ENVIRONMENTAL AND CLIMATIC INTERCONNECTIONS: IMPACTS OF FOREST FIRES IN THE MATO GROSSO REGION OF THE AMAZON

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ABSTRACT

Wildfires in the Amazon biome cause extensive environmental, economic, and health damages, including biodiversity loss and high greenhouse gas emissions. This study used remote sensing to examine the relation among fire severity and climatic factors, focusing on Differenced Normalized Burn Ratio, precipitation, Land Surface Temperature, Standardized Precipitation Index, NDVI and VCI for data analysis based on the period from 2001 to 2022 in the Mato Grosso Amazon. Only LST showed a significant trend, with the highest impact in the Northeast mesoregion. dNBR correlated positively with NDVI and VCI, and negatively with precipitation and SPI. The northern mesoregion showed vulnerability due to its proximity to the Amazon rainforest and agricultural activities, indicating increased fire susceptibility with reduced humidity.

Key words **—** Trend analysis; Ecoregion; Remote sensing; Environmental damages.

1. INTRODUCTION

The Amazon Rainforest is one of the main contributors to global carbon storage [1]. However, deforestation remains a significant problem in the Amazon region, driven by the establishment of an agricultural frontier [2], [3]. Such dynamics are based on forest burning [4], which means a plethora of environmental impacts [5] in the biome with the highest contribution to GHG emissions in Brazil [6].

The detection of fire foci via satellite has proven to be a promising alternative for environmental monitoring and hazard management [7], [8], enabling the measurement of variables and temporal analysis of areas at a low cost. The dNBR is based on the modifications that occur in the soil and vegetation due to the fire [9]. This study utilizes remote sensing as a tool to obtain information on climatic variables, vegetation indices, and the impact of fire severity over a time series to investigate (i) interactions between fire severity (dNBR) and other climatic variables, (ii) behavior of the studied variables in each mesoregion, and (iii) identification of trends and change points.

2. MATERIAL AND METHODS

2.1. Study area

The study area comprised the Amazon biome in the state of Mato Grosso, located between 09°00′ to 18°00′S and 49°00′ to 61°00′W (Figure 1). The mesoregions belonging to the Amazon biome in the state were evaluated, covering an area of approximately 661,000 km^2 and encompassing four mesoregions: Norte (North), Nordeste (Northeast), Sudoeste (Southwest), and Centro-sul (Central-South), designated as mesoregions 1 to 4, respectively.

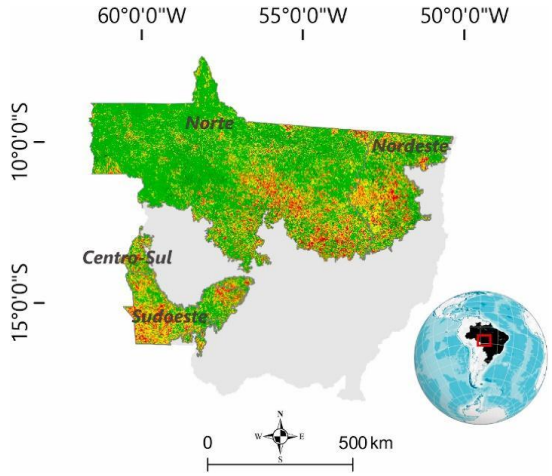


Figure 1. The study area was subdivided into mesoregions, Mato Grosso state, Brazil.

2.2. Burned areas and dNBR

Fire detection is executed through a contextual algorithm that exploits the high emission of mid-infrared radiation generated by fire [10], [11]. The product generated by the MODIS sensor on the Terra and Aqua satellites, which combines monthly burning data, MCD64A1 version 6, with a global 500-m grid containing burned area data, was used.

Afterwards, the regeneration of areas after burning was calculated. The normalized burn rate (or area) is a powerful tool for better understanding the extent and severity of fire when used after calculating the difference between pre- and post-fire conditions.

For this purpose, we used the spectral bands of the MOD13Q1 product to calculate PrefireNBR (March to May) and PostfireNBR (October to November), with the wavelengths of NIR (sur_refl_b02) and MIR (sur_refl_b07), between the years 2001 and 2022, given that the highest occurrences of wildfires are close to the October and November period. Fire severity was categorized in High sprouting (−500 to −250), Low sprouting (−250 to −100), No burning (−100 to 100), Low moderate severity (100–270), Moderate (270–440), High moderate (440–660), and High moderate severity (660–1300) [12].

2.3. SPI (Standardized Precipitation Index) and rainfall

The SPI was developed by McKee et al. (1993) to quantify rainfall deficit or excess over different time scales. The SPI calculation is based on the total accumulated rainfall records for over 20 years, which is adjusted to a probability distribution function.

2.4. VCI (Vegetation Condicition Index)

This index was applied to the time series to show the multitemporal analysis of the VCI based on MODIS (MOD13Q1 version 6 Terra) to support drought monitoring and early post-fire warning. The VCI, compares the current Vegetation Index (VI), such as NDVI or Enhanced Vegetation Index (EVI), with the values observed in the same period in previous years within a specific pixel [13].

2.5. Statistical analyses

Initially, the Shapiro-Wilk normality test was applied to check the distribution of the data for the variables. Next, the Tukey test was used to compare the annual means of each analyzed variable by mesoregion. To assess the trend of the variables over the time series, the Mann-Kendall test followed by the Pettitt test was employed, identifying the likely point of change when the trend is significant. Finally, a correlation analysis and a canonical variables analysis were used to study the association between variables. In all cases, a significance level of 5% was adopted for the statistical tests.

Regarding the location points, we used regression kriging for a better distribution of the data. The location points of the samples were the occurrences of fire outbreaks, which were interpolated in the spatial domain.

3. RESULTS

3.1. Visual analysis

Based on the collected data, it is evident that for the dNBR with the registered fire outbreaks and from a general overview of the study area (Figure 2), there was a higher concentration of fire outbreaks in the northern, northeastern, and southwestern mesoregions. It is possible to identify a greater concentration of high dNBR values in the years 2010, 2012, 2015, and 2020, indicating a greater degradation of the region.

3.2. Descriptive statistics

From the analysis of data normality, a comparison between means by mesoregion was performed using the Tukey test, with only the LST variable showing significant differentiation by mesoregions.

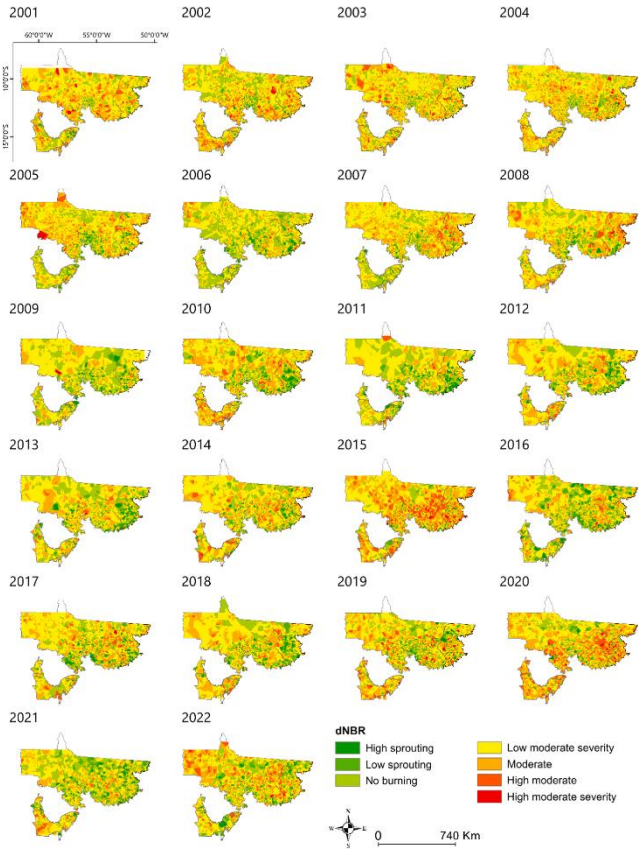


Figure 2. Differenced Normalized Burn Ratio (dNBR) interpolated using kriging for the locations identified with fire outbreaks over time.

The comparisons of means presented were significant for 2 variables, dNBR and LST. The former showed significant differentiation in the comparison between means, but all variables were in the same group. As for the latter, there was discrimination by groupings, with three main groups identified: mesoregion A (northeastern mesoregion),

B (central-southern mesoregion), and C (southwestern and northern mesoregions).

The non-parametric Mann-Kendall trend test was applied, this allowed the identification of significant trends and their direction, whether increasing or decreasing. Then, Pettitt test was carried to verify the probable point of change in the trend present in the variables. Only the LST variable showed a significant trend, with the probable point of change occurring in 2009.

3.2.1. Correlation

3.2.1.1 General correlation

Examining precipitation, it was found to be related to SPI and dNBR, with positive and negative correlations, respectively, suggesting that higher precipitation tends to mitigate the impacts of forest fires.

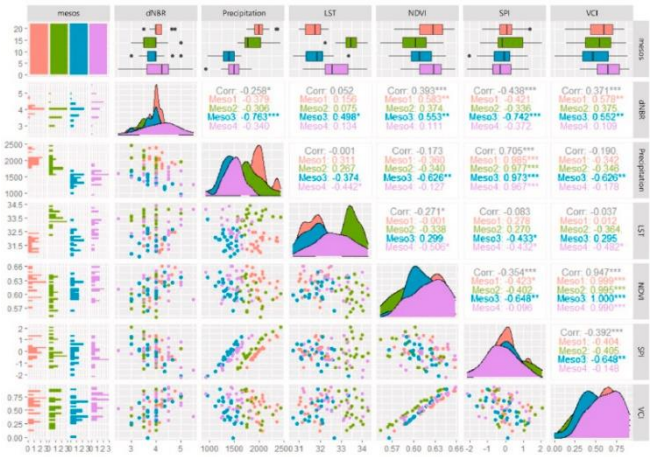


Figure 3. Pearson correlation graph by mesoregion and overall. Note: * represents significance at the 5% level, ** represents significance at the 1% level, * represents significance at the 0.1% level.**

SPI showed positive correlations with Precipitation and negative correlations with dNBR, NDVI, and VCI, indicating that fire severity can cause greater drought and drought leads to greater fire severity, thus generating a vicious cycle between drought and severity. Finally, VCI correlations were positive for dNBR and NDVI, but negative for SPI, suggesting that vegetation recovery in this area occurs rapidly, as fire impact is attenuated by high local recovery rates. Conversely, SPI had a negative relationship, indicating that during periods of high humidity, vegetation may not respond optimally.

3.2.1.2. By mesorregions

The dNBR, there was a change in correlation, with the inclusion of the LST variable for the southwestern mesoregion. Additionally, a significant correlation of LST with SPI was observed for this mesoregion, suggesting an indirect influence on forest fire impact based on temperature.

LST correlation was observed with precipitation, NDVI, SPI, and VCI for the central-southern mesoregion (Meso4), reinforcing the idea that for this region, temperature has strong negative influences on environmental maintenance. For the southwestern mesoregion, LST was correlated with dNBR and SPI, showing positive and negative correlations, respectively (Figure 3), indicating a relationship between temperature, drought, and fire impact.

SPI in the southwestern mesoregion stood out, showing positive correlations with Precipitation and negative correlations with dNBR, LST, NDVI, and VCI, reinforcing the idea that higher severity leads to greater drought and showing that for this mesoregion, temperature is directly dependent on drought (Figure 3).

4. DISCUSSION

The analysis of the dNBR maps reveals a higher concentration of impacts in the northeast and north mesoregions, likely due to the presence of the deforestation arc located in the Northeast of the state of Mato Grosso, which greatly influences forest fires [14], as well as the agricultural expansion directed towards the Amazon rainforest in the northeastern mesoregion [15].

The LST, there is a predominance in the northeastern mesoregion, indicating a trend of temperature increase, influenced by climatic events and deforestation in the area [16]. The dNBR had moderate negative correlations with Precipitation and SPI, suggesting that for Amazonian vegetation, lower local humidity increases susceptibility to fires and fire severity [17]. Meanwhile, the SPI indicated a temporal configuration of drought, suggesting that past droughts may influence fire severity and vice versa.

When analyzing LST, a correlation was found only with NDVI, showing a negative relationship, suggesting that local temperature may interfere with the maintenance of large-scale vegetation functionality [18], [19], which is a major global environmental concern.

Through canonical analysis, it can be observed that the northeastern mesoregion is the most affected by dNBR, Precipitation, NDVI, VCI, and SPI. This region, known as the deforestation arc, is more sensitive, with a higher frequency of fires, causing various impacts in the region.

5. CONCLUSIONS

From the present study, we observed that, in the analysis of the study area as a whole, the main positive correlations for dNBR were with the NDVI and VCI variables. On the other hand, we found negative correlations with SPI and precipitation.

The second most important variable was LST, which showed a significant growth trend, affecting the northeastern region of the state and indicating a danger of high temperatures, with a probable change point occurring in 2009. LST was also significant in the northern mesoregion,

related to the severity of wildfires, aggravating environmental and public health issues.

Finally, the influence of wildfires in this region is affected by geopolitical considerations, highlighting the importance of defining preservation areas. We suggest greater attention to the North and Northeast mesoregions in terms of environmental care, due to the higher incidence of wildfires and their correlations with the presented variables.

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