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Article

Analysis of the Influence of Climatic Variables and Land Use and Land Cover on the Normalized Difference Vegetation Index (NDVI)

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ABSTRACT
Advances in remote sensing have opened up new perspectives for environmental monitoring, enabling a better understanding of phenomena such as deforestation and climate change. This study analyzed the responses of the Normalized Difference Vegetation Index (NDVI) to climatic variables (precipitation and temperature) and to land use and land cover in a microbasin located in the southwest of the state of Pará, for the years 2000, 2006, 2012, 2018, and 2023. To calculate the NDVI, MODIS data were used, extracted from the Google Earth Engine (GEE) platform, specifically from the MOD13A1.061 collection, which provides 16-day composites with a spatial resolution of 1 km. Precipitation data were obtained from the CHIRPS product, while temperature data were derived from the MOD11A2.061 product; both were processed on the GEE platform. Data from MapBiomas (Collection 9), reclassified using QGIS software, were used to characterize land use and land cover. The results indicated a decline in vegetation quality, particularly due to the expansion of pasture areas. It was observed that higher temperatures had a significant impact on the reduction of the NDVI, while precipitation showed a low correlation with the index. Areas of preserved forest maintained high NDVI values, highlighting the importance of conserving these areas. The use of geoprocessing was essential for identifying spatio-temporal patterns, confirming that anthropogenic pressure negatively affects vegetation. Therefore, the results indicate that climatic variables, such as temperature and precipitation, and changes in land use and land cover, such as the expansion of pastures, have a major influence on vegetation quality in the microbasin.
Keywords: NDVI; Land use and land cover; Climatic variables.

RESUMO
O avanço do sensoriamento remoto trouxe novas perspectivas para o monitoramento ambiental, permitindo compreender fenômenos como o desmatamento e as mudanças climáticas. Este trabalho analisou as respostas do Índice de Vegetação por Diferença Normalizada (NDVI) às variáveis climáticas (precipitação e temperatura) e ao uso e cobertura da terra em uma microbacia localizada no sudoeste do Estado do Pará, nos períodos de 2000, 2006, 2012, 2018 e 2023. Para calcular o NDVI, foram utilizados dados do MODIS extraídos da plataforma Google Earth Engine (GEE), especificamente da coleção MOD13A1.061, que oferece composições de 16 dias com resolução espacial de 1 km. Dados de precipitação foram obtidos do produto CHIRPS, enquanto os dados de temperatura foram derivados do produto MOD11A2.061, ambos processados na plataforma GEE. Para a caracterização do uso e cobertura da terra utilizou-se dados do MapBiomas (Coleção 9), reclassificados no software QGIS. Os resultados indicaram um declínio na qualidade da vegetação, especialmente devido à expansão de áreas de pastagem. Observou-se que temperaturas mais altas tiveram impacto significativo na redução do NDVI, enquanto a precipitação apresentou correlação baixa com índice. Áreas de floresta preservada mantiveram valores elevados de NDVI, destacando a importância da conservação desses espaços. O uso de

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geoprocessamento foi essencial para identificar padrões espaço-temporais, corroborando que a pressão antrópica afeta negativamente a vegetação. Portanto, os resultados indicam que as variáveis climáticas, como a temperatura e precipitação, e as mudanças no uso e cobertura da terra, como a expansão das pastagens, têm grande influência na qualidade da vegetação na microbacia.
Palavras-chave: NDVI; Uso e cobertura da terra; Variáveis climáticas.

Introduction

Advances in remote sensing technologies have revolutionized the way we observe and understand terrestrial phenomena. Earth observation satellites enable continuous, large-scale monitoring of the Earth's surface, providing essential data for analyzing environmental changes, such as deforestation, urbanization, natural disasters, and climate change. These systems enable the detection of environmental variables, such as air temperature, precipitation, humidity, and, especially, vegetation cover and land use, contributing significantly to environmental planning and the sustainable management of natural resources (Barbosa et al. 2023; Wulder et al. 2022).

With improvements in remote sensing techniques, benefits can be observed in numerous fields, particularly in the environmental sector. In Brazil, deforestation is one of the main environmental problems, and its intensification has led to severe ecological, social, and economic consequences (Fearnside 2006; Leite et al. 2023). According to Hu et al. (2019), vegetation ecosystems are the result of long-term interactions between climate, human activities, and topographic characteristics. In the context of global warming and the intensification of human activities, terrestrial vegetation ecosystems are undergoing unprecedented changes (Huang et al. 2021), particularly in the Brazilian Amazon region, where, according to a study by Ziccardi et al. (2024), deforestation reached a decade-high between August 2020 and July 2021, largely due to agricultural expansion, particularly soybean cultivation and livestock farming.

In this context, monitoring changes in vegetation and analyzing the factors driving these changes have become extremely important topics for study (Lin et al. 2020). One of the tools that has been widely used to assist and facilitate this monitoring is the use of vegetation indices (VI), particularly the Normalized Difference Vegetation Index (NDVI). The NDVI is widely used to assess vegetation dynamics due to its simplicity, accessibility, and effectiveness in monitoring vegetation at different spatial and temporal scales (Li et al. 2024). This index was initially proposed by Rouse et al. (1974) and allows for the identification of green vegetation and the characterization of its spatial distribution, as well as changes over time.

According to Joiner et al. (2018), climatic variables such as temperature and precipitation are frequently studied as potential factors influencing the NDVI. However, the relationship between these variables and the index is complex and varies depending on the region and ecosystem type (Piedallu et al. 2019). Recent studies show that, although the NDVI responds to precipitation and temperature, the strength and nature of this response are not uniform and may differ significantly between areas (Chen et al. 2023; Kumar et al. 2023; Wang et al. 2024). Furthermore, anthropogenic factors, such as changes in land use and land cover—including overgrazing and intensive use of water resources—further complicate the interpretation of these relationships (Zewdie et al. 2017).

The growing demand for cropland and pastureland is causing vegetation cover in the Amazon region to decline dramatically each month (Miranda et al. 2021). According to data from the Deforestation Alert System (SAD), in January 2025, 133 km² of deforestation were detected in the Legal Amazon, and according to the survey, the states that contributed most to this scenario were Mato Grosso with 45%, Roraima with 23%, and Pará with 20% (Amorim et al. 2025). Southwestern Pará is one of the fastest-growing livestock-raising regions in the Brazilian Amazon, with high rates of deforestation (Klingler et al. 2018), making environmental monitoring and control in this region necessary.

Several studies conducted in the Amazon have used the NDVI as a tool to monitor changes in vegetation cover and assess the effects of climate change and land use. Souto et al. (2019), in their analysis of the Iriri River basin in the state of Pará, observed that the relationship between precipitation and NDVI varies spatially and can be influenced by extreme weather events, such as El Niño and La Niña. The study by Moura et al. (2023) analyzed the dynamics of vegetation indices in protected areas of the Amazon using images with high spatial and temporal resolution, finding that NDVI is an effective tool for monitoring phenological variations in the forest and for detecting changes in vegetation cover resulting from environmental factors. Meanwhile, the study by Marques et al. (2024) evaluated the effectiveness of different vegetation indices in detecting forest disturbances in the southeastern Amazon and found that these indicators are sensitive tools for identifying changes in vegetation structure and vigor resulting from forest fires.

Although there are numerous studies using NDVI in the Brazilian Amazon, there are still few studies that comprehensively assess the simultaneous influence of climatic variables and changes in land use and land cover on NDVI behavior in micro-watersheds located in the southwest of the state of Pará, a region experiencing rapid expansion of livestock farming and agriculture.

In this context, the present study aims to analyze NDVI responses by considering climate variability and changes in land use and land cover in a micro-watershed located in the southwest of the state of Pará between the years 2000 and 2023. To this end, NDVI data from the MODIS sensor, precipitation data from CHIRPS, land surface temperature data from the MOD11A2 product, and land use and land cover data provided by MapBiomas were used.

Materials and Methods

Study Area

The microbasin used in the study is located in the southwestern part of the state of Pará, covering an area of approximately 11,401.78 km² (Figure 1). More than 80% of its area lies within the municipality of Novo Progresso, while the remainder is located in Itaituba. Due to this territorial distribution, climatic variables, as well as land use and land cover, exhibit patterns that are predominantly similar to those observed in Novo Progresso, since most of the microbasin belongs to that municipality.

The region is part of the Amazon Biome and is characterized by a hot and humid equatorial climate, with an average annual temperature ranging from 25 °C to 28 °C. Average annual rainfall is approximately 2,200 mm, divided into two climatic periods: the rainy season, which runs from December to June, and the drier season, from July to November (Barros et al. 2021; Mendes & Dos Santos 2019).

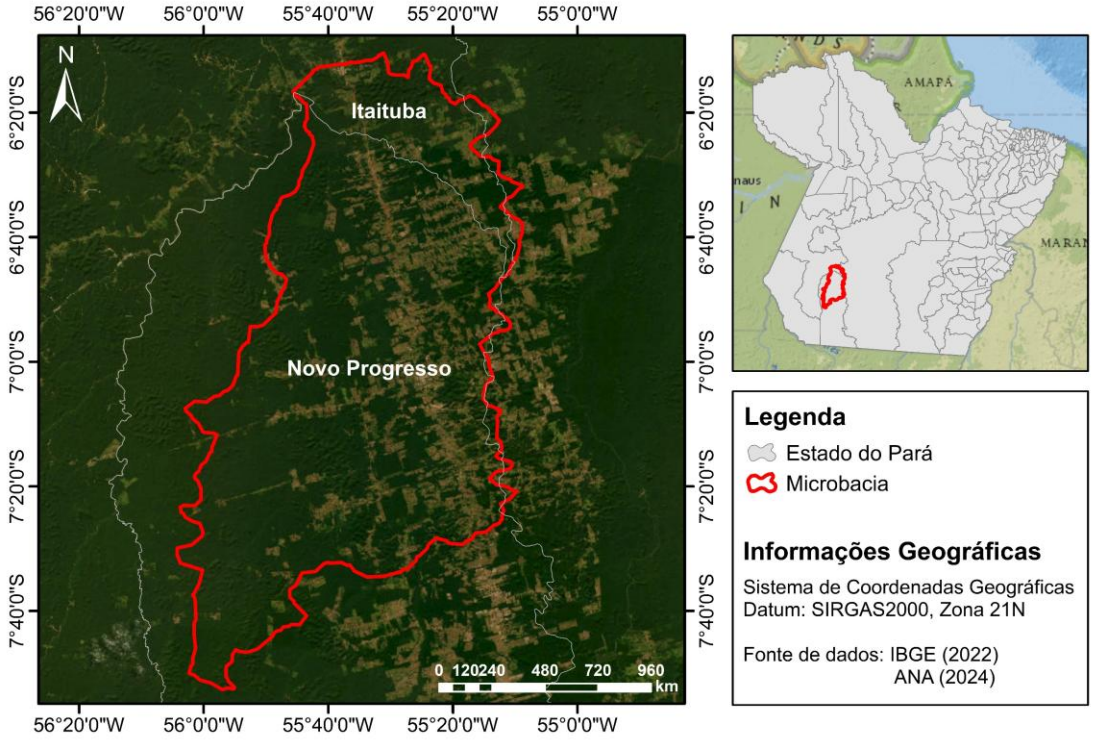


Figure 1. Location of the Microbasin. Source: Elaborated by the authors

According to Nascimento et al. (2019), the local economy has historically been dominated by extensive livestock farming, gold mining, and logging. With the recent expansion of soybean cultivation in the region, grain farming and livestock raising have become the main drivers of deforestation and land-use change in this agricultural frontier (Nascimento et al. 2019; Nascimento et al. 2020).

Normalized Difference Vegetation Index

The NDVI analysis in the microbasin was conducted for the years 2000, 2006, 2012, 2018, and 2023, at regular six-year intervals. Given that the study began in 2024 and the available data extended only through 2023, the analysis was limited to this period. For each selected year, the annual average of the index values was used.

The data used to calculate the NDVI were obtained from the MODIS sensor via the MOD13A1.061 collection available on the Google Earth Engine (GEE) platform. MODIS provides 16-day composites with a spatial resolution of 1 km, covering continuous records since the year 2000 (Spruce et al. 2016). These collections are widely used in studies of vegetation cover monitoring, analysis of seasonal patterns, and assessment of vegetation health in various ecosystems. As noted by Salgado et al. (2023), the MODIS satellite uses specific algorithms to detect and reduce cloud interference in the images, which is essential for ensuring greater accuracy in the classification of time series such as the NDVI.

The theoretical basis for using combinations of the red and near-infrared bands in vegetation monitoring was originally proposed by Rouse et al. (1974) and further developed by Tucker (1979). The index is calculated using reflectance values from the red and near-infrared bands, allowing for the assessment of vegetation greenness over time (Equation 1).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (1)$$

Where NIR is the near-infrared band and RED is the red band. According to Morshed et al. (2020), index values range from -1 to 1 and are interpreted based on vegetation density and vigor. Healthy vegetation strongly reflects NIR, while chlorophyll absorbs intensely in the red band. Values close to zero or negative (below 0.1) indicate surfaces with little or no vegetation cover, such as exposed rocks, sand, or snow. On the other hand, high NDVI values indicate dense and healthy vegetation, such as tropical and temperate forests (above 0.6). Intermediate values (between 0.2 and 0.3) are typical of sparse vegetation, while moderate values (between 0.4 and 0.6) are associated with areas of shrubs and grasslands.

Precipitation and Temperature Data

In this study, annual averages were calculated using precipitation and temperature datasets for the years 2000, 2006, 2012, 2018, and 2023.

Precipitation data were obtained using the GEE platform, based on daily rainfall time series from the Climate Hazards Group's InfraRed Precipitation with Station (CHIRPS) dataset. CHIRPS was developed by researchers at the Earth Resources Observation and Science (EROS) and the United States Geological Survey (USGS) and provides daily rainfall information for nearly the entire globe, with geographic coverage from 50°S to 50°N, a spatial resolution of 0.05° x 0.05° (approximately 5 km), and daily precipitation data from 1981 to the present (Funk et al. 2015).

Temperature data were obtained using the MOD11A2.061 product from the MODIS/Terra sensor, which provides Land Surface Temperature (LST) and Emissivity data with a spatial resolution of 1 km, in 8-day composites. MOD11 is an essential product for obtaining variables that help describe land surface processes and is widely used in various climate and hydrological studies (Wan et al. 2021).

Land Use and Land Cover Data

To characterize land use and land cover, microbasin data for the years 2000, 2006, 2012, 2018, and 2023 from Collection 9 of the Annual Land Cover and Land Use Mapping Project for Brazil (MapBiomas) were used, with a resolution of 30 m, available on the official platform (https://brasil.mapbiomas.org/).

The images were downloaded and reclassified using the open-source software QGIS (version 3.36.2), employing an RGB color palette provided by the platform. During the reclassification of land use and land cover categories in QGIS, the classes were organized as follows, based on the class code from Collection 9 provided by MapBiomas itself: Class 1 corresponds to Forest, Class 2 to Savanna, Class 3 to Pasture, Class 4 to Agriculture, Class 5 to Non-vegetated Area, and Class 6 to Water Body.

Correlation Analysis

The statistical analysis between the NDVI series, climatological variables, and land use and land cover variables was performed using Pearson's correlation coefficient (r), a parametric estimator that measures the degree of linear association and the direction of the relationship between two continuous quantitative variables

(Figueiredo Filho & Silva Júnior, 2009). The sample estimator of Pearson's correlation coefficient is mathematically defined as the ratio of the covariance of the two variables to the product of their respective standard deviations (Equation 2).

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X}).(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 . \sum_{i=1}^{n}(Y_i - \bar{Y})^2}} \quad (2)$$

Where r is the Pearson correlation coefficient, which ranges from −1 (perfect negative correlation) to +1 (perfect positive correlation); Xi and Yi correspond to the observed individual values of NDVI and the analyzed variables; X and Y are the sample arithmetic means of the respective variables; and n represents the total number of paired observations.

Results and Discussion

Average Annual NDVI, 2000–2023

Analysis of the NDVI calculated for the microbasin revealed significant changes in vegetation quality over the years, as shown in Figure 2. The index allowed us to identify changes in vegetation cover, and the maps generated for each year illustrate these variations. These maps present the annual NDVI averages, highlighting variations in vegetation cover both spatially and temporally. According to Alves and Loverde-Oliveira (2020), it is possible to identify areas with higher vegetation density, indicated by higher NDVI values, as well as regions with lower vegetation cover density, indicated by lower values.

Based on an analysis of the map presented (Figure 2), it is clear that the year 2000 stands out as the period with the best vegetation quality. According to studies by Vale (2020) and Souza et al. (2022), in the state of Pará, vegetation was dense in the year 2000; however, in subsequent years, a significant increase was observed in areas used for pasture and agriculture, which became the state's primary economic activities. In this context, pasture and agriculture—which in the year 2000 accounted for only 7.38% and 0.0003% of the total area of the microbasin—expanded significantly by 2023, coming to occupy 36.34% and 0.24% of the territory, respectively.

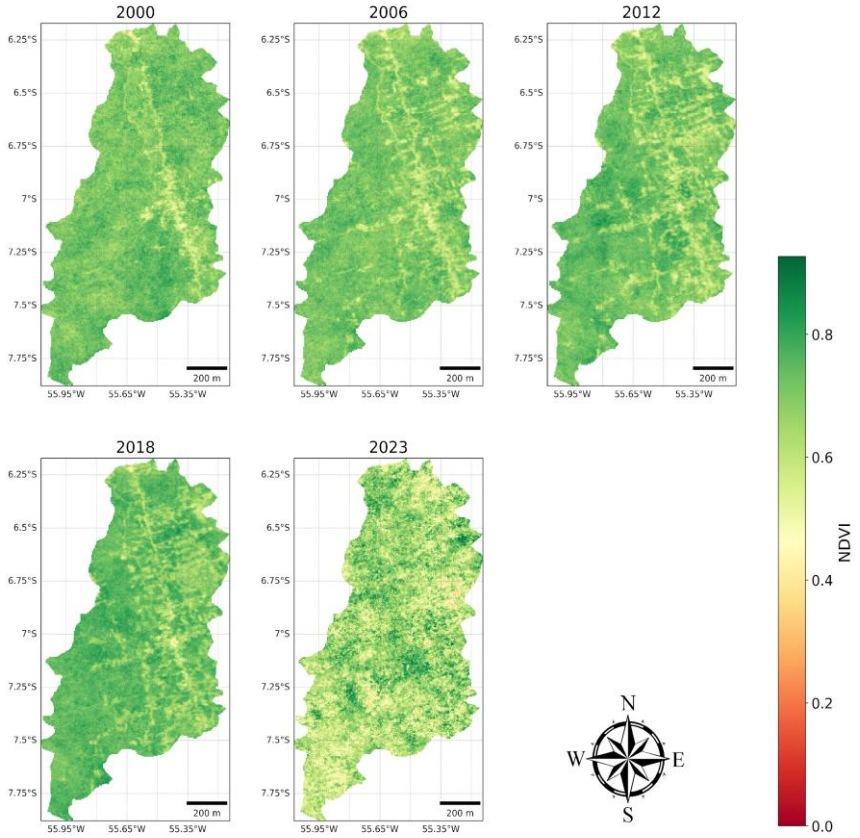


Figure 2. Normalized Difference Vegetation Index for the Years 2000–2023. Source: Elaborated by the authors.

In 2023, a greater change was observed in terms of vegetation quality and density. According to Barros et al. (2021), this phenomenon may be associated with various factors, including increased anthropogenic pressure driven by the expansion of agricultural areas or other impactful activities, which ultimately lead to environmental degradation. Furthermore, Sales (2023) highlights that the variations observed in the NDVI may be related to climate change, particularly rising temperatures.

Average Annual Precipitation from 2000 to 2023

Figure 3 presents maps of average annual precipitation between 2000 and 2023 for the study area. During the analyzed period, average annual precipitation ranged from 1,990 mm to 2,710 mm. According to data released by the Foundation for Research Support and Development (FAPESPA) in 2021, the municipality of Novo Progresso, PA, is characterized by an annual average precipitation of around 2,200 mm, with high air humidity throughout most of the year.

The years 2012 and 2018 stood out as having the highest precipitation levels, while 2000 and 2006 recorded the lowest volumes. In 2023, however, the worst scenario for rainfall indices was observed, with minimum and maximum precipitation of 1,991 mm and 2,250 mm, respectively. This decrease in precipitation occurred across much of the Amazon region due to the El Niño phenomenon in 2023, which was characterized by high intensity. In northern Brazil, this scenario resulted in severe climatic impacts, with a marked water deficit that led several states to face droughts of extreme severity (INPE, 2024).

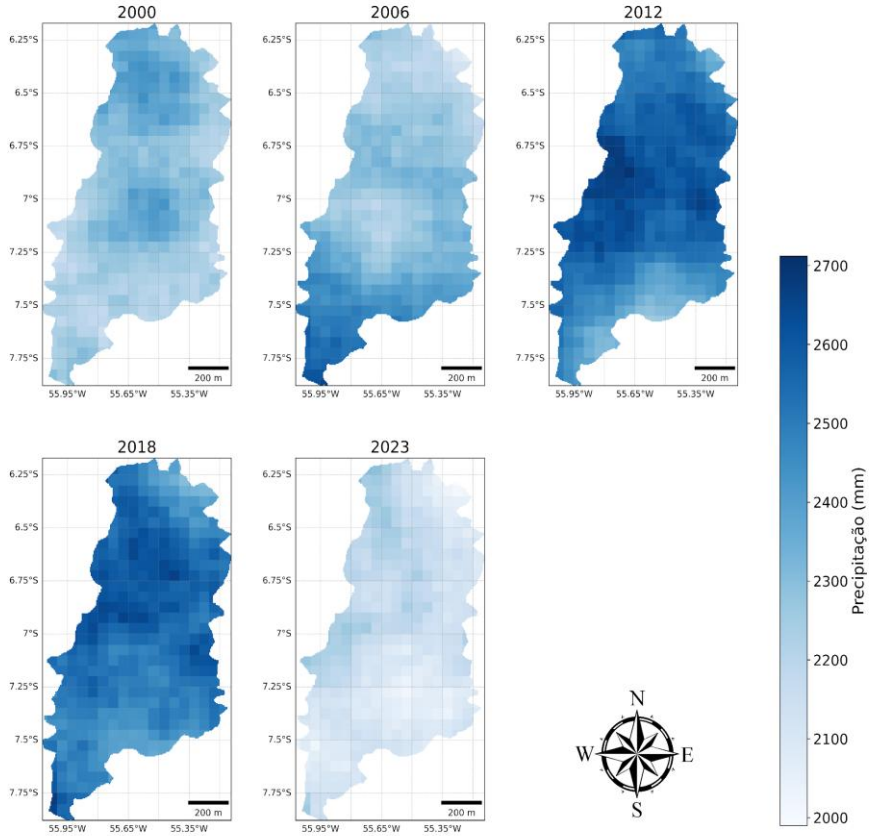


Figure 3. Average annual precipitation from 2000 to 2023. Source: Elaborated by the authors.

According to Dickmann and Liotti (2024) and Gonçalves et al. (2016), this reduction in average precipitation may be influenced by various factors, such as atmospheric phenomena, environmental changes, and processes of urbanization and industrialization, all of which also affect other meteorological elements. In the Fifth Assessment Report (AR5) of the Intergovernmental Panel on Climate Change (IPCC), the Amazon region will experience a 25% to 30% decrease in rainfall volume from 2041 to 2070 and a 40% to 45% decrease from 2071 to 2100, under scenarios with higher greenhouse gas emissions. Furthermore, according to Bottino et al. (2024), the combined effects of land-use change and global warming have led to a substantial reduction in annual precipitation, with an average decrease of 44% across the entire Amazon basin.

Average Annual Temperature, 2000–2023

According to Santos et al. (2021), the climate of the municipality of Novo Progresso is of the humid equatorial type, with an average annual temperature of 25.6 °C, which can reach values between 29 °C and 30 °C. These climatic conditions contribute significantly to the frequency of wildfires in the region, especially during periods of drought, high temperatures, and low relative humidity (Lopes et al. 2017). Rising temperatures exacerbate drought conditions and increase the risk of fire spread. Ma et al. (2024) emphasize that the combination of warming and reduced rainfall considerably increases the likelihood of fires in areas of native vegetation.

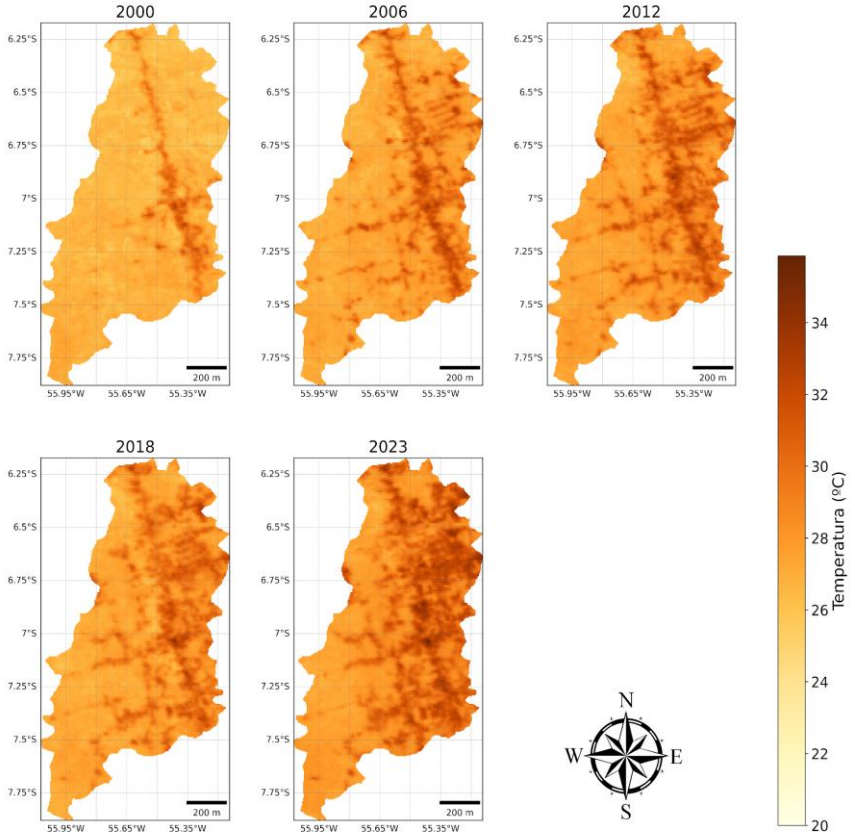


Figure 4. Annual average temperature from 2000 to 2023. Source: Elaborated by the authors.

An analysis of the annual average temperature between 2000 and 2023 (Figure 4) reveals a range between 20 °C and 34 °C, with 2000 recording the lowest values. Starting in 2006, a trend of gradually rising temperatures is observed, with 2023 being the year with the highest values for the entire period analyzed. This sharp increase may indicate negative impacts on the environmental balance and the regional climate. According to Santos et al. (2021), the region experienced a significant increase in the number of wildfires between 2019 and 2021, which contributed significantly to the rise in local temperatures.

Among the years analyzed, La Niña occurred in three of them (2000, 2012, and 2018), while 2006 and 2023 were marked by the El Niño phenomenon, with 2023 standing out as a year in which the event was particularly intense. According to Pirani et al. (2024), during El Niño episodes, temperatures in the region typically rise by an average of 0.5°C, contributing to a scenario of environmental stress exacerbated by extreme droughts and negative anomalies in soil moisture. Historical records indicate a persistent trend of rising both maximum and minimum temperatures across much of the North, a pattern that is intensified by the configuration and intensity of the phenomenon (Costa et al., 2025). However, even in years associated with La Niña events (2000, 2012, and 2018), temperature increases were observed in certain areas of the studied basin, suggesting that, in these cases, the rise in temperature may be related to the influence of other factors.

Land Use and Land Cover from 2000 to 2023

Between 2000 and 2023, land use and land cover in the microbasin underwent significant changes (Figure 5). In 2000, the region had greater vegetation cover and a lower incidence of environmentally degrading

activities. Among the land use and land cover classes classified by MAPBIOMAS, pasture was the one that expanded the most over the years. According to Rosário et al. (2021), livestock farming is the most prominent activity in the region, both for beef cattle production and dairy farming, due to the municipality's proximity to slaughterhouses and dairy processing plants.

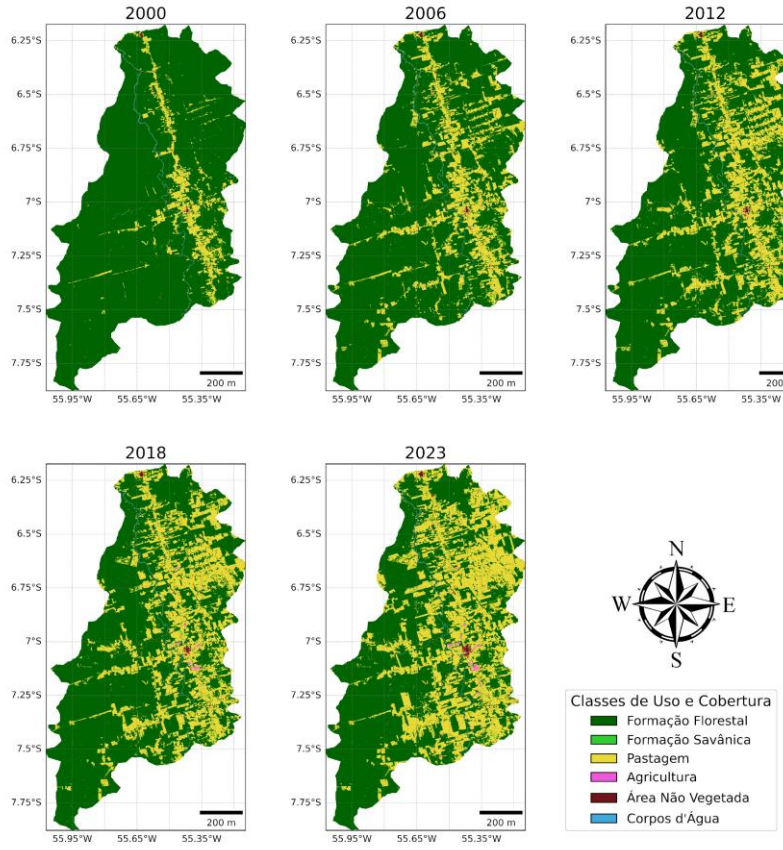


Figure 5. Land use and land cover from 2000 to 2023. Source: Elaborated by the authors.

In 2000, the area designated for pasture in the microbasin was 841.21 km²; from that year onward, an intensification of this activity was observed in the region, with a considerable increase in 2018 and 2023, +283.17% and +392.56%, respectively. This expansion may have contributed to the results observed in the NDVI index, reflecting a decline in vegetation quality and significant changes in the region's ecological balance. Carneiro et al. (2022), in their study, found that between 2009 and 2019, the municipality of Novo Progresso experienced significant deforestation, with 38,924.31 hectares cleared, mainly due to the expansion of livestock farming.

Correlation of NDVI with Climate Variables and Land Use and Land Cover

Figure 6 illustrates the relationships between NDVI, precipitation, annual average temperature, and land use and land cover for the years 2000, 2006, 2012, 2018, and 2023. Each variable is analyzed individually to ultimately identify which one exerts the greatest influence on NDVI in the study area and period.

In all years, the relationship between NDVI and precipitation showed a weak correlation, with 0.14 being the highest Pearson's correlation coefficient found, indicating that precipitation had a limited impact on NDVI. Furthermore, in 2000 and 2018, the correlation between NDVI and precipitation was negative, at -0.15 and -0.06, respectively, suggesting that as precipitation increased, the index decreased.

On the other hand, temperature showed more significant correlations with the NDVI, especially in 2023 (-0.73). In all years, the coefficient values were negative, indicating that higher temperatures may have contributed to a reduction in vegetation density. According to Dusenge et al. (2019), high temperatures can alter plants' metabolic pathways, compromising their growth and development. According to Azevedo and Barbosa (2020), rising temperatures can have negative impacts on vegetation, hindering its growth and compromising its density. This phenomenon occurs because higher temperatures intensify environmental stress, affecting overall vegetation health and cover.

Regarding changes in land use and land cover, a moderate negative correlation was observed in virtually every year, with 2023 showing the highest correlation value, approximately -0.70. These correlations indicate that anthropogenic changes, such as the conversion of forests into pastures or agricultural areas, negatively influenced the NDVI. According to Mahesh et al. (2022), the relationship between land use and land cover and the NDVI highlights the direct impacts of human activities on vegetation. The conversion of natural areas into spaces used for agriculture, livestock, and urbanization reduces vegetation cover and, consequently, NDVI values.

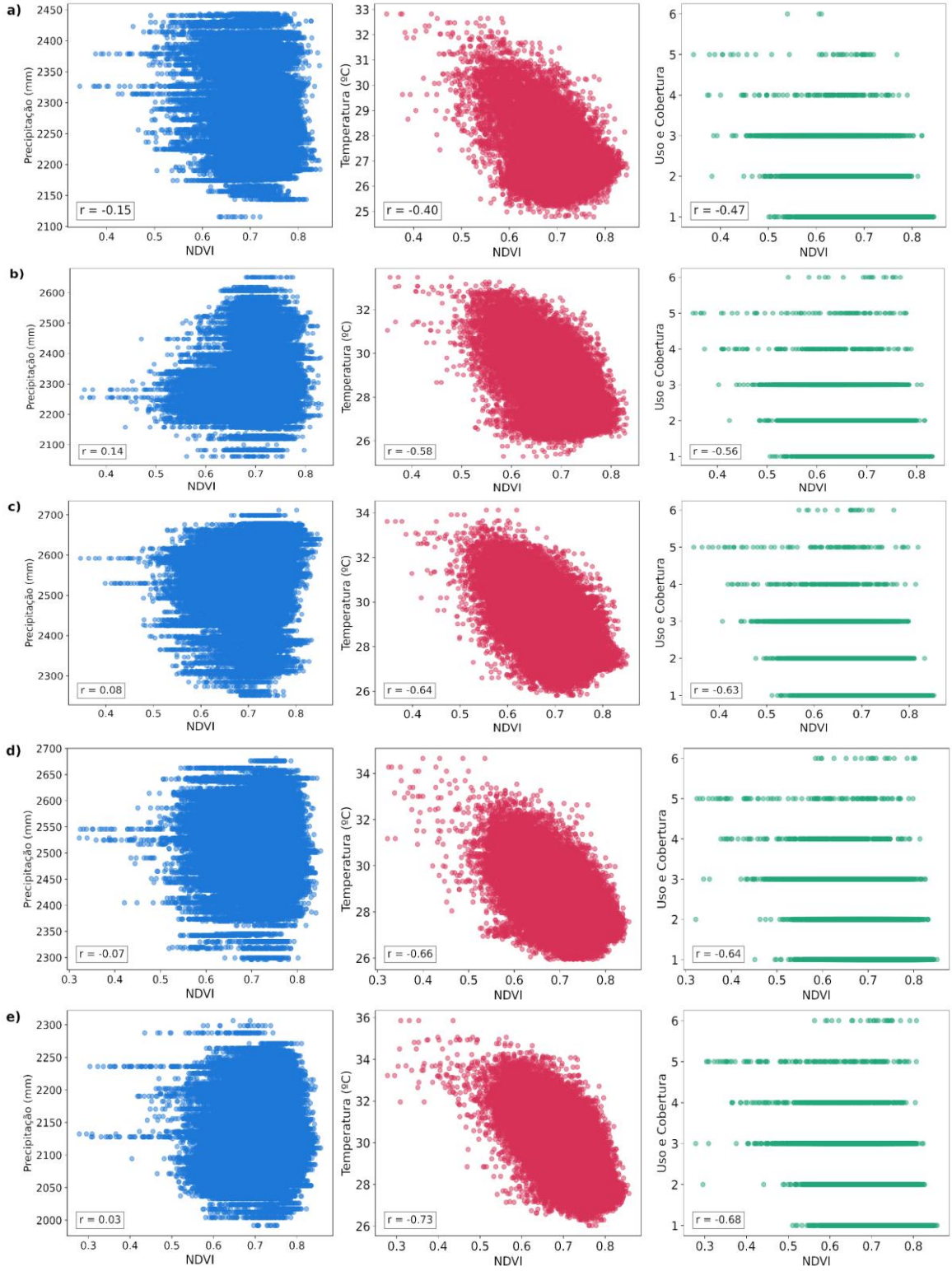


Figure 6. Scatter plots of NDVI against climatic variables and land use and land cover in a) 2000, b) 2006, c) 2012, d) 2018, and e) 2023. Source: Elaborated by the authors

Among the land use and land cover classes studied (Table 1), it was found that in all years—especially 2023—the "Forest" class consistently stood out with a positive correlation, demonstrating that forests played a crucial role in maintaining high NDVI values. Meanwhile, the Pasture class exhibited the strongest negative correlations; thus, as areas designated for livestock farming increase, NDVI values tend to decrease, which would reflect a negative impact of the conversion of native vegetation into pasture areas. The remaining classes (savanna, agriculture, bare land, and water bodies) exhibited weak, negative correlations, suggesting a lesser influence.

Table 1. Correlation values between NDVI and climate variables and land use and land cover variables.

Classes	***NDVI***				
	2000	**2006**	**2012**	**2018**	**2023**
Forest Formation	0.46	0.53	0.60	0.61	0.65
Savanna Formation	0.20	-0.17	-0.17	-0.15	-0.10
Pasture	0.42	-0.50	-0.55	-0.56	-0.59
Agriculture	0.08	-0.09	-0.08	-0.11	-0.13
Non-vegetated area	0.07	-0.07	-0.07	-0.09	-0.11
Water body	0.02	-0.004	-0.01	-0.004	-0.006

Source: Elaborated by the authors.

In this context, in their study, Lykhovyd et al. (2024) analyzed the correlation between NDVI and air temperature in agricultural crops such as wheat, corn, and soybeans, highlighting that temperature directly influences the index by affecting processes such as photosynthesis. The authors identified a significant relationship between temperature and critical phases of the plant life cycle, emphasizing that temperature monitoring is essential for efficient agricultural management adapted to climate change. On the other hand, it was found that the correlation between NDVI and precipitation is generally weaker, suggesting a more dominant role for temperature.

In contrast, Jiao et al. (2021) and Pei et al. (2019) emphasized that precipitation was a dominant factor in vegetation changes, with its intensity directly influencing the NDVI. In Khyber Pakhtunkhwa, Pakistan, Mehmood et al. (2024) observed that a significant decrease in precipitation was accompanied by an increase in NDVI, suggesting that vegetation had adapted to changes in climatic conditions. Furthermore, Chen et al. (2023) noted that NDVI responses also exhibit regional variability, as the authors identified a decrease in NDVI in northern China between 2000 and 2012, while eastern China recorded an increase during the same period.

In the present study, the weak correlation between NDVI and precipitation may be associated with the delayed response of vegetation to the water regime. Lucas and Schuler (2007), for example, observed that rainfall from the previous month had a greater influence on the NDVI than that of the current month, highlighting this time lag. In addition, climatic events such as El Niño and La Niña alter precipitation patterns and water availability, indirectly affecting vegetation. Souto et al. (2019) point out that these events can keep the NDVI elevated even after the rainy season or, conversely, cause water deficits that reduce plant biomass, explaining weak or even negative correlations.

Another factor that influences the correlation between NDVI and precipitation is land use. Land use—primarily driven by the expansion of agriculture, particularly soybean cultivation—that is, the conversion of native vegetation into monocultures—alters soil moisture retention and modifies the phenological cycle of plants, making them more dependent on agricultural management than on natural rainfall. Soares et al. (2020) analyzed NDVI behavior in Sorriso, Mato Grosso—the world's largest single soybean-producing region—and observed that the rapid expansion of soybean cultivation influenced vegetation cover and local climate variables. The authors suggest that this expansion may be making the relationship between NDVI and precipitation less predictable. Similarly, Souto et al. (2019) found that in the Iriri River basin, seasonal variations in precipitation were not always reflected in the NDVI, especially in areas that had been deforested or converted to agriculture. Both studies support the hypothesis that the expansion of soybeans and other crops may be decoupling the NDVI response from precipitation, which explains the findings of this study, given that the study area is also experiencing significant agricultural expansion.

In this context, Liu et al. (2021) and Meng et al. (2020) emphasize that, although many studies using NDVI focus on isolated factors, such as temperature or precipitation, vegetation changes result from highly complex dynamics characterized by the interaction between multiple climatic elements and human activities. Thus,

considering that changes in vegetation constitute a multifactorial process, driven by both climatic variability and human interventions, it is necessary to adopt an integrated approach that comprehensively addresses the various factors capable of influencing NDVI values.

Final Considerations

The objective of this study was to analyze variations in the Normalized Difference Vegetation Index (NDVI) in relation to climatic variability and changes in land use and land cover in a microbasin located in the southwest of the state of Pará. Throughout the study, it was observed that, between 2000 and 2023, there were significant changes in the vegetation of the study region, particularly due to the expansion of land-use activities such as pasture, which resulted in a decline in vegetation quality, reflected in lower NDVI values.

The study revealed that temperature has been an important factor in vegetation degradation, with a gradual increase in temperatures over the years, particularly in 2023, which recorded the highest values. This trend may be associated with the influence of the 2023/2024 El Niño phenomenon, which contributed to above-average temperatures and reduced precipitation in different areas of the Amazon. This trend of rising temperatures may have caused heat stress, affecting the health of the vegetation. Furthermore, precipitation, although important, showed a weaker correlation with the NDVI, especially in recent years, when a reduction in rainfall was observed.

Changes in land use and land cover, particularly the expansion of pasture areas, showed a stronger correlation with the decline in NDVI. The replacement of native vegetation with pastures has had a negative impact on the quality of the region's vegetation cover. Preserved forest areas, on the other hand, maintained higher NDVI values, highlighting the importance of conserving these areas to maintain dense and healthy vegetation.

Analysis of the NDVI, in conjunction with these variables, is essential for understanding the dynamics of land use and land cover and the impacts of human activities on the local environment, offering important insights for strategies aimed at the sustainable conservation and management of natural resources. The results contribute to our understanding of the impacts of climate change and land use on Amazonian vegetation, providing a basis for monitoring, land-use planning, and natural resource conservation in one of the most strategically important regions for global climate balance.

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