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FUTURE DYNAMICS OF LAND USE AND LAND COVER IN THE CERRADO BIOME

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Abstract

The Cerrado, recognized as a global biodiversity hotspot, is under intense pressure from agricultural expansion. To support public policy planning, this study projected future land use and land cover scenarios up to 2100 using a spatial modeling framework developed in Python, based on Markov Chains, Weights of Evidence, and neighborhood metrics. PRODES deforestation rates were used to define three scenarios: optimistic (6,512.6 km²/year), trend (8,140.8 km²/year), and pessimistic (11,551 km²/year). The results indicate that the optimistic scenario slows the loss of native vegetation, whereas the trend scenario maintains recent conversion patterns and the pessimistic scenario intensifies landscape fragmentation. The highest annual losses are concentrated between 2030 and 2050 (optimistic: –2,707 km²; trend: –6,342 km²; pessimistic: –15,711 km²), followed by a decline due to the scarcity of remaining natural areas. By 2100, native vegetation may be reduced to 1.3–1.7 million km², corresponding to 47–61% of its original extent. These findings indicate that maintaining current trajectories may compromise the biome's ecological resilience, highlighting the need for stricter conservation and deforestation control policies.

Keywords: Land-Use Change; Spatial Modeling; Cerrado Biome; Deforestation Scenarios; Environmental Policy.

Resumo / Resumen

DINÂMICAS FUTURAS DE USO E COBERTURA DA TERRA NO BIOMA CERRADO

O Cerrado, reconhecido como hotspot global de biodiversidade, enfrenta intensa pressão decorrente da expansão agropecuária. Com o objetivo de subsidiar políticas públicas, este estudo projetou cenários futuros de uso e cobertura da terra até 2100 por meio de modelagem espacial em Python, baseada em Cadeias de Markov, Pesos de Evidência e métricas de vizinhança. As taxas de desmatamento do PRODES foram utilizadas para definir três cenários: otimista (6.512,6 km²/ano), tendencial (8.140,8 km²/ano) e pessimista (11.551 km²/ano). Os resultados indicam que o cenário otimista reduz o ritmo de perda da vegetação nativa, enquanto o tendencial mantém padrões recentes de conversão e o pessimista intensifica a fragmentação da paisagem. As maiores perdas anuais concentram-se entre 2030 e 2050 (otimista: –2.707 km²; tendencial: –6.342 km²; pessimista: –15.711 km²), com posterior desaceleração em razão da redução de áreas remanescentes. Em 2100, a vegetação nativa poderá ser reduzida para 1,3 a 1,7 milhão de km², correspondendo a 47–61% da cobertura original. Conclui-se que a continuidade das trajetórias atuais compromete a resiliência ecológica do bioma, reforçando a necessidade de políticas rigorosas de conservação e controle do desmatamento.

Palavras-chave: Modelagem Espacial; Uso e Cobertura da Terra; Cerrado; Cenários de Desmatamento; Geotecnologias.

DINÁMICAS FUTURAS DE USO Y COBERTURA DE LA TIERRA EN EL BIOMA CERRADO

El Cerrado, reconocido como un hotspot global de biodiversidad, enfrenta una intensa presión derivada de la expansión agropecuaria. Con el objetivo de subsidiar políticas públicas, este estudio proyectó escenarios futuros de uso y cobertura de la tierra hasta 2100 mediante un modelo espacial desarrollado en Python, basado en Cadenas de Markov, Pesos de Evidencia y métricas de vecindad. Las tasas de deforestación del PRODES se utilizaron para definir tres escenarios: optimista (6.512,6 km²/año), tendencial (8.140,8 km²/año) y pesimista (11.551 km²/año). Los resultados indican que el escenario optimista reduce el ritmo de pérdida de vegetación nativa, mientras que el tendencial mantiene los patrones recientes de conversión y el pesimista intensifica la fragmentación del paisaje. Las mayores pérdidas anuales se concentran entre 2030 y 2050 (optimista: –2.707 km²; tendencial: –6.342 km²; pesimista: –15.711 km²), seguidas de una desaceleración debido a la escasez de áreas remanentes. Para 2100, la vegetación nativa podría reducirse a entre 1,3 y 1,7 millones de km², equivalentes al 47–61% de su cobertura original. Se concluye que la continuidad de las trayectorias actuales compromete la resiliencia ecológica del bioma, lo que refuerza la necesidad de políticas estrictas de conservación y control de la deforestación.

Palabras-clave: Modelación Espacial; Uso y Cobertura de la Tierra; Cerrado; Escenarios de Deforestación; Geotecnologías.

INTRODUCTION

Brazil is one of the largest producers and exporters of grain and meat in the world (FAO, 2010), and the Cerrado has established itself as one of the main global agricultural regions (Oliveira et al., 2019). This process was driven by favorable topographical conditions, with a predominantly flat or gently undulating relief, soil suitability for mechanization, and low land costs (Lapola et al., 2014; Klink; Machado, 2005).

Covering approximately 2 million km², the Cerrado is the second largest biome in Brazil in terms of territorial extension, second only to the Amazon. Its strategic location in the center of the country connects it primarily to two biomes: the Caatinga to the northeast, and the Amazon to the north and northwest.

The biome is considered the most threatened hotspot among the world's tropical savannas (Silva et al., 2002). Currently, only 43% of its area consists of native vegetation, while about 47% has already been converted to agricultural use (Mapbiomas, 2024). Historically, the deforestation rate in the Cerrado has exceeded that recorded in the Brazilian Amazon, with agricultural expansion, especially over the last three decades, being the main driver of these landscape transformations (Colman et al., 2024).

The conversion of the Cerrado into one of the largest agricultural frontiers in the world is directly associated with the expansion of soy and extensive cattle ranching, especially from the 2000s onward. The region accounts for about 60% of the country's soy production, making it the primary destination for Brazilian agribusiness investments in recent decades (Gibbs et al., 2015). Furthermore, recent research highlights that a large part of deforestation occurs in compliance with current legislation, evidence of a land-use model that combines formal legality with significant socio-environmental impacts (Soterroni et al., 2019).

Environmental legislation regarding the Cerrado biome is less restrictive compared to other biomes in Brazil, as evidenced by the fact that it has the lowest proportion of legally protected areas in the country. Only about 8.3% of its extension is included within Conservation Units or Indigenous Lands (Brasil, 2023), a figure lower than international conservation targets and far from the 47% of the territory that has already been converted to productive activities (Mapbiomas, 2024). Moreover, the biome is not included in the Soy Moratorium, an instrument that helped reduce deforestation in the Amazon (Gibbs et al., 2016), which favors the continuous advance of agricultural production even in recently deforested areas. This institutional gap reinforces the Cerrado's vulnerability to global market pressures and the absence of specific, effective public conservation policies.

Considering this context of intense anthropogenic pressures and low representation in legally protected areas, it is urgent to understand future territorial dynamics in the Cerrado. This study seeks to simulate land use and land cover scenarios up to 2100 for the Cerrado through predictive spatial modeling, with a special focus on Indigenous Lands and Conservation Units. The analysis allows for the identification of areas most susceptible to anthropogenic conversion and contributes to conservation-oriented territorial planning.

MATERIALS AND METHODS

STUDY AREA

The study area (Figure 1) encompasses the entire Cerrado biome, including areas in different states across the country: Goiás (GO), Tocantins (TO), Bahia (BA), Maranhão (MA), Piauí (PI), Mato Grosso (MT), Mato Grosso do Sul (MS), Minas Gerais (MG), São Paulo (SP), and the Distrito Federal (Brasília).

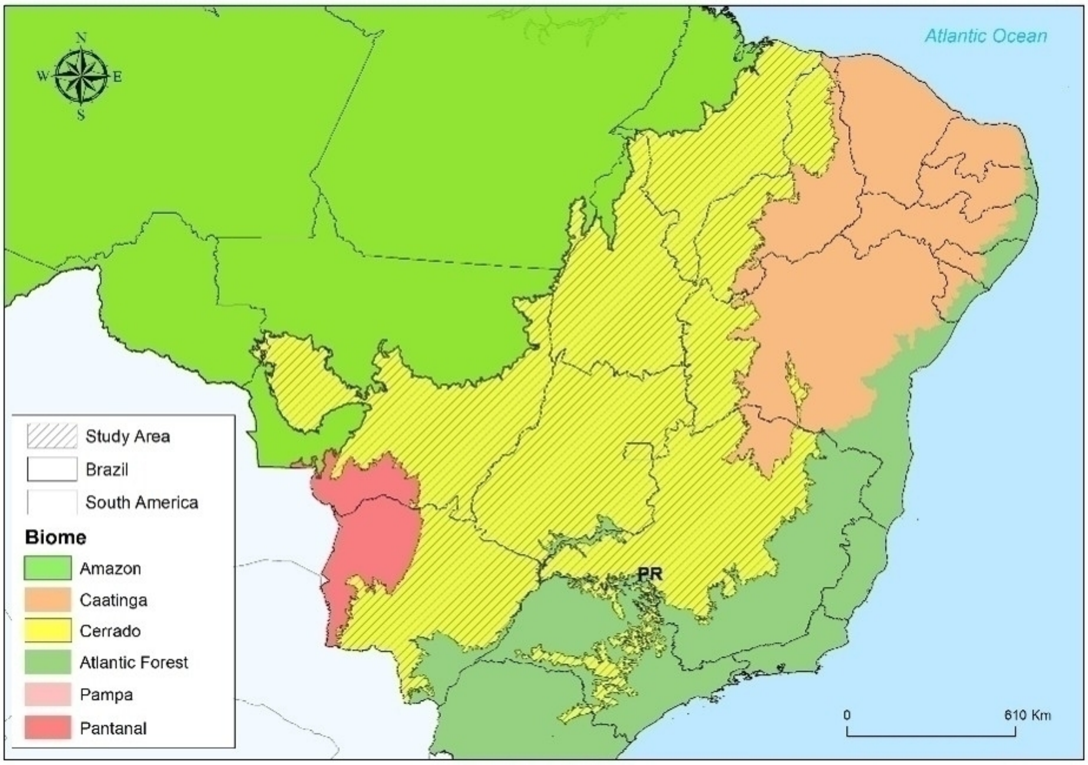

Figure 1 – Location map of the Cerrado biome Source: Prepared by the authors (2025)

The Cerrado has a seasonal tropical climate, with two well-defined seasons (one dry and one rainy), and features predominantly savanna vegetation composed of open fields, shrubs, and twisted trees. The predominant soils are generally acidic and have low natural fertility. The biome is recognized as a global biodiversity hotspot due to its high richness of endemic species and high level of threat, with more than 50% of its original vegetation already converted to anthropogenic uses (Sano et al., 2019).

In addition to the significant conversion of natural areas, the Cerrado harbors parts of Brazil's main hydrographic basins, such as the Tocantins-Araguaia, São Francisco, Paraná, and Parnaíba basins, giving it a central role in national water regulation. Its dense drainage network, associated with high climate variability and the expansion of agricultural activities, makes the biome particularly sensitive to changes in land use and land cover, an essential aspect for understanding and modeling the environmental scenarios proposed here.

METHODOLOGICAL FLOWCHART

The methodology employed in this study can be broken down into four main stages: data acquisition, reclassification and generation of spatial variables, predictive modeling, and finally, validation of results. Figure 2 presents a schematic flowchart with the details of each of these stages, providing an overview of the adopted methodological process to better understand each step taken.

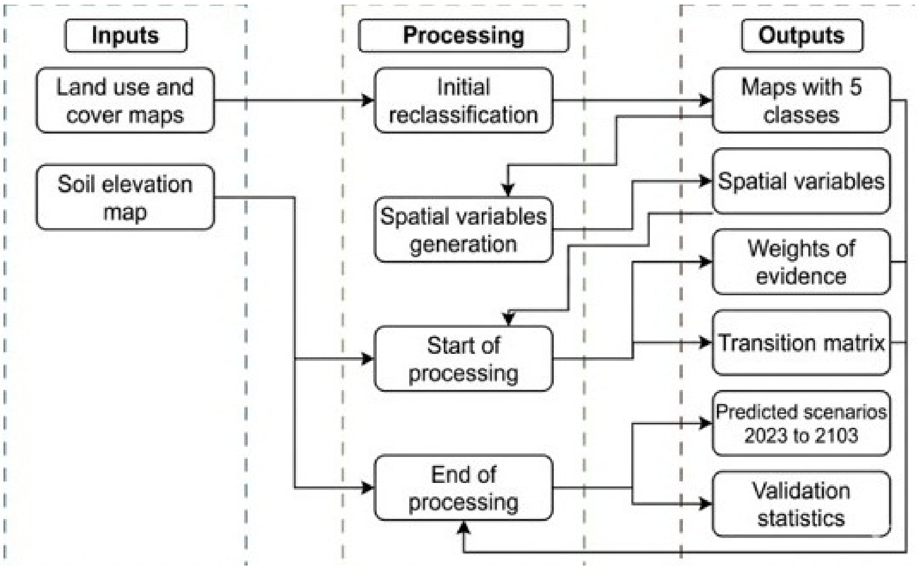

Figure 2 – Methodological flowchart. Internal box text translates as: Inputs (Land use/cover maps, Elevation map) -> Processing (Initial reclassification, Spatial variables generation, Processing execution) -> Outputs (5-class maps, Spatial variables, WoE, Transition matrix, Predicted scenarios, Validation stats). Source: Prepared by the authors (2026).

DATABASE

Accordingly, the databases used in this study are listed below, accompanied by their corresponding analytical procedures.

1.Land Use Map (initial state of the biome's landscape, namely T1, T2, and T3): The land use and land cover map from Collection 9 of MapBiomas was selected, which constitutes the largest data collection on Brazilian biome use, featuring data from 1986 to 2023. Collection 9 offers mapping for the Cerrado with a global accuracy of 90% at Level 1 and 85% at Level 2 (MapBiomas, 2024). These data have a spatial resolution of 30 meters and are generated from the analysis of Landsat image time series using automated classifiers based on machine learning and validation with field samples. The thematic classification is organized into six major land use and land cover classes, and each is broken down into subclasses, allowing for a more precise identification of elements present in each pixel, such as pasture, forest, and consolidated urban area, among others. Thus, data for the Cerrado biome area were used for the years 2003, 2013, and 2023.

2.Slope: Derived from a Digital Elevation Model (DEM) generated based on altimetry imagery from the SRTM (Shuttle Radar Topography Mission) mission. For the calculation, a neighborhood statistic was applied using the standard deviation in a 3x3 matrix, which captured not only the terrain slope but also the variation of this slope between adjacent pixels. This procedure allowed the identification and highlighting of areas with lower altitude standard deviation, representing flatter regions, and those with higher altimetric variation, indicating steeper terrains.

3.Road Map: Obtained from the OpenStreetMap (OSM) database, a collaborative platform that gathers geospatial information updated by users worldwide. Linear features corresponding to paved, unpaved, and under-construction highways were extracted and clipped to the Cerrado biome boundaries. This database stands out for its wide coverage, constant updates, and rich attributes, enabling detailed analyses of the region's transport infrastructure.

4.Hydrography Map: Made available by the National Water and Basic Sanitation Agency (ANA), this map represents the country's watercourses according to the official hydrographic database of the National Water Resources Information System (SNIRH) at a scale of 1:1,000,000. Hydrographic features were clipped according to the Cerrado biome boundary, encompassing main rivers, tributaries, and other segments of the drainage network.

RECLASSIFICATION

To simplify the modeling, the original MapBiomas classes were reclassified into five main categories: natural vegetation, agriculture, pasture, urban area, and water bodies. This reclassification allows for a better understanding of land use and cover transitions, reducing model complexity and computational effort without compromising the representation of observed spatial processes (Alamanos, 2023).

For the reclassification of land use and land cover data obtained through the MapBiomas platform, the Reclassify tool in ArcGIS Pro was utilized. This tool allows altering the values of each pixel in a raster according to a pre-established standard, facilitating future analysis and data interpretation. Thus, the reclassification was performed by converting all original MapBiomas classes and assigning the new values.

SPATIAL VARIABLES

To improve the explanatory capacity of the predictive model and increase its analytical relevance, spatial variables representing the distance to the main anthropogenic use classes were incorporated: agriculture, pasture, urban areas, roads, and hydrography. The inclusion of these variables allows the model to capture more complex spatial relationships across the territory, recognizing external factors that influence transitions between land use and land cover classes.

Based on the 2022 land use and cover map and the slope, road, and hydrography maps, the Euclidean Distance tool in ArcGIS software was used to generate continuous distance rasters for each of the selected classes. These rasters were subsequently reclassifed into a scale from 1 to 10, where higher values represent greater proximity to anthropogenic features, while lower values indicate greater distance.

Reclassifying into a common scale facilitates variable standardization, promoting efficient integration into the model and allowing greater scalability. This approach eliminates the need for individual adjustments between different types of variables, in addition to contributing to the correct assignment of weights by the model according to the principles of Bayesian inference.

CHANGE MODELING AND FUTURE SCENARIO SIMULATION

The simulation of future land use and land cover scenarios was performed using a hybrid model that integrates Weights of Evidence (WoE), based on Bayes' Theorem, with Cellular Automata coupled with Markov Chains (CA-Markov). This approach allows representing both the statistical dimension and the spatial structure of transitions between land use and land cover classes, being widely employed in studies of environmental change focused on anthropogenic dynamics (Marko et al., 2016; Pedrosa; Câmara, 2002).

CALCULATION OF WEIGHTS OF EVIDENCE (WOE)

The initial step of the process consists of applying the Weights of Evidence model, as proposed by Bonham-Carter (1994), based on the following Bayesian formulation: (Eq. 01):

$$W^{+} = \ln\left(\frac{P(B|A)}{P(B|\neg A)}\right) \quad \text{e} \quad W^{-} = \ln\left(\frac{P(\neg B|A)}{P(\neg B|\neg A)}\right) \qquad \text{Eq. 01}$$

Where W^{+} represents the evidence weight favorable to the occurrence of the transition; W^{-} represents the weight against the occurrence of the transition; $P(B|A)$ is the conditional probability of transition B occurring in the presence of variable A; $P(B|\neg A)$ is the probability of the transition occurring in the absence of the variable; and ln is the natural logarithm. These weights were calculated from reclassified maps of the explanatory variables into values from 1 to 10.

GENERATION OF THE TRANSITION MATRIX

Based on two land use and land cover maps spaced 10 years apart, a Markov transition matrix is constructed, estimating the probability of change between classes within the considered interval. The general formula is:

$$P_{ij} = \frac{n_{ij}}{\sum_j n_{ij}} \qquad \text{Eq. 02}$$

Where P_{ij} is the transition probability from class i to class j; n_{ij} is the number of pixels that changed from i to j; and the summation is performed across all classes j. This matrix represents the temporal component of the model and serves as the baseline for future simulation.

SIMULATION WITH MARKOV CELLULAR AUTOMATA (CA-MARKOV)

Spatial simulation is performed by integrating the transition matrix with Cellular Automata, which consider the state of neighboring pixels to define the transition of each cell. Spatial influence is evaluated using a 7×7 neighborhood window according to the logic:

$$P_{ij}(x,y) = P_{ij} \cdot f(N_{xy}) \qquad \text{Eq. 03}$$

Where $P_{ij}(x,y)$ is the adjusted transition probability for pixel (x,y) and $f(N_{xy})$ is a function of the neighbors' influence. The Cellular Automata Markov (CAM) is one of the most reliable models used by researchers for spatial and temporal analysis of land use and land cover changes (Marko et al., 2016).

PREDICTIONS UP TO 2100

The resulting model (Figure 3) was applied to generate decadal predictions of land use and land cover up to the year 2100, totaling eight predictive maps (from 2030 to 2100), along with one validation map (2023). This projection allows visualizing possible future scenarios and supporting territorial planning.

The process workflow begins by reading the land use and land cover map of the most recent available year, along with the explanatory variables required to calculate the weights of evidence. Then, a loop is initiated that runs through pairs of maps at 10-year intervals. At this point, the Deforestation Pressure Index (DPI) is applied, which is responsible for adjusting transition probabilities based on the influence exerted by the neighborhood and the anthropogenic pressure context defined for each scenario. The DPI was standardized on a scale from 0 to 10.

DPI calibration was performed using the historical series of Cerrado deforestation (PRODES/INPE). Initially, three baseline rates were defined: (i) a trend rate, obtained from the recent average (2018–2022); (ii) an optimistic rate, equivalent to 80% of the trend rate; and (iii) a pessimistic rate, based on the average of peak deforestation years (2013, 2014, 2015, and 2022).

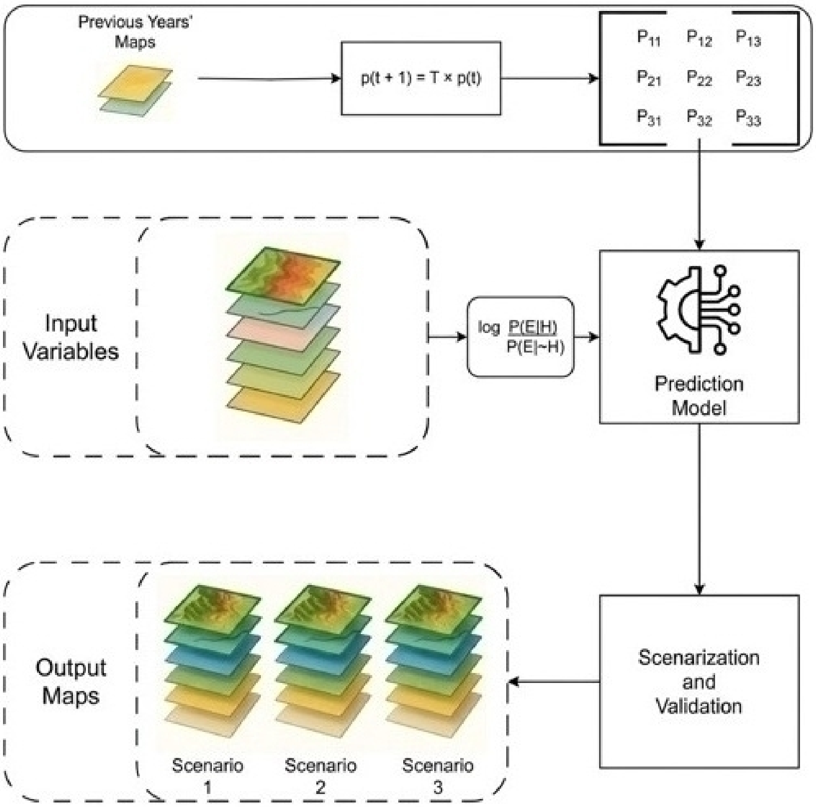

Figure 3 – Scenario simulation processes. Schematic diagram showing input maps leading to forecast model and final outputs. Source: Prepared by the authors (2026).

Scenario	Description	Calculation Baseline	Annual Rate (km2/year)	Reference Years (PRODES)
Optimistic	Percentage reduction of the trend rate, simulating effective environmental policies and greater control	80% of the recent average	6,512.60	2018–2022 (adjusted)
Trend	Maintenance of the recent average rate	Average 2018–2022	8,140.80	2018–2022
Pessimistic	Rates from peak years, reflecting sharp expansion of the agricultural frontier	Average of peak years	11,551.00	2013, 2014, 2015, 2022

Table 1 – Cerrado deforestation rates used to calibrate pressure scenarios. Source: authors (2025).

Following this step, the influence of the explanatory variables (slope, distance to pasture, agriculture, urban areas, hydrography, and roads) is incorporated to adjust the transition probability for each available class and estimate the likely transition of the pixel under analysis. Once processing is complete, the new map is saved, and the cycle repeats for the next pair of years, allowing the sequential generation of predictive maps over time.

The DPI is grounded in the concept of spatial weight matrices, which are widely used to represent dependency between adjacent territorial units in spatial statistics (Zhou et al., 2008; Getis, 2004). In these matrices, each element wij expresses the degree of relationship between locations i and j, serving as an essential resource for modeling spatial autocorrelation and effects. In practical terms, higher DPI values indicate a strong influence of preserved areas on their surroundings, favoring ecological connectivity and reducing conversion probability. Conversely, lower values indicate less influence from neighboring areas, favoring fragmentation processes and greater vulnerability to conversion. This logic aligns with the spatial spillover effects discussed by Zhang et al. (2023), who demonstrate how deforestation in one area can negatively influence adjacent areas.

This parametrization, calibrated with PRODES data, allows the model to capture more realistic spatial and temporal patterns, aligning simulation results with trends observed in the Cerrado over recent decades.

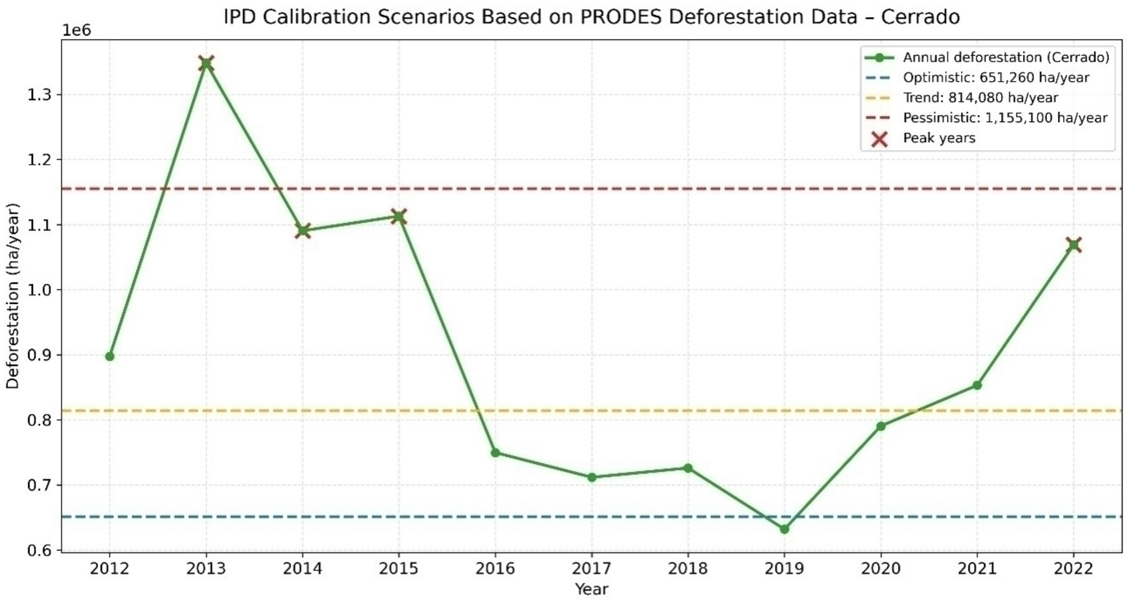

Figure 4 – DPI calibration scenarios based on PRODES – Cerrado. (Graph label translations: Desmatamento anual = Annual deforestation, Otimista = Optimistic, Tendencial = Trend, Pessimista = Pessimistic, Ano de pico = Peak year, Ano = Year, Desmatamento = Deforestation). Source: authors (2025). Source: Prepared by the authors (2026).

MODEL VALIDATION

Before generating future scenarios, a model validation stage was carried out. For this purpose, the 2023 map was simulated based on transitions observed between 2003 and 2013. The result was compared with the actual 2023 map to assess model accuracy.

Three statistical metrics were used to evaluate forecast quality: the similarity index (Kappa), mean absolute error (MAE), and root mean square error (RMSE).

1. Mean Absolute Error (MAE) (Eq. 04):

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad \text{Eq. 04}$$

Where:

•yi is the observed value,

•ŷi is the predicted value,

•n is the total number of observations.

2. Root Mean Square Error (RMSE) (Eq. 05):

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad \text{Eq. 05}$$

Where:

1.yi is the observed value for pixel i;

2.ŷi s the predicted value for pixel i;

3.n is the total number of pixels evaluated.

Like MAE, RMSE measures the deviation between observed and predicted values but penalizes larger errors more heavily due to squaring. With validation showing satisfactory results, we proceeded with generating future land use and cover scenarios up to 2100.

ACCURACY

Accuracy is a widely used metric to evaluate the performance of thematic classifications, such as land use and cover maps. It represents the proportion of correct predictions made by the model relative to the total evaluated observations, indicating how close simulation results are to observed reality or reference data. It is a simple and direct measure that summarizes the overall rate of agreement between classified data and validation data. Thus, accuracy values above 90% are considered excellent, between 80% and 90% are good, between 70% and 80% are acceptable, and below 70% indicate low reliability.

Overall accuracy (A) is calculated from the confusion matrix using the following (Eq. 06):

$$A = \frac{\sum_{i=1}^{n} x_{ii}}{N} \qquad \text{Eq. 06}$$

Where:

•x ii represents values on the main diagonal of the confusion matrix (correct classifications for each class),

•N is the total number of evaluated samples,

•n is the total number of classes.

RESULTS AND DISCUSSION

MODEL VALIDATION

The validation of spatial simulation models applied to the Cerrado biome was conducted based on three widely used performance metrics: accuracy, mean absolute error (MAE), and root mean square error (RMSE) [Note: corrected text typo "MSE" to match the equations]. The results obtained were consistent across the three analyzed scenarios: Optimistic, Trend, and Pessimistic, demonstrating the structural stability of the model against the variables used.Model accuracy reached 0.97, indicating that approximately 97% of simulated transitions matched patterns observed during the calibration period, reflecting a high capability to represent historical spatial dynamics. The mean absolute error was 0.04, representing an average discrepancy of 4% between predicted and actual values. The root mean square error was 0.09, a value that penalizes larger discrepancies and remains within a range considered appropriate for highly complex spatial simulation models.The homogeneity of validation results across scenarios indicates that variations in the Deforestation Pressure Index (DPI) parameterization exclusively affect future projections, without compromising the model's ability to reproduce spatial patterns during the reference period. These results reinforce the robustness of the calibrated model, validating its application for generating land use and cover scenarios in the Cerrado.3.2 Land Use and Land Cover Changes from 2030 to 2100 under Different ScenariosPredictive scenarios indicate contrasting dynamics for the Cerrado over the 2030–2100 period, reflecting differences in both the intensity of native vegetation conversion and the expansion of anthropogenic uses. Table 2 presents absolute areas by land use and cover class for each scenario and year, while Figure 5 illustrates the spatial distribution of these changes, highlighting regional expansion and contraction patterns across classes.Under the Optimistic scenario, native vegetation declines from 973,101 km² in 2030 to 918,967 km² in 2050 and 855,532 km² in 2100. Despite this loss, the biome maintains 40% of its natural cover by the end of the period. Pasture is the predominant anthropogenic use, occupying 556,140 km² in 2030 and reaching 605,568 km² in 2100, followed by agriculture, which increases from 490,687 km² to 538,461 km² within the same interval. Urban expansion is residual, increasing by only 23,677 km² throughout the century. This scenario reflects limited encroachment into new areas and the maintenance of mosaics where agricultural activities coexist with vegetation remnants.The Trend scenario shows a more intense reduction in vegetation, from 922,668 km² in 2030 to 795,818 km² in 2050 and 721,560 km² in 2100, leaving 34% of natural cover. Pasture predominates among anthropogenic uses, growing from 582,901 km² to 676,656 km², while agriculture increases from 515,824 km² to 604,935 km². In this case, productive area expansion is more balanced between pasture and agriculture, suggesting a continuation of current conversion dynamics, with advances over savanna and grassland vegetation areas in zones with high agricultural suitability.In the Pessimistic scenario, native vegetation undergoes a sharp reduction: from 799,365 km² in 2030 to 485,149 km² in 2050 and 398,004 km² in 2100, corresponding to just 18% of the biome. By the end of the period, pasture heavily dominates, reaching 849,541 km², followed by agriculture with 763,479 km², which equivalent to 78% of the entire biome. The advance of these two classes represents a massive replacement of remaining vegetation, leaving natural areas concentrated in isolated enclaves, permanent conservation units, or regions with lower agricultural viability.

Year	Scenario	Vegetation	Pasture	Agriculture	Urban Footprint	Water
2030	Optimistic	973.101,84	556.140,41	490.687,18	33.676,98	14.223,66
2030	Trend	922.667,65	582.900,58	515.824,34	32.695,80	13.741,70
2030	Pessimistic	799.365,72	648.046,40	576.355,25	31.458,47	12.604,24
2050	Optimistic	918.966,86	579.165,93	513.025,01	44.023,90	13.273,37
2050	Trend	795.818,22	644.893,85	574.003,69	41.823,31	11.916,00
2050	Pessimistic	485.149,24	810.701,88	725.881,36	38.350,97	8.371,62
2100	Optimistic	855.532,01	605.568,42	538.460,94	57.353,95	12.164,37
2100	Trend	721.560,30	676.655,67	604.934,95	55.286,76	10.642,01
2100	Pessimistic	398.003,78	849.540,51	763.479,32	51.202,38	6.853,71

Table 2 – Areas km² by land use and land cover class in the Cerrado for the Optimistic, Trend, and Pessimistic scenarios in 2030, 2050, and 2100. Source: authors (2025).

Comparison between scenarios confirms that pasture and agriculture are the dominant anthropogenic land uses in the Cerrado. In the Optimistic scenario, the difference between both is smaller; in the Trend scenario, a balance prevails; and in the Pessimistic scenario, pasture expands expressively, separating itself significantly from agriculture. Spatial analysis indicates that areas most susceptible to conversion are concentrated in the central and western portions of the biome, associated with fertile soils and proximity to logistics corridors. This pattern corroborates studies pointing to extensive cattle ranching as the primary vector of conversion in the Cerrado in recent decades (Sano et al., 2019; Strassburg et al., 2017) and reinforces the overlap between zones of high agricultural suitability and areas under greater anthropogenic pressure (Vieira et al., 2021).

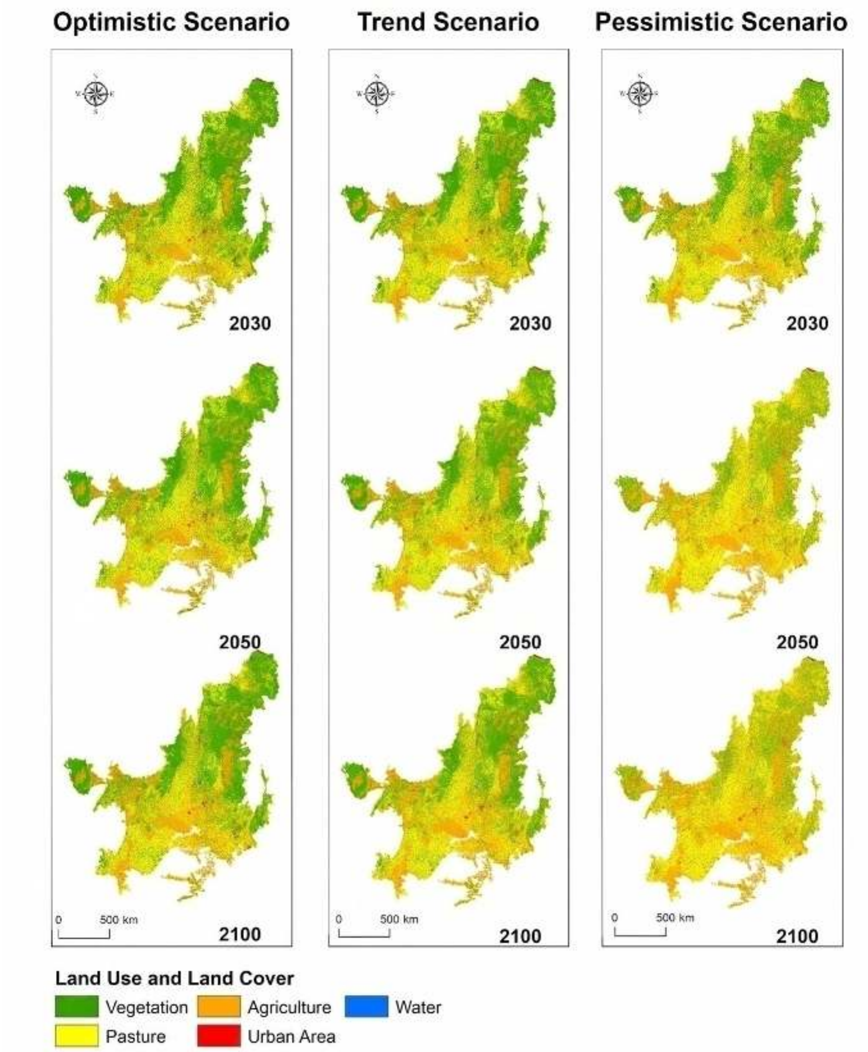

Figure 5 – Spatial distribution of land use and land cover in the Cerrado for the Optimistic, Trend, and Pessimistic scenarios in the years 2030, 2050, and 2100. (Legend translation: Vegetação = Vegetation, Pastagem = Pasture, Agricultura = Agriculture, Mancha Urbana = Urban Footprint, Água = Water). Source: authors (2025)

PRESSURES AND VULNERABILITIES IN THE CERRADO

The Cerrado is the Brazilian biome with the largest Legal Reserve deficit, concentrating about 42,000 km² of native vegetation that needs restoration (Guidotti et al.). Furthermore, only 8.3% of its extension is formally protected. This low protection status, combined with the environmental deficit, has been compounded by the biome's prominent role in grain and meat production and export, which has consolidated it as one of the world's primary agricultural frontiers (FAO).This context partly explains the high recent deforestation rates observed in the biome. According to RAD 2024 (Mapbiomas, 2025), the Cerrado accounted for 60.4% of all deforested area in Brazil in 2023 (11,098.50 km²) and, even after a 41.2% reduction the following year, it still concentrated 52.5% of the national total (6,521.97 km²), remaining the country's most impacted biome. This pressure is strongly associated with agricultural expansion, which accounts for more than 97% of native vegetation loss in Brazil over the last six years.Data from the Rural Credit Monitor (Mapbiomas, 2024) reinforce this picture, showing that Cerrado states, such as Mato Grosso do Sul and Tocantins, have the highest average financed area per public fund operation (1.72 km²) and concentrate a significant portion of financed plots overlapping with deforestation. Between 2019 and 2024, 98,000 of financed plots in Brazil showed some level of overlap with deforested areas, with 67% of these operations allocated to crop farming and 25% to cattle ranching.

Our models indicate that the future trajectory of the Cerrado will depend directly on annual deforestation rates and the effectiveness of control policies. Between 2030 and 2050, the models project average annual deforestation rates of –2,707 km²/year in the optimistic scenario, –6,342 km²/year in the trend scenario, and –15,711 km²/year in the pessimistic scenario, indicating that the largest losses occur in the next two decades. These values align closely with observed dynamics: in recent years, according to PRODES and RAD MapBiomas, the Cerrado presented annual rates between 6,000 and 11,000 km²/year, with a peak of over 11,000 km² in 2023, establishing itself as the most deforested biome in Brazil. In this context, the trend scenario realistically reproduces the recent average, while the pessimistic scenario represents a further intensification of agricultural pressure. The optimistic scenario, with about –2,707 km²/year until 2050, finds support in the historical values analyzed by Miziara and Ferreira (2008), who estimated rates around 2,000 to 3,000 km²/year in the 1990s and early 2000s. This suggests that under more effective environmental policies and controlled expansion, it would be possible to return to levels similar to the past. After 2050, a relative deceleration of rates is observed across all scenarios—dropping to –1,269 km²/year (optimistic), –1,485 km²/year (trend), and –1,743 km²/year (pessimistic) up to 2100. This reduction, however, does not reflect lower anthropogenic pressure, but rather the decrease in remaining areas available for conversion, since most native vegetation would have been suppressed by mid-century.

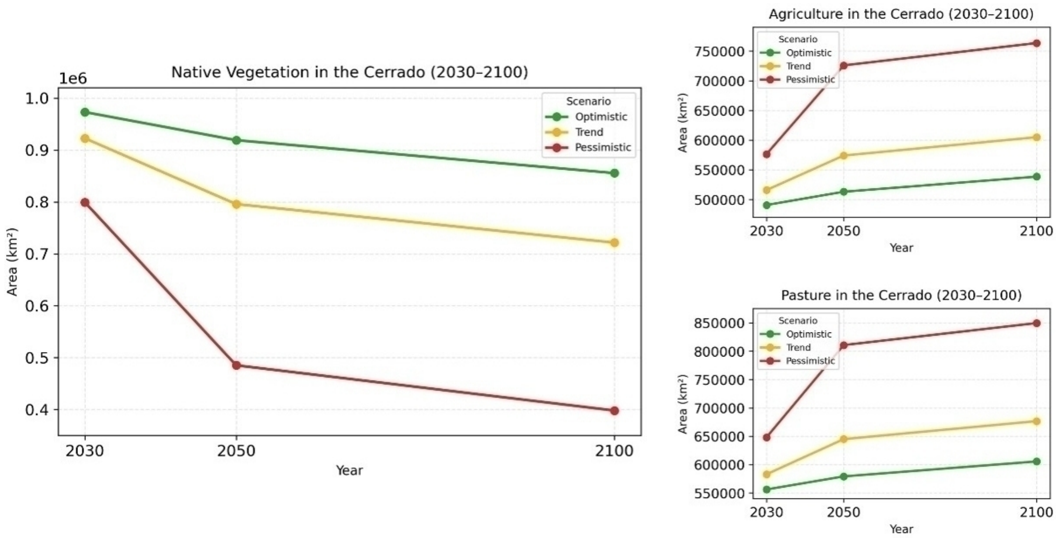

Figure 6 – Projections of native vegetation, pasture, and agriculture evolution in the Cerrado between 2030 and 2100 under three deforestation scenarios. (Graph translations: Evolution of Vegetation/Agriculture/Pasture in the Cerrado = Evolution of Vegetation/Agriculture/Pasture in the Cerrado, Scenario = Scenario, Optimistic = Optimistic, Trend = Trend, Pessimistic = Pessimistic, Vegetation (km²) = Vegetation (km²), Year = Year). Source: authors (2025).

Analysis of future trajectories shows that although the pace of loss varies across scenarios, all point to a continuous decline in native vegetation until 2100, accompanied by the expansion of agricultural areas. In the optimistic scenario, vegetation retraction is less severe, maintaining approximately 82% of the baseline cover in 2050, while the trend scenario drops to 76% and the pessimistic scenario to 68%. These values contrast with results from Ferreira et al. (2013), who projected the retention of around 87% of native vegetation in 2050. The difference can be explained by the recent worsening of deforestation rates, which have fluctuated between 6,000 and 11,000 km²/year according to PRODES and RAD MapBiomas, well above historical averages observed in the 1990s and 2000s. Thus, our models reinforce that without a shift in control policies and funding for agricultural expansion, the loss of remaining areas in the Cerrado tends to be faster than predicted in previous scenarios.

ECOLOGICAL RESILIENCE AND CLIMATE VULNERABILITY OF THE CERRADO FACING EXTREME DROUGHTS AND INSTITUTIONAL REGRESSIONS

The results presented for future Cerrado scenarios (2030–2100) highlight the convergence between extreme climate forcing, vegetation cover loss, and institutional weaknesses, configuring a framework of high ecological vulnerability. The biome, which plays a strategic role in national water regulation and South American climate stability (Oliveira et al., 2019), shows signs of approaching a functional collapse threshold, where natural resilience mechanisms are no longer sufficient to guarantee the balance of essential ecological processes.

On a global scale, Ohlert et al. (2025) demonstrated that drought intensity and duration interact non-linearly, significantly amplifying losses in terrestrial primary productivity. Analysis of 74 grassland and savanna ecosystems showed that while some systems partially acclimate to multi-year drought, this capacity collapses under extreme events, with cumulative productivity losses 2.5 times higher after four consecutive years of drought. This pattern is particularly relevant for the Cerrado, whose dynamics depend on moisture recycling and the deep root system of native vegetation.

Replacing this vegetation with annual crops and compacted pastures alters soil structure, reduces infiltration, and compromises hydrological recharge, making the biome more susceptible to the combined effects of drought and intensive land use (Sano et al., 2019; Colman et al., 2024). Complementarily, Rosenfield et al. (2025) mapped landscape resilience to climate at a national scale and identified the Cerrado as one of the biomes with the highest proportion of low climate resilience areas, reaching about 37% of the territory. This vulnerability stems from high fragmentation, landscape homogenization, and the loss of ecological connectivity—factors that reduce microclimate diversity and species dispersal, essential elements for ecological stability.

These processes reflect the progressive replacement of native vegetation by monocultures and pastures concentrated in regions with fertile soils and consolidated infrastructure, as also observed by Strassburg et al. (2017) and Vieira et al. (2021). The result is an environmental mosaic with low capacity for ecological reorganization under climate disturbances, which increases the risk of functional collapse at regional scales. In parallel, the advancement of regulatory changes and regressive environmental policies has contributed to worsening this situation.

Araújo et al. (2025) show that the enactment of Law No. 22,017/2023 in Goiás represents one of the largest recent environmental rollbacks. The legislation relaxes the state Forest Code, allowing the clearing of fragments up to 2 hectares, including ecologically sensitive areas such as murundus (moundfields) and capões (forest patches), in addition to redefining areas deforested up to 2019 as "consolidated" — practically amnesty-providing for more than a decade of illegal clearings. This flexibilization reduces protection for more fragile vegetation formations, disrupts ecological connectivity, and weakens the constitutional principle of non-regression in environmental protection, compromising national commitments like Planaveg and the zero-deforestation targets by 2030.

The conjunction of climate change, low landscape resilience, and institutional regression reinforces the notion that the Cerrado is undergoing a process of systemic erosion. The results of this thesis, which point to a reduction of up to 82% of native vegetation under the pessimistic scenario, converge with previous studies that already projected a sharp decline in natural cover if there were no shift in control policies (Ferreira et al., 2013; Lapola et al., 2014). In line with findings by Ohlert et al. (2025), productivity losses associated with severe and prolonged droughts can act as triggers for irreversible ecological transitions, leading the biome to be replaced by impoverished landscapes with low carbon sequestration capacity.

This trend may be exacerbated by the persistence of public financing for agricultural activities in areas under high anthropogenic pressure, as demonstrated by recent data from the Rural Credit Monitor (Mapbiomas, 2024).

To face this scenario, it is urgent to rearticulate multi-scale public policies integrating conservation, restoration, and territorial governance. The repeal of permissive legislations, such as Law No. 22,017/2023, and the strengthening of monitoring instruments such as PRODES/Cerrado and MapBiomas RAD, are central measures to contain degradation. Identifying high-resilience areas

(Rosenfield et al., 2025) can guide ecological restoration efforts and connectivity between fragments, promoting vegetation corridors capable of sustaining biological flows and mitigating the impact of extreme droughts. These actions must be accompanied by economic and fiscal incentives for forest restoration and policies that value native vegetation as natural infrastructure for climate adaptation (Gibbs et al., 2015; Soterroni et al., 2019).

In summary, the Cerrado finds itself in a critical transition zone, where the continuation of current trends could irreversibly compromise its ecological, climatic, and social functions. Protecting the Cerrado means ensuring the country's water and climate stability, biodiversity maintenance, and food security for future generations (Klink; Machado, 2005; Silva et al., 2002). The convergence of science, policy, and territorial management is, therefore, the indispensable path for the biome to continue sustaining life and production in the 21st century.

CONCLUSION

The results obtained in this study demonstrate that the future of the Cerrado will depend directly on the interaction between annual deforestation rates and the effectiveness of environmental public control policies. The optimistic scenario, calibrated with rates 20% lower than the recent average, projects the maintenance of more continuous ecological corridors and a deceleration in native vegetation loss, indicating that under more effective policies, it would be possible to return to levels close to those observed in the 1990s and early 2000s.The trend scenario, in turn, realistically reproduces the recent average, maintaining significant losses but still preserving some strategic areas. Conversely, the pessimistic scenario projects a sharp acceleration in fragmentation and reduction of continuous vegetation areas, reflecting the uncontrolled advance of the agricultural frontier. Projections up to 2050 reveal that the largest losses occur over the next two decades, converging with previous studies (Miziara and Ferreira, 2008; Ferreira et al., 2013; Guidotti et al., 2020), which also identified the Cerrado as one of the country's most vulnerable areas. After this period, a relative deceleration in deforestation rates is observed across all scenarios, not due to a reduction in anthropogenic pressure, but because of the scarcity of remaining areas available for conversion.

This pattern reinforces the risk of reaching tipping points, where ecological resilience will be severely compromised. From a methodological standpoint, this work contributes by integrating a spatial simulation model developed in Python, based on Markov chains, weights of evidence, and cellular automata calibrated with PRODES/INPE data. This framework allows for greater automation, methodological transparency, and the integration of multiple explanatory variables into long-term simulations.

Regarding public policies, our results reinforce the need to review the protection framework in the Cerrado. The Legal Reserve deficit, estimated at 42,000 km², combined with the low percentage of formally protected areas (only 8.3%), limits the biome's resilience. Linking part of deforestation to public rural credit operations reveals structural inconsistencies between agribusiness promotion and environmental conservation.

This work should not be interpreted as a deterministic prediction, but rather as a prospective exercise capable of illuminating alternatives and risks. It is recognized, however, that there are limitations, particularly regarding the ability to anticipate socio-economic and political variables over a long time scale. Even so, the simulations point to clear paths: strengthening command-and-control policies; expanding protected areas and regularizing Legal Reserves; and aligning agricultural financing with sustainability. In summary, the future of the Cerrado remains open.

The optimistic scenario shows that it is still possible to contain vegetation loss and preserve the biome's ecological resilience. The pessimistic scenario, on the other hand, warns of a trajectory of fragmentation and depletion of natural capital. It is up to society, the productive sector, and public authorities to decide which of these paths will be followed.

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DATA AVAILABILITY

Not applicable.

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