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Towards Uncovering Three Decades of LULC in the Brazilian Drylands: Caatinga Biome Dynamics (1985–2019)

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Abstract: Dryland regions around the world are facing intricate challenges due to climate change and human activities. The Caatinga biome in Brazil, an exceptional dryland ecosystem covering approximately 86.3 million hectares, is particularly impacted by human influence. We conducted an extensive study analyzing changes in land use and land cover within the Caatinga region over a span of 35 years, from 1985 to 2019. This study leverages collective knowledge and collaborative effort with the MapBiomas project to provide valuable insights into the biome's landscape. It maps eight principal land cover classes using Landsat Collection 1 Tier 1 data normalized to top-of-atmosphere reflectance. All data processing was carried out within the Google Earth Engine platform, and the graphics were generate using R version 3.6.2. This study achieved an impressive 80% global accuracy in the time series of Caatinga land use and land cover (LULC) changes, with allocation and area discrepancies of 11.6% and 8.5%, respectively. The extensive 35-year LULC dataset reveals a substantial 11% reduction in natural vegetation in the Caatinga biome, translating to a loss of 6.57 million hectares. This decline is primarily attributed to the expansion of cattle ranching and agriculture; all types of natural vegetation have experienced decreases, with Savanna Formation (SF) areas declining by 11% and Forest Formation (FF) areas declining by 8%. In contrast, pasturelands expanded by 62% and agricultural land expanded by 284% during this period. With their urgent and significant real-world for informing social, economic, and environmental policy decisions within the Caatinga and other dryland regions globally, these findings underscore the importance and immediacy of our research.

Keywords: landscape dynamics; LULC trajectory; drylands dynamics; caatinga dynamics; savanna formation

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1. Introduction

The development of sustainable societies relies on a nuanced interaction between social and economic progress and their intricate connection with the preservation of environmental resources over time and space. Finding a careful equilibrium between meeting the changing needs of human populations and safeguarding the ecological health of natural systems is not just essential but also urgent for long-term sustainability [1–5].

Drylands, which cover 41.3% of the Earth's land surface and are home to 2 billion people, are vital ecosystems facing complex challenges [6–8]. Despite their rich biodiversity and crucial role in combating global issues, they are often mistakenly perceived as barren. Defined by water scarcity and extreme conditions, drylands encompass diverse landscapes and cultures. While scientifically recognized as areas with high evapotranspiration relative to precipitation, they remain some of the world's most overlooked and threatened ecosystems [6–9].

In this sense, drylands face numerous threats from influential human activities, like deforestation, agricultural expansion, and mining, which have led to the degradation of these areas, consequently impacting critical facets like the carbon and water cycles, biodiversity, and overall ecosystem dynamics. Furthermore, the impacts of climate change pose additional challenges, further endangering these fragile ecosystems [6–9].

However, our understanding of land use and land cover changes in dryland ecosystems requires further enhancement. This is evident from disparities in spatial data quantification observed between global and regional satellite-based maps, despite significant advances in remote sensing technology. These differences can be attributed to varying satellite data characteristics, mapping approaches, and forest definitions, encompassing factors like spatial resolution, mapping criteria, and tree cover thresholds. Despite their crucial role in sustaining ecological processes, biodiversity, and socio-economic functions, these indications emphasize the need for more comprehensive research into land use and land cover changes in drylands [10–13].

South American drylands cover an extensive area of 545 million hectares, accounting for 8.7% of the Earth's total dryland ecosystems [6,14]. Among dryland regions in South America, the Caatinga biome stands out as a significant ecological entity profoundly influenced by human activities [2,4,15]. This biome is distinguished by its rich biological diversity, notably high rates of endemism, and an imperative demand for comprehensive data to inform strategic choices regarding the preservation of biodiversity and the sustainable management of lands within fragmented landscapes [2,15,16].

A prominent natural system among global drylands, the Caatinga biome is profoundly influenced by human activities [3,16–20]. The Caatinga, a distinctly Brazilian biome, spans 86.3 million hectares, roughly 10% of the nation's land area [15,16]. Approximately 27 million people inhabit this region, and many face socio-economic challenges and rely on the biome's resources for their livelihoods [2,15].

Several attributes underscore the Caatinga biome's significance as an area urgently requiring scientific information and the implementation of policies aimed at biological conservation, sustainable use, and landscape and land use management, especially when compared to other Brazilian biomes. The Amazon and Atlantic Forest biomes have been the primary focus of specific monitoring initiatives, such as PRODES (Amazon Forest Satellite Monitoring), DETER (Deforestation Detection in Real Time), and SOS Mata Atlântica for the Atlantic Forest biome. These monitoring initiatives have been in place longer than those in the Caatinga, Cerrado, and Pampa regions. In addition, only two vegetation mapping initiatives have covered the entire national territory: the Radam Brasil Project (1970–1985) and the national vegetation mapping exercise under the Conservation and Sustainable Use Project of Brazilian Biological Diversity (PROBIO) (2004–2007) for the Caatinga biome. Consequently, the Cerrado and Caatinga biomes have not received as much attention with respect to land cover change assessments as the extensive efforts to monitor the Amazon Rainforest and Atlantic Forest [21,22].

The Caatinga biome is one of the least studied regions in Brazil in terms of biodiversity and ecosystems [4,15,16]. Conservation units only cover about 8% of its territory, and just over 1% receive complete protection [2,15,23]. Given the limited scientific data and the current state of fragmentation in the biome [17], the Caatinga biome is highly vulnerable to desertification. Deforestation in the area also plays a significant role in greenhouse gas emissions [12,24–26]. Changes in Caatinga land use have resulted in a net emission of over 300 million tons of CO_2. More recent estimates suggest that between 2002 and 2009, deforestation in the Caatinga biome led to a net emission of over 88.7 million metric tons of carbon dioxide equivalent ($MtCO_2e$) [27].

The expansion of agricultural land, deforestation, and other land use practices such as fires have caused significant damage to the Caatinga biome. These activities have resulted in soil salinization, increased water evaporation, and accelerated desertification, all of which have greatly impacted the ecosystem and increased its vulnerability to desertification. Consequently, the natural equilibrium of the biome has been disturbed, leading to soil nutrient depletion, heightened soil erosion, and reduced water availability. The use of fires for land clearance has further worsened these problems, intensifying the desertification process in the Caatinga biome [12,26,28].

The understanding of land cover changes in the Caatinga biome is still quite limited due to a scarcity of studies and available data [2,17,29]. The PMDBSS project estimated deforestation rates for the 2002–2008, 2008–2009, and 2009–2010 periods. However, it focused solely on gross vegetation losses without accounting for regrowth. Additionally, there is a lack of data on annual deforestation rates before 2002 for the Caatinga and Cerrado biomes, which has impeded a comprehensive understanding of transformation dynamics in the Caatinga biome. The limited availability of data on land use and land cover changes, combined with the absence of consistent monitoring in these biomes, has hindered the thorough assessment of the spatial and temporal patterns of land cover modifications in the Caatinga region [30].

Another study in the Caatinga region focused on estimating the "road effect zone" which assessed anthropogenic activities using geospatial tools [29]. This study revealed that when considering agricultural activities and the road system, approximately 45.3% of the Caatinga biome had been altered by human activities, making it the third most modified Brazilian biome, following the Atlantic Forest and Cerrado biomes [29]. Moreover, utilizing LANDSAT images, the annual rate of natural vegetation cover loss in the Caatinga increased from 0.19% yr^{-1} to 0.44% yr^{-1} between the 1990s and the 2000s [22]. Consequently, the annual gross loss of natural vegetation slightly increased between the periods of 2000 to 2005 (4240 km^2 yr^{-1}) and 2005 to 2010 (4928 km^2 yr^{-1}) [22].

Understanding the impact of LULC (land use and land cover) changes on the Caatinga biome is vital, and we are proud to be part of the collaborative MapBiomas initiative in Brazil, working alongside public and private institutions and experts in remote sensing, land use dynamics, cloud computing, and data science [31]. Together, we are focused on reconstructing LULC trajectories using Landsat data collected from 1985 to 2019 [32]. Employing cloud processing algorithms and Google Earth Engine (GEE) [33] image classification, we utilize machine learning techniques to effectively map LULC classes across Brazilian biomes and other global regions [32].

The digital image processing and remote sensing paradigm strongly emphasizes cloud processing to boost capacity, efficiency, and scalability for handling spatiotemporal data series. In this context, the Google Earth Engine (GEE) emerges as a remarkably adaptable platform for the cloud-based analysis and processing of geospatial data and is widely employed in a broad spectrum of studies encompassing deforestation, drought, disasters, diseases, food security, water management, climate monitoring, and environmental protection [33]. GEE provides a comprehensive array of tools, including a satellite imagery catalog of global time series, vector data, cloud-based computing, software, and algorithms for processing such data, all supported by a high-performance intrinsically parallel computing service [33].

This study aimed to reconstruct a yearly series of land use and land cover maps for the Caatinga biome from 1985 to 2019. The approach involved leveraging Landsat data, the Google Earth Engine, and machine learning to create a comprehensive land use and land cover map collection. Furthermore, the study evaluates land use and land cover changes in the Caatinga biome over the same timeframe using the compiled land use and land cover time series. The primary objective of this study was to quantify shifts in land use and land cover dynamics in the Caatinga biome. This involved the annual reconstruction of land use and land cover maps for the Caatinga biome from 1985 to 2019 using Landsat data and the Google Earth Engine. Additionally, we evaluated the extent, rates, and drivers of land use and land cover change in the Caatinga biome over this period.

2. Materials and Methods

2.1. Study Area

Located in the semi-arid region of northeastern Brazil and covering 10% of the country's land area, the Caatinga biome hosts the largest seasonally dry tropical forest and woodlands in the Americas [2,15,16]. It is home to a diverse array of flora uniquely adapted to thrive in the region's challenging environment, which is marked by sporadic rainfall and extended dry periods [2,15,16], as depicted in Figure 1. The Caatinga's rich biodiversity and unique adaptations make it a significant ecosystem within the Americas.

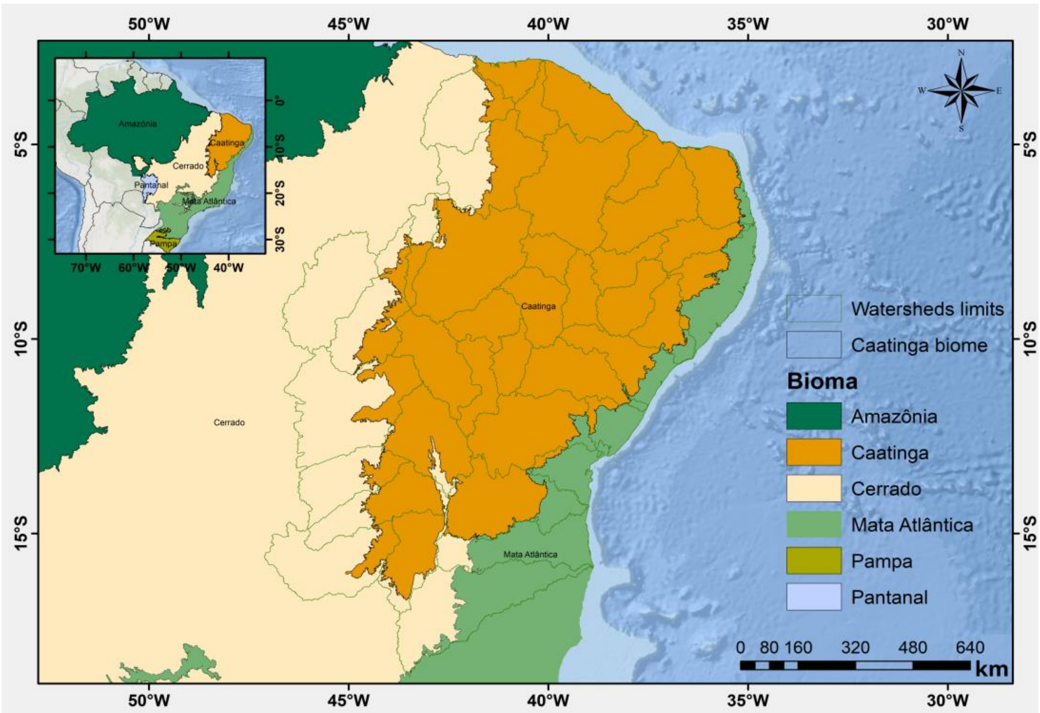


Figure 1. The map displays the boundaries of Brazilian biomes, with the specific demarcations of the Caatinga Biome highlighted in orange.

This region experiences high temperatures, high evapotranspiration rates, and erratic rainfall patterns that range from 240 mm to 1500 mm annually and mainly occur within two or three consecutive months. The area experiences severe droughts and has intermittent rivers. The hot and semi-arid climate supports various vegetation types, such as humid tropical forests, savannas, and rocky grasslands [15,16].

The Caatinga's vegetation comprises small-leaved, thorny trees, shrubs, and herbaceous plants. It is well-adapted to prolonged droughts and is characterized by its xerophytic and deciduous nature [15,16]. The landscape is mainly shrubby with thorny vegetation, often featuring bromeliads, euphorbias, and cacti [34]. The Caatinga's vegetation cover is classified as a steppe savanna and is the predominant vegetation type in Brazil's Northeast Region, with forested areas being scarce, dispersed, and fragmented [34–36].

2.2. Land Use and Land Cover Strategy Mapping

In the present study, we used a hierarchical classification system with a combination of LULC classes similar to those presented in MapBiomas Collection 5 [32].

We produced comprehensive land use and land cover (LULC) Caatinga biome maps that encompass a 35-year timeframe ranging from 1985 to 2019. This initiative entailed a series of procedural phases, as shown in Figure 2.

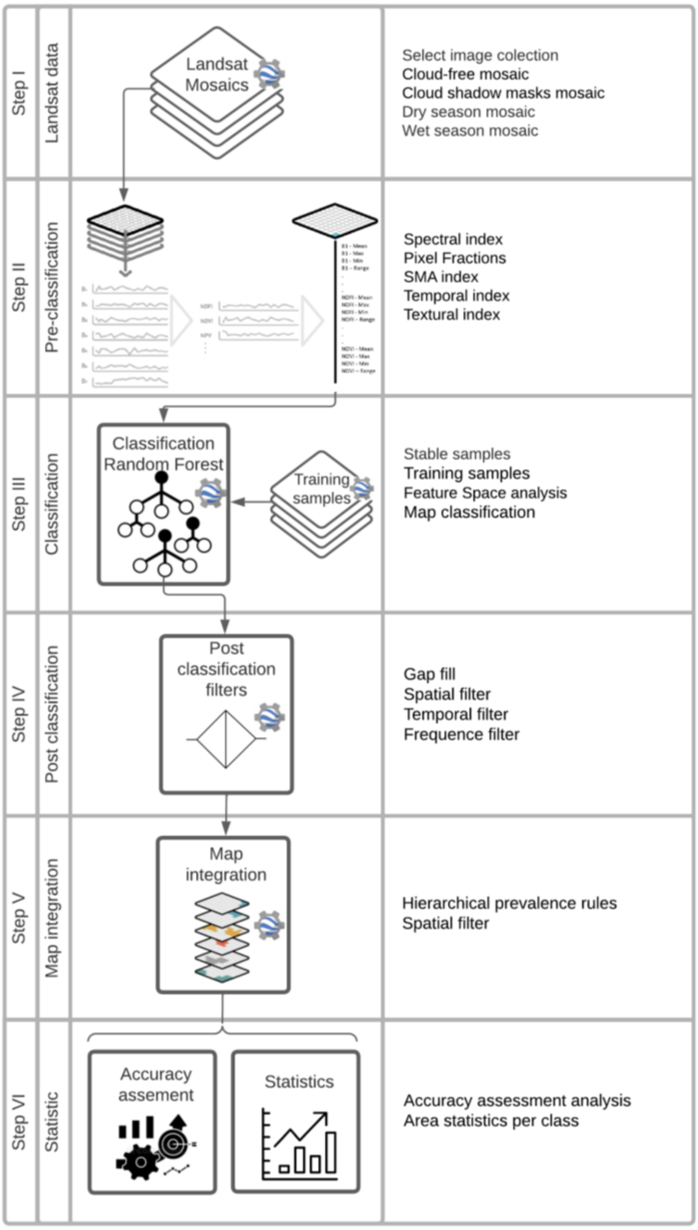
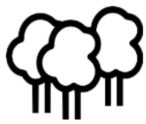


Figure 2. Methodological scheme for data processing Caatinga Biome land use and land cover (LULC) classification in the Google Earth Engine.

Based on the legend adopted in this study, it is essential to point out that the data from the cross-cutting themes used during the integration of the maps were Agriculture, Forest Plantation, and Pasture. The other classes come from the base map of the Caatinga biome. We used eight classes from the mix of hierarchical levels of the classification used by MapBiomas [32]. The classification legend used was as follows: Forest Formation, Savanna Formation, Non-Forest Natural Formation, Pasture, Agriculture, Mosaic of Agriculture and

Pasture, Non-vegetated area, and Water. The table below shows the details of the legend used in this study (Table 1).

Table 1. The land cover and land use classification system for the Caatinga Biome is presented. The table colors reflect the class representations used in the LULC maps.

LULC Classification	Description	Symbology
Forest Formation	Natural Vegetation tree with a high-density continuous canopy, or resulting from different disturbances such as fire, selective logging, and forest resulting from natural regrowth. This level includes Natural Forest Formation Vegetation types with a predominance of tree species with high density and canopy in different states of disturbance.	
Savanna Formation	Savana vegetation types have a tree layer varying in density, distributed over a continuous shrub-herbaceous cover.	
Non-Forest Natural Formation	Vegetation with a shrub-herbaceous stratum, including patches with a shrub-herbaceous stratum. This level includes wetlands (Floodplain with river and lake influence, herbaceous shrub vegetation, and/or arboreal and pioneer formations), marshes (marine influence), Salt flats (Apicuns formations often without tree vegetation, associated with saline and a less flooded area in the mangrove), Grassland Formation (Vegetation with a predominance of herbaceous stratum and shrub-herbaceous stratum), and Rocky Outcrop with a partial presence of rock vegetation and a high slope.	
Pasture	Pasture areas planted are related to farming activity.	
Agriculture	Areas predominantly occupied by annual crops, perennial crops, and semi-perennial Crops.	
Mosaic of Agriculture and Pasture	Farming areas where it was not possible to distinguish between pasture and agriculture.	
Non-vegetated area	Non-vegetated surface areas. This level includes Beach and Dune (Sandy areas), Urban Infrastructure (Urban areas with non-vegetated surfaces, including roads, highways, and construction), and Mining (Areas related to large mineral extraction. Only areas belonging to the National Department of Mineral Production's (DNPM) chart (SIGMINE) were considered).	
Water	Rivers, lakes, dams, reservoirs, and other water bodies. This level includes Natural and Artificial lakes, aquaculture, and salt production activities.	

To carry out the classification of the 1985–2019 time series for the Caatinga biome, we used the set of images from the Landsat sensors Collection 1 Tier 1 converted to top of the atmosphere (TOA) reflectance (Landsat 5—Thematic Mapper (TM); Landsat 7—Enhanced Thematic Mapper Plus (ETM+); Landsat 8—Operational Land Imager (OLI)). The Google Earth Engine obtained and processed all the data. Landsat Collection 1 Tier 1 features offset the error correction (orthorectification) and were normalized to the TOA reflectance (Figure 2, Step I). Cross-cutting themes (i.e., pasture, agriculture, and non-vegetation areas such as coastal zones, mining areas, and urban infrastructure) were integrated annually with the maps of the Caatinga biome. In the section discussing the integration of the maps, the specifics of how the integration was carried out are detailed.

After selecting the dataset, the next step was to build annual and intra-annual (dry and rainy periods) Landsat mosaics free of clouds and cloud shadows (Figure 2, Step I). We used dark temporal outlier mask (TDOM) and band quality assessment (BQA) information in the Landsat Collection. We then applied cloud and cloud shadow masks to all Landsat scenes. The annual and intra-annual mosaics were produced using statistical reducers (i.e., math functions in Earth Engine), including the median, standard deviation, minimum, and maximum (Figure 2, Step II). The image selection period for the Caatinga biome was defined to minimize confusion between natural vegetation and other types of land use and land cover (LULC) (e.g., cultivated areas) due to extreme phenological changes. The Caatinga biome exhibits significant seasonal variation in precipitation, which is the main factor determining the physiological behavior of vegetation throughout the year. The vegetation in the Caatinga biome is mainly classified as seasonal, expressing great deciduousness over the year, and only a tiny fraction of tree species does not lose their leaves during the dry season, so the savanna formations in the Caatinga biome are expected to show significant variation in spectral response throughout the year. Based on the analysis of historical precipitation data for the Caatinga biome, we selected a period from January to July to compose the annual mosaic. During this period, it is possible to obtain images with a greater probability of obtaining images with spectral contrast capable of separating different classes of LULC for the biome. To delimit the dry and wet periods, we used interquartile periods.

After obtaining the mosaics resulting from the processing of the different reducers, the next step was to build a feature space for the random forest classifier. We built the feature space with spectral bands and index, fractions, and an index obtained via spectral mixture analysis (SMA), a temporal index (based on a median, min, amplitude, and standard deviation reducers), and a textural index. One hundred and four features were available to select from to obtain the best features. The best features for the digital classification of LULC classes in the Caatinga biome comprised a subset of 40 variables. These variables included the original Landsat reflectance band vegetation indexes and spectral mixture modeling-derived variables. The definitions of this subset and the classifier parameters were formulated based on tests conducted through machine learning-based libraries. All codes used are available in the MapBiomas Github repository "https://github.com/mapbiomas-brazil/caatinga (accessed on 6 October 2023)".

The digital classification was performed by using watersheds, year by year, using a random forest algorithm [37] available in the Google Earth Engine. The parameters used in the random forest classifier were as follows: 'number of trees':60; 'variablesPerSplit':6; 'minLeafPopulation':3; 'maxNodes':10; and 'seed':0 (Figure 2, Step III).

To facilitate the land cover classification, the Caatinga biome was divided into 39 regions based on watershed data provided by the Agência Nacional de Águas, which can be accessed through the link "https://www.ana.gov.br (accessed on 6 October 2023)". Performing classification in homogenous regions, such as watersheds, reduces the confusion of samples and classes and allows for a better balance of samples. We merged watersheds from levels 3 and 4 to facilitate processing (Figure 1). Training samples for each watershed were defined following a strategy of using pixels in which the vegetation cover/land use remained the same in the five-year window of Collection 4.1, which we named "stable samples" (for the years 1985 to 2018) (Figure 2, Step III). The extraction of stable samples from the previous map (Collection 4.1) followed several steps to ensure their confidence as training areas. First, we generated random stable samples based on the class cover percentage in each watershed and the five-year windows. A minimum of 300 samples were used for rare classes that did not cover at least 10% of the region. All codes used are available in the MapBiomas Github repository "https://github.com/mapbiomas-brazil/caatinga (accessed on 6 October 2023)".

Due to the classification method used (temporal classification pixel by pixel), we applied a set of post-classification filters. The sequence of temporal and space filters used in the Caatinga biome was as follows: (1) GapFill; (2) Temporal; (3) Frequency; (4) Spatial (Figure 2, Step IV). We now describe each of the filters used. GapFill is a temporal filter that fills values without data and the time series classification. This filter mainly acts in regions affected by clouds. In practice, values without data ("Gaps") are theoretically not allowed and are replaced by the closest temporal validity classification. In this procedure, if a valid position is available in the "future", the no-data value is replaced by its previous valid class.

Data from up to three previous years can fill positions without persistent data. Therefore, gaps should only exist if a specific pixel is permanently classified as lacking data in the entire temporal domain. A spatial filter was applied to avoid unwanted modifications to the edges of the pixel groups. Based on the "connectedPixelCount" function, the filter is native to the GEE platform and locates connected components (neighbors) that share the same pixel value. Thus, only pixels that do not share connections to a predefined number of identical neighbors are considered isolated. This filter needs at least five connected pixels to reach the minimum connection value.

Consequently, the applied spatial filter directly affects the minimum mapping unit, which was defined as 5 pixels (~0.5 ha). A frequency filter was applied only to pixels considered "stable natural vegetation". If a "stable natural vegetation" pixel comprised at least 80% of the same class years, all of the years were changed to that class. This frequency filter resulted in a more stable classification between natural classes (e.g., forest and savanna). Another significant result was the removal of noise in the first and last years of classification (i.e., 1985 and 2019). The applied temporal filter uses the subsequent years to replace pixels with invalid transitions. For example, a pixel classified as non-forest in a given year t_i (where i = 2008, 2009, . . ., 2015) and forest in years t_i and t_{i+1} was reclassified as forest for the year t_i. (For more details, see [32]).

The integration of the maps of the Caatinga biome with the maps of cross-cutting themes was accomplished through the hierarchical overlapping of each mapped class (on a pixel-by-pixel basis), according to specific prevalence rules (Figure 2, Step V).

2.3. Cross-Cutting Themes

To carry out the mapping of classes associated with cross-cutting themes such as Pasture, Agriculture, and Forest plantation, different methods were used, and we detail each one below.

For the classification of Agriculture (Annual, Semi-perennial, and Perennial Agriculture) and Forest Plantation, Brazil was divided into six regions considering the regional crop calendar. For the composition of the mosaics associated with the classification of temporary agriculture, different periods for the temporal composition of the Landsat mosaics were used, considering each region's dry and rainy seasons within each year. Intra-annual variations based on bimonthly compositions were used to classify perennial agriculture and planted forests. It was used for the supervised classification of the random forest classifier. The present study grouped the Annual, Semi-perennial, Perennial Agriculture, and Forest Plant classes into the general class Agriculture [31,32].

In the pasture classification, the whole set of scenes comprises the coverage of Brazil. From these images, a set of metrics was generated considering spectral variations over 24 months to capture pasture seasonality. Forty spectral metrics were used to create a feature space, and images were classified via random forest. About 31,000 training points were used, and at the end of the classification, a post-classification space-time filter was applied to correct small, abrupt transitions. A filtering algorithm based on a time window of 5 years and 3 × 3 pixels was used to replace the central kernel value with the median of 45 probability values (for more details, see [31,32]).

2.4. Accuracy Assessment

An accuracy analysis was based on statistical techniques using independent sample points with a visual interpretation of the entire time series. Analyses were performed based on ~75,000 independent samples at the Landsat pixel level for each one of the years from 1985 to 2017 in all of Brazil. In the Caatinga biome, 9738 samples were used (Figure 2, Step VI), and three independent interpreters inspected each sample. In case of any confusion, a senior interpreter decided on the final class of the pixel. This evaluation was based on the Temporal Visual Inspection web platform (TVI, tvi.lapig.iesa.ufg.br), developed by LAPIG/UFG. The TVI platform allowed for an evaluation of all the classes mapped using MapBiomas Collection 5 [32]. A classification error matrix and several metrics were created (i.e., overall accuracy, quantity, and allocation disagreement) [32].

2.5. General Analysis

Our research employed the Google Earth Engine platform to develop customized methods for calculating area statistics across categories, occurrences, and geographic regions. We used R version 3.6.2 [38,39], RStudio version 1.2.5033 [40,41], and the Ggplot2 package version 3.2.1 [42] for all visualizations, including plots, flowcharts, and maps.

3. Results

The present study represents the first initiative to systematically and continuously build an annual land use and land cover mapping series for the Caatinga biome, covering a 35-year period between 1985 and 2019. Our maps achieved an average global accuracy of 80%, with an 11.6% allocation disagreement and an 8.5% area disagreement, providing a comprehensive and reliable understanding of the spatial and temporal patterns of land cover modifications in the Caatinga region. This research fills a critical gap in the literature, addressing the limited studies and data availability that previously hindered a thorough assessment of the transformation dynamics within this important tropical semi-arid ecosystem (Figure 3).

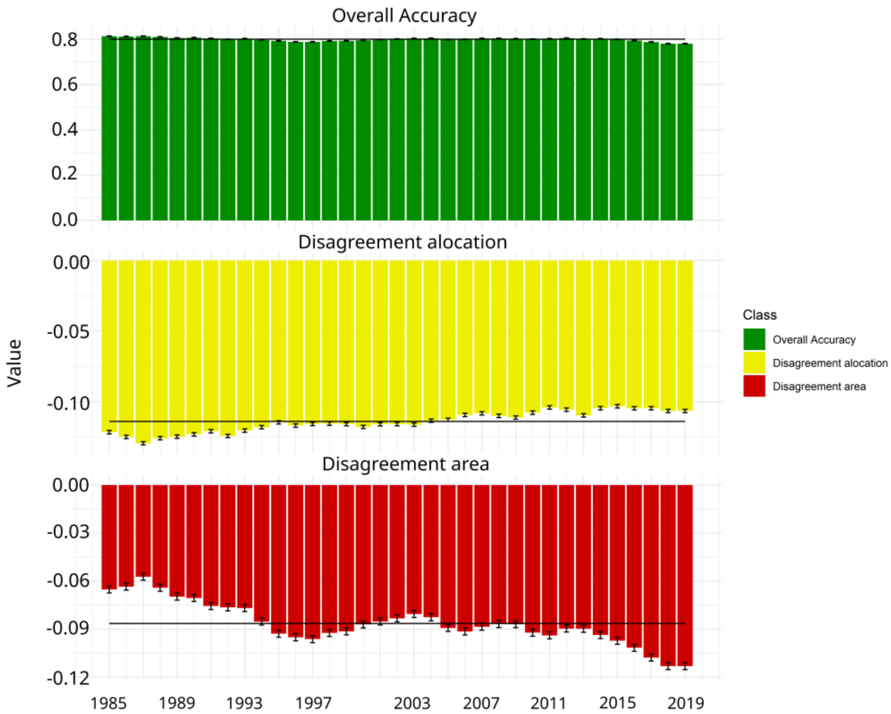


Figure 3. Summary of accuracy statistics for each year of the 1985 to 2019 time series for the Caatinga Biome. The figure shows the global accuracy, allocation errors, and area data. The black line across the series indicates the average of the time series. The bars in each year represent the standard error of the mean.

The Savanna Formation (SF) and Pasture (PAT) areas, which covered 46.17 million hectares and 21.78 million hectares in 2019, are the dominant features of the Caatinga biome. Their combined area, precisely calculated to be 79% (67.94 million hectares) of the entire biome, is a testament to the accuracy of our research. In contrast, the other categories, with a combined area of 21% (18.30 million hectares), represent a smaller but still noteworthy portion of the biome (Figure 4; Table 2).

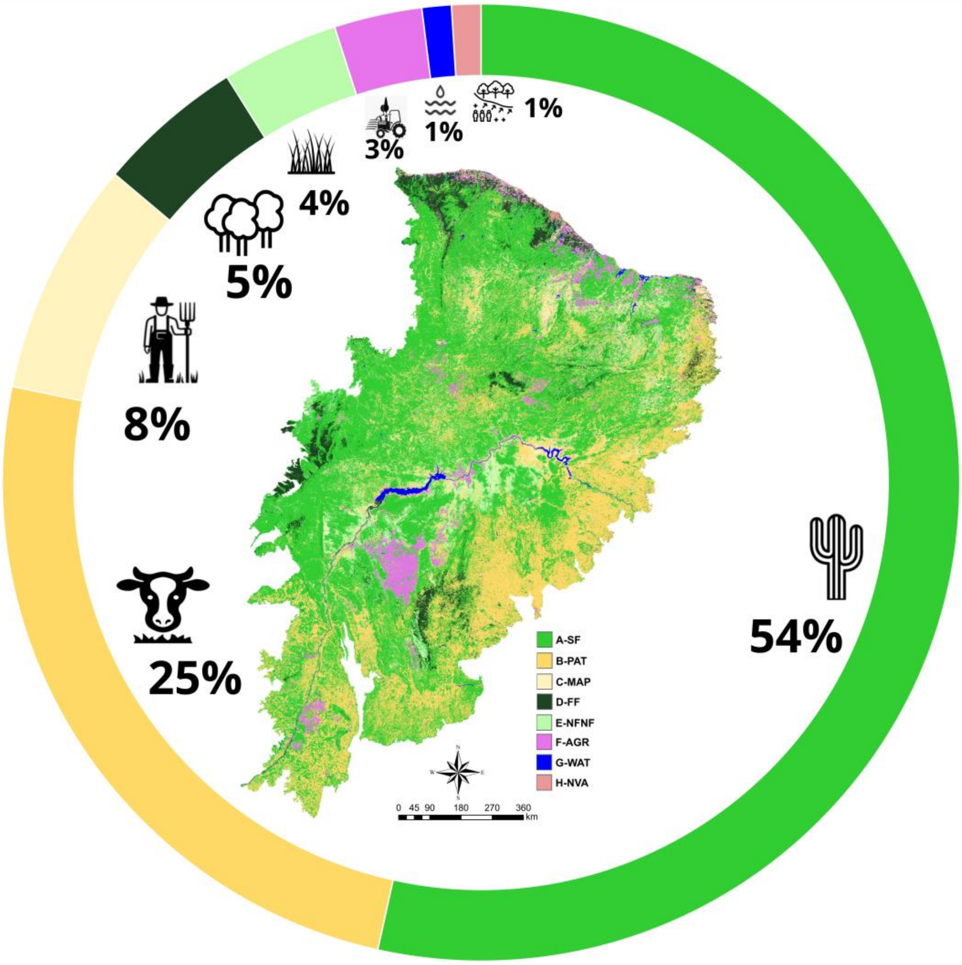


Figure 4. Percentage statistics of land use and land cover (LULC) Caatinga Biome classification in 2019. A-SF (Savana Formation), B-PAT (Pasture), C-MAP (Mosaic Agriculture Pasture), D-FF (Forest Formation), E-NFNF (Non-Forest Natural Formation), F-AGR (Agriculture), G-WAT (Water), H-NVA (Nom vegetated area).

Table 2. Calculation of loss and increase variation in an area between LULC classes for the Caatinga Biome between 1985 and 2019.

Class		1985 (Mha)	2019 (Mha)	Variation
Natural vegetation	Forest Formation	4.37	4.03	−8%
	Savanna Formation	51.96	46.17	−11%
	Non Forest Natural Formation	3.76	3.33	−12%
Nom natural	Mosaic of Agriculture and Pasture	10.76	6.82	−37%
	Pasture	13.41	21.78	62%
	Agriculture	0.75	2.89	284%
	Non Vegetated Area	0.36	0.57	58%
Water		0.87	0.67	−24%

It has been confirmed that in 2019, the native vegetation cover accounted for 62% of the Caatinga biome. However, an analysis of the area's statistics from 1985 to 2019 reveals a concerning trend. During this time, the Caatinga biome experienced an 11% reduction in its native vegetation, equivalent to approximately 6.57 million hectares. This significant loss underscores the urgent need for comprehensive conservation initiatives and sustainable land use practices to safeguard the Caatinga biome's unique and invaluable ecosystem (Figure 5; Table 2).

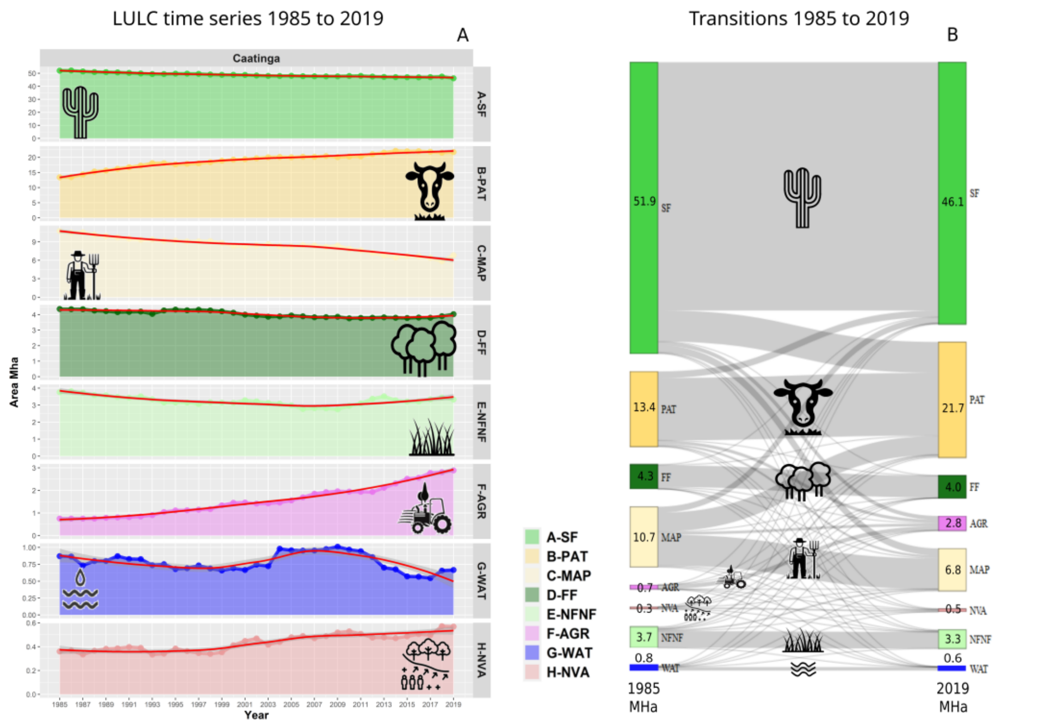


Figure 5. The figures illustrate the changes in land use and land cover in the Caatinga Biome from 1985 to 2019. (**A**) shows the area dynamics in millions of hectares for the mapped classes, with the red line indicating the trends. (**B**) displays the area transitions in millions of hectares between 1985 and 2019 among the mapped classes.

Our research has revealed a concerning trend: a reduction in all categories of native vegetation as a percentage. The Non-Forest Natural Formation (NFNF) classes have seen a 12% (−0.43 Mha) decline, followed by the Savanna Formation with an 11% (−5.79 MHa) decrease, and the Forest Formation with an 8% (−0.34 Mha) drop (Table 2; Figure 5). This decrease in native vegetation classes is a stark reminder of the significant loss of natural coverage in the Caatinga biome over the past 35 years, emphasizing the pressing need for comprehensive conservation efforts and sustainable land use practices to safeguard this unique ecosystem.

Over the years, the Caatinga biome has witnessed a distressing decline in its native vegetation. This trend is underscored by a staggering 27% (Figure 5; Table 2) surge in non-natural areas, which now sprawl across a vast 6.78 million hectares, constituting a significant 27% of the biome's total area (Figure 4).

When we delve into the specifics, we find that the Pasture (PAT) class dominates the non-natural landscape, encompassing a significant 25% (21.78 million hectares) of the biome. This reflects a substantial 62% increase, a change that cannot be overlooked. Following closely is the Mosaic of Agriculture and Pasture (MAP) class, covering 8% (6.68 million hectares) with a decrease of 37%. The Agriculture (AGR) class covers 3% (2.89 million hectares) with a staggering 284% increase, while the non-vegetated area 1% (NVA) (0.57 million hectares) shows a 58% increase (Figure 4; Table 2). The water (WAT) class, however, decreased to around 1% (0.57 million hectares) in 2019, indicating a 24% decrease in the Caatinga biome in that year.

Examining temporal trends in class variation across the 1985–2019 time series, a clear pattern emerges. The natural vegetation classes experienced their most significant decline in the 1985–1995 period, followed by the periods 1995–2005, 2005–2015, and 2015–2019. In contrast, farming areas saw their most significant increase between the years 1985 and 1995, followed by the periods 1995–2005, 2005–2015, and 2015–2019 (Figures 5A and 6).

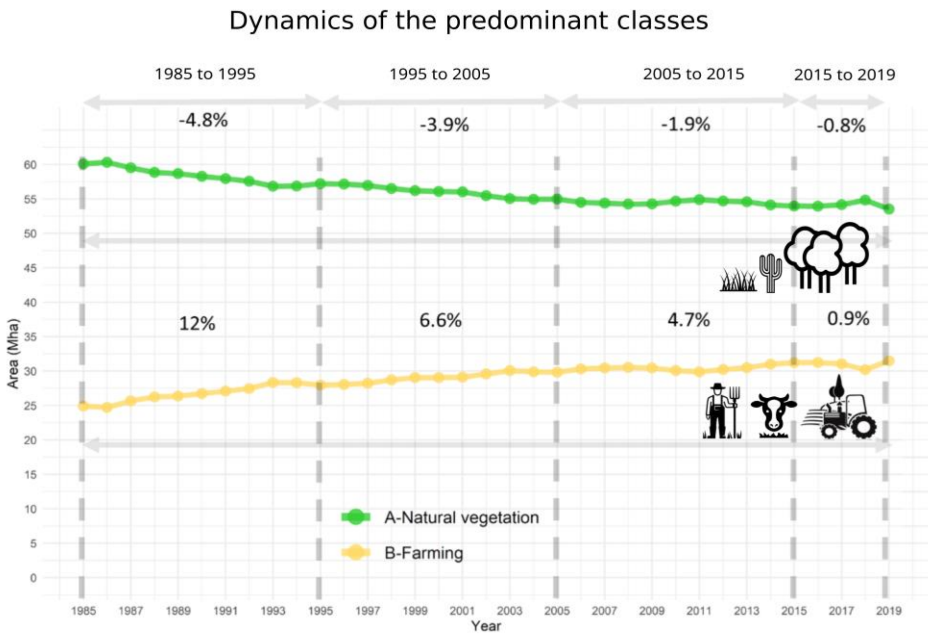


Figure 6. Dynamics statistics and percentage by decade variation in land use and land cover (LULC) Caatinga Biome classification 1985 to 2019.

When considering the transitions that occurred from 1985 to 2019, it is particularly intriguing that the natural class 'SF' underwent the most significant alterations in terms of area; these changes included transitions to 'PAT' (5.52 million hectares), 'MAP' (1.24 million hectares), 'AGR' (0.67 million hectares), 'NFNF' (0.14 million hectares), 'WAT' (0.05 million hectares), 'FF' (0.04 million hectares), and 'NVA' (0.03 million hectares) (refer to Figures 5B and 7).

In terms of natural classes, the most substantial area-related transitions occurred in 'NFNF', encompassing shifts to 'PAT' (0.33 million hectares), 'MAP' (0.27 million hectares), 'SF' (0.10 million hectares), 'AGR' (0.071 million hectares), 'PAT' (0.021 million hectares), 'WAT' (0.008 million hectares), and 'FF' (0.003 million hectares). Likewise, 'FF' experienced significant changes with transitions to 'MAP' (0.17 million hectares), 'AGR' (0.16 million hectares), 'PAT' (0.11 million hectares), 'SF' (0.10 million hectares), 'NVA' (0.02 million hectares), 'WAT' (0.009 million hectares), and 'NFNF' (0.002 million hectares) (Figures 5B and 7).

Conversely, among unnatural classes, 'MAP' underwent the most substantial alterations in terms of area, involving transitions to 'PAT' (3.34 million hectares), 'SF' (1.06 million hectares), 'AGR' (0.46 million hectares), 'NFNF' (0.162 million hectares), 'NVA' (0.12 million hectares), 'FF' (0.10 million hectares), and 'WAT' (0.047 million hectares). Following this, 'PAT' experienced significant changes with transitions to 'SF' (1.15 million hectares), 'AGR' (0.53 million hectares), 'MAP' (0.37 million hectares), 'NFNF' (0.091 million hectares), 'NVA' (0.070 million hectares), 'FF' (0.037 million hectares), and 'WAT' (0.026 million hectares). Additionally, 'NVA' demonstrated noteworthy transitions to 'PAT' (0.043 million hectares), 'MAP' (0.021 million hectares), 'NFNF' (0.010 million hectares), 'SF' (0.005 million hectares), 'WAT' (0.004 million hectares), 'AGR' (0.003 million hectares), and 'WAT' (0.001 million hectares). Finally, 'AGR' experienced changes in area with transitions to 'SF' (0.024 million hectares), 'PAT' (0.012 million hectares), 'MAP' (0.0019 million hectares), 'NFNF' (0.0016 million hectares), 'NVA' (0.0013 million hectares), 'FF' (0.00024 million hectares), and 'WAT' (0.00001 million hectares) (Figures 5B and 7).

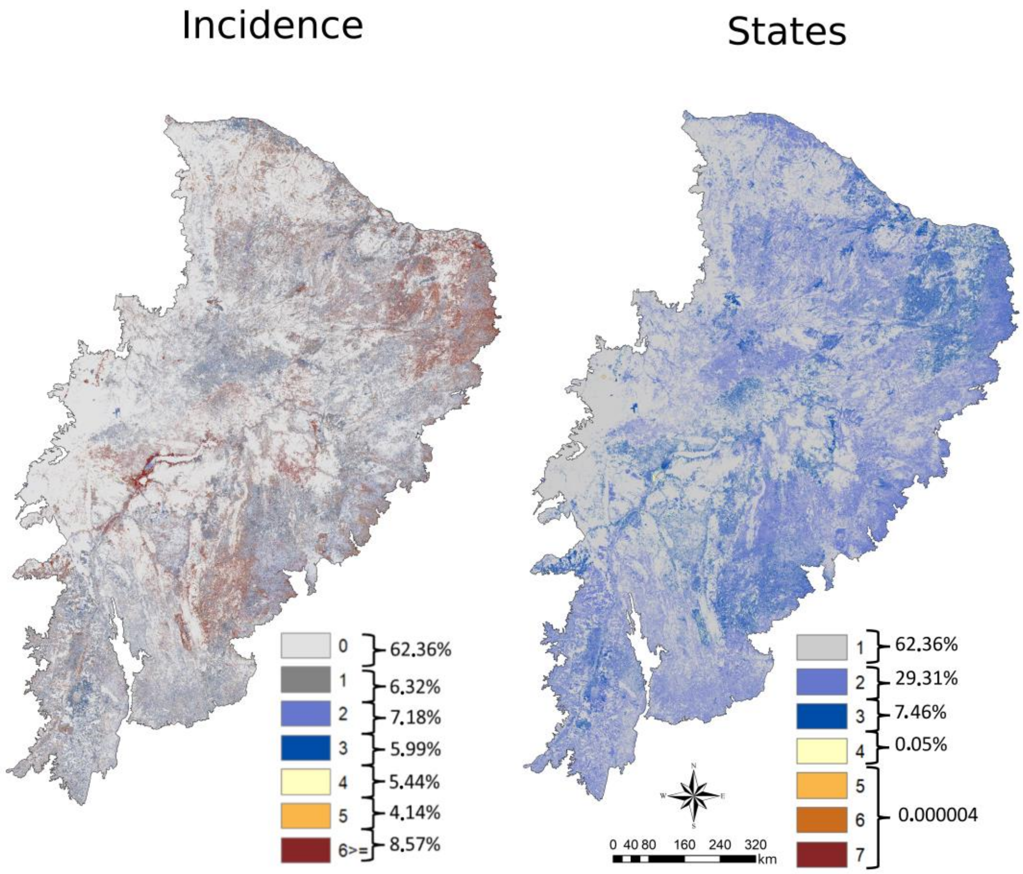


Figure 7. Spatial dynamics maps summarize all four-time intervals: Incidents, States of land use, and land cover (LULC) in the Caatinga Biome.

In terms of transitions involving the water class 'WAT', the following changes in land cover area were observed: 'WAT' transitioned to 'PAT' covering 0.13 million hectares, to 'SF' covering 0.064 million hectares, to 'MAP' covering 0.051 million hectares, to 'FF' covering 0.041 million hectares, to 'NFNF' covering 0.009 million hectares, to 'AGR' covering 0.006 million hectares, and once again to 'PAT' covering 0.003 million hectares (see Figure 5B).

Utilizing incidence and state change data, we estimated that a substantial portion of the Caatinga biome, precisely 62.36% (equivalent to 53.8 million hectares), remained consistent regarding class transitions over the 35 years spanning 1985 to 2019 (refer to Figure 7). Our analysis further delineated the dynamic nature of pixels, revealing transitions ranging from one to six instances within the 35-year series. The corresponding percentages and land areas for these transitions were as follows: (one transition) accounting for 6.32%, covering 5.45 million hectares; (two transitions) representing 7.18%, encompassing 6.19 million hectares; (three transitions) constituting 5.99%, spanning 5.17 million hectares; (four transitions) amounting to 5.44%, covering 4.69 million hectares; (five transitions) accounting for 4.14%, encompassing 3.57 million hectares; and (six transitions) representing 8.57%, across 7.39 million hectares (see Figure 7).

Regarding changes in land state, we analyzed pixel dynamics in terms of the number of transitions between different mapped classes over 35 years. Within this context, class transitions ranged from two to seven instances, with the corresponding percentages and land areas detailed as follows: (2 classes) accounting for 29.31%, equivalent to 25.28 million hectares; (3 classes) representing 7.46%, encompassing 6.43 million hectares; and (4–7 classes) constituting a minimal 0.05%, covering 0.043 million hectares.

4. Discussion

This research explores the systematic and ongoing mapping of land use and cover in the Caatinga biome spanning 35 years, from 1985 to 2019, as part of the broader MapBiomas initiative. Leveraging advanced remote sensing and geospatial analysis, this study comprehensively understands the spatial and temporal patterns of land cover changes in this distinct tropical semi-arid ecosystem. The detailed maps produced offer valuable insights into dynamics and trends within the Caatinga biome, underscoring the importance of implementing effective conservation and management strategies.

An important finding from this study is the steady but persistent conversion of native vegetation, particularly in savannas and other non-forest natural areas, to land increasingly used for agriculture and pasture. This transition underscores the mounting pressures from livestock grazing and regular land use, contributing to soil erosion, the loss of vegetation cover, and decreased land productivity [43]. These changes present significant challenges to the long-term sustainability and ecological health of the Caatinga biome [44]. The conversion of native vegetation into human-modified land impacts biodiversity, disrupts ecosystem services, and intensifies susceptibility to climate change. Tackling these issues necessitates collaborative efforts among policymakers, land managers, and local communities to formulate strategies that reconcile sustainable development with environmental preservation.

Our study has uncovered a notable decrease in native vegetation cover between 1985 and 2019, highlighting the pressing requirement for all-encompassing conservation efforts and sustainable land use practices. The diminishing presence of various natural formations emphasizes the widespread loss of vital natural habitats necessary for sustaining biodiversity and ecosystem strength. The preservation of native vegetation is essential for upholding biodiversity and ecosystem services. Consequently, concerted actions are vital for formulating and executing sustainable development and conservation plans [45,46].

Moreover, the research highlights a significant increase in agricultural land attributed to local and global food demand, economic incentives, and policies promoting agricultural intensification [47–49]. This expansion frequently comes at the cost of native vegetation, resulting in habitat fragmentation, heightened strain on natural areas, and potential impacts on biodiversity. It is crucial to adopt sustainable agricultural techniques to effectively manage the demands of agricultural production while safeguarding the Caatinga biome's ecosystem. This requires coordinated efforts among policymakers, land managers, and local communities.

This study's temporal analysis reveals clear phases of change, with notable decreases in natural vegetation observed from 1985 to 1995, aligning with the considerable expansion of agricultural areas. This trend indicates a shift in land use priorities driven by policy adjustments and economic reforms. The enduring impact of agricultural growth on the Caatinga biome underscores the necessity of a holistic approach to land management that prioritizes environmental sustainability. The recent literature supports these findings, indicating that agricultural expansion and intensification primarily drive land use changes in tropical and semi-arid regions [50]. The significant changes observed in the initial decade studied could be attributed to policy shifts and economic reforms that promoted agricultural expansion, often at the expense of environmental sustainability [51].

Comparing this study with others reveals slight variations in natural vegetation cover due to differences in methodology and changes in biome delineation. Despite these discrepancies, there is a consistent and concerning agreement that the Caatinga biome's natural vegetation is steadily diminishing. This loss is mainly attributed to human activities, including agricultural expansion and intensification, which pose a threat to the biome's stability. It is imperative to coordinate conservation efforts to develop effective strategies that balance sustainable development with conservation.

Our research offers comprehensive insights into land cover transitions, specifically from the classification of Savanna Formation to Pasture, Agriculture, and Mosaic of Agriculture and Pasture. These transitions exemplify larger land use patterns and the intricate interplay between land cover types, influenced by economic factors and land management strategies [52]. The worldwide pattern of agricultural expansion as a primary driver of deforestation and habitat destruction is reflected in the Caatinga biome, underscoring the urgency of adopting sustainable land use approaches. These detailed transitions reflect the complex and ongoing interactions between land cover types, driven by various economic and environmental factors [53].

Addressing these land cover transitions by implementing sustainable land use practices and preserving native vegetation is essential to ensuring the long-term resilience and conservation of the Caatinga biome. Our study's findings emphasize the pressing need for focused conservation activities to prevent additional degradation and enhance the biome's resilience. Effective conservation and land management policies necessitate coordinated collaboration among government agencies, local communities, and international organizations.

Promoting sustainable agricultural practices, restoring degraded lands, and establishing protected areas are essential. Nevertheless, the real power lies in environmental education programs and community engagement initiatives. These efforts can raise awareness and cultivate a deeper understanding among local stakeholders of the significance of safeguarding the Caatinga's fragile ecosystem. Through these coordinated efforts, we can strive for a future in which the Caatinga's natural resources are managed responsibly, its biodiversity is protected, and its ecosystem services are maintained for the benefit of current and future generations.

5. Conclusions

Our research is the first attempt to reconstruct and analyze in detail the patterns of land use and land cover changes across the entire Caatinga biome over a 35-year period from 1985 to 2019.

This emphasizes the critical importance of implementing thorough conservation measures and sustainable land management practices. Protecting native vegetation is essential for maintaining biodiversity and ecosystem services, necessitating unified actions to formulate and execute sustainable development and conservation strategies. The rise in agricultural land driven by food demand and economic incentives often harms native vegetation and biodiversity. Embracing sustainable farming practices is crucial to meeting production demands while safeguarding the Caatinga's ecosystem, requiring cooperation among policymakers, land managers, and local communities.

The temporal data analysis performed herein indicates that significant agricultural expansion caused marked decreases in natural vegetation from 1985 to 1995. Policy shifts and economic reforms influenced this change, resulting in lasting effects on the Caatinga biome. Recent studies suggest that farming activities are key factors driving land use transformations in tropical and semi-arid areas. This research revealed a significant decrease in the natural vegetation of the Caatinga biome, primarily due to the expansion and intensification of agriculture, which threatens the biome's stability. Coordinated conservation endeavors are necessary to harmonize sustainable development and conservation.

Considering the urgent need for data on changing land use and land cover in the Caatinga biome, which is essential for effective landscape management, our research, in conjunction with other relevant efforts, emphasizes the necessity of implementing solid public policies. These policies should focus on the preservation and sustainable coexistence of natural areas with expanding agro-pastoral activities.

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S.G.D., J.S.B.L., D.T.M.S., S.M.H., N.A.S., R.O.F.R., J.F.-F., M.O., L.d.S.B., C.L.C., and W.M.A.; software execution, R.N.V., D.P.C., and S.G.D.; writing—original draft preparation, W.J.S.F.R., R.N.V., R.O.F.R., J.F.-F., M.O., L.d.S.B., C.L.C., and W.M.A.; writing—review and editing, D.T.M.S., S.M.H., N.A.S., R.O.F.R., J.F.-F., M.O., L.d.S.B., C.L.C., and W.M.A.; supervision, W.J.S.F.R. and R.N.V.; funding acquisition, W.J.S.F.R. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are openly available in Google earth Engine public at 'projects/mapbiomas-workspace/public/collection5/mapbiomas_collection50_integration_v1'.

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