

# Analysis of the fire season in Chapada dos Guimarães National Park/MT using geotechnology data

## Análise da temporada de incêndio no Parque Nacional de Chapada dos Guimarães/MT com uso de dados de geotecnologias

Vanusa de Souza Pacheco Hoki \*, Osvaldo Borges Pinto Junior \*\*, Luciana Sanches \*\*\*

\* Instituto de Física, Universidade Federal de Mato Grosso, vanusa.hoki@fisica.ufmt.br

\*\* Departamento de Ciências Ambientais, Universidade de Cuiabá, osvaldo.borges@gmail.com

\*\*\* Departamento de Engenharia Sanitária e Ambiental, Universidade Federal de Mato Grosso, luciana.sanches@ufmt.br

<http://dx.doi.org/10.5380/raega.v64i1.100598>

### Abstract

The use of geotechnologies, such as remote sensing and Geographic Information Systems (GIS), enables the monitoring of vegetation dynamics at different phenological stages associated with fire events. This study aimed to characterize the duration and spatiotemporal variability of the fire season in the Chapada dos Guimarães National Park (PNCG), from 2003 to 2023, based on an integrated analysis of the Perpendicular Moisture Index (PMI), the Normalized Difference Vegetation Index (NDVI), and Kernel density estimation. Fire hotspot data from BDQueimadas/INPE and FIRMS/NASA were used, combined with vegetation moisture maps and the spatial distribution of fire occurrences. The lowest PMI values, recorded in August and September of 2015 and 2019, indicated greater vegetation water stress compared to 2017. The NDVI for September 2017 ranged from 0.0050 to 0.229, reflecting changes in vegetation cover. A high density of fire hotspots was particularly concentrated in the buffer zone of the PNCG. The PMI proved to be effective in indicating fire susceptibility, corroborating NDVI patterns. Kernel density analysis allowed the identification of areas with the highest recurrence of forest fires, highlighting critical regions for monitoring and preventive management actions.

### Keywords:

Kernel Density, Live Fuel Moisture Content (LFMC), Environmental Monitoring, Perpendicular Moisture Index (PMI), Normalized Difference Vegetation Index (NDVI).

### Resumo

O uso de geotecnologias, como o sensoriamento remoto e os Sistemas de Informação Geográfica (SIG), permite monitorar a dinâmica da vegetação em diferentes estágios fenológicos associados a eventos de incêndio. Este estudo teve como objetivo caracterizar a duração e a variabilidade espaço-temporal da temporada de incêndios no Parque Nacional da Chapada dos Guimarães (PNCG), no

período de 2003 e 2023, com análises nos anos 2015, 2017 e 2019, com base na análise integrada do Índice de Umidade Perpendicular (PMI), do Índice de Vegetação por Diferença Normalizada (NDVI) e da estimativa de densidade de Kernel. Foram utilizados dados de focos de calor do BDQueimadas/INPE e FIRMS/NASA, combinados com mapas de umidade da vegetação e da distribuição espacial dos incêndios. Os menores valores de PMI, observados em agosto e setembro de 2015 e 2019, indicaram maior estresse hídrico da vegetação em comparação a 2017. O NDVI de setembro de 2017 variou entre 0,0050 e 0,229, refletindo alterações na cobertura vegetal. A densidade de focos de calor foi classificada como muito alta na Zona de Amortecimento do PNCG. O PMI demonstrou-se eficaz na indicação de suscetibilidade ao fogo, corroborando os padrões de NDVI. Análise de Kernel permitiu mapear as áreas com maior recorrência de incêndios florestais, destacando regiões críticas para ações de monitoramento e manejo preventivo.

**Palavras-chave:**

Densidade de Kernel, Umidade do Combustível Vivo (LFMC), Monitoramento ambiental, Índice de Umidade Perpendicular (PMI), Índice de Vegetação por Diferença Normalizada (NDVI).

## I. INTRODUCTION

Fire occurs naturally in various ecosystems around the world, from boreal forests to tropical savannas, with the fire regime defined by the timing and frequency of fire events (Certini et al., 2021; Oliveira et al., 2021). Wildfires impact major biomes, altering ecosystem structure, biogeochemical cycles, and atmospheric composition (Chuvieco et al., 2019; Ivo et al., 2020). Intensive fire management aims to reduce fire frequency, severity, and extent through prescribed burning, land-use management, control of ecosystem processes, and continuous monitoring. These measures can play a key role in drought management, wildfire risk mitigation, and the attenuation of future climate change impacts (Andela et al., 2019; Hoki et al., 2021; Alves et al., 2023).

Factors such as deforestation, land-use change, and climate change have contributed to the increasing frequency and severity of wildfires on a global scale, making it essential to understand fire risk conditions in order to promote sustainable management (Vadrevu et al., 2012). According to a report by the United Nations Environment Programme (UNEP), the number of extreme wildfire events could rise by 14% by 2030 and by 30% by 2050, indicating a growing trend in both the frequency and intensity of such events (CNN Brasil, 2022).

Climate exerts a strong influence on global wildfire activity, and recent outbreaks may indicate pyrological shifts driven by changes in fire-conducive climate regimes. Winter drought occurrence is considered a key antecedent predictor of burned area, typically assessed through anomalies in soil and fuel moisture, as well as reduced atmospheric humidity, which favors fire spread. In Chapada dos Guimarães National Park, the fire regime is shaped by seasonality and event frequency, with the highest concentration of wildfires and active

fire hotspots occurring at the end of the dry season, between August and September, due to low rainfall and relative humidity (Ivo et al., 2020; Nascimento; Novais, 2020; Hoki et al., 2021). This water stress promotes the production and accumulation of litter, increasing vegetation vulnerability to fire (Carvalho et al., 2021).

Savannas, such as the Cerrado, represent the most fire-prone biome in the world (Moura et al., 2019; Edwards et al., 2021). Among the vegetation types present in the Cerrado, grasses and other herbaceous plants predominate. The Amazon and the Cerrado host the largest remaining areas of natural non-forest formations in Brazil (MAPBIOMAS, 2024). Covering approximately 24% of Brazil's territory, the Cerrado is the second-largest biome in South America and encompasses various phytophysionomies, including grassland formations (Campo Limpo, Campo Sujo, and Campo Rupestre), savanna formations (Vereda, Palmeiral, Cerrado Park, and Cerrado sensu stricto), and forest formations (Cerradão, Dry Forest, Gallery Forest, and Riparian Forest) (IBGE, 2019). The vegetation of Chapada dos Guimarães National Park (PNCG) is representative of the Brazilian Cerrado, composed of 16.14% forest formations and 67.40% non-forest formations (mainly *campo sujo*). The remaining 0.016% of the park includes silviculture areas and water bodies, with 517 km of small rivers and 385 springs, primarily located in the southwestern portion of the park (Ivo et al., 2020; Kuhn; Santos, 2021).

Remote sensing is a powerful tool for assessing the effects of fire on vegetation (Szapkowski; Jensen, 2019). Information on affected areas is essential for better understanding of the causes and dynamics of fire (Hoki et al., 2021). Spectral indices derived from satellite data play a crucial role in mapping burned areas and evaluating post-fire environmental conditions (Smiraglia et al., 2020), including near real-time assessments (as in the case of ABI-derived products, among others). These indices are calculated using different spectral bands (such as near-infrared and shortwave infrared) and allow the detection of specific features related to fire-induced vegetation changes. One of the most widely used indices is the Normalized Difference Vegetation Index (NDVI), commonly employed to evaluate fire severity and to differentiate between types of affected vegetation (Rouse et al., 1974; Da Silva Júnior; Pacheco, 2022). NDVI enables the monitoring of phenological stages of vegetation in tropical environments, as it reflects photosynthetic activity based on the contrast between near-infrared (reflected by healthy vegetation) and red wavelengths (absorbed by chlorophyll) (Ramos et al., 2023; Pettorelli et al., 2005).

As a result, vegetation moisture becomes a key factor in determining its susceptibility to ignition and fire spread. Several spectral indices have been proposed to estimate the Equivalent Water Thickness (EWT), defined as the mass of liquid water per unit of leaf area (Maffeu; Menenti, 2014; 2019). For instance, the index proposed

by Gao (1996), known as the Normalized Difference Water Index (NDWI), was developed to estimate the Equivalent Water Thickness (EWT) in vegetation, based on the difference between the near-infrared (NIR) and shortwave infrared (SWIR) bands. It is one of the first spectral indices sensitive to vegetation moisture; however, it has been observed that the time series of the Normalized Difference Water Index (Gao, 1996) are associated with the seasonality of fire occurrence (Huesca et al., 2014).

However, fire models commonly use Live Fuel Moisture Content (LFMC) as an indicator of vegetation moisture. LFMC is defined as the ratio between the mass of liquid water in a leaf and the mass of its dry matter. Studies have shown that traditional spectral indices are less effective than EWT in capturing the variability of LFMC (Maffei; Lindenbergh; Menenti, 2021; Yahia et al., 2023).

Therefore, the direct observation of water content in plant leaves, represented by LFMC, can significantly enhance the assessment of fire occurrence and the hazard indices associated with fire behavior. Earth Observation technologies offer a substantial advantage, as they enable frequent and systematic monitoring of land surface conditions. With advancements in remote sensing technologies and the growing availability of high-resolution satellite data, the use of the Perpendicular Moisture Index (PMI) has expanded, allowing for detailed large-scale analyses. When integrated with Geographic Information Systems (GIS), PMI enables spatial analyses that improve the visualization of vegetation moisture across different geographic contexts (Maffei; Menenti, 2014; Maffei; Menenti, 2019; Maffei; Lindenbergh; Menenti, 2021).

However, the use of geotechnologies has facilitated the analysis of large territorial extents, such as conservation units. For monitoring fire outbreaks in the Chapada dos Guimarães National Park (PNCG), satellite data from INPE's BDQueimadas and NASA's FIRMS platforms were employed, along with Landsat 8 imagery and georeferenced cartographic datasets provided by IBGE.

Thus, through remote sensing data, it becomes possible to estimate fire hotspots using the Kernel density estimation technique, enabling the identification of areas most susceptible to wildfires. Despite anthropogenic interferences, scientific research can benefit from such information to support the monitoring of conservation units and to detect changes in vegetation cover using the NDVI.

## II. MATERIALS AND METHODS

The study area is located within the municipalities of Cuiabá and Chapada dos Guimarães, in the state of Mato Grosso, as shown in Figure 1. It encompasses the Chapada dos Guimarães National Park (PNCG), which

covers an area of 32,642.70 hectares and was established by Decree No. 97,656 of April 12, 1989. The park has a tropical savanna climate (Aw), according to the Köppen-Geiger classification, with two well-defined seasons: a dry winter (from May to September) and a rainy summer (from October to March). The mean annual temperature is approximately 21.5 °C, and the average annual rainfall is 1,838 mm (Vecchi Júnior, 2018; De Oliveira Aparecido et al., 2020; Nascimento; Novais, 2020).

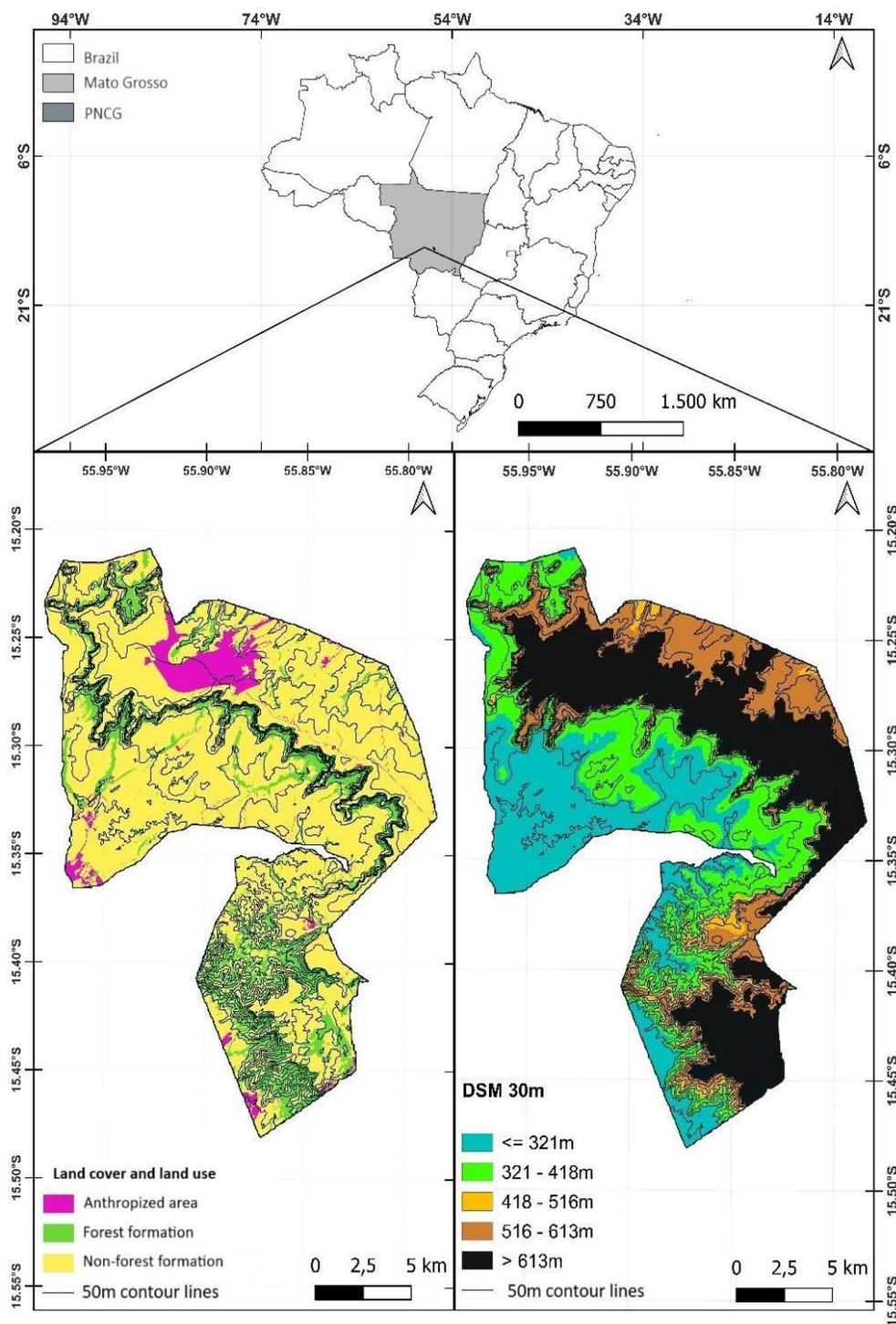


Figure 1 – Location, elevation, land cover, and land use of Chapada dos Guimarães National Park, Mato Grosso, Brazil.  
 Source: IBGE (2019), COPERNICUS (2024), FBDS (2024).

The image database was obtained from the European Space Agency (ESA) through the Copernicus mission, available at: <https://climate.copernicus.eu/climate-datasets> (COPERNICUS, 2024). For this study, images corresponding to the years 2015, 2017, and 2019 were selected, referenced to the WGS84 datum, UTM

Zone 21S (USGS, 2024). The images underwent atmospheric corrections, were reprojected to the Southern Hemisphere using the SIRGAS 2000 UTM Zone 21 reference system, and were clipped to the study area (IBGE, 2019; COPERNICUS, 2024).

The satellite reflectance data used in this study correspond to Collection 6.1 of the Aqua-MODIS 8-day composite product (MYD09A1), with a spatial resolution of 500 m (NASA, 2024). The MOD09A1 V6.1 product provides estimates of surface spectral reflectance in seven bands located in the visible and infrared regions (0.470  $\mu\text{m}$ ; 0.555  $\mu\text{m}$ ; 0.648  $\mu\text{m}$ ; 0.858  $\mu\text{m}$ ; 1.240  $\mu\text{m}$ ; 1.640  $\mu\text{m}$ ; 2.130  $\mu\text{m}$ ), corrected for atmospheric effects. For each pixel, a representative value is selected from all acquisitions within the 8-day composite. In this study, data from the period between 2003 and 2023 were analyzed (Maffei; Lindenbergh; Menenti, 2021; NASA, 2024).

In real-world conditions, variations in Live Fuel Moisture Content (LFMC) may result from changes in both Equivalent Water Thickness (EWT) and Dry Matter Content (DMC). This observation led to the development of a new spectral index directly related to LFMC: the Perpendicular Moisture Index (PMI). This index measures the distance of a point, defined by reflectance measurements from MODIS bands 2 (0.86  $\mu\text{m}$ ) and 5 (1.24  $\mu\text{m}$ ), from a reference line that represents fully dry vegetation. Based on this, it is possible to identify LFMC isolines, which are represented as straight and parallel lines.

The Perpendicular Moisture Index (PMI) was developed based on simulated spectral reflectance data of vegetation, using MODIS bands 2 (0.86  $\mu\text{m}$ ) and 5 (1.24  $\mu\text{m}$ ). From these data, it was possible to identify isolines of Live Fuel Moisture Content (LFMC), which appear as parallel straight lines. These observations supported the development of the index, as described in Equation 1. Taking as a reference the line corresponding to an LFMC value of zero, i.e., completely dry vegetation, the PMI is calculated as the distance between the reflectance points and this reference line.

$$PMI = -0.73(R_{1.24\mu\text{m}} - 0.94R_{0.86\mu\text{m}} - 0.028) \quad (1)$$

In this sense, the PMI represents a direct measure of LFMC, with higher values indicating greater vegetation moisture content. PMI maps for the study area were generated using 8-day composite surface reflectance data acquired by the MODIS sensor onboard the Terra satellite (Maffei; Menenti, 2014; 2019; Maffei; Lindenbergh; Menenti, 2021). This analysis led to the definition of LFMC isolines in the plane formed by reflectance measurements from bands 2 and 5, characterized as parallel straight lines, organized from the lowest to the highest LFMC values. This observation enabled the creation of a new spectral index, called the Perpendicular Moisture Index (PMI), which quantifies the distance of a point in this plane relative to the

reference line representing fully dry vegetation. Validation using simulated data demonstrated that PMI exhibits a linear relationship with LFMC (Maffei; Menenti, 2014).

The fire dataset used in this study consists of daily active fire information with a spatial resolution of 375 meters, derived from the Visible Infrared Imaging Radiometer Suite (VIIRS) onboard the Suomi National Polar-orbiting Partnership (S-NPP) satellite, available through NASA's FIRMS platform (<https://firms.modaps.eosdis.nasa.gov/>) (NASA, 2024). Data from the Burned Area Database (BDQueimadas), available at <http://queimadas.dgi.inpe.br/queimadas/bdqueimadas>, covering the period from 2003 to 2023, were also used (INPE, 2024).

The vector files in shapefile format, containing the boundaries of the municipality, urban areas, and Chapada dos Guimarães National Park (PNCG), were obtained from the INTERMAT website: <http://www.intermat.mt.gov.br/-/11303036-banco-de-dados-cartograficos> (INTERMAT, 2023).

Reflectance data extracted from satellite imagery acquired by the Operational Land Imager (OLI) sensor were used, with a temporal resolution of 16 days and a spatial resolution of 30 m, corresponding to spectral bands 2 (blue), 3 (green), and 4 (red), with a radiometric resolution of 16 bits (Long et al., 2019). The images were freely obtained for path 226, row 71, from the Center for Platform Architecture Processing (ESPA), with the acquisition date of September 19, 2024 (USGS, 2023).

After acquisition, the images underwent atmospheric correction, conversion from digital number to surface reflectance, reprojection to the Southern Hemisphere using the SIRGAS 2000 UTM Zone 21 reference system and clipping to the study area. The Normalized Difference Vegetation Index (NDVI), proposed by Rouse et al. (1974), enables vegetation assessment by using wavelengths from the near-infrared and red spectral regions (Equation 2). NDVI values range from -1 to 1, where values close to 1 indicate high vegetative vigor, while values near 0 indicate sparsely vegetated surfaces or low photosynthetic activity.

Based on reflectance values obtained from spectral bands B4 (red – VIS) and B5 (near-infrared – NIR) of the OLI sensor, it was possible to calculate the Normalized Difference Vegetation Index (NDVI). The images were corrected using the Semi-Automatic Classification Plugin (SCP) in QGIS software, based on metadata provided by USGS (2024). NDVI allows for the estimation of vegetation photosynthetic activity through differences in reflectance between near-infrared and red wavelengths, as described in Equation 2.

$$NDVI = \frac{\rho_5 - \rho_4}{\rho_5 + \rho_4} \quad (2)$$

Where  $\rho_4$  corresponds to the reflectance in the red band (VIS), with a wavelength range between 0.630 and 0.680  $\mu\text{m}$ , and  $\rho_5$  represents the reflectance in the near-infrared band (NIR), with a wavelength range between 0.845 and 0.885  $\mu\text{m}$ . The NDVI spectral index is applied through a simple and dynamic method for mapping fire-affected areas.

In the context of geotechnologies, Kernel Density Estimation refers to a statistical method used to estimate the spatial distribution of event intensity, such as fire hotspots, based on georeferenced data. This technique, originally proposed by Parzen (1962), involves applying a kernel function to each occurrence point, weighting its contribution by the distance to a central location. In this way, a continuous density surface can be generated, representing the spatial probability of event occurrence and enabling the identification of concentration patterns and areas of higher recurrence (Parzen, 1962; Duong, 2007; Barbosa et al., 2014).

Suppose the existence of a random variable  $X$ , from which a random sample  $X_1, X_2, \dots, X_n$ , is drawn, composed of independent and identically distributed (i.i.d.) values. The kernel estimator,  $\hat{f}_h(x)$ , for this sample is given by the following mathematical expression (Eq. 3):

$$\hat{f}_h(x) = \sum_{i=1}^n \frac{1}{nh} K\left(\frac{x - X_i}{h}\right) \quad (3)$$

Where  $\hat{f}_h(x)$  is the density estimate at point  $x$ ,  $K(\cdot)$  is the chosen kernel function;  $n$  is the number of observations in the sample,  $h$  is the smoothing parameter (bandwidth); and  $X_i$  is the position of each point derived from the centroid of each polygon (Bailey; Gatrell, 1995; Duong, 2007; Barbosa et al., 2014; Da Cruz Teixeira et al., 2021).

The method was implemented using QGIS 3.22 software (Da Silva Lima et al., 2021), which was used for database processing, calculation of the daily mean of fire hotspots, and, through the Kernel Density function, the estimation of hotspot density across the entire map of the Chapada dos Guimarães National Park (PNCG). This function allows a smooth surface (kernel) to be placed over each sampled point, resulting in the generation of a continuous probability density surface. This procedure enables the creation of thematic maps representing the spatial concentration of fire hotspots (Barbosa et al., 2014; Da Cruz Teixeira et al., 2021).

As a result of applying the Kernel Density function, a raster file was obtained, corresponding to the sum of the stacking of ( $n$ ) circular surfaces. The resulting maps were classified into five density classes, represented by distinct colors and shades: very low (dark green), low (light green), medium (yellow), high (orange), and very high (red).

The validation of the estimated density obtained through the Kernel Density method was conducted by systematically comparing it with field-observed data and records from INPE’s fire hotspot database, in order to verify whether the estimated patterns reflect the empirical distribution of the events.

The results were integrated with auxiliary data such as land use and land cover maps, fire history, and climatic variables, enabling spatial and temporal cross-analysis and interpretation of the observed phenomena. On-site validation was carried out through field visits to strategically selected locations, where the actual vegetation conditions were verified and compared with NDVI values obtained from remote sensing. This approach contributed to the accuracy and robustness of the analysis, confirming the correspondence between spectral data and environmental characteristics observed in the field.

### III. RESULTS AND DISCUSSIONS

In the assessment of the Perpendicular Moisture Index (PMI) during the period from 2003 to 2023, the years 2015, 2017, and 2019 stood out, presenting the highest values observed within the analyzed interval (Table 1).

Table 1 – Distribution of the Perpendicular Moisture Index (PMI) for the months of July, August, and September in the years 2015, 2017, and 2019, and the overall median value for the analyzed period.

PMI Variation	2015			2017			2019			Median
	Jul	Aug	Sep	Jul	Aug	Sep	Jul	Aug	Sep	
<b>Minimum</b>	-0.082	-0.085	-0.122	-0.030	-0.106	-0.256	-0.119	-0.126	-0.102	-0.106
<b>Maximum</b>	0.014	0.009	0.015	0.087	0.015	0.160	0.029	0.004	0.005	0.015
<b>Mean</b>	-0.034	-0.038	-0.053	0.028	-0.046	-0.048	-0.045	-0.061	-0.048	

Source: The authors, based on data from NASA (2024).

The analysis of PMI variation from 2003 to 2023 reveals significant inter- and intra-annual variability, with particular emphasis on the years 2015, 2017, and 2019. This dynamic can be more clearly visualized through thematic PMI maps (Figure 2), which represent specific composite periods: July 4–12, August 5–13, and September 6–14 of the aforementioned years. These maps clearly illustrate the spatial and temporal differences in the distribution of fire hotspot intensity over time.

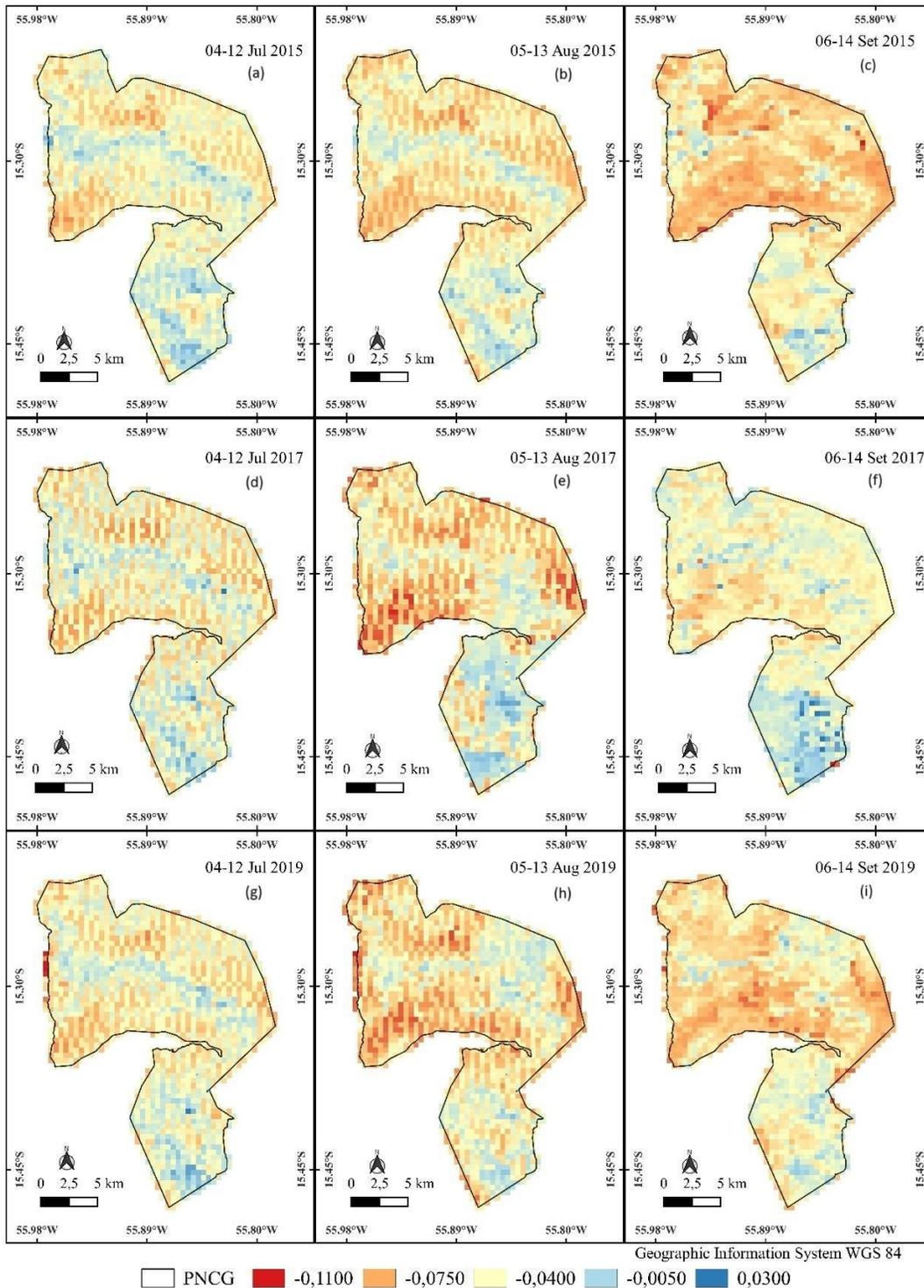


Figure 2 – PMI maps derived from 8-day Aqua-MODIS reflectance composites showing intra- and interannual variability: (a) July 4–12, 2015, (b) August 5–13, 2015, (c) September 6–14, 2015, (d) July 4–12, 2017, (e) August 5–13, 2017, (f) September 6–14, 2017, (g) July 4–12, 2019, (h) August 5–13, 2019, and (i) September 6–14, 2019, in Chapada dos Guimarães National Park (PNCG), Mato Grosso, Brazil.

Source: The authors, based on data from NASA (2024).

For a synthetic visualization of seasonal evolution, the median PMI was calculated for each of the selected years, 2015, 2017, and 2019, throughout the dry season. Although the PMI maps present a continuous distribution of values, discretized into raster cells, this median-based approach allows for a clearer representation of interannual differences in the observed index values and, indirectly, in Live Fuel Moisture Content (LFMC). For all the analyzed years, a consistent decrease in PMI values is observed throughout the dry season, indicating a simultaneous reduction in LFMC and, consequently, an increased susceptibility to the occurrence and spread of wildfires.

Figure 2 shows the spatial variation of the Perpendicular Moisture Index (PMI) in Chapada dos Guimarães National Park (PNCG) for the periods of July 4–12, August 5–13, and September 6–14 in the years 2015, 2017, and 2019. The analysis reveals a well-defined seasonal pattern and interannual differences in the dynamics of surface vegetation and soil moisture. In 2015, PMI values are intermediate in July (Figure 2-a), with a predominance of orange and bluish tones, indicating an early transition into the dry season. In August (Figure 2-b), a decline in index values is observed, with an expansion of low-moisture areas, especially in the western portion of the park. In September (Figure 2-c), although PMI values remain low, a slight increase in moisture is noted in some southern and eastern areas, suggesting the beginning of the transition into the rainy season.

In 2017, the maps indicate a more critical scenario. In July (Figure 2-d), PMI values remain relatively balanced in part of the territory; however, the expansion of dry areas can already be seen in the northern and western regions. In August (Figure 2-e), the PMI reaches the lowest value among all analyzed periods, with most of the park presenting values below -0.0750, especially in the central and western regions, characterizing a condition of severe water stress. In September (Figure 2-f), moisture recovery is limited, with few areas showing improvement in surface moisture levels.

In 2019, an intermediate behavior is observed compared to the previous years. In July (Figure 2-g), moderate PMI values predominate, with some areas in the southern part of the park still showing residual moisture. In August (Figure 2-h), index values decline significantly, though less intensely than in 2017. Finally, in September (Figure 2-i), a more pronounced recovery in moisture is observed, with an increase in bluish-toned areas, particularly in the southern and eastern regions of the park, indicating an earlier transition into the wet season. The PMI maps reveal significant inter- and intra-annual variability, as illustrated by the nine maps representing the composite periods from July 4–12, August 5–13, and September 6–14 in the years 2015, 2017, and 2019. The observed spatial patterns highlight the lowest PMI values during the months of July, August, and

September, with particularly low values recorded in September 2015 (-0.053), August 2017 (-0.046), and August 2019 (-0.061). When comparing the years, 2019 stands out with the lowest average value among the analyzed composites (-0.048). The evaluated methodology proves to be a useful tool for monitoring areas at higher risk of fire outbreaks, enabling the development of strategies to reduce and/or mitigate fire occurrences, especially in regions with drier vegetation and, consequently, higher susceptibility.

A north–south directional pattern was observed in the data distribution, related to the spatial resolution of MODIS products (500 m) and the smoothing applied in the Kernel density estimation. This effect may reflect both the actual structure of the landscape and artifacts from data processing and should therefore be interpreted with caution in spatial analyses.

These results reinforce the importance of monitoring soil and vegetation moisture for fire risk assessment, especially under conditions of seasonal drought. Recent studies have shown that negative soil moisture anomalies are strongly associated with increased frequency and intensity of wildfires (Hou et al., 2020). Moreover, the relationship between drought and fire has already been documented in other regions of Brazil, particularly in the Cerrado and Amazon biomes (Nogueira et al., 2017), where seasonal water deficits contribute to fire intensification, especially in areas with drier vegetation.

The literature also highlights that the use of moisture indices such as the Keetch–Byram Drought Index (KBDI) and the Fire Weather Index (FWI) has proven effective for fire risk prediction and monitoring, by integrating meteorological and soil moisture information (Krueger et al., 2022). These indices are widely used in operational early warning systems and fire management planning. The incorporation of remote sensing data and climate modelling, such as those used in the development of PMI maps, represents an effective strategy for detecting critical areas and guiding preventive actions (Krueger et al., 2022; Nogueira et al., 2017).

Thus, the methodology adopted in this study proved to be promising for the spatial and temporal monitoring of regions at higher risk of wildfire occurrence. Its application provides a basis for mitigation strategies and environmental management, especially during periods of drier climatic conditions, contributing to the reduction of the socio-environmental impacts caused by fire.

The moisture content of the fuel material varied according to the type of vegetation cover, with average values ranging between 30% and 50% in areas of dense forest and transitional vegetation (Figure 3), which are above the critical ignition moisture threshold. The differences observed in fuel moisture indicate variations in the structural characteristics of vegetation, which influence fire behavior and ignition probability. These

variations are modulated by seasonal factors, burning, deforestation, pollution, among others, which can alter ecological dynamics and compromise ecosystem balance (De Oliveira et al., 2018, Carvalho et al., 2021). In addition, atmospheric factors associated with air dryness, such as temperature, play a more significant role in the occurrence of wildfires than variables such as soil moisture (Tang et al., 2024).



Figure 3 – Vegetation in the study area (relative air humidity of 47.4%).  
Source: The authors, based on fieldwork.

In the state of Mato Grosso, an intense dry period is observed between July and September. During this interval, the region of Cuiabá-MT experiences drought conditions that increase the probability of ignition and the spread of fire hotspots. The climatic conditions, combined with the characteristics of the local vegetation, create an environment highly conducive to fire propagation. The intensity of wildfires and the resulting environmental damage vary according to the specific features of the ecosystem and the distribution of fuels on the soil surface (Hoki al., 2020; Da Cruz Teixeira et al., 2021).

Based on the analyzed data, the years with the highest number of fire outbreaks and the largest burned areas, 2015, 2017, and 2019, were selected. Table 2 presents the quantification of these events, considering both the Buffer Zone (BZ) and the internal area of Chapada dos Guimarães National Park (PNCG).

Table 2 – Number of fire hotspots and burned area in Chapada dos Guimarães National Park (PNCG) and its Buffer Zone (BZ), based on supervised classification for the years 2015, 2017, and 2019.

Year	Number of fire hotspots			Burned area (km <sup>2</sup> )		
	PNCG	ZA	Total	PNCG	ZA	Total
<b>2015</b>	91	335	426	47.47	130.11	177.59
<b>2017</b>	65	139	204	16.21	62.16	78.38
<b>2019</b>	193	666	859	65.81	223.13	288.94

Source: INPE, 2024; NASA, 2024.

Records of fire hotspots are a key resource for studying fire dynamics in landscapes prone to wildfires, as well as for supporting the planning of controlled fire management actions. In this context, the PMI proves to be a valuable tool for researchers and environmental managers, contributing to the assessment of climate change impacts on ecosystems (Meng et al., 2022).

The results obtained highlight the importance of effective biomass management at the beginning of the fire season as a preventive strategy to reduce wildfire occurrence. This underscores the need for a well-structured operational framework, supported by geotechnologies, to predict, identify, and prioritize zones with high fire potential through synergistic strategies involving local community engagement.

Fire severity refers to the intensity of the effects caused by fire on the environment and can be assessed through various approaches, including field-based metrics and remote sensing data. Soil degradation severity from heat considers the fire's impact on edaphic properties such as physical structure, organic matter content, and erodibility, as well as effects on the underground parts of plants. In turn, vegetation burn severity is related to the damage and mortality of aboveground vegetation (Mclauchlan et al., 2020).

Detecting and predicting changes in fire activity remains a challenge due to short historical records, variability across different biogeographic regions, and the complex influence of human activities. To understand how fire regimes have been shifting in the context of the Anthropocene, and how human societies must adapt to these changes, it is essential to promote integration among researchers from the biological, physical, and social sciences, as well as professionals specialized in fire management (Bowman et al., 2020; Machado et al., 2024).

For the year 2019, the fire event recorded on September 19 (the event with the highest number of fire hotspots during the period) was analyzed. The analysis included the Normalized Difference Vegetation Index (NDVI) and the supervised classification of the burned area within the PNCG, aiming to identify changes in vegetation cover associated with this extreme event. The supervised image classification was conducted in QGIS

software using the LF Tools plugin, through the Parallelepiped method, applying three standard deviations (99.7%) to define the spectral classes (Figure 4).

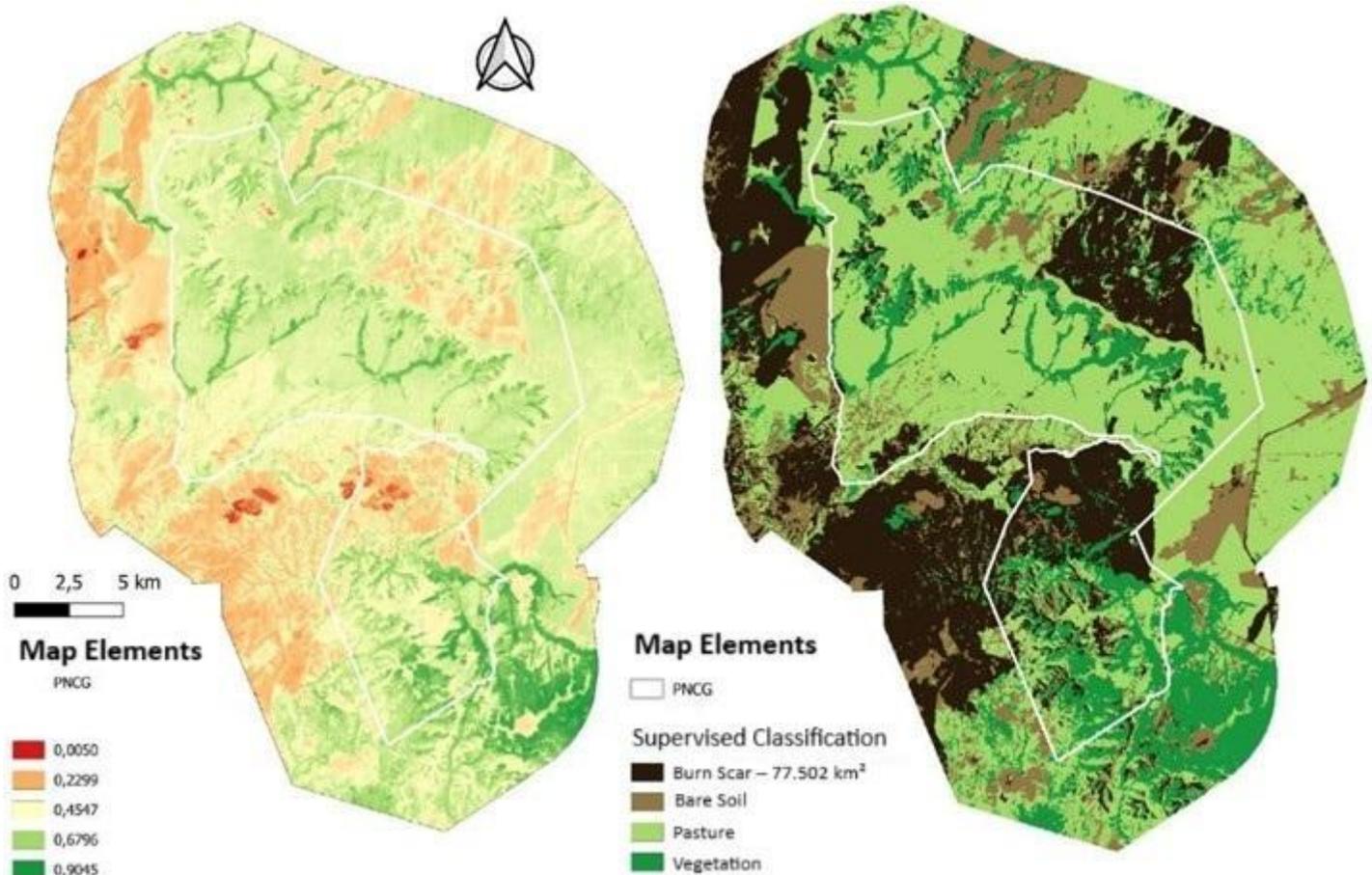


Figure 4 – Normalized Difference Vegetation Index (NDVI) and supervised classification of the burned area in PNCG, based on OLI/LANDSAT 7 imagery from 19/09/2019 – Path 226 / Row 71.

Source: The authors, based on data from NASA (2024).

NDVI was used to infer variations in vegetation cover between areas with and without fire occurrence. Significant differences in index values were observed between these areas, based on the spectral bands used (Figure 4). Fire-affected regions showed reflectance values ranging from 0.0050 to 0.229, indicating lower photosynthetic activity. The reduction in NDVI in burned patches highlights the effects of fire on vegetation, resulting in biomass loss and reduced photosynthetic function (Ivo et al., 2020). The analyses confirmed changes in vegetation cover after the extreme event, as reflected by the extent of the burned area. These findings are likely important, as climate change is causing warming and severe vegetation moisture loss in the Cerrado, thereby increasing fire potential in the PNCG.

NDVI is an effective indicator for assessing water availability and vegetation productivity, and it is particularly useful in the Cerrado, where climatic seasonality influences species phenology. In fire-affected areas, significant reductions in NDVI values are observed, reflecting biomass loss and decreased photosynthetic activity (Ivo et al., 2020). In addition to enabling the monitoring of seasonal and interannual variations, the index also contributes to fire risk mapping. However, variables such as long-term ecological dynamics and accumulated water stress in woody plants should be integrated into analyses, as they play a crucial role in fire ignition and spread (Franke et al., 2018; Michael et al., 2021). Climate change, by intensifying warming and vegetation dryness, increases fire risk in the Cerrado, especially in protected areas such as the PNCG.

In September 2019, a total of 9,204 fire hotspots were detected in Chapada dos Guimarães National Park (PNCG). A notable fire concentration was observed (highlighted by the red circle) in the northeastern region in August and in the southeastern region in September, near the Buffer Zone. The first fire outbreaks were recorded in the northeastern portion of the park, progressing toward the southwestern region (Figure 4). Based on the detection dates and spatial analysis of the hotspots, it was determined that the fire originated outside the park boundaries, in anthropized areas. The burn scar identified on September 19, 2019, covered approximately 77 km<sup>2</sup>, spanning from the northeastern to the southwestern regions of the park (INPE, 2023; USGS, 2024).

Most fire risk maps are developed based on static information such as topography, vegetation density, and instantaneous fuel moisture, typically derived from orbital sensors. However, key variables such as long-term vegetation dynamics and the accumulated dryness of woody vegetation, which directly influence fire occurrence and spread, are rarely considered in risk models. Therefore, it is essential to incorporate vegetation analysis over extended temporal scales through the use of long-term average NDVI, which represents vegetation dryness and can significantly improve the mapping of fire-prone areas (Michael et al., 2021). In this context, the fuel load mapping approach has proven to be an effective tool for integrated fire management, contributing to the planning and implementation of prescribed burns, the promotion of pyrodiversity, the definition of suppression priorities, and the evaluation of management actions, in alignment with ecological conservation goals (Franke et al., 2018).

The kernel density estimation survey conducted for the period from 2003 to 2023 enabled the assessment of the spatial distribution of fire hotspots (fire pixels), identifying the most affected areas within Chapada dos Guimarães National Park (Figure 5).

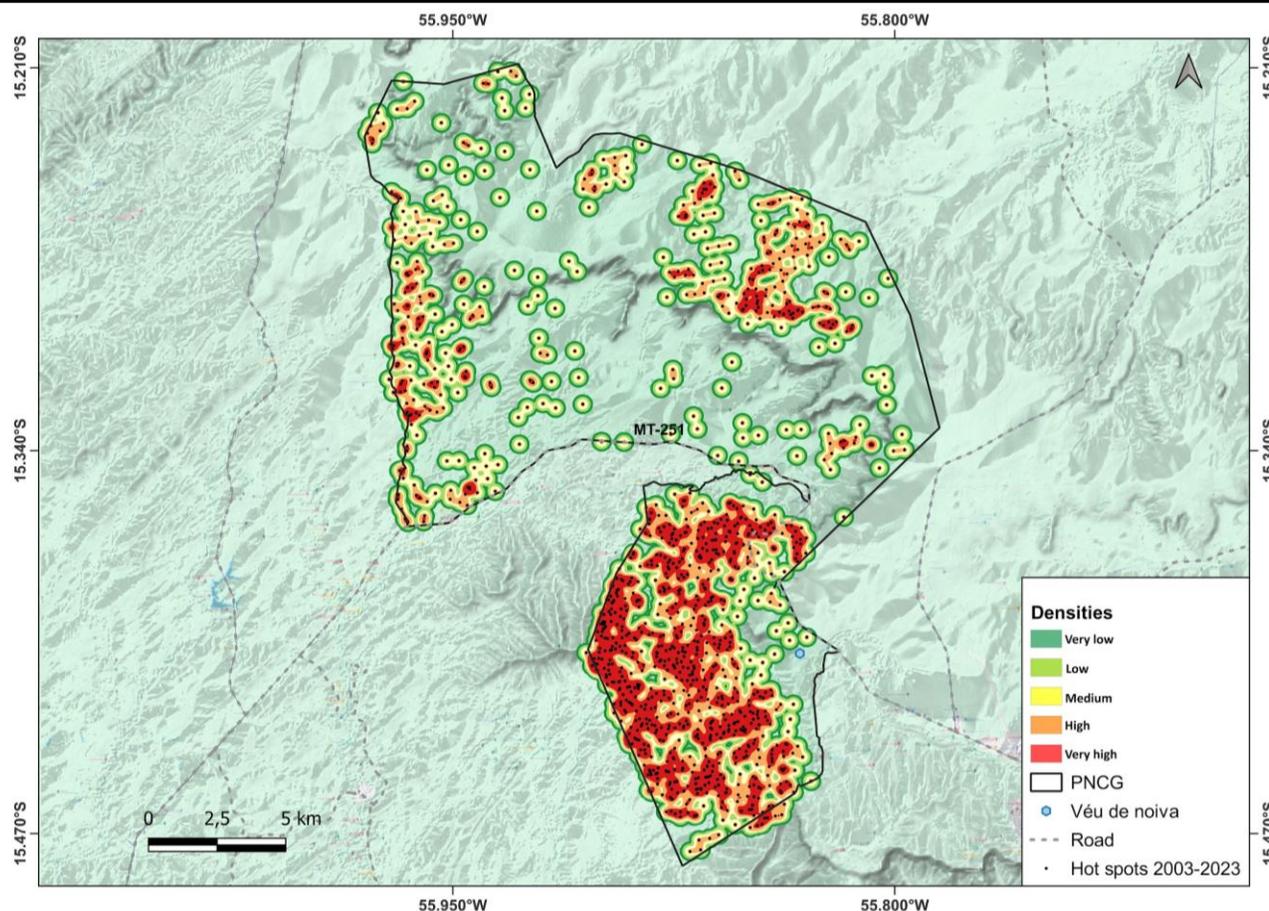


Figure 5 – Spatial distribution of fire scars from 2003 to 2023 in Chapada dos Guimarães National Park (PNCG).

Source: The authors, based on data from INPE and NASA, 2024.

The analysis of fire hotspot density variation from 2003 to 2023 (Figure 5) revealed higher intensity in the southwestern region of Chapada dos Guimarães National Park (PNCG), highlighted by a red circle. Kernel density classification of fire hotspots for the analyzed years was based on percentiles. In 2019, the density was classified as "very high" (above 32 hotspots/km<sup>2</sup>), while in 2015 it was medium, and in 2017, very low (Table 3).

Table 3 – Data on the distribution of fire hotspots (FH, %), area of influence (km<sup>2</sup>), and density (hotspots/km<sup>2</sup>) in 2015, 2017, and 2019 in Chapada dos Guimarães National Park (PNCG).

Year	FC (%)	Area of influence (Km <sup>2</sup> )	Density (spots/km <sup>2</sup> )	Classification
2015	19	87.97	16.71	Medium
2017	19	62.19	11.82	Very low
2019	33	98.00	32.34	Very high

Source: The authors, based on data from INPE and NASA, 2024.

These results can be visualized in the maps generated through Kernel density estimation (Figure 6).

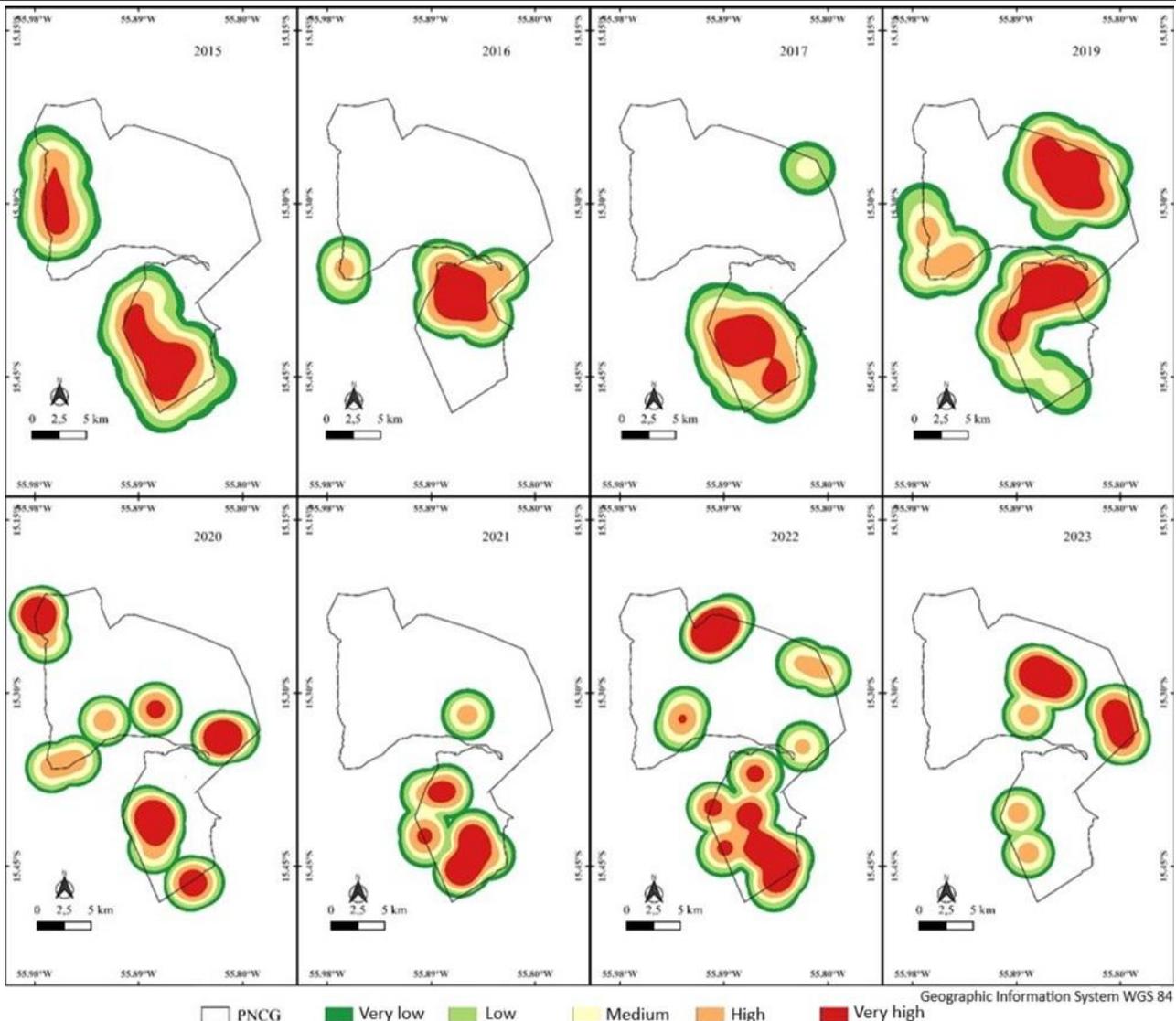


Figure 6 – Spatial distribution of fire scars from 2015 to 2023 in Chapada dos Guimarães National Park.

Source: The authors, based on data from INPE and NASA, 2024.

The annual spatial distribution analysis of fire hotspots in PNCG indicated very high density in the years 2015, 2017, and 2019, with a predominant concentration in the southwestern portion of the park, particularly in the waterfall circuit region. Several phytophysiognomies have been identified in this area: semi-deciduous forest, riparian forest, *cerradão*, *cerrado sensu stricto*, *campo sujo*, *campo cerrado*, and *campo cerrado rupestre* (Vieira Júnior et al., 2012). In 2019, two areas with high hotspot density stood out—one in the southwest and another in the northwest of the park, the latter located in an anthropized area, as indicated by the red rectangle in Figure 6.

Kernel density estimation, also known as a heatmap, is a statistical technique that allows for a smoothed representation of the concentration of events in a geographic area, based on a set of observed points. Using a

bidimensional function, it weights the occurrence of events within a given radius of influence, highlighting areas with higher or lower density (Barbosa et al., 2014; Da Cruz Teixeira et al., 2021). In the context of Chapada dos Guimarães National Park, this technique proved effective for environmental monitoring and the planning of wildfire prevention and control actions, especially due to its low cost and operational applicability. Accurately estimating the spatiotemporal dynamics of wildfires is essential for understanding their ecological impacts and supporting public policies aimed at the conservation of protected areas.

An increase in fire intensity has been observed over longer intervals, highlighting the importance of understanding its spatiotemporal application on biodiversity. Specific modeling approaches can support the development of strategies tailored to local conditions and integrated fire management objectives, as in the case of PNCG (Franke et al., 2018; Chuvieco et al., 2019; Alencar et al., 2022). In Brazil, approximately 83% of wildfires occur in the Cerrado and Amazon biomes, where increases in fire frequency and burned area have been recorded, driven by intensified human ignitions and climate change (Alencar et al., 2022; Mengue, 2022).

Wildfire management services are among the main users of remote sensing products, which are widely available through regional geographic information systems. Annual fire risk assessments are primarily based on data from the most recent events, obtained via burned area mapping, contributing to the planning and implementation of fire prevention and control actions over the past decade (COREY et al., 2020; DAVIES et al., 2021). In this context, intensive fire management aims to reduce the frequency, severity, and extent of wildfires (COREY et al., 2019).

The use of prescribed fire and land management practices plays a strategic role in mitigating drought effects and reducing fire risk, both under current conditions and in the face of climate change (NOWELL et al., 2018). The implementation of prescribed burns with distinct management objectives has become increasingly common in protected areas (SILVA et al., 2022), especially in fire-prone landscapes (DAVIES et al., 2021). In such regions, Integrated Fire Management (IFM) is a systematic planning approach to sustainably protect assets and forest resources.

Between 2003 and 2023, wildfires in Chapada dos Guimarães National Park (PNCG) occurred between July and September, except in 2019, when they extended into October, with a peak in September. The spatial distribution indicated ignition points starting in the northeastern and southwestern regions of the park, progressing respectively toward the north and south, as shown in Figures 5 and 6. Areas with very high hotspot density were located in the northeastern and southwestern portions, identified through Kernel density

estimation, an efficient, low-cost technique applicable to environmental monitoring and preventive wildfire management.

A pattern of increasing fire intensity over longer intervals reinforces the importance of spatiotemporal approaches and modeling strategies tailored to local conditions, such as Integrated Fire Management (IFM), which is particularly effective in fire-prone ecosystems like the Cerrado (Franke et al., 2018; Chuvieco et al., 2019; Alencar et al., 2022).

The “Zero Fire” policy, which predominates in the management of Conservation Units in Brazil, has proven inadequate for the Cerrado, an ecosystem ecologically adapted to fire. Fire exclusion in fire-adapted vegetation areas, such as the Cerrado, can alter vegetation structure and composition, leading to the accumulation of dry plant material that becomes fuel during drought periods (Schmidt et al., 2018). Periodic controlled burning is recognized as a viable alternative for the management of Conservation Units in the Cerrado (Durigan; Ratter, 2016; Fidelis et al., 2018; Schmidt et al., 2018).

Several studies have highlighted the negative effects of fire suppression on the Cerrado, particularly the reduction in the diversity of underground organs and in bud density (Bombo et al., 2022). However, knowledge about the resilience of plant communities to fire disturbance remains limited (Buisson et al., 2019), especially concerning the effects of long-term fire exclusion on ecological recovery mechanisms. Given the high vulnerability of these areas and their frequent neglect in environmental public policies, efforts aimed at understanding these processes represent a strategic opportunity to integrate theoretical and practical knowledge focused on the conservation and restoration of savanna physiognomies in the Cerrado.

In light of this, it is recommended that the management of Chapada dos Guimarães National Park (PNCG) expand its preventive actions throughout the entire year, encompassing all phases of the fire management cycle, prevention, preparedness, response, and accountability, rather than relying solely on reactive fire suppression. The dataset generated in this study can support more effective public policies for wildfire prevention and control in the Brazilian Cerrado.

#### **IV. FINAL CONSIDERATIONS**

- The application of the Perpendicular Moisture Index (PMI) enabled the assessment of inter- and intra-annual variability in vegetation susceptibility to fire during the dry season, providing valuable input for the planning of preventive actions during critical periods.

- The wildfire event of 2019 in Chapada dos Guimarães National Park resulted in a significant reduction in NDVI values, reflecting substantial biomass loss and changes in vegetation photosynthetic activity during the dry period.
- Kernel density estimation proved to be an effective tool for identifying spatial patterns of fire recurrence, highlighting critical burn scar areas over two decades. This information is essential for guiding adaptive fire management and the conservation of protected areas in the Cerrado.

### Acknowledgements

The authors express their sincere gratitude to the institutions that supported the development of this research: the Federal University of Mato Grosso (UFMT), the Brazilian Coordination for the Improvement of Higher Education Personnel (CAPES), and the administration of Chapada dos Guimarães National Park, represented by ICMBIO.

### V. REFERENCES

- ALENCAR, A. A.; ARRUDA, V. L.; SILVA, W. V. D.; CONCIANI, D. E.; COSTA, D. P.; CRUSCO, N., ...; Vélez-Martin, E. Long-term landsat-based monthly burned area dataset for the Brazilian biomes using deep learning. *Remote Sensing*, v. 14, n. 11, p. 2510, 2022. DOI: <https://doi.org/10.3390/rs14112510>.
- ALVES, L. K.; FIGUEIREDO, T. D.; ROYER, A. C.; NÓVOA-MUÑOZ, J. C.; MÉNDEZ-LÓPEZ, M.; FONSECA, F. Erosão do solo em áreas de matos de montanha: efeito do fogo controlado. *Revista de Ciências Agrárias*, v. 45, n. 4, p. 541-545, 2023. DOI: <https://doi.org/10.19084/rca.28636>.
- ANDELA, N.; MORTON, D. C.; GIGLIO, L.; PAUGAM, R.; CHEN, Y.; HANSON, S.; VAN DER WERF, G. R.; RANDERSON, J. T. "The Global Fire Atlas of individual fire size, duration, speed, and direction." *Earth System Science Data*, 11, 529–552, 2019. DOI: <https://doi.org/10.5194/essd-11-529-2019>.
- ANG, R.; JIN, M.; MAO, J.; RICCIUTO, D. M.; CHEN, A.; ZHANG, Y. Quantifying wildfire drivers and predictability in boreal peatlands using a two-step error-correcting machine learning framework in TeFire v1. 0. *Geoscientific Model Development*, v. 17, n. 4, p. 1525-1542, 2024. DOI: <https://doi.org/10.5194/gmd-17-1525-2024>.
- BAILEY, T. C.; GATRELL, A. C. *Interactive spatial data analysis*. Essex: Longman Scientific & Technical, 1995.
- BARBOSA, N. F.; STOSIC, B. D.; STOSIC, T.; LOPES, P. M.; MOURA, G. B. D. A.; MELO, J. S. Kernel smoothing of rainfall data from the Northeast of Brazil. *Revista Brasileira de Engenharia Agrícola e Ambiental*, v. 18, n. 7, p. 742-747, 2014. DOI: <https://doi.org/10.1590/S1415-43662014000700011>.
- BOMBO, A. B.; APPEZZATO-DA-GLÓRIA, B.; FIDELIS, A. Fire exclusion changes belowground bud bank and bud-bearing organ composition jeopardizing open savanna resilience. *Oecologia*, 199(1), 153–164. 2022. DOI: <https://doi.org/10.1007/s00442-022-05172-1>.

BOWMAN, D. M.; KOLDEN, C. A.; ABATZOGLOU, J. T.; JOHNSTON, F. H.; VAN DER WERF, G. R.; FLANNIGAN, M. Vegetation fires in the Anthropocene. *Nature Reviews Earth & Environment*, v. 1, n. 10, p. 500-515, 2020. DOI: <https://doi.org/10.1038/s43017-020-0085-3>.

BUISSON, E.; LE STRADIC, S.; SILVEIRA, F. A. O.; DURIGAN, G.; OVERBECK, G. E.; FIDELIS, A.; FERNANDES, G. W.; BOND, W. J.; HERMANN, J. M.; MAHY, G.; ALVARADO, S. T.; ZALOUMIS, N. P.; VELDMAN, J. W. Resilience and restoration of tropical and subtropical grasslands, savannas, and grassy woodlands. *Biological Reviews*, 94, 590–609, 2019. DOI: <https://doi.org/10.1111/brv.12470>.

CARVALHO, A. C. X.; JUSTI, A. C. A.; SANCHES, L.; DE SOUZA NOGUEIRA, J. Influência da temperatura do ar, umidade relativa do ar e precipitação na produção de serrapilheira no norte do Pantanal Mato-Grossense. *Revista Brasileira de Climatologia*, [S.l.], v. 29, oct. 2021.

CERTINI, G.; MOYA, D.; LUCAS-BORJA, M. E.; MASTROLONARDO, G. The impact of fire on soil-dwelling biota: A review. *Forest Ecology and Management*, v. 488, p. 118989, 2021. DOI: <https://doi.org/10.1016/j.foreco.2021.118989>.

CHUVIECO, E.; MOUILLOT, F.; VAN DER WERF, G. R.; SAN MIGUEL, J.; TANASE, M.; KOUTSIAS, N.; ...; GIGLIO, L.I. Historical background and current developments for mapping burned area from satellite Earth observation. *Remote Sensing of Environment*, v. 225, p. 45-64, 2019. DOI: <https://doi.org/10.1016/j.rse.2019.02.013>.

CNN BRASIL. Estudo da ONU sobre incêndios florestais: é hora de “aprender a viver com fogo”. Disponível em: <https://www.cnnbrasil.com.br/internacional/estudo-da-onu-sobre-incendios-florestais-e-hora-de-aprender-a-viver-com-fogo/>. Acesso em: 19 maio 2022.

COPERNICUS. Climate Change Service. Climate datasets. Disponível em: <https://scihub.copernicus.eu/dhus/#/home>. Acesso em: 16 abr. 2024.

COREY, B.; ANDERSEN, A. N.; LEGGE, S.; WOINARSKI, J. C.; RADFORD, I. J.; PERRY, J. J. Better biodiversity accounting is needed to prevent bioperversity and maximize co-benefits from savanna burning. *Conservation Letters*, v. 13, n. 1, p. e12685, 2020. DOI: <https://doi.org/10.1111/conl.12685>.

TEIXEIRA, N. C. C.; DE MORAIS DANELICHEN, V. H.; PEREIRA, O. A.; SEIXAS, G. B. Dynamics of fires in the municipality of Cuiabá-MT by remote sensing. *Revista Brasileira de Geografia Física*, v. 14, n. 02, p. 607-618, 2021. DOI: <https://doi.org/10.26848/rbfg.v14.2.p607-618>.

DANTAS, V. L.; HIROTA, M.; OLIVEIRA, R. S.; PAUSAS, J. G. Disturbance maintains alternative biome states. *Ecology Letters*, 19(1), 12–19, 2016. DOI: <https://doi.org/10.1111/ele.12537>.

DA SILVA JÚNIOR, J. A.; PACHECO, A. P. Avaliação de índices espectrais e Classificação Normal Bayes usando imagens OLI e TIRS para o mapeamento de áreas queimadas no Cerrado. *Revista Brasileira de Meio Ambiente*, v. 10, n. 3, 2022.

LIMA, E. G. S.; KATO, O. R.; DE FREITAS, T. P. M.; NAGAISHI, T. Y. R.; COSTA, M. D. S. S.; DA SILVA, J. D. S. L.; ...; MALTAROLO, B. M. Uso de sistemas alternativos e a redução das queimadas: uma análise temporal de focos de calor nos municípios de Igarapé-Açu e Marapanim, Pará. *Brazilian Journal of Development*, v. 7, n. 1, p. 11345-11371, 2021. DOI: <https://doi.org/10.34117/bjdv7n1-775>.

DAVIES, H. F.; VISINTIN, C.; GILLESPIE, G. R.; MURPHY, B. P. Investigating the effects of fire management on savanna biodiversity with grid-based spatially explicit population simulations. *Journal of Applied Ecology*, v. 58, n. 3, p. 677-686, 2021. DOI: <https://doi.org/10.1111/1365-2664.13801>.

DE OLIVEIRA, M. V. N.; WHITE, B. L. A.; RIBEIRO, G. T. Quantificação do material combustível em fragmento de Mata Atlântica no nordeste brasileiro. *Pesquisa Florestal Brasileira*, v. 38, 2018. DOI: <https://doi.org/10.4336/2018.pfb.38e201701449>.

DE OLIVEIRA, F. R. V.; DANELICHEN, V. H. M. Mapping the dynamics of fire scars in the municipalities of Cuiabá and Chapada dos Guimarães - MT. *UNICIÊNCIAS*, v. 27, n. 2, p. 95-99, 2023. DOI: <https://doi.org/10.17921/1415-5141.2023v27n2p95-99>.

DE OLIVEIRA APARECIDO, L. E.; MORAES, J. R. S. C.; DE MENESES, K. C.; TORSONI, G. B.; DE LIMA, R. F.; COSTA, C. T. S. Köppen-Geiger and Camargo climate classifications for the Midwest of Brazil. *Theoretical and Applied Climatology*, v. 142, p. 1133-1145, 2020. DOI: <https://doi.org/10.1007/s00704-020-03358-2>.

DUONG, T. Kernel density estimation and kernel discriminant analysis for multivariate data in R. *Journal of Statistical Software*, v. 21, n. 7, p. 1-16, 2007. DOI: <https://doi.org/10.18637/jss.v021.i07>.

DURIGAN, G.; RATTER, J. A. The need for a consistent fire policy for Cerrado conservation. *Journal of Applied Ecology*, 53(1), 11–15, 2016. DOI: <https://doi.org/10.1111/1365-2664.12559>.

EDWARDS, A.; ARCHER, R.; DE BRUYN, P.; EVANS, J.; LEWIS, B.; VIGILANTE, T.; ...; RUSSELL-SMITH, J. Transforming fire management in northern Australia through successful implementation of savanna burning emissions reductions projects. *Journal of environmental management*, v. 290, p. 112568, 2021. DOI: <https://doi.org/10.1016/j.jenvman.2021.112568>.

FIDELIS, A.; ALVARADO, S.; BARRADAS, A.; PIVELLO, V. The Year 2017: Megafires and Management in the Cerrado. *Fire*, 1(3), 49, 2018. DOI: <https://doi.org/10.3390/fire1030049>.

FRANKE, J.; BARRADAS, A. C. S.; BORGES, M. A.; COSTA, M. M.; DIAS, P. A.; HOFFMANN, A. A.; ...; SIEGERT, F. Fuel load mapping in the Brazilian Cerrado in support of integrated fire management. *Remote Sensing of Environment*, v. 217, p. 221-232, 2018. DOI: <https://doi.org/10.1016/j.rse.2018.08.018>.

FUNDAÇÃO BRASILEIRA PARA O DESENVOLVIMENTO SUSTENTÁVEL (FBDS). Projeto de Mapeamento em Alta Resolução dos Biomas Brasileiros. Disponível em: <https://geo.fbds.org.br/>. Acesso em: 10 mar. 2023.

GAO, B. C. NDWI — A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment*, v. 58, n. 3, p. 257-266, 1996. DOI: [https://doi.org/10.1016/S0034-4257\(96\)00067-3](https://doi.org/10.1016/S0034-4257(96)00067-3).

HOKI, V. D. S. P.; SANCHES, L.; JUNIOR, G. N. R. C.; PINTO JÚNIOR, O. B. P. Análise dos focos de calor em diferentes faixas de áreas de influência da rodovia BR-242, Nova Ubiratã-MT. *Nativa*, v. 9, n. 2, p. 129-134, 2021. DOI: [10.31413/nativa.v9i2.10794](https://doi.org/10.31413/nativa.v9i2.10794).

HOU, X.; ORTH, R. Observational evidence of wildfire-promoting soil moisture anomalies. *Scientific reports*, v. 10, n. 1, p. 1-8, 2020. DOI: <https://doi.org/10.1038/s41598-020-67530-4>.

HUESCA, M.; LITAGO, J.; MERINO-DE-MIGUEL, S.; CICUENDEZ-LÓPEZ-OCAÑA, V.; PALACIOS-ORUETA, A. Modeling and forecasting MODIS-based Fire Potential Index on a pixel basis using time series models. *International Journal of Applied Earth Observation and Geoinformation*, v. 26, p. 363-376, 2014. DOI: <https://doi.org/10.1016/j.jag.2013.09.003>.

IBGE [INSTITUTO BRASILEIRO DE GEOGRAFIA E ESTATÍSTICA]. Biomas e sistema costeiro-marinho do Brasil: compatível com a escala 1:250.000. Rio de Janeiro, Coordenação de Recursos Naturais e Estudos Ambientais. 168 p. (Relatórios metodológicos, v. 45). 2019.

INMET [INSTITUTO NACIONAL DE METEOROLOGIA]. Seção de Armazenamento de Dados Meteorológicos (SADMET). Disponível em: <https://portal.inmet.gov.br/>. Acesso em: 25 mar. 2024.

INTERMAT [INSTITUTO DE TERRAS DE MATO GROSSO]. Banco de dados cartográficos. Disponível em: <http://www.intermat.mt.gov.br/-/11303036-banco-de-dados-cartograficos>. Acesso em: 25 jan. 2023.

IVO, I. O.; BIUDES, M. S.; VOURLITIS, G. L.; MACHADO, N. G.; MARTIM, C. C. Effect of fires on biophysical parameters, energy balance and evapotranspiration in a protected area in the Brazilian Cerrado. *Remote Sensing Applications: Society and Environment*, 19, 100342, 2020. DOI: <https://doi.org/10.1016/j.rsase.2020.100342>.

KRUEGER, E. S.; LEVI, M. R.; ACHIENG, K. O.; BOLTEN, J. D.; CARLSON, J. D.; COOPS, N. C.; ...; OCHSNER, T. E. Using soil moisture information to better understand and predict wildfire danger: a review of recent developments and outstanding questions. *International journal of wildland fire*, v. 32, n. 2, p. 111-132, 2022. <https://doi.org/10.1071/WF22056>.

KUHN, C. E. S.; SANTOS, F. R. P. Geoparque Chapada dos Guimarães: uma viagem pela história do planeta. Cuiabá/MT. Associação Profissional dos Geólogos do Estado de Mato Grosso – AGEMAT, Federação Brasileira de Geólogos – FEBRAGEO, 2021.

LONG, T.; ZHANG, Z.; HE, G.; JIAO, W.; TANG, C.; WU, B.; ZHANG, X.; WANG, G.; YIN, R. 30 m Resolution Global Annual Burned Area Mapping Based on Landsat Images and Google Earth Engine. *Remote Sens.* 2019, 11, 489. DOI: <https://doi.org/10.3390/rs11050489>.

MACHADO, M. S.; BERENQUER, E.; BRANDO, P. M.; ALENCAR, A.; OLIVERAS MENOR, I.; BARLOW, J.; MALHI, Yal. Emergency policies are not enough to resolve Amazonia's fire crisis. *Communications Earth & Environment*, v. 5, n. 1, p. 204, 2024. DOI: <https://doi.org/10.1038/s43247-024-01344-4>.

MAFFEI, C.; MENENTI, M. A MODIS-based perpendicular moisture index to retrieve leaf moisture content of forest canopies. *International Journal of Remote Sensing*, v. 35, n. 5, p. 1829-1845, 2014. DOI: <https://doi.org/10.1080/01431161.2013.879348>.

MAFFEI, C.; MENENTI, M. Predicting Forest fires burned area and rate of spread from pre-fire multispectral satellite measurements. *ISPRS Journal of Photogrammetry and Remote Sensing*, v. 158, p. 263-278, 2019. DOI: <https://doi.org/10.1016/j.isprsjprs.2019.10.013>.

MAFFEI, C.; LINDENBERGH, R.; MENENTI, M. Combining multi-spectral and thermal remote sensing to predict forest fire characteristics. *ISPRS Journal of Photogrammetry and Remote Sensing*, v. 181, p. 400-412, 2021. DOI: <https://doi.org/10.1016/j.isprsjprs.2021.09.016>.

MAPBIOMAS. Coleção da Série Anual de Mapas de Cobertura e Uso de Solo do Brasil disponível no site <https://plataforma.mapbiomas.org/map#coverage>. <https://mapbiomas.org/estatisticas>. Acesso em: 18 jan. 2024.

MCLAUHLAN, K. K.; HIGUERA, P. E.; MIESEL, J.; ROGERS, B. M.; SCHWEITZER, J.; SHUMAN, J. K.; ...; WATTS, A. C. Fire as a fundamental ecological process: Research advances and frontiers. *Journal of Ecology*, v. 108, n. 5, p. 2047-2069, 2020. DOI: <https://doi.org/10.1111/1365-2745.13403>.

MENGUE, V. P. Análise espacial dos registros de focos de calor na área de proteção ambiental do Parque Nacional da Chapada dos Guimarães/MT entre os anos de 2002 a 2021. *Revista Georaguai*, v. 12, n. 2, p. 84-105. 2022. DOI: <https://doi.org/10.46636/recital.v3i3.219>.

MICHAEL, Y.; HELMAN, D.; GLICKMAN, O.; GABAY, D.; BRENNER, S.; LENSKY, I. M. Forecasting fire risk with machine learning and dynamic information derived from satellite vegetation index time-series. *Science of The Total Environment*, 764, 142844. 2021. DOI: <https://doi.org/10.1016/j.scitotenv.2020.142844>.

MOURA, L. C.; SCARIOT, A.; OSCHMIDT, I. B.; BEATTY, R.; RUSSELL-SMITH, J. I. The legacy of colonial fire management policies on traditional livelihoods and ecological sustainability in savannas: Impacts, consequences, new directions. *Journal of Environmental Management*, v. 232, p. 600-606, 2019. DOI: <https://doi.org/10.1016/j.jenvman.2018.11.057>.

NASCIMENTO, D. T. F.; NOVAIS, G. T. Clima do Cerrado: dinâmica atmosférica e características, variabilidades e tipologias climáticas. *Eliséé*, v. 9, n. 2, p. e922021, 2020.

NASA. Application for Extracting and Exploring Analysis Ready Samples (AppEEARS). Ver. 3.53. NASA EOSDIS Land Processes Distributed Active Archive Center (LP DAAC), USGS/Earth Resources Observation and Science (EROS) Center, Sioux Falls, South Dakota, USA. Disponível em: <https://appears.earthdatacloud.nasa.gov>. Acesso em: maio 2024.

NASA. Fire Information for Resource Management System (FIRMS). Disponível em: <https://earthdata.nasa.gov/firms>. Acesso em: 10 mar. 2024.

NOGUEIRA, J. M.; RAMBAL, S.; BARBOSA, J. P. R.; MOUILLOT, F. Spatial pattern of the seasonal drought/burned area relationship across Brazilian biomes: Sensitivity to drought metrics and global remote-sensing fire products. *Climate*, v. 5, n. 2, p. 42, 2017. DOI: <https://doi.org/10.3390/cli5020042>.

NOWELL, H. K.; HOLMES, C. D.; ROBERTSON, K.; TESKE, C.; HIERS, J. K. A new picture of fire extent, variability, and drought interaction in prescribed fire landscapes: Insights from Florida government records. *Geophysical research letters*, v. 45, n. 15, p. 7874-7884, 2018. DOI: <https://doi.org/10.1029/2018GL078679>.

OLIVEIRA, A. S.; SOARES-FILHO, B. S.; OLIVEIRA, U.; VAN DER HOFF, R.; CARVALHO-RIBEIRO, S. M.; OLIVEIRA, A. R., ...; RAJÃO, R. G. Costs and effectiveness of public and private fire management programs in the Brazilian Amazon and Cerrado. *Forest Policy and Economics*, v. 127, p. 102447, 2021. DOI: <https://doi.org/10.1016/j.forpol.2021.102447>.

OLIVEIRA, J. F.; PINTO, J. A.; COSTA, D. A.; PASSOS, A. K. A.; SILVA, W. B. Uma Análise das Ocorrências de Fogo e Incêndios Florestais no Parque Nacional da Chapada Diamantina entre 2015 e 2020. In: *Anais do XVI Escola Regional de Banco de Dados*. SBC, p. 71-80, 2021. DOI: <https://doi.org/10.5753/erbd.2021.17240>.

PARZEN, E. On estimation of a probability density function and mode. *The annals of mathematical statistics*, v. 33, n. 3, p. 1065-1076, 1962.

PETTORELLI, N.; VIK, J. O.; MYSTERUD, A.; GAILLARD, J. M.; TUCKER, C. J.; STENSETH, N. C. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends in ecology & evolution*, v. 20, n. 9, p. 503-510, 2005.

RAMOS, D. M.; ANDRADE, J. M.; ALBERTON, B. C.; MOURA, M. S.; DOMINGUES, T. F.; NEVES, N.; ...; CUNHA, J.

Multiscale phenology of seasonally dry tropical forests in an aridity gradient. *Frontiers in Environmental Science*, v. 11, p. 1275844, 2023. DOI: <https://doi.org/10.3389/fenvs.2023.1275844>.

ROUSE, J. W.; HAAS, R. H.; SCHELL, J. A.; DEERING, D. W. Monitoring vegetation systems in the Great Plains with ERTS. *NASA Spec. Publ*, v. 351, n. 1, p. 309, 1974.

SCHMIDT, I. B.; MOURA, L. C.; FERREIRA, M. C.; ELOY, L.; SAMPAIO, A. B.; DIAS, P. A.; BERLINCK, C. N. Fire management in the Brazilian savanna: First steps and the way forward. *Journal of Applied Ecology*, 55(5), 2094–2101, 2018. DOI:<https://doi.org/10.1111/1365-2664.13118>.

SILVA, C.; VIANA, I.; SOUZA, D. D.; SILVA, D.; PORTELLA, A.; GIONGO, M. Efeito do fogo na abundância e diversidade fúngica no solo do Cerrado. *Ciência Florestal*, v. 31, p. 1910-1929, 2022. DOI: <https://doi.org/10.5902/1980509854717>.

SMIRAGLIA, D.; FILIPPONI, F.; MANDRONE, S.; TORNATO, A.; TARAMELLI, A. Agreement index for burned area mapping: Integration of multiple spectral indices using Sentinel-2 satellite images. *Remote Sensing*, v. 12, n. 11, p. 1862, 2020. DOI: <https://doi.org/10.3390/rs12111862>.

SUNGMIN, O.; ORTH, R.; SENEVIRATNE, S. I. Observational evidence of wildfire-promoting soil moisture anomalies. *Scientific Reports*, [S.l.], v. 10, 11008, 2020. DOI: <https://doi.org/10.1038/s41598-020-67864-2>.

SZPAKOWSKI, D. M.; JENSEN, J. L. R. A review of the applications of remote sensing in fire ecology. *Remote sensing*, v. 11, n. 22, p. 2638, 2019.

USGS. Birgit Peterson, PhD. Centro de Observação e Ciência de Recursos Terrestres (EROS). Disponível em: <https://www.usgs.gov/centers/eros/news/remote-sensing-characterization-post-fire-vegetation-recovery>. Acesso em: 12 jun. 2024.

USGS. Landsat Surface Reflectance-Derived Spectral Indices. Disponível em: <https://www.usgs.gov/land-resources/nli/landsat/landsat-normalized-burn-ratio>. Acesso em: 27 set 2024.

VADREVU, K. P.; SISZAR, I.; ELLICOTT, E.; GIGLIO, L.; BADRINATH, K. V. S.; VERMOTE, E.; JUSTICE, C. Hotspot analysis of vegetation fires and intensity in the Indian region. *IEEE Journal of selected topics in applied Earth Observations and Remote Sensing*, v. 6, n. 1, p. 224-238, 2012. DOI: 10.1109/JSTARS.2012.2210699.

VECCHI JUNIOR, K. Variação espacial e temporal da composição de assembleias de gafanhotos (Orthoptera: Caelifera) em áreas de Cerrado na Chapada dos Guimarães -MT, Brasil. 2018.

VIEIRA JÚNIOR, H. T.; MORAES, J. M; PAULA, T. L. F. D. "Geoparque Chapada Dos Guimarães (MT): Proposta." CPRM, 2012.

YAHIA, O.; GHABI, M.; KAROUI, M. S. The Prediction of Regional Wildfire Risk Using High-Resolution Remotely Sensed Soil Moisture Content Estimation, Case Study: Sidi Douma Forest, Saida, Algeria. In: *IGARSS 2023-2023 IEEE International Geoscience and Remote Sensing Symposium*. IEEE, 2023. p. 3387-3390. DOI: 10.1109/IGARSS52108.2023.10281986.

