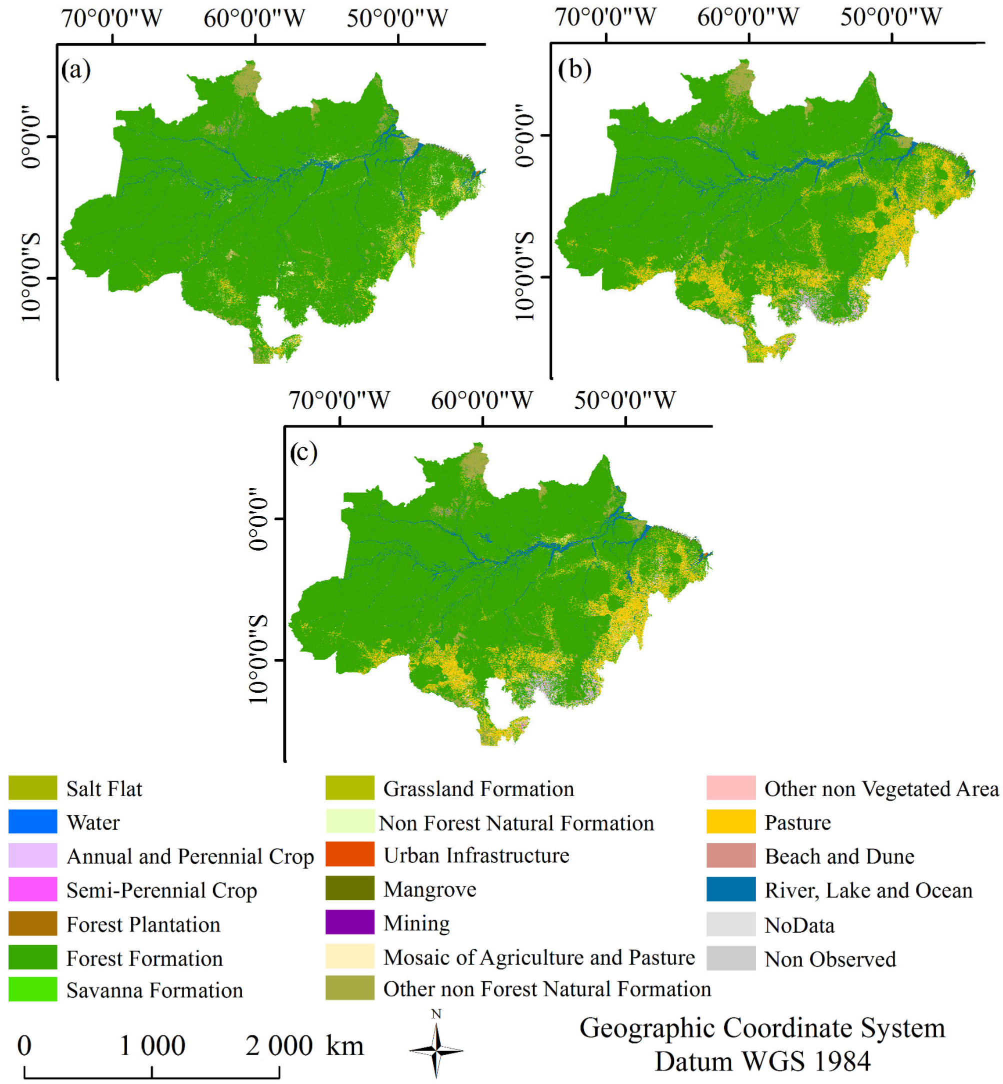

Figure 3. Land use and land cover in 1985 (**a**), 2014 (**b**), and 2017 (**c**).

Table 3. Quantification of land use and land cover classes for the years 1985, 2014, and 2017.

	1985		**2014**		**2017**	
Classes	**Area (km^2)**	**%**	**Area (km^2)**	**%**	**Area (km^2)**	**%**
Forest Formation	3,844,800.75	91.20	3,452,129.25	81.89	3,482,721.50	82.61
Savanna Formation	4708.50	0.11	4804.50	0.11	3060.25	0.07
Mangrove	7234.25	0.17	7510.25	0.18	6827.50	0.16
Planted Forest	25.00	0.00	305.25	0.01	438.00	0.01
Non-Forest Natural Formation	0.50	0.00	0.00	0.00	0.00	0.00
Grassland Formation	3340.75	0.08	5573.75	0.13	3574.25	0.08
Salt Flat	139.25	0.00	283.00	0.01	401.75	0.01
Other Non-Forest Natural Formation	117,054.50	2.78	110,970.75	2.63	114,915.75	2.73
Pasture	71,046.50	1.69	437,670.00	10.38	375,159.50	8.90
Annual and Perennial Culture	793.25	0.02	41,232.50	0.98	44,500.50	1.06
Semi-Perennial Culture	0.00	0.00	709.00	0.02	608.75	0.01
Mosaic of Agriculture and Pasture	58,849.75	1.40	33,311.75	0.79	69,413.25	1.65
Urban infrastructure	1939.75	0.05	2798.50	0.07	2781.25	0.07
Mining	13.25	0.00	119.00	0.00	146.75	0.00
Beach and Dune	31.00	0.00	53.50	0.00	43.00	0,00
Other Non-Vegetated Area	6299.25	0.15	3079.25	0.07	3316.50	0.08
Water bodies	6.00	0.00	0.00	0.00	8.25	0.00
River, Lake, and Ocean	99,112.25	2.35	114,814.50	2.72	107,465.25	2.55
Not observed	53.75	0.00	160.75	0.00	57.75	0.00
No Data	195.00	0.00	117.75	0.00	203.50	0. 00
Total	4,215,643.25	100	4,215,643.25	100	4,215,643.25	100

When analyzing the three scenarios, it is visually apparent that the Forest Formation class occupies a larger territorial extension in general. However, over the years, its area has concurrently been reduced due to the increase in Pasture.

According to the results (Figure 3 and Table 3), the predominant land use and land cover class for all analyzed periods (1985, 2014, and 2017) is represented by the Forest Formation. In 1985, this category covered an area of 3,844,800.75 km^2 (91.20%), and in 2014, it decreased to 3,452,129.25 km^2 (81.89%). However, in 2017, there was a 0.72% increase, representing a total forest area of 3,482,721.50 km^2 (82.61%).

In 1985, the Pasture class had an area of 71,046.50 km^2 (1.69%). In 2014, there was a significant increase to 437,670.00 km^2 (10.38%), and in 2017, a slight reduction to 375,159.50 km^2 (8.90%).

Anthropic classes such as the Annual and Perennial Culture class and Mining class have continually increased from 793.25 km^2 (0.02%) to 44,500.00 km^2 (1.06%) and from 13.25 km^2 (0.00%) to 146.75 km^2 (0.00%), respectively. The Semi-Perennial Culture class showed no evidence in 1985, but in 2014, it presented an area of 709.00 km^2 (0.02%). In 2017, there was a small reduction to 608.75 km^2 (0.01%). The Urban Infrastructure class covered an area equivalent to 1939.75 km^2 (0.05%) in 1985, increasing to 2798.50 km^2 (0.07%) in 2014. In 2017, it slightly decreased to 2781.25 km^2, but still accounting for 0.07% of the total area.

3.2. Graphical and Tabular Analysis of Changes between 1985 and 2014

Figure 4 and Table 4 represent the gains and losses of each class in the analyzed period. The results show that the class with the greatest increase in area was Pasture, with a 381,386.25 km^2 increase. Forest Formation was the class with the greatest area loss, with a reduction of 447,377 km^2. The Annual and Perennial Culture class decreased by 167.5 km^2 and subsequently significantly increased by 40,606.75 km^2. The other classes showed slight variations in gain and loss of area.

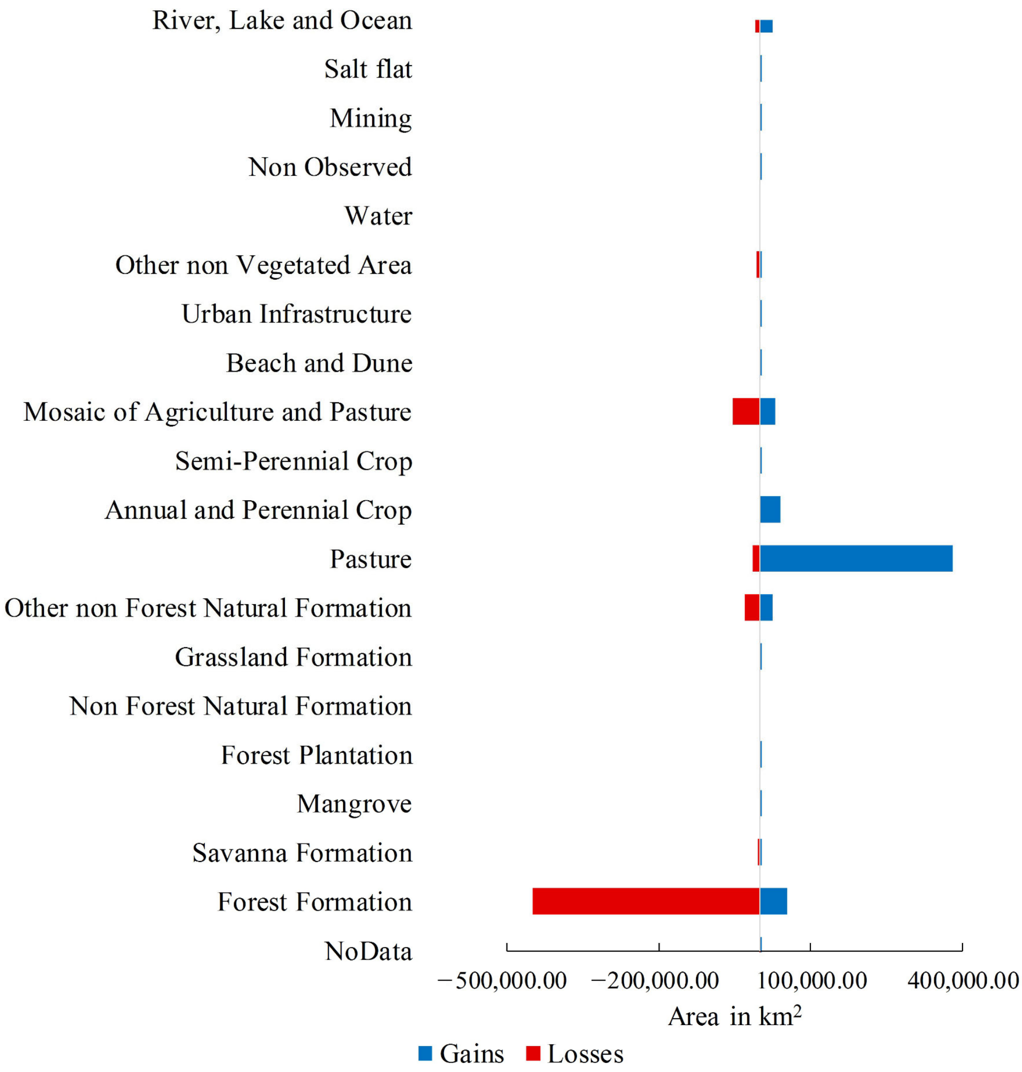

Figure 4. Area gains and losses by category between 1985 and 2014.

Table 4. Gains and losses in km^2 by category.

Classes	Losses (km^2)	Gains (km^2)	Classes	Losses (km^2)	Gains (km^2)
No Data	−115.75	38.50	Semi-Perennial Crop	0.00	709.00
Forest Formation	−447,377.00	54,705.50	Mosaic of Agriculture and Pasture	−54,230.25	28,692.25
Savana Formation	−3517.50	3613.50	Beach and Dune	−18.25	40.75
Mangrove	−1290.25	1566.25	Urban Infrastructure	−306.25	1165.00
Forest Plantation	−22.50	302.75	Other Non-Vegetated Area	−6087.75	2867.75
Non-Forest Natural Formation	−0.50	0.00	Water	−6.00	0.00
Grassland Formation	−1526.26	3759.25	Non-Observed	−33.25	140.25
Other Non-Forest Natural Formation	−31,115.25	25,031.50	Mining	−10.50	116.25
Pasture	−14,762.75	381,386.25	Salt flat	−103.50	247.25
Annual and Perennial Crop	−167.50	40,606.75	River, Lake, and Ocean	−9566.50	25,268.75

The net variation for each land use class is presented in Figure 5 and Table 5. Forest Formation (−392,671.50 km^2) and Pasture (366,623.50 km^2) exhibited the greatest net variations, followed by Annual and Perennial Culture (40,439.25 km^2), Mosaic of Agriculture and Pasture (−25,538 km^2), and River, Lake, and Ocean (15,702.25 km^2). The other classes showed only minor variations.

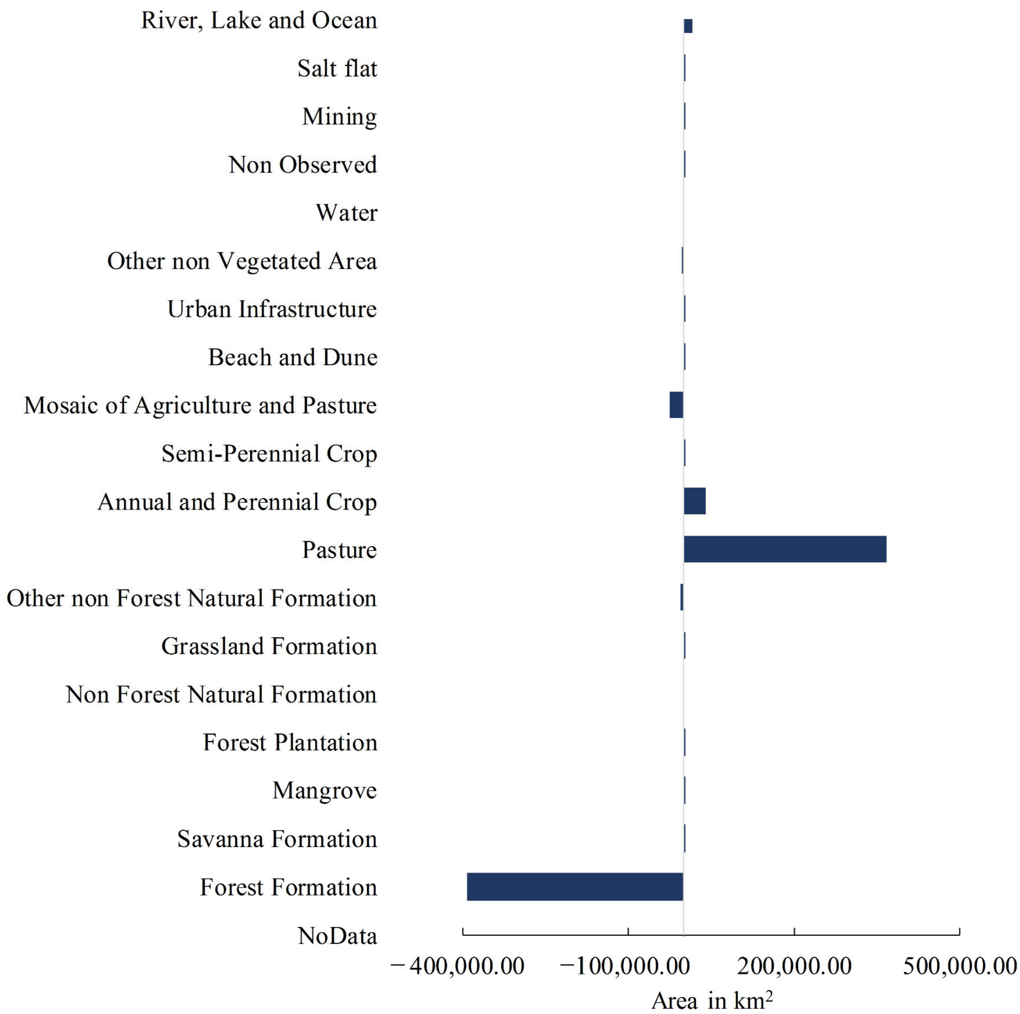

Figure 5. Net variation by category between 1985 and 2014.

Table 5. Net change by category between 1985 and 2014 in km^2.

Classes	Variation (km^2)	Classes	Variation (km^2)
No Data	−77.25	Semi-Perennial Crop	709.00
Forest Formation	−392,671.50	Mosaic of Agriculture and Pasture	−25,538.00
Savana Formation	96.00	Beach and Dune	22.50
Mangrove	276.00	Urban Infrastructure	858.75
Forest Plantation	280.25	Other Non-Vegetated Area	−3220.00
Non-Forest Natural Formation	−0.50	Water	−6.00
Grassland Formation	2233.00	Non-Observed	107.00
Other Non-Forest Natural Formation	−6083.75	Mining	105.75
Pasture	366,623.50	Salt flat	143.75
Annual and Perennial Crop	40,439.25	River, Lake, and Ocean	15,702.25

As the Forest Formation and Pasture classes exhibited the largest net variations, the focus of the results will be on these two classes. The variations of the Forest Formation and Pasture classes in relation to the other classes are presented in Figure 6 and Table 6, as well as in Figure 7 and Table 7.

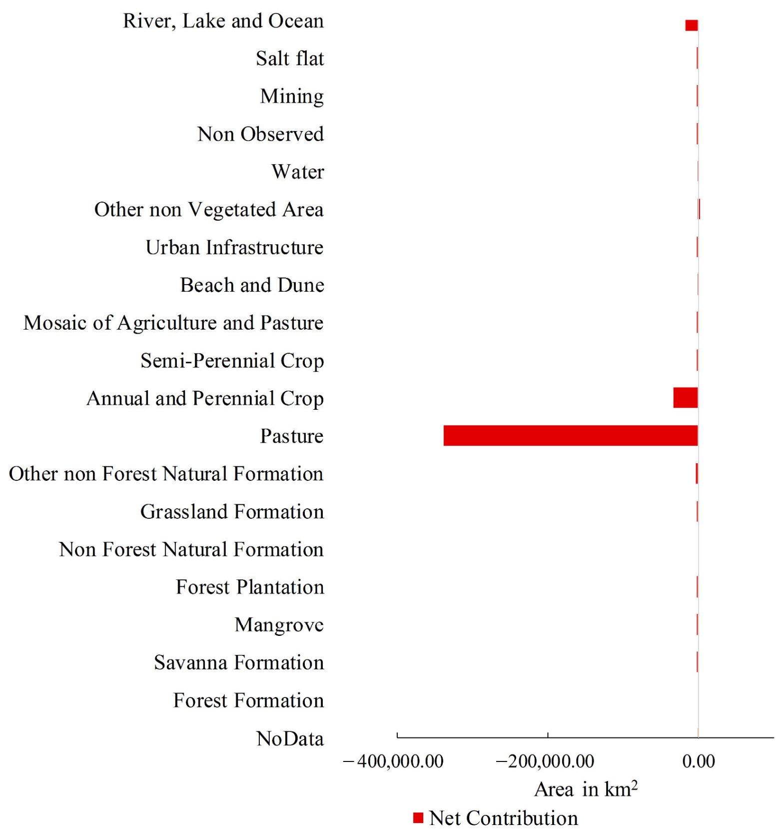

Figure 6. Variation of Forest Formation class in relation to the other classes.

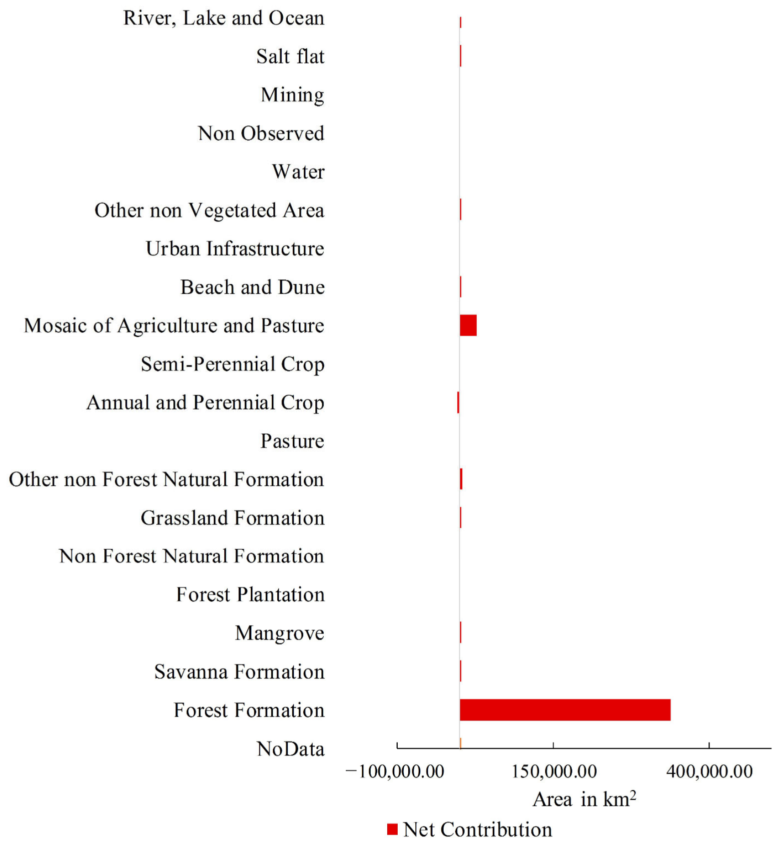

Figure 7. Variation of Pasture class in relation to the other classes.

Table 6. Variation of Forest Formation class in relation to the other classes.

Classes	Contribution (km^2)	Classes	Contribution (km^2)
No Data	10.50	Semi-Perennial Crop	−186.50
Forest Formation	0.00	Mosaic of Agriculture and Pasture	−236.25
Savana Formation	−1032.75	Beach and Dune	0.50
Mangrove	−382.25	Urban Infrastructure	−651.75
Forest Plantation	−232.75	Other Non-Vegetated Area	1691.00
Non-Forest Natural Formation	0.00	Water	4.00
Grassland Formation	−417.50	Non-Observed	−24.50
Other Non-Forest Natural Formation	−3116.75	Mining	−91.25
Pasture	−337,845.00	Salt flat	−81.50
Annual and Perennial Crop	−33,603.25	River, Lake, and Ocean	−16.475.50

Table 7. Variation of Pasture class in relation to the other classes.

Classes	Contribution (km^2)	Classes	Contribution (km^2)
No Data	7.00	Semi-Perennial Crop	−321.75
Forest Formation	337,845.00	Mosaic of Agriculture and Pasture	26,178.25
Savana Formation	1229.50	Beach and Dune	0.50
Mangrove	12.25	Urban Infrastructure	−61.50
Forest Plantation	−21.75	Other Non-Vegetated Area	1188.75
Non-Forest Natural Formation	0.00	Water	0.00
Grassland Formation	406.25	Non-Observed	0.00
Other Non-Forest Natural Formation	3553.50	Mining	0.75
Pasture	0.00	Salt flat	0.50
Annual and Perennial Crop	−3873.25	River, Lake, and Ocean	481.00

In Figure 6, it was observed that the Forest Formation lost 337,845.00 km^2 to Pasture areas, 33,603.25 km^2 to Annual and Perennial Cultures, and 16,475.50 km^2 to Rivers, Lakes, and Oceans. The other classes had little influence on the reduction or increase of forest formation. Regarding Figure 7 and Table 7, Pasture lost 3873.25 km^2 to Annual and Perennial Cultures but gained 337,845.00 km^2 from Forest Formation areas and 26,178.25 km^2 from Agriculture and Pasture Mosaic areas.

3.3. Land Use and Cover Change Analysis

The analysis of land use and cover change between 1985 and 2014 is presented in Figure 8.

The areas where classes have persisted correspond to 86.47% of the study area, which is equivalent to 3,645,436.75 km^2, while the changing areas correspond to 13.53%, representing 570,206.50 km^2. Even though the percentage of changes showed a lower value than the persistence percentage, these results demonstrate a significant variation in land use and coverage. Any minimal percentage of change represents vast areas due to the biome's large territorial extension.

It was found that the changes were not diffuse in general, mainly occurring in the south and west of the biome as well as close to the Amazon and Solimões rivers (Figure 8).

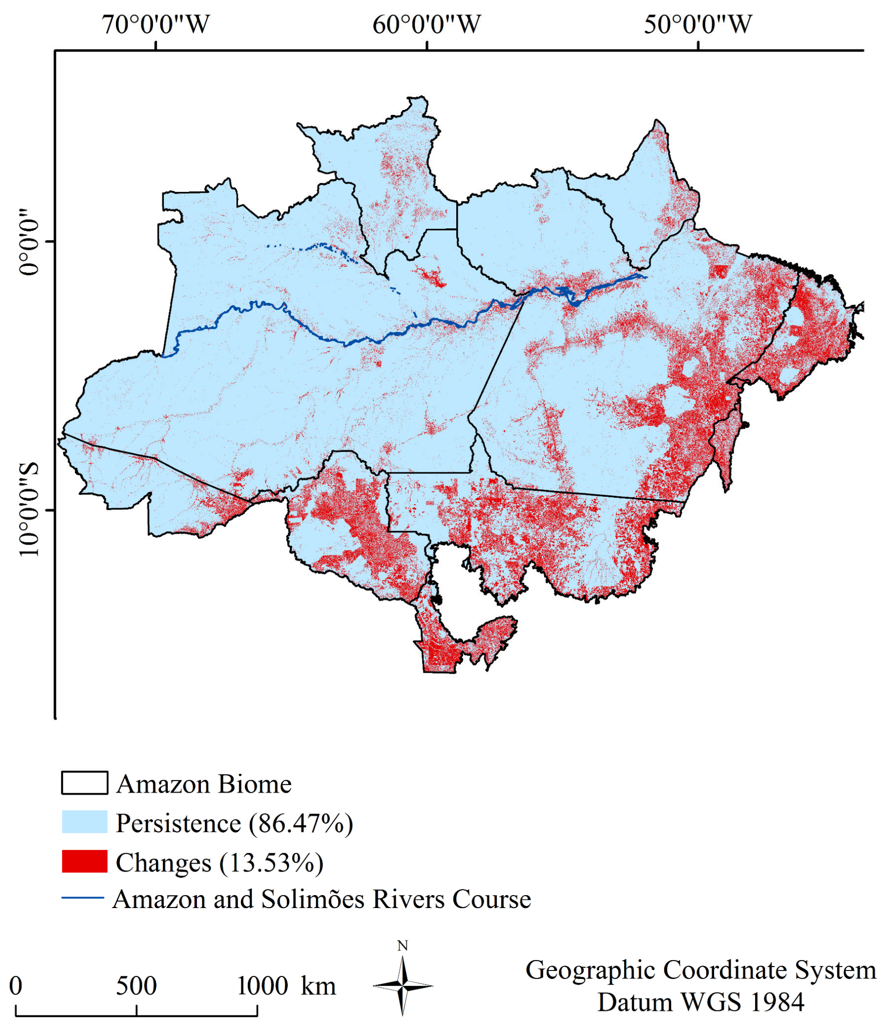

Figure 8. Changing areas of land use and land cover in the Amazon biome between 1985 and 2014.

3.4. Calibration and Validation of the Potential Transition Sub-Model

3.4.1. Test and Selection of Explanatory Variables First Bullet

The test and selection of explanatory variables related to changes in land cover are shown in Table 8, with their respective Cramer-V test values. All variables were selected, except for Variations in Annual and Perennial Cultures and Distance of Semi-Perennial Culture. Although their values were above 0.15, it was verified through several tests that their exclusion increased the MLP neural network modeling performance.

Variables with the highest Cramer-V values were Average Annual Precipitation (0.3056), Declivity (0.3021), and Altitude (0.3015), followed by Distance from areas of change (0.2597) and Mosaic Distance of Agriculture and Pasture (0.2517).

Table 8. Testing and selection of explanatory variables to be included in the potential transition sub-model.

Explanatory Variables	Unit	Cramer-V	Selection Status
Altitude	m	0.3015	Selected
Slope	%	0.3021	Selected
Annual Average Precipitation	mm	0.3056	Selected
Distance from Highways	m	0.2142	Selected
Distance from Water Courses	m	0.2467	Selected
Distance from Urban Infrastructure	m	0.2361	Selected
Distance from Pasture	m	0.2214	Selected

Table 8. *Cont.*

Explanatory Variables	Unit	Cramer-V	Selection Status
Distance of Annual and Perennial Culture	m	0.1601	* Not Selected
Distance from Semi-Perennial Culture	m	0.1561	* Not Selected
Distance from Agriculture and Pasture Mosaic	m	0.2517	Selected
Distance from Mining	m	0.1604	Selected
Distance from Protected Areas	m	0.2159	Selected
Distance from Change Areas	m	0.2597	Selected

where: * = excluded variable in order to improve the Neural Network modeling performance.

3.4.2. Modeling Potential Transitions through MLPNN

The best result achieved in training the MLPNN model to model potential transitions, based on the interaction between explanatory variables and the transitions of interest, was 87.86% after 10,000 iterations. This value exceeded the minimum acceptable value for a good accuracy rate by 75% [50]. Consequently, selecting the appropriate calibration period was considered critical.

The sub-model execution generated a soft prediction map (Figure 9), where red tones indicate areas most likely to become pastures, while blue tones represent areas with less potential for such transitions. The model prioritized the representation of the Forest Formation to Pasture transition since it was the main transition occurring in the study area.

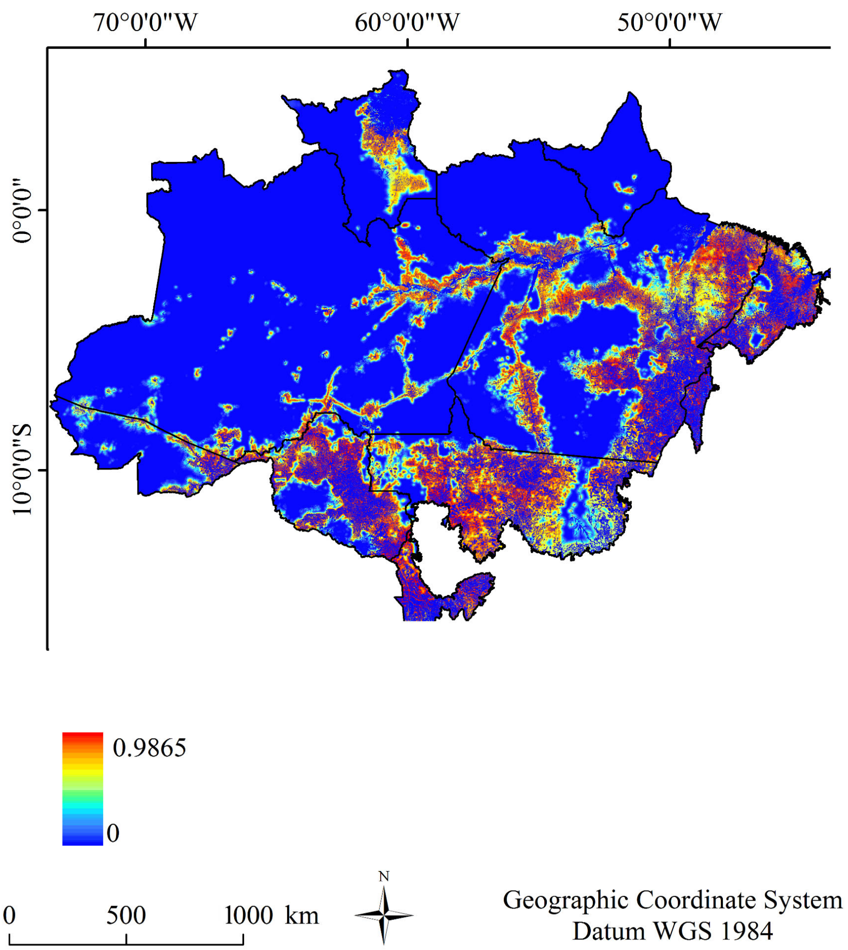

Figure 9. Conversion potential of Forest Formation to Pasture.

3.5. Modeling Land Cover Changes

Based on the land cover transition matrix between 2014 and 2017 obtained through the Markov Chain, it was possible to simulate land use and cover for the year 2017.

To assess the accuracy of the modeled changes, Figure 10 shows the mapped land use and cover (MapBiomas) along with the simulated land use and cover for 2017. Visually, it can be observed that the maps exhibit high similarity to each other.

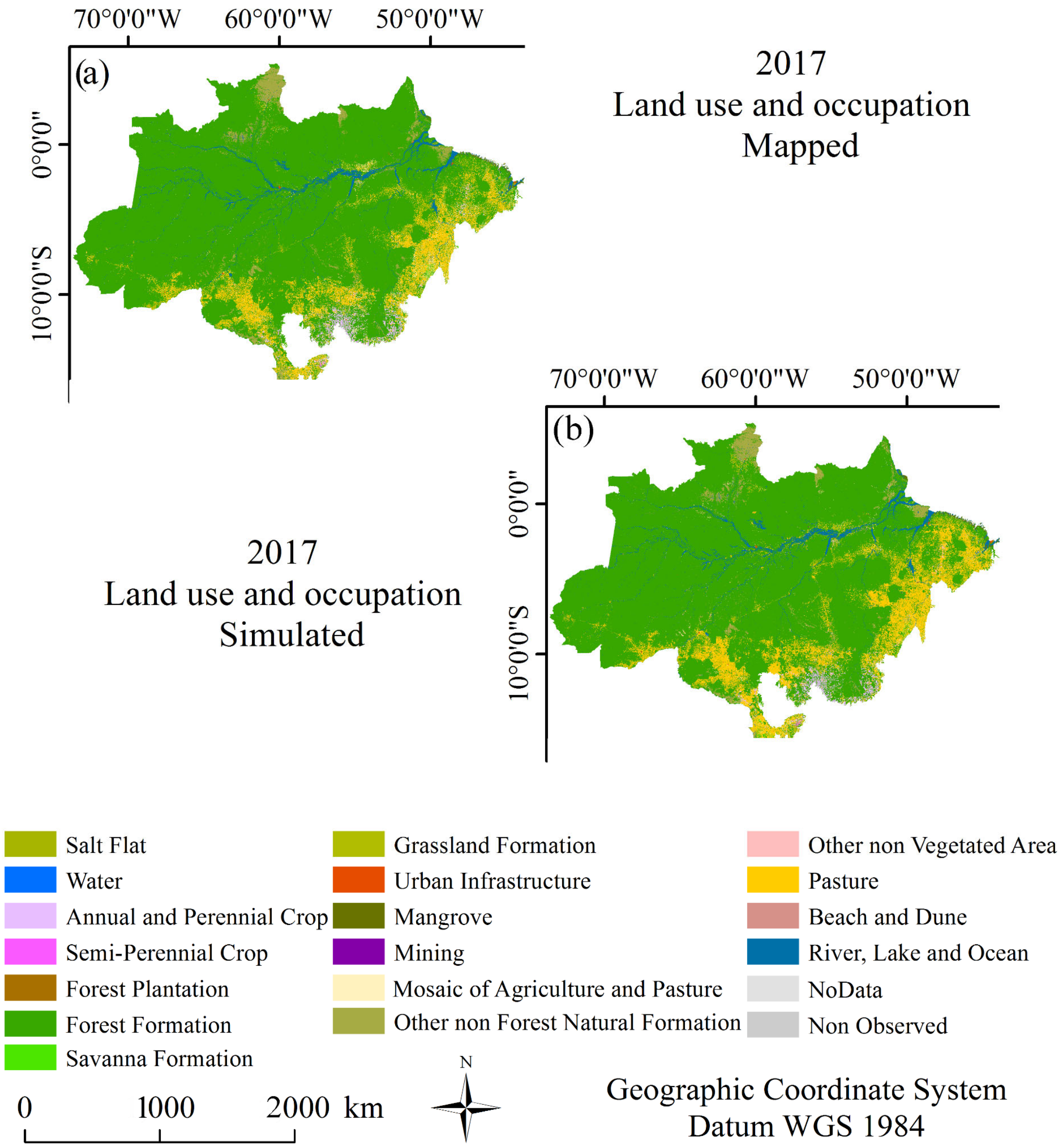

Figure 10. Shows the map (MapBiomas) (**a**) and simulation (**b**) of land use and cover for 2017.

To comprehensively assess the agreement between the mapped and simulated land use and cover for 2017, Figure 11 presents the spatial output from the Minus tool (accurately and inaccurately classified pixels), along with the agreement indicators and kappa indices.

Results indicate that the simulated image is 93.76% equivalent to the mapped image (hits), while the simulated classes that do not comply with the mapped ones (commission errors) represent 6.24%, which is considered a satisfactory result.

It was verified that the agreement indicators M (m) and P (m), which concern pixel location and the amount by category, respectively, present values close to 1.00, indicating excellent accuracy. According to the N (m) indicator, where pixel locations were scrambled, model performance started with low accuracy (0.40), but increased with an increase in pixels, being classified as reasonable.

All indices showed values above 0.94 concerning the Kappa indicators, which are considered excellent. As the pixel window increases, index values increased proportionately, except for the Kstandard indicator, which decreased after the resolution of 512.

Based on these results, the calibrated LCM was considered suitable to predict future urban expansion scenarios.

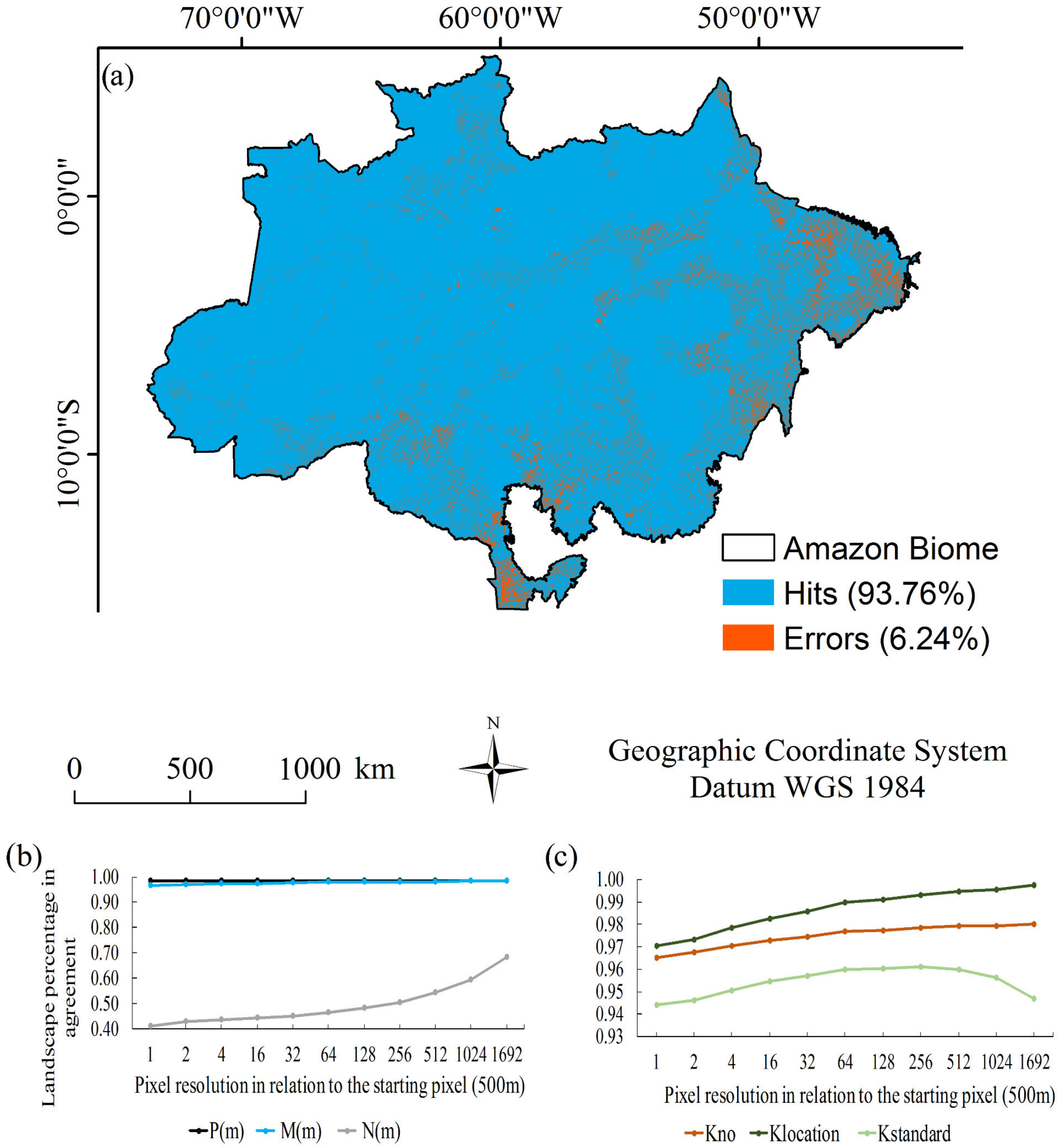

Figure 11. The validation of the land use and cover simulation for 2017, with (**a**) the spatial distribution of accurate and inaccurate classifications, (**b**) agreement indicators, and (**c**) kappa indices.

3.6. Land Cover Simulation and Future Prediction for 2044

Based on the results, there were significant changes in the land use and cover of the biome from 1985 to 2014, particularly a reduction in Forest Formation. Assuming that this reduction would continue to increase, as observed during the period from 1985 to 2014, a simulation of the land cover was conducted for the year 2044.

Thus, according to the land cover transition matrix between 2014 and 2044, which was also obtained using the Markov Chain, the allocation of land cover for 2044 (hard prediction) is shown in Figure 12. Visually and in general, it can be observed that the Forest Formation will still be the largest representative class, followed by the Pasture class.

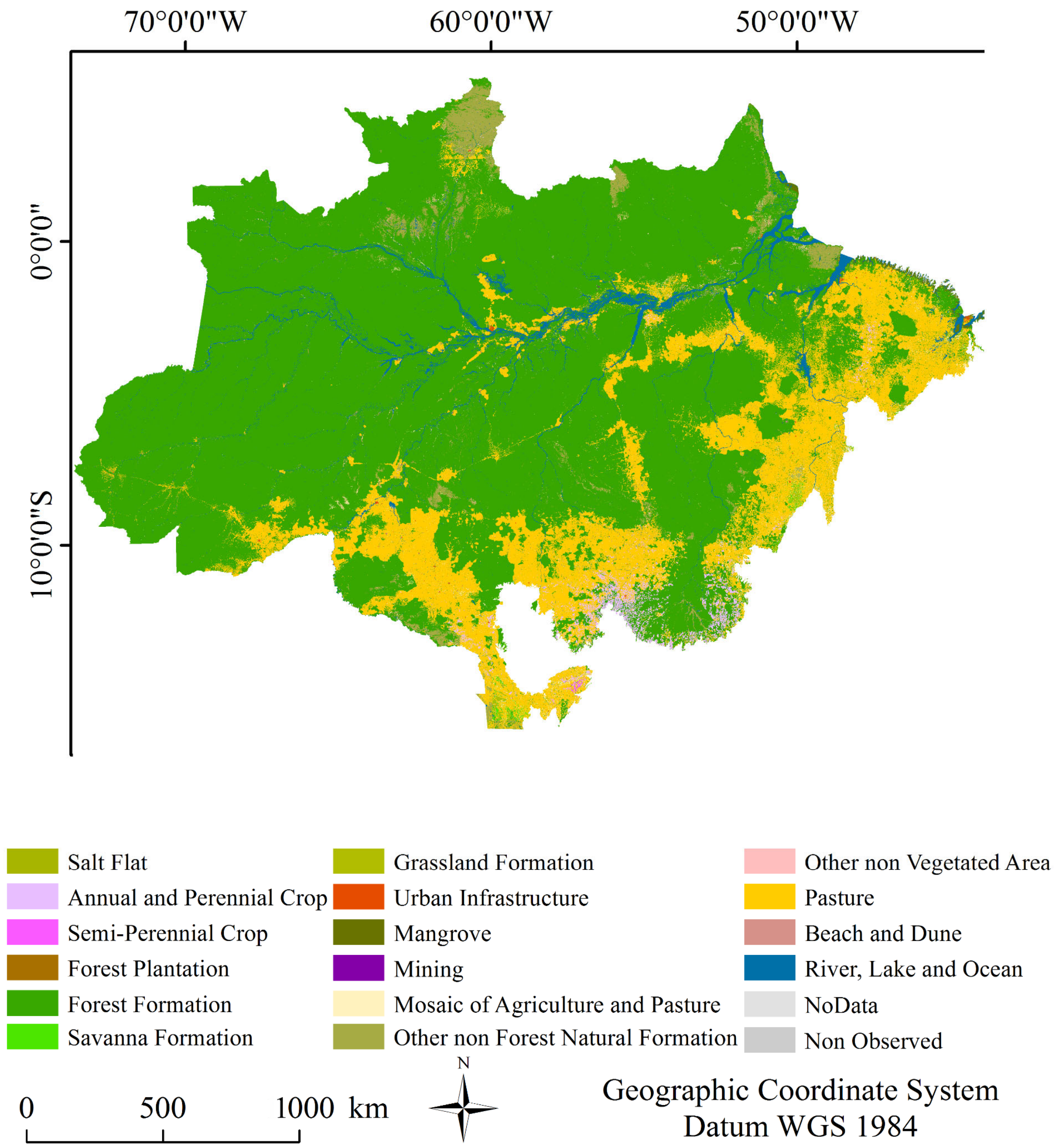

Figure 12. Future land use and land cover simulation for 2044.

Vulnerability to change for 2044 (soft prediction) is shown in Figure 13. The largest representative class corresponds to "very low" vulnerability to change, comprising 56.12% (2,365,716.25 km^2) of the study area, followed by the "there will be no changes" class with 18.11% (763,514.00 km^2). The "high" vulnerability to change class corresponds to 7.35% (309,718.50 km^2) of the study area, while the "very high" vulnerability to change class corresponds to 9.90% (417,463.75 km^2). In this, the image (Figure 13) of the states that make up the Amazon biome was added. Thus, it is better understood which state has the greatest increase in deforestation.

The states with the highest percentages for the "very high" class stand out in this study, Mato Grosso, Maranhão, Rondônia, and Pará (Figure 13). Figure 14 shows the state of Mato Grosso, which stands out with the largest areas with a very high vulnerability index in 2044.

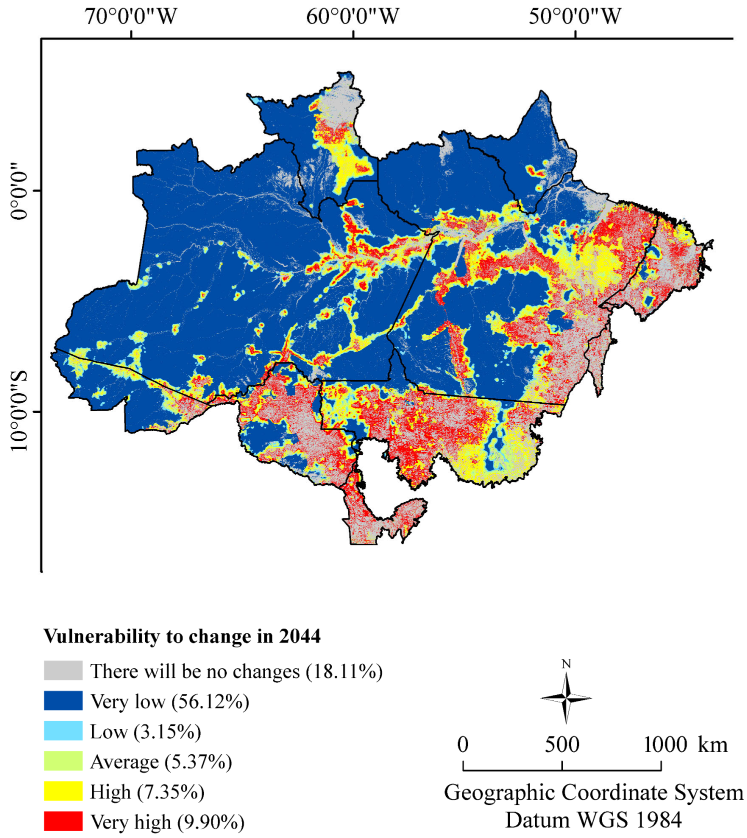

Figure 13. Vulnerability of change for the year 2044.

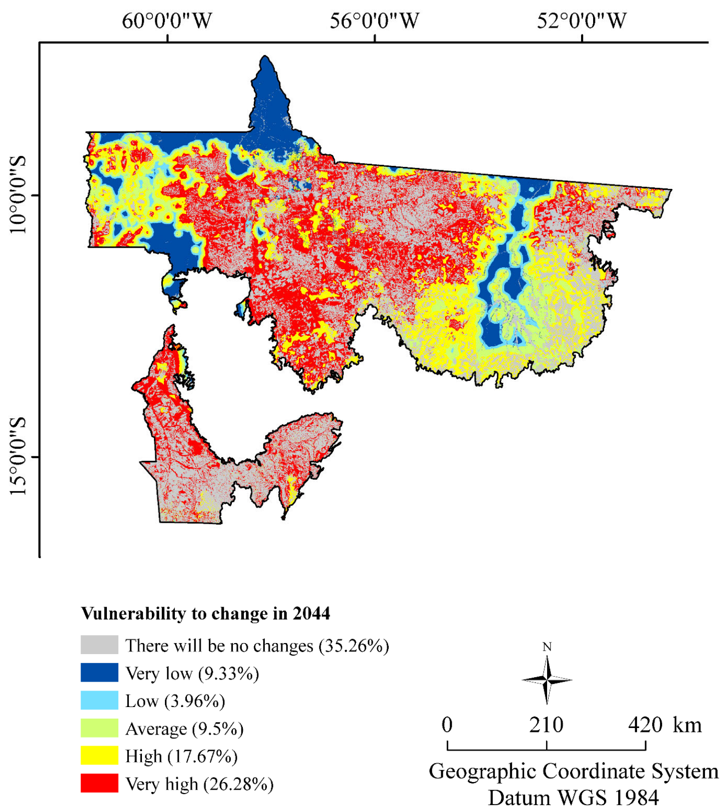

Figure 14. Vulnerability of change in the year 2044 in the state of Mato Grosso.

The graphical representation of the comparison between land use and land cover for the years 1985, 2017, and 2044 is depicted in Figure 15. Upon analyzing the three scenarios (past, present, and future), it can be visually observed that there is a substantial reduction in the Forest Formation class and a significant increase in pasture areas. It is important to note that these changes can only occur if the observed behavior from 1985 to 2014 continues under similar conditions as represented in this study.

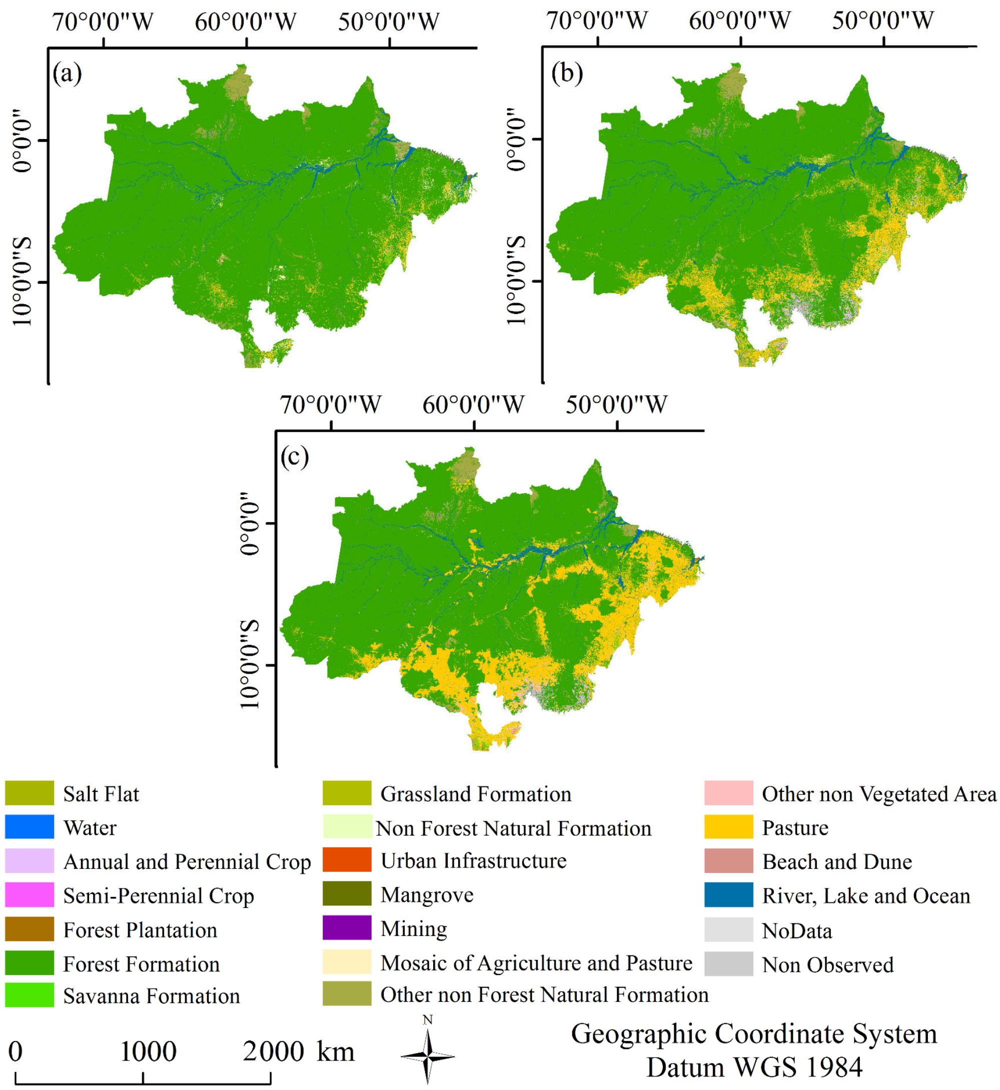

Figure 15. Land use and land cover for the years 1985 (**a**), 2017 (**b**), and 2044 (**c**).

The 1985, 2017, and 2044 land use and coverage classes, along with their respective quantifications in square kilometers and percentages in relation to the study area, are shown in Table 9.

Table 9. Quantification of land use and land cover classes for the years of 1985, 2017, and 2044.

	1985		2014		2017		2044	
Classes	**Area (km^2)**	**%**	**Area (km^2)**	**%**	**Area (km^2)**	**%**	**Area (km^2)**	**%**
Forest Formation	3,844,800.75	91.20	3,452,129.25	81.89	3,482,721.50	82.61	3,115,892.25	73.91
Savanna Formation	4708.50	0.11	4804.50	0.11	3060.25	0.07	4804.50	0.11
Mangrove	7234.25	0.17	7510.25	0.18	6827.50	0.16	7510.25	0.18
Planted Forest	25.00	0.00	305.25	0.01	438.00	0.01	305.25	0.01
Non-Forest Natural Formation	0.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grassland Formation	3340.75	0.08	5573.75	0.13	3574.25	0.08	5573.75	0.13
Salt Flat	139.25	0.00	283.00	0.01	401.75	0.01	283.00	0.01
Other Non-Forest Natural Formation	117,054.50	2.78	110,970.75	2.63	114,915.75	2.73	110,970.75	2.63
Pasture	71,046.50	1.69	437,670.00	10.38	375,159.50	8.90	773,907,00	18.36
Annual and Perennial Culture	793.25	0.02	41,232.50	0.98	44,500.50	1.06	41,232.50	0.98
Semi-Perennial Culture	0.00	0.00	709.00	0.02	608.75	0.01	709.00	0.02
Mosaic of Agriculture and Pasture	58,849.75	1.40	33,311.75	0.79	69,413.25	1.65	33,311.75	0.79
Urban infrastructure	1939.75	0.05	2798.50	0.07	2781.25	0.07	2798.50	0.07
Mining	13.25	0.00	119.00	0.00	146.75	0.00	119.00	0.00
Beach and Dune	31.00	0.00	53.50	0.00	43.00	0.00	53.50	0.00
Other Non-Vegetated Area	6299.25	0.15	3079.25	0.07	3316.50	0.08	3079.25	0.07
Water bodies	6.00	0.00	0.00	0.00	8.25	0,00	0.00	0.00
River, Lake, and Ocean	99,112.25	2.35	114,814.50	2.72	107,465.25	2.55	114,814.50	2.72
Not observed	53.75	0.00	160.75	0.00	57.75	0.00	160.75	0.00
No Data	195.00	0.00	117.75	0.00	203.50	0.00	117.75	0.00
Total	4,215,643.25	100	4,215,643.25	100	4,215,643.25	100	4,215,643.25	100

4. Discussion

4.1. Land Use and Land Cover Dynamics

The changing dynamics of land use and land cover in the Amazon biome for the studied period (Figure 3 and Table 3) showed a direct link with human influence, and consequently, deforestation. When assessing the pattern dynamics of deforestation in protected areas of the Brazilian Legal Amazon through remote sensing data, Cabral et al. also found that the region suffered high rates of forest loss for decades, and the fragmentation and deforestation resulted from changes in land use [57].

According to Nascimento et al., changes in land use result from decisions made by several actors in response to economic and political contexts [58]. Local, regional, and global processes—such as direct conversions from forest to pasture; regional processes of indirect land use change described by converting pastures to arable land, which increases pasture demands elsewhere; and teleconnections, fueled by global demands for soy and animal fodder—affect deforestation and land use change in the Brazilian Amazon [59]. These factors corroborate the results found in this study.

The strong relationship between the loss of forest formation class caused by deforestation and pastures in the biome agrees with the results of other studies, who found that livestock is the main driver of deforestation in the Brazilian Amazon, responsible for 80% of the illegal deforestation [60–62].

The areas of land use and land cover change detected in this study coincide with the ones considered as agricultural frontiers, which are conducive to reducing forest formation due to other land uses.

Navarro, Calamari, and Mosciaro [63] also studied the dynamics of land use and cover, using modeling to predict changes and soil degradation in the Misones Tropical Forest in Argentina. The results showed that 19% of the remaining native forest would be transformed into agriculture or cultivated forest by 2030, in addition to a significant loss of soil. Pokhariya [64], using a similar methodology to that used in this study, demonstrated a significant increase in urban and agricultural areas in India in the last two decades. However, the sharp decrease in forest and water body areas is a concerning factor considering the country's increasing population. These results raise an environmental alert for the need to implement mitigating measures against the harmful effects of human activities over the years.

Thus, such changes can have negative impacts on the environment. Deforestation can lead to the loss of important ecosystem or environmental services, which in Brazil and South America have an immeasurably greater value than the current uses that replace the forest, such as agriculture and livestock. These services include maintaining biodiversity, climatic and hydrological balance, and balancing carbon stocks in forest biomass and soil [65,66].

Brazil has adopted measures to reduce deforestation in the Amazon, which reduced the loss of forest biomass to historically low levels in some years. In 2015, for example, the federal government and the German government signed an agreement to promote the conservation and environmental regularization of rural properties located either in the Amazon region or in transition areas to the Cerrado biome [67]. This agreement may have influenced the small increase in Forest Formation and reduction of Pasture observed between 2014 and 2017 (Table 3). Despite efforts to conserve the Amazon biome, the pressures over it are still very intense [68].

There is great concern about the occurrence of deforestation in the Amazon Biome, which has been intensifying over the years. The authors of previous studies [12,69–71] observed the increase in pasture areas, which are replacing forest areas. Among the factors responsible, anthropic practices such as burning for opening agricultural areas cause forest fires.

Pismel et al. demonstrates in his work that forest fires can become transboundary disasters and that there is a problem of political articulation between the countries on the trinational border in the southwest Amazon [72]. Thus, studies that show how land use and occupation changes occur in the Amazon Biome contribute to more assertive forecasts and for adopting preventive measures to conserve the Biome, as well as to assist in the adoption of public policies and to contain the advance of deforestation.

4.2. Area Gain, Loss, and Net Variation by Categories

In terms of gains and losses by land use category for the period between 1985 and 2014, which corresponds to the calibration period of the model, the category that showed the greatest increase in area is Pasture, while the category with the greatest loss is Forest Formation. Both categories, along with Annual and Perennial Culture, Mosaic of Agriculture and Pasture, and River, Lake, and Ocean categories, presented the greatest net variations in area.

When analyzing which categories have contributed to the changes in Forest Formation (Figure 6), it is possible to see that it has been replaced by agricultural practices, represented by Pasture and Culture categories, either Annual or Perennial. These results support the conclusion of Ometto, Sousa-Neto, and Tejada [73], that over the last 40 years, the Amazon has undergone significant changes in land use and coverage, primarily due to the conversion of forests into agricultural land. The lesser loss of Forest Formation for the River, Lake, and Ocean category may be related to the installation of reservoirs or possible errors in image classification, either for the year 1985 or 2014.

The Pasture category has lost less area to Annual and Perennial Culture, while gaining extensive areas from Forest Formation and the Agriculture and Pasture Mosaic (Figure 7). The increase in Pasture due to the loss of Forest Formation is consistent with the behavior observed in previous results (Figure 9) and with the Mosaic category of Agriculture and Pasture. It was expected that this category would become Pasture, due to its similarity and the presence of Pasture in it.

The loss and gain of forested areas have an impact on biodiversity. The loss of habitat for species, many of which are endemic, in areas such as the Amazon region, causes imbalances in these natural environments, which could take years or may not be able to recover depending on the size of the impact [13,74,75].

The environmental resilience of an ecosystem is considered its ability to maintain its ecological relationships and environmental services even after a disturbance [76]. However, the loss of this resilience can lead to an ecosystem collapse and irreversible changes in the landscape, affecting not only biodiversity but also human communities that depend on its services [77]. According to Boulton, Lenton, and Boers [78], the Amazon forest has been losing its resilience since the year 2000. The authors related the distance of human activities to the resilience of the forest in their work and found that they are statistically correlated with land use and the increase in atmospheric temperatures, with the release of greenhouse gases.

4.3. Land Use and Land Cover Change Analysis

When analyzing the dynamics of change, including areas of persistence (86.47%) and change (13.53%) in Figure 8, the Forest Formation class stood out for its persistence, which covers most of the study area due to its significant representation in the biome. Additionally, the lowest percentage of changes is also noteworthy, as it corresponds to an area larger than Bahia State, the fifth largest Brazilian state.

This trend coincides with the areas represented by the "arc of deforestation", which extends from the east and south of Pará State in a westerly direction, passing through Mato Grosso, Rondônia, and Acre States [71,74,79].

The state of Mato Grosso, seen in Figure 14, suffers strong pressures due to several economic interests, such as the exploitation of minerals and wood, expansion of livestock, and population growth [80].

4.4. Calibration and Validation of the Potential Transition Sub-Model

Regarding the testing and selection of explanatory variables related to changes in land cover using the Cramer-V test (Table 5), all variables were deemed suitable for modeling.

Based on the variables that stood out the most and presented the highest values, areas of change are located in the lowest slopes and altitudes that intersect rainfall ranges between 655 and 4000 mm year^{-1}, corresponding to the largest area of the biome. These characteristics may have influenced the higher Cramer-V values. It was expected that the "Distance from change areas" variable would have a greater value, as the closer an area is to a changing area, the greater the chance of land cover conversion, as well as the value of Agriculture Mosaic Distance and Pasture.

When analyzing the transition potential of Forest Formation to Pasture (Figure 9), a product of the neural-network-based sub-model, the greatest potential for transition is located in areas of change (Figure 8), mainly in the Arc of Deforestation region, which tend to have their land use converted. Areas with a lower tendency of change may be linked to their proximity to Protected Areas at the national level, which may have reduced the conversion potential due to environmental inspection and protection.

4.5. Modeling Land Cover Changes and Simulations Validation

Regarding the validation of the land cover change modeling, which compares the mapped (MapBiomas) and simulated land use and land cover for 2017, the results indicate excellent accuracy, as demonstrated by the agreement indicators M (m) and P (m) being close to 1. A value equal to or greater than 0.80 is considered strong and reasonable for making plausible future projections [46]. The N (m) agreement starts with low accuracy (0.4), but its performance improves as pixel increases, and is classified as reasonable. Its initial behavior may be associated with the indicator's own characteristic, where the pixels' location is scrambled.

Regarding the Kappa indicator, all indexes have shown values above 0.94 for all resolutions (Figure 11). In general, the Kappa indices showed strong to perfect agreement between the predicted and observed maps, since all values were greater than 0.80 [41,64].

4.6. Land Cover Simulation and Future Prediction for 2044

The modeling on which the projection for 2044 is based used data on changes between 1985 and 2014, and was validated for changes between 2014 and 2017. Conditions and dynamics in the Amazon for the coming two decades are likely to differ from preceding years, due to changes in policy, social and economic drivers, global and regional climate dynamics, as well as loss of biodiversity and ecosystem collapse. For example, some research shows that the rate of deforestation and forest degradation in indigenous protected areas of the Brazilian Amazon increased dramatically in the 2019–2020 period, compared to the 2013–2018 period, with changes driven by mining rather than conversion to pasture [81].

According to the land cover allocation carried out for 2044 (Figure 12), the Forest Formation will still be the largest class, followed by Pasture, if the same transition dynamics are maintained. These results are associated with the higher persistence probability presented by both classes in the potential transition matrix between 2014 and 2044.

Regarding the change vulnerability for 2044 (Figure 13), the "very high" and "high" vulnerability areas coincide with those pointed out in the hard prediction simulation for 2044, mostly represented by areas adjacent to Pasture. The "average" vulnerability is also associated with pasture areas, but at a greater distance from them. Together, the "very high," "high," and "average" vulnerability areas add up to 22.62%, equivalent to an area superior to Mato Grosso State (Figure 14), which is considered the third-largest state in Brazil. These areas are also close to the changes between 1985 and 2014. According to Luiz [56], the closer an area is to one that has changed, the greater the chance of any conversion in land use and coverage.

The "very low" vulnerability areas, which correspond to the largest representative area, may be related to the proximity and influence of Protected Areas at the national level, which consequently favors their protection. Some areas that are not vulnerable to change correspond to consolidated pastures and other natural non-forest formation areas in the northern portion of the biome.

When analyzing land use and cover for the three main periods, 1985, 2017, and 2044, and assuming that the same change in behavior that occurred during the calibration period will remain, there is a significant linear reduction in Forest Formation and an increase of pasture areas. In general, there was a variation for all land use classes. Regarding agricultural classes, the Semi-Perennial Culture class showed a continuous increase in area, while the Annual and Perennial Culture and Agriculture and Pasture Mosaic classes showed an increase between 1985 and 2017, which was expected but presented reductions of 0.98% and 0.79%, respectively, for 2044. These reductions may be associated with the conversion of these areas to Pasture.

In the study on deforestation and forest fires in the Brazilian Amazon from 2001 to 2020, a significant increase in the use and coverage of agricultural and pasture lands was demonstrated. Compared to this increase, the forest class decreased by 2.5% for the total area of the biome in this study [82]. This shows concern about the replacement of native forest areas with agricultural areas over the years.

When comparing 1985 to 2017, there was an increase in the Urban Infrastructure class, which is expected to stabilize in 2044. It was anticipated that the areas of urban infrastructure would expand over time, as urbanization and regional development are closely related. The allocation of facilities and business specialization influences urban growth, which further benefits the surrounding landscape [83].

In general, the simulation of land cover, through the LCM module for a period of 30 years, represents a simplification of reality based on the modeling propositions built in this work. This has some intrinsic limitations since it assumes that change trends would remain under the influence of explanatory variables, although being a complex process that can change over time.

Land use and coverage for the year 2044 point to a scenario where the main land cover, in terms of representativeness, will still be Forest Formation and Pasture areas. However, the notable increase in Pasture areas is worrying because, according to a previous study [84], pasture management in the Amazon generally follows traditional practices, leaving a high potential for intensification. Burning is a common land management practice with a long cultural tradition [85], and together with a lack of protective measures, results in uncontrolled fires that also regularly affect adjacent forests [12,86].

Simulating land cover using LCM modeling was satisfactory, and MLPNN training resulted in an accuracy of 87.86%. However, there is a variation in the difference between simulated and mapped land cover, which may be due to the presence or absence of classes between 1985 and 2014, the size of the analysis area, and the influence of explanatory variables.

The main determinant of deforestation in the Amazon region is human activity, manifested by the growth of agricultural activities and wood extraction. A critical scenario for the Amazon Rainforest is demonstrated in a study, with the risk of a structural change in the biome due to an increase in average temperature in recent years and a longer dry season, facts that are related to the increase in deforestation and wildfires, which have reduced the forest in large extensions [87]. Given the current economic scenario and the projected future, it is necessary to reconcile conservation practices with the mode of consumption, which depends on suitable planning for the implementation of public policies.

The use of cost-effective techniques, which are more accessible for the management of these areas, in relation to the impacts of the loss of native forest area, provides preventive action to combat illegal deforestation, fires, and climate change in the future, and contributes to the environmental zoning provided for Brazilian legislation according to the National Environmental Policy (PNMA) [88,89]. The PNMA's main goal is to seek actions that promote sustainable development in the country [89].

The study presented here is a tool to assist environmental management in locations vulnerable to the impacts of deforestation presented in this study. Environmental agencies will have support to monitor areas with greater changes in land use and cover over time [90], and will therefore help in understanding the main phenomena related to these changes.

As recommendations for future studies, a careful evaluation of the choice of explanatory variables is suggested, as they directly influence land use dynamics. Simulations of different optimistic scenarios are also encouraged through the implementation of diverse conservation policies to provide support for evaluating future practices that are less adverse to the environment.

The simulations foreseen by this work constitute an essential instrument that can provide subsidies for planning territorial occupation in the region, management of protected areas, implementation of public policies, and incentivization of best practices with reduced impact in pasture areas.

5. Conclusions

The analysis carried out showed that the land use classes that underwent the greatest changes between 1985 and 2014 were Silviculture and Pasture Formation, followed by Annual and Perennial Cultivation, and Agricultural and Pasture Mosaic.

Human activity is the main determinant of deforestation in the Amazon region, as there is a substitution of forest formation due to agricultural practices, mainly represented by the increase in pasture areas.

The use of the Land Change Modeler tool generated a robust model for predicting land use change, as evidenced via validation. Land use and cover in the year 2044 point towards a scenario of reduced forest formation and a significant increase in pasture areas.

The simulations predicted in this study are an important tool that can provide subsidies for territorial planning, the creation and management of protected areas, the implementation of public policies, the encouragement of better management practices related to pasture areas, and demonstrate the need for incentives to reduce greenhouse gas emissions from deforestation.

The modeling represents a simplification of reality based on the propositions of this study and has some intrinsic limitations, as it assumes that the trends of change would remain under the influence of explanatory variables, which are complex and can be altered over time. However, if the trends of change are similar in the future, we will have a possible approximate estimate of reality.

Although the projection of the present study can serve as a comprehensive baseline scenario against which future improvements or deterioration in land use and forest cover can be easily assessed, the findings also point to the localities and areas that will likely be most vulnerable to changes, and to the most significant types of land use change, thereby providing highly useful information to guide national policy and local conservation efforts.

The modeling of land use and cover becomes a tool for the country's environmental legislation, allowing for the delimitation of more suitable areas for certain economic activities so that the exploitation of natural resources is sustainable and compatible with the environmental characteristics of the ecosystem.

The methodology used has the potential for use and adaptation to other biomes, as well as to the study region.

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