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Resposta da Vegetação Campos de Altitude às Mudanças Climáticas na Faixa Altitudinal Acima de 400 Metros na Serra do Amolar e Morraria do Urucum, Pantanal Brasileiro

Response of Altitude Grassland Vegetation to Climate Change in the Altitudinal Range Above 400 Meters in the Serra do Amolar and Morraria do Urucum, Brazilian Pantanal

Respuesta de la Vegetación Hierba de Montaña al Cambio Climático en el Rango Altitudinal por Encima de los 400 Metros en la Serra do Amolar y Morraria do Urucum, Pantanal Brasileño

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Resumo: Este estudo examina os efeitos impulsionadores das mudanças climáticas na distribuição espacial da vegetação dos Campos de Altitude ao longo de uma faixa altitudinal acima de 400 m na Serra do Amolar e Morraria do Urucum, ambas inseridas no Pantanal do Mato Grosso do Sul, Brasil. Dados foram obtidos a partir da plataforma *Google Earth Engine* de 1982 a 2022 para dados climáticos e de 1985 a 2022 para dados de NDVI (*Normalized Difference Vegetation Index)*. Empregou-se o software R para métricas de análise sobre os dados *raster* na identificação da variação espacial das médias do NDVI, e correlação de Pearson e regressão linear simples para estimar a força da relação entre as variáveis climáticas e o NDVI. Foi observada uma tendência crescente de temperatura, NDVI e precipitação ao longo dos 37 anos analisados e as variáveis de temperatura e precipitação foram significativamente relacionadas com os dados de NDVI e de mudança espacial na cobertura vegetal. O estudo revelou assim o mérito desta análise com uma abordagem técnica para avaliar a contribuição das alterações climáticas versus alteração na dinâmica da vegetação em ecossistemas montanhosos.
Palavras-chave: clima, aquecimento global, vegetação montanhosa, NDVI, Pantanal

Abstract: This study aims to examine the driving effects of climate change on the spatial distribution of altitude grassland vegetation along an altitudinal range above 400 m in Serra do Amolar and Morraria do Urucum, both inserted in the Pantanal wetlands located in the State of Mato Grosso do Sul, Brazil. Data variables from Google Earth Engine was obtained to the 1982-2022 period for climate data and from 1985 to 2022 for NDVI (Normalized Difference Vegetation Index) data. The data were processed and analyzed using the R software, in which the analysis metrics were applied on the raster data to identify spatial variation of the NDVI means and statistical methods such as Pearson's correlation and simple linear regression were applied to identify the strength of the relationship between climate variables and the NDVI. The results showed that there was an increasing trend in temperature, NDVI and precipitation over the 37 years analyzed. The climatic variables were statistically relevant in the tests of the relationship between the NDVI and the variables of temperature, precipitation and spatial change in vegetation cover. The study thus revealed the merit of this analysis with a technical approach to assess the contribution of climate change versus alteration in vegetation dynamics in mountainous ecosystems.
Keywords: clime, global warming, mountainous vegetation, NDVI, Pantanal

Resumen: Este estudio examina los efectos impulsores del cambio climático en la distribución espacial de la vegetación hierba de montaña a lo largo de un rango altitudinal por encima de los 400 m en Serra do Amolar y Morraria do Urucum, ambos ubicados en el Pantanal de Mato Grosso do Sul, Brasil. Los datos se obtuvieron de la plataforma Google Earth Engine de 1982 a 2022 para datos climáticos y de 1985 a 2022 para datos NDVI (Índice de Vegetación de Diferencia Normalizada). El software R se utilizó para analizar métricas en datos ráster para identificar la variación espacial de los promedios del NDVI, y la correlación de Pearson y la regresión lineal simple para estimar la fuerza de la relación entre las variables climáticas y el NDVI. Se observó una tendencia creciente en la temperatura, el NDVI y la precipitación durante los 37 años analizados y las variables de temperatura y precipitación se relacionaron significativamente con los datos del NDVI y el cambio espacial en la cubierta vegetal. El estudio reveló así el mérito de este análisis con un enfoque técnico para evaluar la contribución del cambio climático frente a los cambios en la dinámica de la vegetación en los ecosistemas montañosos.
Palabras clave: clima, calentamiento global, vegetación montañosa, NDVI, Pantanal

INTRODUCTION

Tropical mountainous ecosystems are considered particularly vulnerable to climate change due to the large percentage of endemic flora with narrow distributions that are sometimes restricted to a single mountain range (Kattan et al., 2004, Ramirez-Villegas et al., 2014). Plant species restricted in certain altitudinal distribution ranges should have narrow habitat tolerances to those ranges in the elevation profile. Therefore, high rates of plant species loss and renewal are expected with climate warming in mountainous ecosystems (Ramirez-Villegas et al., 2014), especially in tropical zones where the climate undergoes the greatest changes, and with the expectation that 60% of the flora could be lost or seriously threatened by 2050 (Leon-Garcia & Lasso, 2019). Responses to climate change may define the distribution of vegetation; those with high migration capacity may be able to track the displacement of their niche, while those others with high heat tolerance may be able to cope with new conditions and suffer a reduction in elevation profile or even disappear giving way to other species more adapted to those new climatic conditions (Broennimann et al., 2006, Leon-Garcia & Lasso, 2019).

The spatiotemporal dynamics of vegetation cover are largely driven by climatic factors (temperature and precipitation), such as climate change and human activities (Assaadia et al., 2022). The Normalized Difference Vegetation Index (NDVI) is widely used to indicate vegetation changes in mountainous ecosystems and can be used as an indicator of vegetation response to climate change (Kogo, Kumar & Koech, 2019; Chu et al., 2019; Lin et al., 2020; Matas-Granados et al., 2022; Prăvălie et al., 2022; Zhang et al., 2018; Duarte et al., 2018; Huang et al., 2021; Assaadia et al., 2022; Zhu et al., 2021; Muradyan et al., 2019; Nejadrekabi et al., 2022). These researchers and many others have studied the response of vegetation cover to climatic factors at different spatial and temporal scales based on NDVI time series, and the results show a high dependence of vegetation dynamics on precipitation and temperature (Ezaidi et al., 2022; Assaadia et al., 2022).

There are few studies on the heat tolerance of tropical mountainous species when contrasted with that of temperate climate, where mountainous plant species with wide thermal tolerance and significant warming acclimation potential have been reported in some studies (Leon-Garcia & Lasso, 2019; Smillie & Nott, 1979). Other studies in southwestern China that investigated climate change and its effects on altitudinal/mountainous vegetation change reported that this region of China experienced climate warming during the last four decades of the 20th century (Zhai et al, 2005, Ding et al., 2007, Li Z. et al., 2012, Tao et al., 2016), and that the warming trend exhibits variations, spatially and temporally, and has brought widespread impacts on vegetation change (Zhang et al., 2010, 2012, Barriopedro et al., 2012).

Climate warming since the 1980s has exerted a more significant effect on vegetation change than other factors (Wang et al., 2008, Hou et al., 2015), and the significant effect showed a variation in the distribution of mountain vegetation (Li X. et al., 2015). Considering that the upper-temperature limit in areas with high-altitude grasslands has been rarely studied, the evaluation of heat tolerance in this ecosystem can help to assess the vulnerability of high-altitude grassland vegetation and improve predictions about the impact of warming in tropical regions, such as the Brazilian Pantanal.

It is expected, therefore, that the heat tolerance of the altitude grassland will respond to the degree of decoupling that the species can achieve, which will be mainly related to characteristics such as the form of spatial distribution along the altimetric profile, as well as the replacement of the altitude grassland vegetation by other types of phytophysiognomies, which may be more adapted to climatic changes at that site. Most of the knowledge about the heat tolerance of mountainous vegetation at high altitudes comes from temperate regions, whose heat tolerance is higher than would be expected from their thermal environment (Korner 2003). Studies on mountainous vegetation in tropical regions, as is the case of the altitude grassland in Pantanal, become necessary to understand the reflections of climate fluctuation and its impacts on the distribution of mountainous vegetation and the impacts on the biodiversity of these environments.

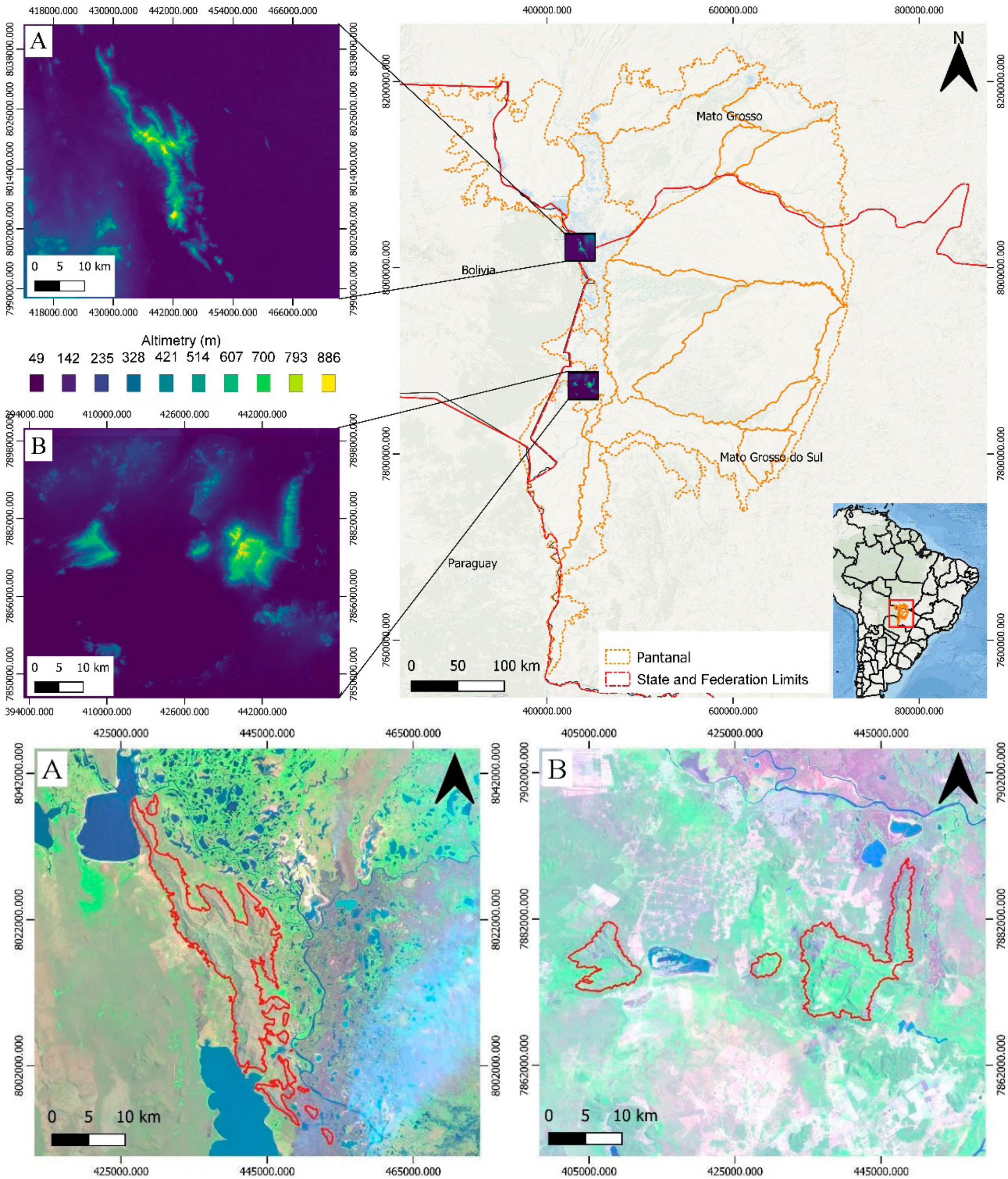
In this context, the (scientific) objective is to analyze the multidimensional change of mountainous vegetation driven by climatic effects. For this, data from remote sensors were analyzed using the NDVI technique and compared with temperature and precipitation data, using trend and correlation analysis. We consider for this study the montane vegetation of altitude grassland, found along an altitudinal range above 400 m in the Serra do Amolar and Morraria do Urucum, both inserted in the Pantanal Sul-mato-grossense, Brazil. The value of this study lies in the fact that it can provide a crucial basis for decision making in terms of vegetation protection measures and green development for different ecological units in mountain ecosystems under different global warming scenarios.

METHODOLOGY

Study area

This study encloses two areas: Serra do Amolar and Morraria do Urucum, both located in the Pantanal Sul-mato-grossense, in the municipality of Corumbá-MS (Figure 1). The high mountainous regions in the southwestern part of the Pantanal Sul-mato-grossense have elevations varying from 700 m to 1000 m above sea level like the Serra do Amolar. Elevation increases from south to northwest in the Serra do Amolar study area and increases from east to north in the Morraria do Urucum. Land use data (Pessi et al., 2022) show that tree forests, altitude grassland and pastures cover 14,577 hectares, 16,494 hectares and 420 hectares of the vegetated areas, respectively (Figure 1). Most of the areas vegetated by altitude grassland in Serra do Amolar (SA) and Morraria do Urucum (MU) are located in ecologically fragile areas, with a total area of approximately 21,470 hectares for SA and 10,633 hectares for MU. The region where the SA and MU areas are located is classified as a tropical humid zone, typical of the tropics, with very hot and humid summers, abundant rainfall between the months of October and March (monthly averages of 300 mm), and a dry period in winter between the months of April and September (monthly averages of 100 mm), average temperatures is between 25 ºC, and can reach 40 ºC.

Figura 1: Location of the studied areas and their polygons generated from the altimetry data. A) Serra do Amolar; B) Morraria do Urucum.



Source: Landsat 8 images (U.S. Department of the Interior U.S. Geological Survey, 2020); Vector data of states and municipalities (Instituto Brasileiro de Geografia e Estatística [IBGE], 2021); UTM coordinate system SIRGAS 2000, 21S; Elevation image data from TOPODATA (2021).

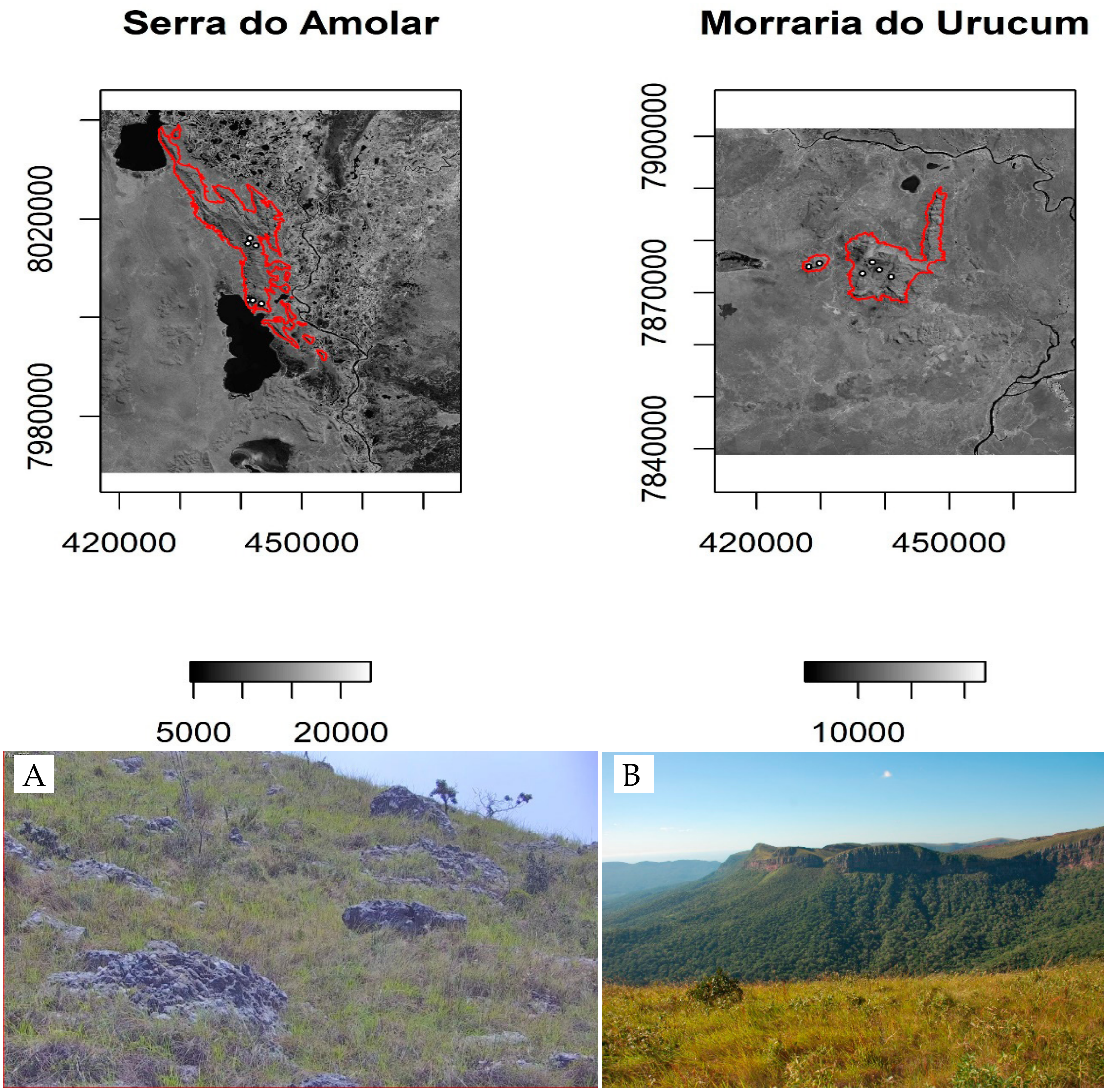
Altitudinal range for meteorological analysis

The altimetry data (Topodata 2021) of the study areas (available on the INPE website at http://www.webmapit.com.br/inpe/topodata/) were reclassified to values above 400 meters, because from this attitude the whole area of interest for this study was expressed, containing the highest parts of the Altitude Grassland. After the reclassification, the raster was converted into a shapefile with the areas re-sampled to the areas pre-defined as locations above 400 meters of altitude (Figure 2). The Serra do Amolar has a total area of 21,470 hectares, and the Morraria do Urucum has a total area of 10.633 hectares (Pessi et al., 2022).

Altitude Grassland Vegetation

In order to identify the presence of altitude grassland, fieldwork was carried out to identify the points where there was the presence of altitude grassland and to collect points of location with GNSS (Global Navigation Satellite System), so that from these points the places where there were fragments of altitude grassland vegetation could be characterized. Thus, six checkpoints were collected at Morraria do Urucum and six sampling points at Serra do Amolar (Figure 3). The field work was carried out within the selected areas and these areas were pre-defined as locations above 400 meters of altitude.

Figura 2: Point locations of the sites with presence of altitude grassland in the areas of Serra do Amolar and Morraria do Urucum. In red, delimitation of the study areas. White points, presence of altitude grassland. In A) Serra do Amolar; in B) Morraria do Urucum.



Meteorological and NDVI data acquisition

This research used the Google Earth Engine (GEE) (https://earthengine.google.com/) (accessed February 1, 2023) to obtain the meteorological and NDVI datasets. The NDVI data were obtained through two main sensors, being through the Landsat-5 satellite TM sensor, monthly average data from 01/01/1985 to 31/12/2013, 30 m spatial resolution. Then the NDVI data from 01/01/2013 to 31/12/2022 was obtained through the OLI sensor Landsat-8 satellite, with images of 30 m spatial resolution. There is no data for 2012, since Landsat-7 ended up with flaws in its sensor compromising the images. It is worth remembering that there is no data for all months, as there are scenes that have clouds that compromise the analysis, so only scenes with ≤5% cloud cover were used. The precipitation data were obtained from the UCSB-CHG/CHIRPS/PENTAD dataset, with monthly averages from 1982 to 2022. The temperature data were obtained from the ECMWF/ERA5_LANDdataset, with monthly averages between 1982 and 2022. Table 1 describes the types of data and the source of collection.

Table 1: Information from the data used for the analyses of this research.

Data Set	Analysis Time	Source
Temperature	1982 - 2022	ECMWF/ERA5_LAND, Google Earth Engine (https://earthengine.google.com/ (Taken as of February 6 2023)
Precipitation	1982 - 2022	UCSB-CHG/CHIRPS/PENTAD, Google Earth Engine (https://earthengine.google.com/ (Taken as of February 06 2023)
NDVI	1985 - 2022	Landsat-5 e Landsat-8, Google Earth Engine (https://earthengine.google.com/ (Taken as of February 06 2023)

Raster Data Algebra Analysis Method (NDVI)

The algebra analysis method of raster data mainly uses the cell-by-cell function. This type has data directly stacked on top of each other. The function then applies to the cells aligned with each other to simulate the dynamic variation trend of the NDVI product at each pixel. This method can eliminate the influence of extreme data in individual years to reflect the spatially changing characteristics of NDVI in the areas used in this study (Li, Y. et al. 2022).

NDVI is one of the widely used indexes for image classification, monitoring, and rapid assessment of forest quality. Higher NDVI values correspond to dense vegetation, such as evergreen forests, deciduous trees in the rainy season, or crops at their peak growth stage. Based on growth characteristics, deciduous forest and evergreen forest can be extracted by the difference in NDVI values between the dry and rainy seasons. As a biomass estimator, NDVI values also differ between evergreen forest and herbaceous vegetation (Pessi et al., 2022). In this analysis, NDVI was generated from cloud-free composite images of Landsat 8 and Landsat 5 for the dry season, spectral bands used were RED and NIR, as per Equation (1):

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

Where:
NIR is the surface reflectance value of the near-infrared band;
RED is the surface reflectance value of the red band of Landsat images.

In the raster data algebra process, input data was used considering the annual average of NDVI each year from 1985 to 2022. After the input of the rasters data in the R software, the simulation of the data was performed cell by cell using Equation 2 and an output (output data) was generated with the trends of dynamic variation of the NDVI product over the years of analysis.

The proposed method shows a time series of n = 37, that is, a series of 37 years is being analyzed, where ¯x_i is the NDVI value provided by the program, so soon it can be stated that ¯x_i = NDVI in year i. If the program shows the proportion of the pixel area occupied in each class, this proportion represents the letter k in the formula, so it is possible to generalize a formula for the proposed method, using a mathematical content Weighted Arithmetic Mean.

If a set is given by x1, x2, x3, ..., xn and weights p1, p2, p3, ..., pn. The weighted average is defined by Formula 1:

$$\mathrm{MP} = \frac{x_1 \cdot p_1 + x_2 \cdot p_2 + \ldots + x_n \cdot p_n}{p_1 + p_2 + \ldots + p_n} \tag{1}$$

If you use the same logic, the proposed method can be defined in Equation 2:

$$\overline{X}\mathrm{NDVI} = \frac{\sum_{i=1}^{n} \mathrm{NDVI}_i \cdot K_i}{\sum_{i=1}^{n} K_i} \tag{2}$$

Where ¯XNDVI is the weighted average of NDVI; ∑_(i=1)^n is the sum of n1, n2, n3, ..., ni, which would be the average of each year; NDVI = ¯x_i in each year i and k is the weighted weight in each class, i.e., k is the area of in terrain analyzed.

From this proposed method is possible to know if the NDVI value provided by the program is below, above or equal to the average extracted during the 37 years analyzed and thus draw the appropriate conclusions.

Statistical Analysis (Correlation Method)

To further quantitatively analyze the relationship between NDVI and climatic factors, Pearson's correlation analysis method is adopted to calculate the correlation coefficient of NDVI, annual mean temperature and annual cumulative precipitation data. The calculation formula is Equation 3 proposed by Zhang & Zhou (2021):

$$r = \frac{\sum_{i=1}^{n}[(x_i - \overline{x})(y_i - \overline{y})]}{\sqrt{\sum_{i=1}^{n}(x_i - \overline{x})^2 \sum_{i=1}^{n}(y_i - \overline{y})^2}} \tag{3}$$

where n is a time series, X_i is the average annual temperature or precipitation in i year, and ¯x is the average annual temperature or precipitation in the research period, ¯y_i is the NDVI value of i year, ¯y represents the average NDVI value in the research period. r is the correlation coefficient between the variables, and its range of values is [-1, 1].

A test for normality of the data (Shapiro-Wilk) was also applied by visual inspection using Q-Q plots (quantile-quantile plots). The Q-Q plot draws the correlation between a given sample and its normal distribution. In addition, a 2D density estimation was performed between the climate data and NDVI. A Simple Linear Regression was also performed, to see if there is a linear relationship between NDVI (dependent variable) and VI (independent variable).

The Shapiro-Wilk test is a test of normality in statistics, where the null hypothesis of the Shapiro test is that the residuals of the variables are normally distributed. If the p-value is equal to or less than 0.05, then the hypothesis of normality will be rejected by the Shapiro test. On failing, the test can state that the data will not fit the distribution normally with 95% confidence. However, on passing, the test can state that there is no significant deviation from normality.

The temperature and precipitation data used for the correlation analysis comprised the monthly averages for the warmest and wettest period (October to March), and the NDVI data used were the monthly averages for the driest months (May to September). These months were determined for the climatological data because this period is when climatological fluctuations, such as temperature and precipitation, exert the greatest influence on changes in plant dynamics (Zhang et al., 2020, Yu et al., 2013, Tao et al., 2018). For the NDVI data, the dry period was chosen because it has a better spectral response of the vegetation and better differentiation of the types of vegetation from grassland to forest.

Data analysis and processing

The data were processed and analyzed in R Studio software (R Core Team 2022), where statistical analyses and plotting of the results were performed using the following packages: The R packages ‘ground’, ‘raster’, ggplot2, gridExtra, ggpubr, dplyr, lattice and latticeExtra were used for plotting the rasters and processing raster images. The color scheme feature of the viridis package and RColorBrewer was used for visualization and plotting.

RESULTS

Temperature, precipitation and NDVI from 1985 to 2022

Over the past 37 years the mean annual temperature has increased at an annual rate of +0.041 °C for Morraria do Urucum and +0.038 °C per year for Serra do Amolar. The maximum annual temperature occurred in 2020 (28.66 °C) for Morraria do Urucum. In Serra do Amolar the maximum average temperature occurred in 2020 (29.33 °C). The fluctuation of the accumulated annual precipitation showed a trend of significant increase from 1985 to mid-2014 in Morraria do Urucum and from 1985 to mid-2005 in Serra do Amolar. The maximum accumulated precipitation in Morraria do Urucum occurred in 2011 (698 mm). For Serra do Amolar the maximum accumulated precipitation occurred in 1989 (747 mm).

The rate of change of NDVI in the study areas was positive, increasing with fluctuations throughout the years analyzed, with a more pronounced increase starting in 2010 for both areas analyzed. The maximum annual value of NDVI at Serra do Amolar appeared in 2019 (0.61), minimum annual NDVI value was 0.37 in 2005, and at Morraria do Urucum the maximum annual NDVI value was 0.73 in 2017 and the minimum annual NDVI value was 0.49 in 2001. From the perspective of 2000-2005 there was no significant increasing trend in the two studied areas. In Figures 3 and 4, the variations of temperature, precipitation and NDVI data for both study areas are comparatively presented.

Figure 3: Graph showing the distribution of temperature, precipitation and NDVI values over the years analyzed at Serra do Amolar.

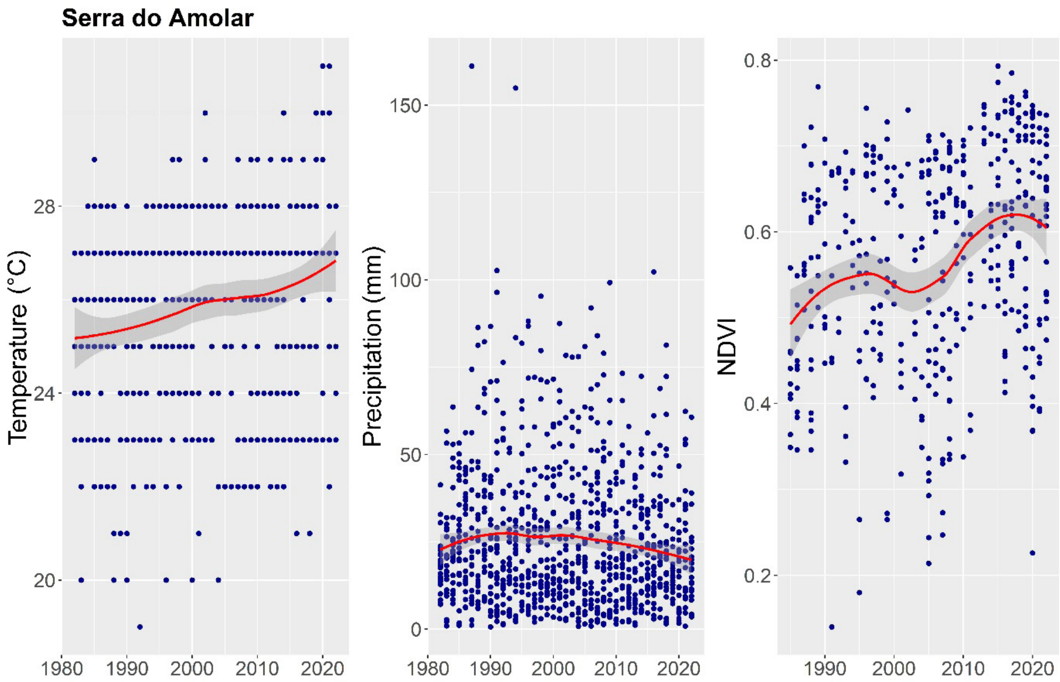
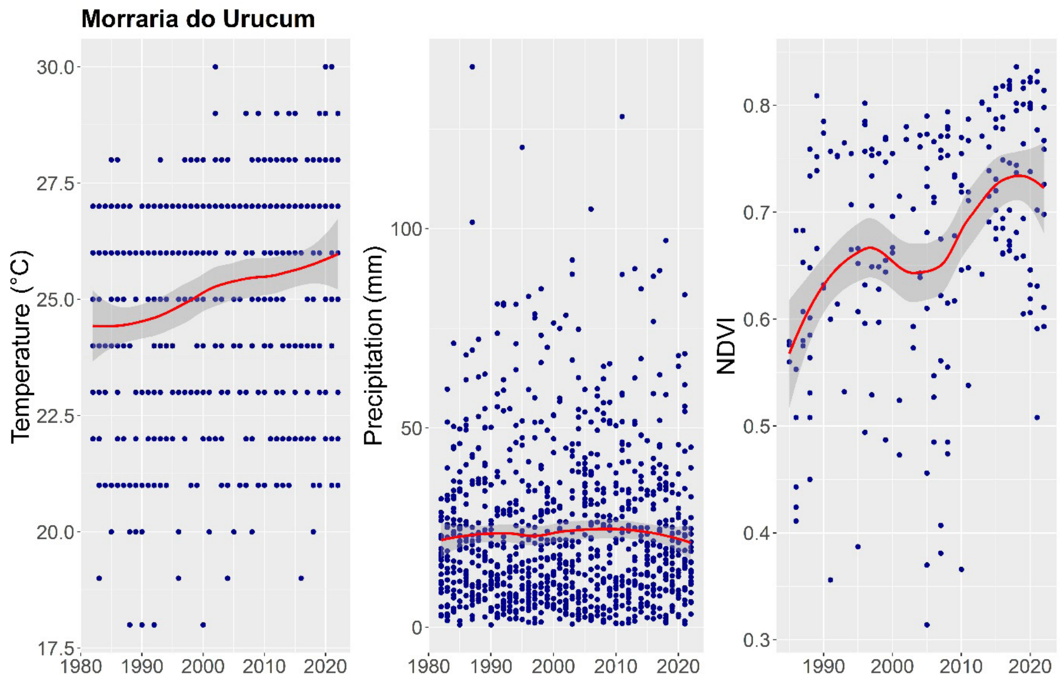


Figure 4: Graph showing the distribution of temperature, precipitation and NDVI values over the years analyzed at Morraria do Urucum.



Spatial distribution characteristics of NDVI

The spatial distribution characteristics of the monthly mean NDVI of vegetation in Serra do Amolar and Morraria do Urucum from 1985 to 2022 are illustrated in Figure 5. NDVI values to altitude grassland were generally low for the 0.17 to 0.44 range at Morraria do Urucum, and the 0.16 to 0.40 range of values at Serra do Amolar. In both areas with apparent spatial differentiation and imbalance of values, showing an increasing trend of values from 0.50 that can be determined as forest (Figure 6).

Figures 7 and 8 illustrate the trend of vegetation change in Serra do Amolar and Morraria do Urucum between the years 1985 and 2022. The vegetation changes in the study areas showed obvious spatial imbalance. The increasing vegetation trend is apparent in the olive-green parts, and the decrease occurs mainly in the higher areas. The results show that the area with increasing NDVI trend in Serra do Amolar represented 43.07% of the total area, and in Morraria do Urucum represented 22.95% of the total area, mainly distributed on the edges of the areas in orange (olive-green). The areas with substantial and non-significant NDVI decrease for the study areas, represented 8.23% and 21.42%, respectively, distributed mainly in the higher parts (in blue). The areas without significant change in NDVI are those in orange and dark green, with the areas in dark green being the parts with more robust vegetation (arboreal size), and the areas in orange being the altitude grassland.

Figure 5: Spatial distribution of the monthly average NDVI between 1985 and 2022.

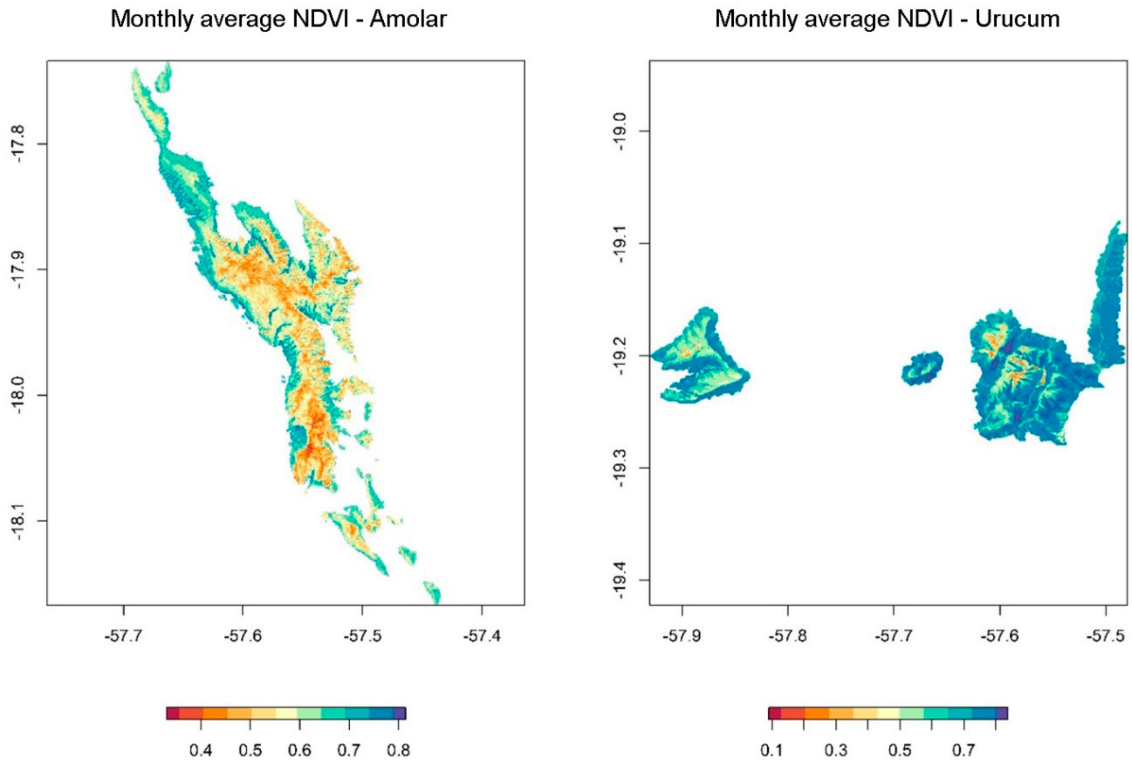


Figure 6: Distribution of NDVI pixels.

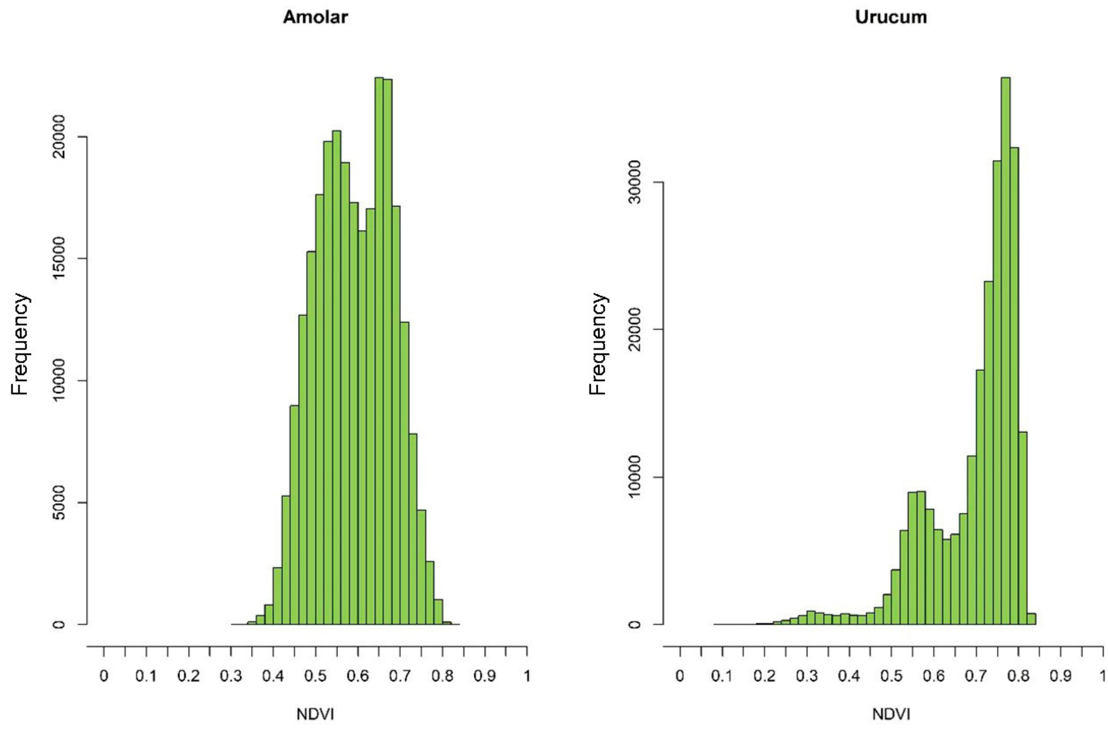


Figure 7: Spatial variation of NDVI in Serra do Amolar (1985-2022).

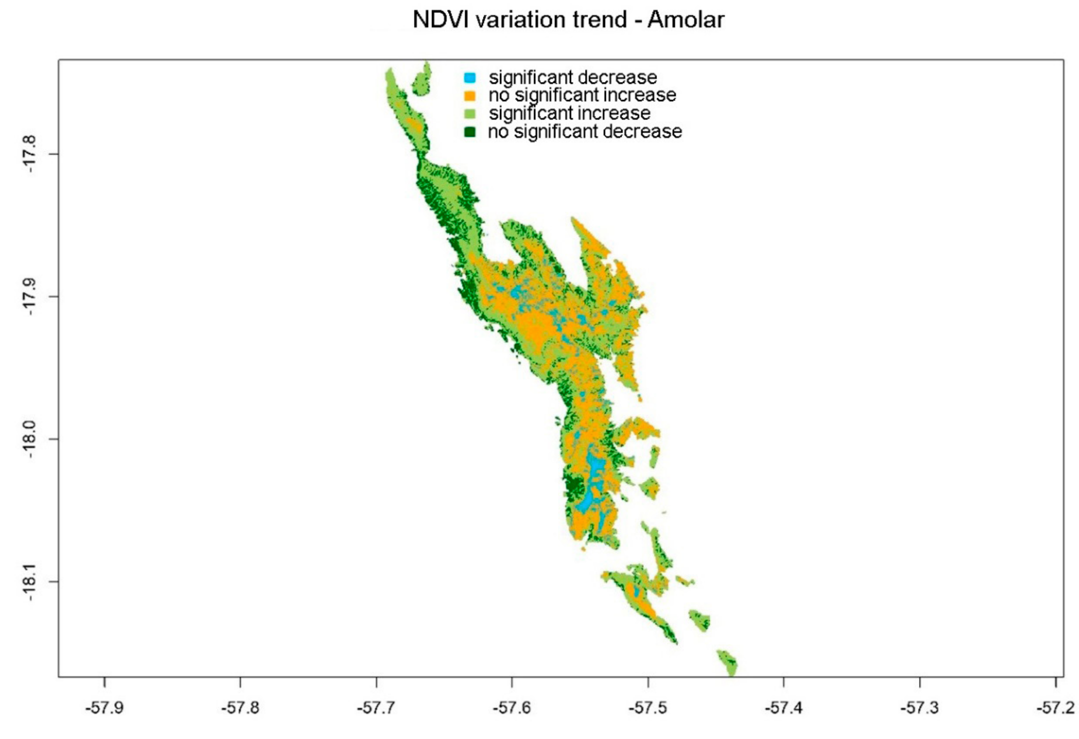
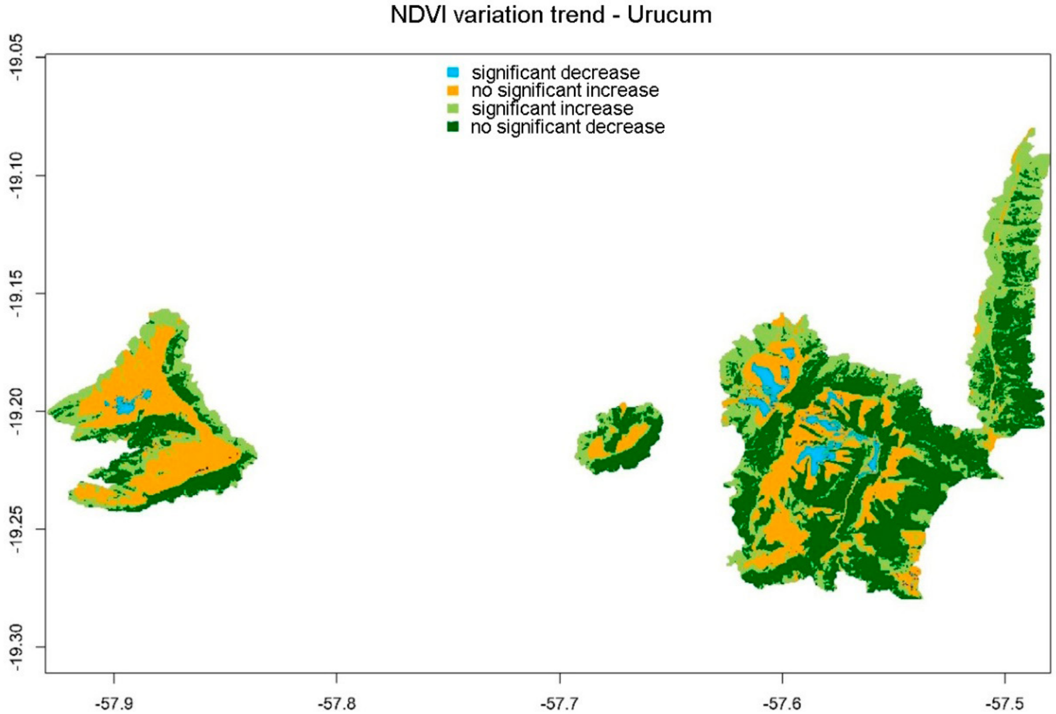


Figure 8: Spatial variation of NDVI in Morraria do Urucum (1985-2022).



Statistical analysis

To further reveal the correlation between NDVI, mean temperature and accumulated precipitation in the study areas between 1985 and 2022, the spatial distribution pattern of Pearson's correlation coefficients is illustrated in Figures 9 and 10. Table 2 illustrates the values of Pearson's correlation statistical results to the studied variables.

To spatialize the correlation data, 2D density plots were made in which they more clearly demonstrate the correlation between NDVI, and the precipitation and temperature variables as illustrated in Figures 11 and 12.

Figure 9: Correlation amid NDVI, monthly average temperature, and accumulated precipitation in the Serra do Amolar (1985-2022).

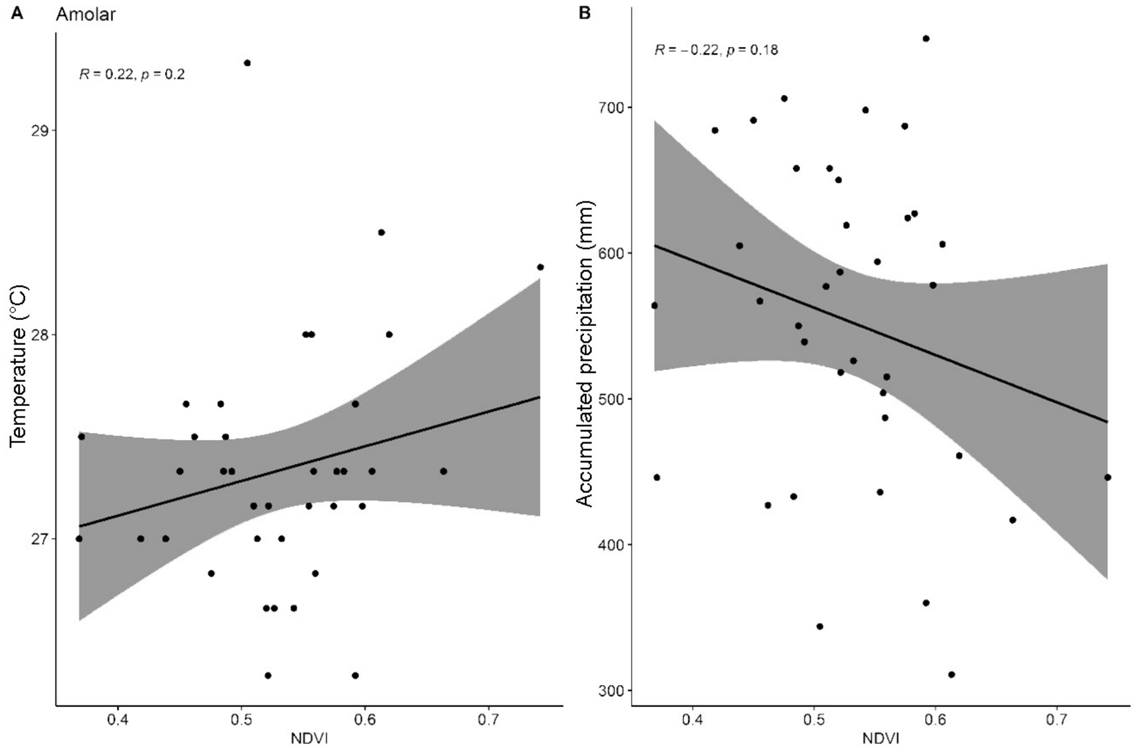


Figure 10: Correlation amid NDVI, monthly average temperature, and accumulated precipitation in the Morraria do Urucum (1985-2022).

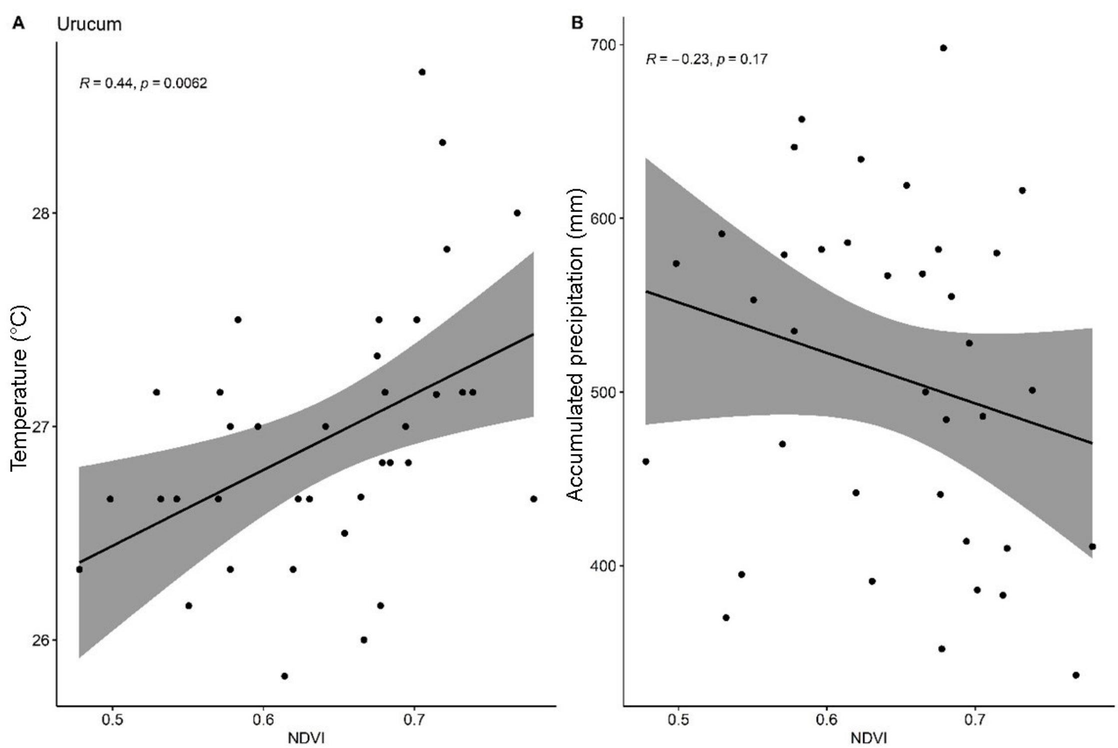


Figure 11: Spatial distribution of correlation density among the variables analyzed in Serra do Amolar (1985-2022).

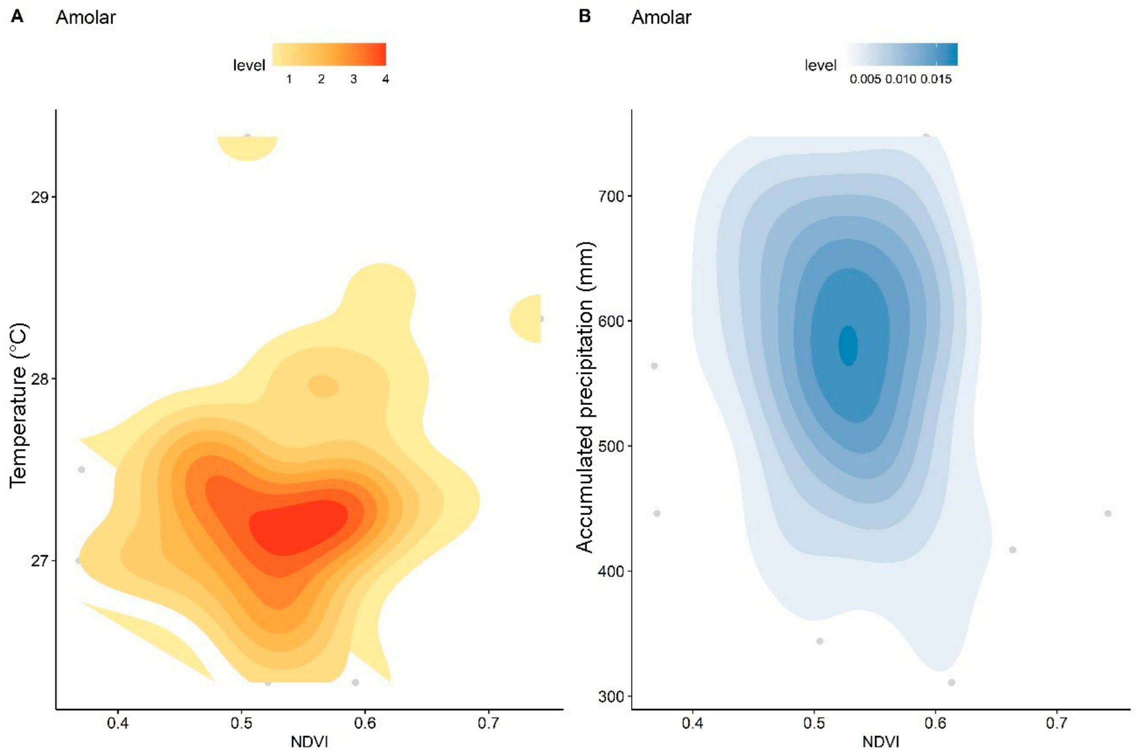


Figure 12: Spatial distribution of correlation density among the variables analyzed in Morraria do Urucum (1985-2022).

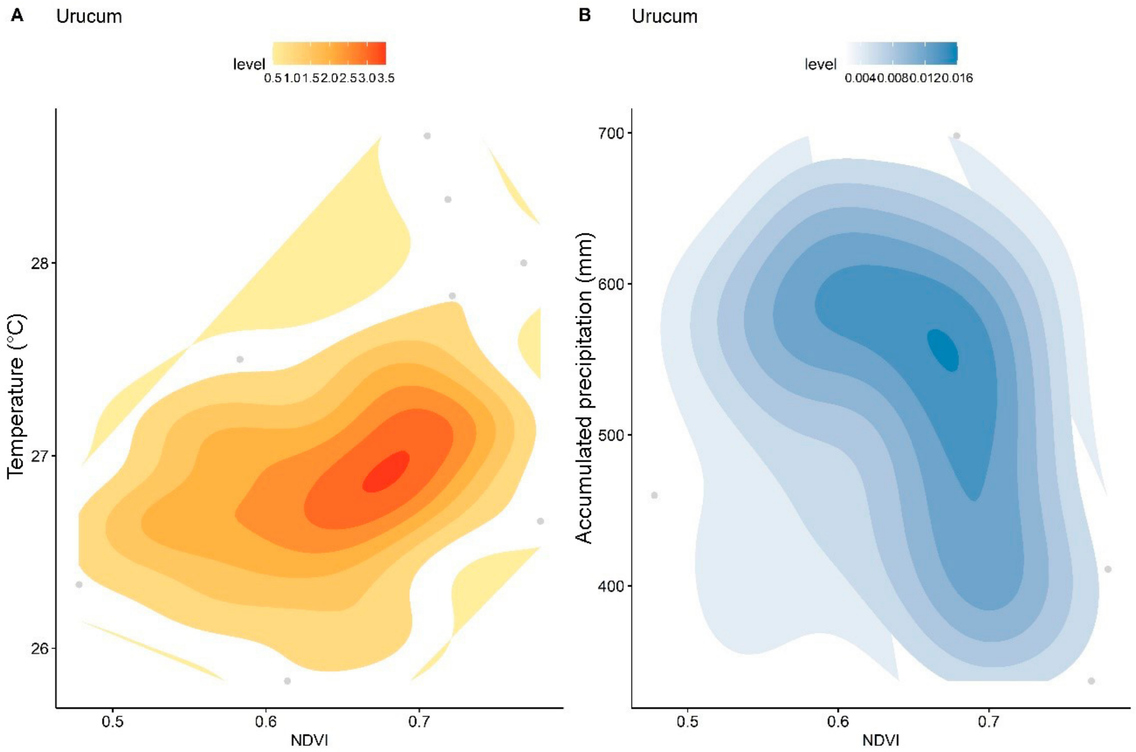


Table 2: Pearson's product-moment correlation between NDVI and climate variables.

Area	Variable	Corr. Coefficient	t	df	p=value	Observation
Amolar	Temp~NDVI	0.2272	1.31	35	0.1964	Small Correlation
	Prec~NDVI	-0.2236	-1.35	35	0.1832	Small Correlation
Urucum	Temp~NDVI	0.4415	2.9115	35	0.006221	Medium Correlation
	Prec~NDVI	-0.2282	-1.3869	35	0.1742	Small Correlation

The Shapiro-Wilk normality tests showed that there is normality of the data according to Table 3 and Figure 13.

Figure 13: QQplot with the Shapiro-Wilk tests for the residuals of the variables analyzed.

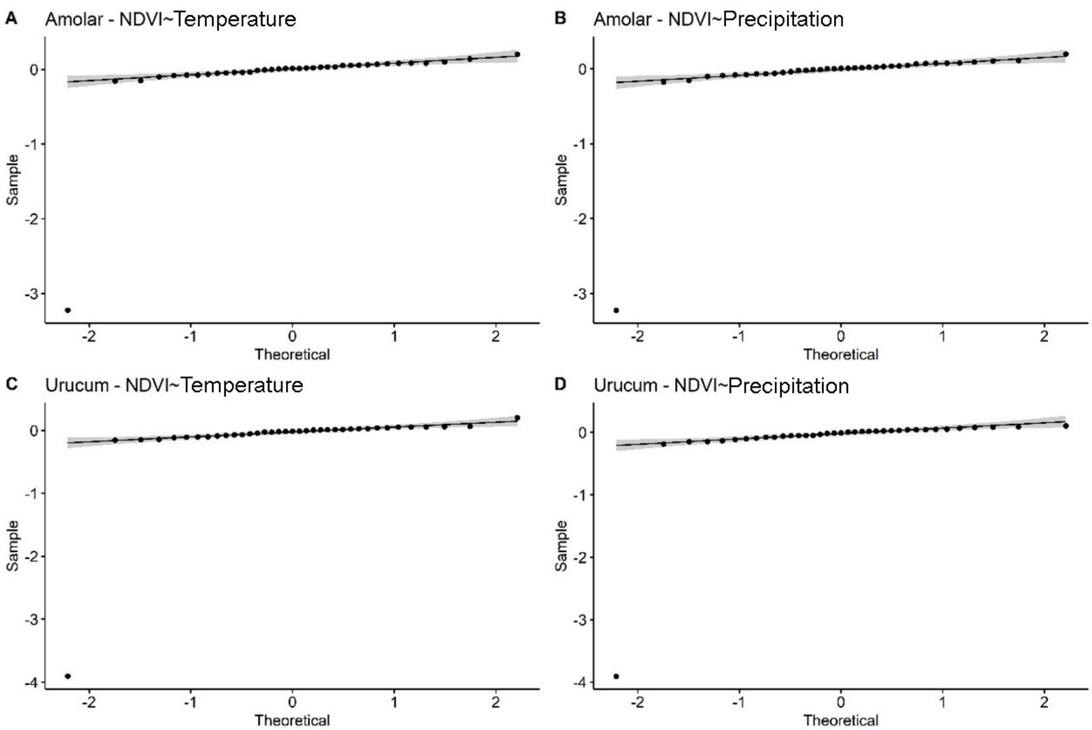


Table 3: Values for the Shapiro-Wilk normality test in the relationship between climate variables and NDVI. Legend: w - normality of residuals; p-value significance at 95%.

Area	Variable	w	p-value
Amolar	Temperature~NDVI	0.9813	0.779
	Precipitation~NDVI	0.9836	0.8519
Urucum	Temperature~NDVI	0.9618	0.2305
	Precipitation~NDVI	0.9587	0.1838

There is a positive linear regression between temperature and NDVI in both study areas as illustrated in Table 4. The relationship of NDVI with precipitation was not linear, with a small negative difference in the relationship between these two variables (-0.00015 in

Amolar, -0.00017 in Urucum). The regressions between the years and the variables (NDVI, temperature, precipitation) have a positive linear regression in both study areas (Table 4).

Table 4: Simple Linear Regression values between the variables studied and the years of analysis.

Areas	Variable	Regression
Amolar	Year ~ Temperature	0.038
	Year ~ NDVI	0.0030
	Year ~ Precipitation	-0.128
	Temperature ~ NDVI	0.027
	Precipitation ~ NDVI	-0.00015
Urucum	Year ~ Temperature	0.041
	Year ~ NDVI	0.0036
	Year ~ Precipitation	0.005
	Temperature ~ NDVI	0.054
	Precipitation ~ NDVI	-0.00017

DISCUSSION

The areas analyzed have experienced significant temperature increase over the past 37 years, with a positive annual change in Morraria do Urucum and with an average rate of positive annual change in Serra do Amolar. This same effect was visualized in the precipitation data, however during period the data from 1982 to 2005 in Serra do Amolar and from 1982 to 2014 in Morraria do Urucum, where from these years the water regime went from a linear increase to a steady decrease in accumulated rainfall values. This event of increasing temperature and decreasing water regime in the study areas may have been the key factors in the higher number of fires that occurred from 2014 onwards in the Pantanal as verified by Moreira et al. (2021).

As observed by some authors, climate change is being observed more in elevated regions such as mountains, ridges, and hills (Hou et al., 2022, Li X. et al., 2022). These same changes in hydrological regime and temperature were observed in the studies conducted by Hou et al. (2022), Li X. et al. (2022), and Yu et al. (2012) in mountainous areas of China (Qilian Mountain and Tibetan Plateau). Temperature changes and hydrological regimes are changing grassland ecosystems. Temperature and precipitation are the two most important climatic factors that influence the presence and distribution of grassland ecosystems. Therefore, climate change affects shifts in precipitation and temperature, altering and affecting soil moisture, soil microorganisms, photosynthesis, and plant respiration, further controlling grassland growth and ecosystem productivity, and affecting degradation or restoration (Hou et al., 2022, Li X. et al., 2022).

Since its original formulation proposed by Rouse et al. (1973), NDVI has been used in many studies on vegetation dynamics and their responses to climate change, especially concerning temperature and precipitation in global change studies (Bao et al., 2015, Zhang et al., 2020, Yu et al., 2013, Tao et al., 2018). Here, the results showed a significant increase in NDVI between 1985 and 2022 as was illustrated in the graphs of monthly averages, which may have a relationship to the rise of forest vegetation in the study areas, since similar results were found by studies developed by Pessi et al. (2023). This study showed that NDVI changed in the same mountainous region and this change in values implied in the ecosystem functioning and ecophysiology of mountain vegetation. There was a small negative variation in the NDVI increase trend between 2000 and 2005. Variations in precipitation and temperature likely played a primary role in determining the trend in vegetation productivity. These findings agree with other studies that observed increased NDVI in mountainous areas (Li Y. et al., 2022, Zhang et al., 2015, Hou et al., 2022, Li X. et al., 2022). In addition, the variation in NDVI was also seen in the data presented in the NDVI distribution change maps, where the olive-green areas that are around the orange-colored areas (higher regions), experienced an average increase in NDVI in these edge areas, which suggests that there was an increase in plant phytomass.

According to Le Quéré et al. (2018), grassland ecosystems play a crucial role in carbon sequestration and storage - therefore, changes in these ecosystems either through degradation or restoration have significant implications for carbon stocks, altering the soil's ability to sequester and store carbon (Le Quéré et al., 2018). Changes in temperature and hydrological regime are reshaping grassland ecosystems in upland regions, as evidenced by several studies in mountainous areas of China, and affect key ecosystem variables, including soil moisture, soil microorganisms, photosynthesis, and plant respiration (Hou et al., 2022, Li X. et al., 2022). Consequently, the observed redistribution of grasslands demonstrates how these systems have adapted to the environmental changes observed in recent years.

The use of NDVI has shown that vegetation dynamics are responding to climate change (Bao et al., 2015; Zhang et al., 2020). The significant increase in NDVI between 1985 and 2022 indicates an increase in vegetation (Figure 4), possibly forest, in the study areas (Li Y. et al., 2022, Zhang et al., 2015, Hou et al., 2022). Denser or different vegetation can significantly alter the carbon stock in a given area since plants take up carbon dioxide during photosynthesis and store carbon in their biomass (Pan et al., 2011). Furthermore, changes in NDVI distribution suggest an increase in plant phytomass, which may lead to an increased carbon sequestration (Li Y. et al., 2022). However, it is worth noting that while an increase in plant biomass generally means an increase in carbon stock, the specific vegetation composition and ecosystem health are also important factors to consider when assessing the overall impact on carbon stock (Pan et al., 2011).

The statistical results showed a relationship between NDVI, and the variables studied whereas the results of Pearson Correlation showed a correlation between NDVI data and climatic variables. However, the relationship of NDVI with precipitation values obtained small and negative correlation values, as this results from the difference in water regime in those years where there was a drop in accumulated values. However, the 2D density plots illustrate something interesting, where the values with the highest density are in the intersections where high-temperature x high NDVI, higher accumulated rainfall x high NDVI are visualized, mainly in the Morraria do Urucum study area. This data shows that there is a relationship between the variables studied, regardless of the fluctuations that occurred over the years analyzed and consolidated in the analysis of Linear Regression that showed a linear relationship of increasing NDVI as the temperature curve increases over the years (0.027, 0.054), and the same occurred in the relationship NDVI ~ Year. The precipitation data were negative, confirming the same visualized in Pearson's Correlation, with an exception for the relation Year ~ Precipitation in the study area Morraria do Urucum. This same result will be related to that variation of the hydric regime.

Historical climate changes (1982-2022) may have been a strong factor in the conversion of altitude grasslands to forests, as the results showed that regional climate has a significant impact on the conversion of mean NDVI values. The result shows that from 1985 to 2022, the conversion from grassland (altitude grassland) to forest led to an increase in annual mean NDVI. The mechanism that could have led to this process of changing the NDVI averages is that grassland vegetation (highland vegetation) is a sparser vegetation type having less leaf area and reflects more solar radiation than forest (Lean & Warrilow, 1989; Yu et al., 2013). The forest, on the other hand, has a greater leaf area and is a much more efficient absorber and scatterer of short-wavelength radiation (Lean & Warrilow, 1989, Yu et al., 2013). Consequently, the net energy absorbed by the surface increased because of the conversion from grassland to forest, which would increase NDVI.

Environmental factors such as changing climatic variables are considered one of the main factors influencing vegetation productivity (Angert et al. 2005), especially in mountainous ecosystems (Xion et al., 2016, Dakhil et al., 2019) that are known for their high sensitivity to changes in climatic conditions, particularly temperature and precipitation (Zhou et al., 2001, Qin & Ren., 2014). With wetter and warmer conditions, the productivity of vegetation increases, and a wetter environment increases the availability of water in the soil for uptake and growth of vegetation (Xiong et al., 2016). In addition, the rise in temperature increases the length of the growing season, promoting soil water availability and ultimately providing more available water for plant growth in a relatively long time. This interpretation could be confirmed in this study by the close linear relationship found between NDVI, precipitation, and temperature.

Under the background of global warming, temperature in the study region increased, while precipitation fluctuated. It was found that NDVI correlates positively with temperature and precipitation over the years. Precipitation is positively correlated until a certain period of analysis, and then there is a drop in the accumulated values, but this does not mean that rainfall did not play an important role in vegetation dynamics in the analyzed areas. Still, temperature is positively correlated in both study areas, which indicates that water resources are not the main determining factor in vegetation change in this region. However, the study area belongs to the mountainous climate, and the main vegetation types are of the grassy type in the higher areas (altitude grassland). Therefore, attention should be paid to the increase in temperature and the decrease in precipitation in the last 17 years in the Serra do Amolar and 10 years in the Morraria do Urucum, because although many scholars believe that mountainous areas will be warmer and wetter (Li D. et al., 2020), what is being visualized in the studied areas is that it is being warmer and drier. Suppose the climate in the studied areas continues to get warmer and with less precipitation in the future, in that case, drought will increase, and soil moisture will challenge vegetation growth, thus inhibiting vegetation growth and worsening desertification. Therefore, the results of this research should draw the attention of public entities to the future monitoring of these fragile areas to climate change, aiming to monitor mainly the water regime that has been changing in the last 15 years.

CONCLUSIONS

In general, the NDVI showed an increasing trend in average monthly NDVI values over the years analyzed. The same was observed for the climatic variables, with a reservation for the precipitation data that had a drop in the values of accumulated rainfall in the last 15 years (2007-2022) in the two study areas. The increase in leaf area and vegetation spreading is a dependent factor under climatic warming and increased water regime and this relationship was observed in the study areas. Temperature change was the main determinant of vegetation change. The driving effect was stronger in Serra do Amolar because of its higher altitude. The interannual/seasonal variation of precipitation and temperature has a great negative reflection on the mountainous vegetation because it is very sensitive to high temperatures in elevated areas.

At first, the climatic conditions in the studied areas became more favorable for plant growth, and the period of thermally favorable conditions was extended. However, low precipitation values were identified, and this may in the medium and long term have lower growth rates of perennial vegetation (forests), and the serious threat of extreme variation of the water regime with high temperatures may be a serious problem in the desertification of these sensitive areas. Therefore, monitoring these areas will significantly improve our understanding of climate change in vegetation change in mountainous areas.

The study thus revealed the merit of this analysis with a technical approach to assessing the contribution of climate change versus change on vegetation dynamics in mountainous ecosystems. However, using more sophisticated analytical modeling could improve our understanding of the respective influence of environmental factors on vegetation dynamics. In this regard, further studies using process-based simulation models that explicitly take into account other factors such as fires and those related to humans (e.g. land cover/land use change) alongside climate change would be useful. This may improve future assessments, management planning, and policy formulation relevant to the mountain ecosystems in the Pantanal and other similar ecosystems in other Brazilian biomes.

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