Fire dynamics in Mato Grosso State, Brazil: the relative roles of gross primary productivity

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ABSTRACT
The fires and biomass burning are responsible for affecting ecosystem processes in a wide range of biomes at regional and global scales. In Brazil, the state of Mato Grosso is one of the most affected by the occurrence of forest fires. Thus, this study aims to quantify the long-term changes in the temporal and spatial patterns of fire occurrence and their effect on gross primary productivity (GPP) in the state of Mato Grosso, Brazil, considering the biomes that compose it. The images used in the study were acquired by satellite Terra and Aqua combined in the product MCD64A1.006, a monthly resolution of 500m by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, during the period from 01/10/2000 to 12/31/2018. The MOD17A2 product derived from the MODIS sensor provides the accumulated value of GPP. The points without the presence of burning presented higher values of GPP for all studied biomes. In some points with the presence of burning the GPP even decreased by 44.20%, 30.04% and 55.78% for Amazonia, Cerrado, and Pantanal, respectively. According to the results presented here, it is concluded that the burnings negatively impact gross primary production in the biomes of the state of Mato Grosso, Brazil and the dynamics of the burns do not keep up with the intensity of drought years. The use of cluster analysis techniques, such as principal component analysis (PCA), is an alternative to bigdata analysis when the objective is to evaluate the presence of forest burning in more than one biome.

1. Introduction
Fires and biomass burning are responsible for affecting ecosystem processes in a wide range of biomes at regional and global scales (Carlson et al., 2013; Kasischke & Hoy, 2012). Within this context, combustion fires are responsible for releasing approximately 7% of total net carbon from vegetation to atmosphere, becoming a relevant element of forest ecosystems and the global carbon cycle (Janhäll, Andreae, & Pöschl, 2009). In addition to the carbon cycle, fires also influence the floristic composition of biomes, surface energy flow that can even affect the water cycle through vegetation removal (Bond & Keeley, 2005; Randerson et al., 2006).
Among the most fire-prone vegetation types are the forest, savannah, grassland and tundra (Chuvieco et al., 2016; Pellegrini et al., 2018). These are responsible for covering almost the entire surface of the earth, with emphasis on the forest which is responsible for 37% of the earth’s surface coverage, which implies a high susceptibility to fire (FAO, 2006). Some studies attribute this susceptibility to extreme periods of drought (Aragão et al., 2018; Silva et al., 2018) which under the current climate of forests can trigger an acceleration of deforestation.

More recently, due to the change in public policies involving the half environment, Brazil has been suffering an environmental crisis, which was very evident with the Amazon fires in 2019 (Nature, 2019). Among the negative points of this crisis, according to Prist et al. (2019), are the loss of biodiversity and ecosystem functions and the suspension of climate regulation.

According to Da Silva Júnior, Delgado, Pereira, Teodoro, and da Silva Junior (2019) the extreme droughts in the Amazon have caused a considerable increase in the occurrence of fires, the results presented in this study revealed that the 2015/2016 drought surpassed the 2010 drought in intensity and extent. In another recent study conducted in the Amazon, researchers assessing fire dynamics under extreme weather events related to the Southern El Niño Oscillation in the Western Amazon found that the largest number of fires were recorded during the neutral phase and the largest burned area was found during La Niña (Da Silva Júnior et al., 2019). These authors also highlighted the vulnerability of the Amazon ecosystem to forest fires and the need to properly understand the impacts of the ENSO event in the Amazon region, as it plays an important role in water regimes.

In contrast, for some biomes, fire, when spontaneous in origin may bring benefits that guarantee its sustainability such as nutrient recycling and the recomposition of certain plant species (Alcañiz, Outeiro, Francos, & Úbeda, 2018; Augustine, Brewer, Blumenthal, & Derner, 2014). In Brazil, the Cerrado biome is characterized by natural fire outbreaks due to its high susceptibility due to the climate and the type of vegetation present in this biome (Dantas, Batalha, & Pausas, 2013; Hoffmann et al., 2012). Some authors report the adaptation and importance of fire for the maintenance of some plant and ant species (Abreu et al., 2017; Durigan & Ratter, 2016). However, for the Cerrado, fire can only be considered beneficial depending on its intensity and exposure time.

Scientists around the world have been using remote sensing techniques to measure the spatial and temporal variability of forest fires (Shi, Sasai, & Yamaguchi, 2014; Silva et al., 2018). Biswas, Lasko, and Vadrevu (2015) quantified the relationship between fires and vegetation disturbance at varying spatial scales using moderate-resolution image radiometer (MODIS) spectrum data sets and observed that biomass burning in the Myanmar rainforests negatively impacted Gross Primary Production (GPP) of large-scale forests.

Understanding the impact of biomass burning on GPP is important since with GPP it is possible to know how much carbon was fixed by the photosynthesis process in the ecosystem (Anav et al., 2015; Chagas et al., 2019). Another key element that is important to note is the restoration of each biome after severe burns since ecosystem resilience is what will contribute to carbon cycling, for example.

The state of Mato Grosso is composed of three biomes, Amazon, Cerrado and Pantanal, which makes it an important agent for the conservation of these biomes against deforestation and control of fire outbreaks. However, according to the Centro de Vida Institute (ICV, 2019), with the recent environmental crisis in Brazil, the state of Mato Grosso alone,
from January to August 2019 13,000 hot spots. According to this institute, this corresponds to an increase of 87% compared to the same period in 2018 and 205% if only the period of prohibition of burning is considered. According to them, in the Amazon Biome the largest number of fire outbreaks occurs in regions with illegal deforestation.

Due to its vast extension, the state of Mato Grosso stands out for its participation in Brazilian agribusiness, which is very much related to illegal deforestation (Ioris, 2016; Silva et al., 2018). Thus, it is important to highlight that, although agribusiness is important for the increase of national GDP, an environmental crisis can affect even the country’s economy, such as agribusiness (Arruda, Candido, & Fonseca, 2019). Therefore, knowing the importance of the state of Mato Grosso for the Brazilian economy, and the impact of burning on the environmental sustainability of ecosystems such as the Amazon and Cerrado, thus, the aim of this study is to quantify the long-term changes in the temporal and spatial patterns of fire occurrence and their effect on gross primary production (GPP) in the state of Mato Grosso, Brazil, considering the biomes that compose it.

2. Methods

2.1. Study area

The study was developed for the state of Mato Grosso (9°09’45.9” S – 61°19’56.1” W and 17°49’18.4” S – 53°19’37.1” W) which is in the Midwest Region of Brazil (Figure 1). Occupying an area of 903,206,997 km² (IBGE, 2019), bordering the north with the states of Pará and Amazonas, south with the state of Mato Grosso do Sul, east and west with the states of Goiás, Tocantins and the states from Rondônia and Bolivia. The climate is classified as tropical with concentrated rainfall in the summer period. The rating is Aw according to the

![Figure 1. Geographic localization of the study area and the composite elevation in the state of Mato Grosso.](image-url)
Köppen and Geiger rating. The average temperature is 26.5 °C and the average annual rainfall is 768mm, which may vary between regions of the state. The state is divided into three domains, two main ones, Rainforest (Amazon) and Cerrado.

The soils of the state were analyzed through a careful and detailed compilation of the documentation produced by the State Socioeconomic Economic Zoning, which resulted in the identification and mapping of the 23 soil classes in the state of MT, in the scale 1: 250,000 (SEPLAN-MT, 2003). Demonstrating that the most frequent soils are: Podzólico Vermelho-Amarelo (24.1%); Latossolo Vermelho-Escuro (23.6%); Latossolo Vermelho-Amarelo (17.18%); Areia Quartzosas (12.94%); Plintossolo (7.32%); Cambissolo (4.75%); Solo litólicos (2.4%); Planossolo (2.04%); other soils (5.6%).

2.2. Biomes

The length of the Amazon biome in the state of Mato Grosso is 482,785.15 km², the Cerrado is 358,801.55 km² and the Pantanal is 60,832.01 km². Each biome has its own diversity of species, climate, and vegetation. The climate in Mato Grosso according to the Köppen-Geiger classification is “Am” (monsoon climate) and “Aw/As” (tropical climate with dry season) (Alvares et al., 2013). The Amazon biome with closed vegetation, high canopy and a continuous layer of crowns, making it difficult for light and winds to pass through, with little undergrowth. In the Cerrado biome, the vegetation has a savannah and country formation, the tree species have tortuous trunks and a low canopy, providing greater wind passage and an intense solar influence. The vegetation of the Pantanal biome is flooded for long periods of the year and is composed of savannas, savannas, and marshes, not having a closed forest and open fields.

2.3. Satellite data preprocessing

The images used in the study were acquired by satellite Terra and Aqua combined in the product MCD64A1.006, a monthly resolution of 500m by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, during the period from 01/10/2000 to 12/31/2018. The MCD64A1.006 product has a hybrid approach that exploits MODIS’s 1 km active fire potential and 500 m surface reflectance input data, the calculation of burns by time series burn-sensitive vegetation index of MODIS in the shortwave, infrared channels and dynamic thresholds are applied to detect persistent spectral changes (Fornacca, Ren, & Xiao, 2017). Cumulative active fire maps are used to generate regional probability density functions for the classification of burnt and unburned training samples that will guide the final determination of burnt and unburned pixels (Giglio et al., 2009).

Preprocessing was done using the Google Earth Engine platform, applying JavaScript programming in its API and downloading GeoTIFF images. The definition of the analysis points containing burning in the three biomes in Mato Grosso, by means of a pre-analysis of pixel presence of the product MCD64A1.006 in each year of the time series, as well as in which point it presented constancy in the time series. In the selected points without burning, the opposite was done, those that did not present burning during the time series.

Quantification of the burned areas in each year of the time series was made using the QGIS 3.4 software.
2.4. Gross primary productivity (GPP)

The MOD17A2 product derived from the MODIS sensor provides the accumulated value of GPP based on the concept of efficiency of solar radiation use by vegetation (ε) so that photosynthetically active absorbed radiation (APAR) and primary production are similarly related as Equation (1). APAR can be calculated as the product of incident photosynthetically active radiation (PAR) in the visible spectral range of 0.4 μm – 0.7 μm, supposedly 45% of total incident solar radiation and fraction of photosynthetically active radiation absorbed by coverage (FPAR) (Delgado et al., 2018; Heinsch et al., 2003).

\[ GPP = \frac{\varepsilon \times PAR}{FPAR} \]  \hspace{1cm} (1)

These models have a greater challenge in obtaining the efficiency of light use “ε” in a large area, due to their dependence on environmental factors and the vegetation itself. One solution is to relate “ε” according to its maximum value (εmax), plus the environmental contributions synthesized by the minimum air temperature (Tminscalar) and the water status in the vegetation (VPDscalar – water vapor pressure deficit) (Field et al., 1995) according to Equation (2).

\[ \varepsilon = \varepsilon_{\text{max}} \times \text{Tminscalar} \times \text{VPDscalar} \]  \hspace{1cm} (2)

Pixel values for the digital numbers of MODIS images were converted to biophysical values (Kg C m⁻²) by scaling factor multiplication (0.0001) (Heinsch et al., 2003) (Equation (3)). GPP values were also transformed from the accumulated value every 8 days to average values every 8 days and converted from Kg C m⁻² day⁻¹ to g C m⁻² day⁻¹.

\[ GPP \left( \text{g C m}^{-2}\text{d}^{-1} \right) = \frac{\text{Biophysical Pixel} \ (\text{Kg C m}^{-2}\text{d}^{-1})}{8} \]  \hspace{1cm} (3)

2.5. Statistical analysis

To better understand the variation of GPP as a function of time and the effect of the burns, two types of descriptive analyzes of temporal and spatial form were performed.

2.5.1. Temporal variation

The data used consist of the daily averages of each sample point for these variables. The means were subjected to analysis of variance with repeated measures over time (Test F) to obtain the standard error values.

2.5.2. Principal component analysis

GPP data were subjected to principal component analysis (PCA) to verify the discriminative capacity of the variable and the relationship of the variable in each set to the biomes. The PCA is based on a multivariate approach consisting of transforming a set of original “p” variables X1, X2, …, Xp, belonging to “n” subjects, to a new set of variables, Y1, Y2, …, Yp of equivalent size, called principal components (Equation (4)). Each major component is a linear combination of the main indicators of the original variables, constructed to explain the maximum total variability of the original and uncorrelated variables (Everitt & Dunn, 1991).
\[ Y_1 = a_1X_1 + a_2X_2 + \ldots + a_pX_p \]  \hspace{1cm} (4)

where \( a_1, a_2, \ldots, a_p \), and are the eigenvectors of the correlation matrix between variables.

3. Results and discussion

3.1. Fire dynamics

The images acquired by MODIS of the product MCD64A1.006 in the time series from November 1, 2000 to December 31, 2018 in the state of Mato Grosso showed an accumulation of 776,766.71 km\(^2\) of the burned area as shown in Figure 2. When we separate the state of Mato Grosso by the Amazon, Cerrado and Pantanal biomes, we find that the difference between them in the burned area is 232,912.37, 488,827.85 and 55,026.48 km\(^2\) respectively, thus showing that the Cerrado biome presents the largest accumulation of burned area in comparison with the other two biomes, with a percentage of 29.99%, 62.93% and 7.08% respectively among the biomes in the state of Mato Grosso.

Due to the differentiation of terrain and vegetation may justify this great characterization in the detection of burned areas, the Cerrado biome is composed of a diverse mix of pastures, scrubland and forests (De Miranda et al., 2014; Noojipady et al., 2017), providing a better spread of fire.

When we verified the number of polygons that were detected in the time series analyzed, we reached a total of 392844 polygons (Figure 3). Of this total, we accounted for the Amazon biome 212,467 polygons, in the Cerrado biome 164,538 polygons and the

![Figure 2](image2.png)

**Figure 2.** Total accumulated of the burned area (Km\(^2\)) on the biomes in Mato Grosso state, Brazil.
Pantanal biome with 15,839 polygons. A proportion of 54.09%, 41.88% and 4.03% respectively among the biomes in the state of Mato Grosso.

The differentiation between the number of polygons and size in km² in the biomes of the state of Mato Grosso can highlight that the region of the Cerrado biome with the predominance of drought periods have a larger area of the fire, other studies point out that the climate-fire relations provide a general basis to understand the natural seasonality and frequency of fire in this region (Nogueira, Ruffault, Chuvieco, & Mouillot, 2017; Rodrigues et al., 2019).

Other factors may influence the increase or decrease in the detection of burned areas during the time series in biomes in the state of Mato Grosso, with the advance of agricultural activity and the extraction of wood to produce firewood and charcoal in the Cerrado or for sale and export in the Amazon. The Brazilian government tries to block this advance with the Plan of Action for Prevention and Control of Deforestation in the Legal Amazon (PPCDAm) (MMA, 2019a) implemented in 2004 and Plan of Action for Prevention and Control of Deforestation and Burning in the Cerrado (PPCerrado) (MMA, 2019b) implemented in 2010, we can highlight an agreement that aims to inhibit the destruction of forests to plant soybeans in the Brazilian Amazon the implementation of the Soy Moratorium, which soybeans produced in legally or illegally deforested areas, after July 24 2006, would not be purchased. However, studies indicate that these

**Figure 3.** Number of fire polygons on the biomes in Mato Grosso state, Brazil.
measures to combat deforestation of areas for soybean planting purposes have not decreased to the desired proportion in the Amazon (Kastens et al., 2017; Silva & Lima, 2018).

When analyzed the values of \( \text{km}^2 \) and burning polygons of the state of Mato Grosso from 2000 to 2018 and took the average, we observed that in 2007 and 2010 they presented a higher average evolution in \( \text{km}^2 \) compared to the other years analyzed and The lowest average of evolution are the years 2009, 2011 and 2018. However, the years 2004 and 2007 presented the highest average of burned polygons and those with the lowest average were the years 2009 and 2011 as shown in Figure 4.

In Figure 4 shows the cumulative burned areas during each year analyzed in the time series acquired by the product MCD64A1.006. To validate some firing polygons, an interaction between the BLUE (496.0 to 492.1nm), RED (664.5 to 665nm) and SWIR2 (2185.7 to 2202.4nm) spectral bands of the Sentinel-2 satellite-derived COPERNICUS/S2 product was used. a highlight in the burn sites in 2018 (Figure 5).

The annual averages for the burned area (\( \text{Km}^2 \)) in the biomes of the state of Mato Grosso are shown in Figure 6. For the Amazon biome, the highest values of the burned area were in 2010 (1.611 ± 0.063 Km\(^2\)) and 2017 (1.328 ± 0.064 Km\(^2\)). In the Cerrado biome, the highest values were repeated for 2010 (4.596 ± 0.320 Km\(^2\)) and 2017 (4.004 ± 0.299 Km\(^2\)), as well as in the Amazon biome, but also for 2001 (3.346 ± 0.257 Km\(^2\)) 2007 (3.374 ± 0.175 Km\(^2\)) and 2012 (3.533 ± 0.240 Km\(^2\)). The burned area for the Pantanal biome was more representative for the years 2001 (4.313 ± 0.607 Km\(^2\)) 2005 (4.015 ± 0.625 Km\(^2\)) 2009 (4.628 ± 1.235 Km\(^2\)) and 2015 (3.431 ± 0.747 Km\(^2\)).

The highest occurrence of fires in 2010 in the Amazon biome is due to the severe drought that occurred in 2010 due to the El Niño-Southern Oscillation (ENSO) phenomenon, which was intensified by the warming of the tropical North Atlantic Ocean (Lewis, Brando, Phillips, Van Der Heijden, & Nepstad, 2011; Marengo, Soares, Tomasella, Alves, & Rodriguez, 2011). High burn rates in 2017 may also reflect El Niño 2015/2016 (Yan, Wang, Huete, & Shugart, 2019). Some authors have noted that El Niño events decrease rainfall and increase evaporation potential which leads to reduced soil moisture, which makes the forest more susceptible to burning (Lee et al., 2013; Doughty et al., 2015; Feldpausch et al., 2016; Liu et al., 2018). For Yan et al. (2019) This mechanism of suppression of the photosynthetic rate by means of water deficit is one of the most important in the forests of the Amazon.

For the Cerrado biome, Rodrigues et al. (2019) attribute the sharp increase in burning between 2013 and 2016 to climatic seasonality with extremely dry, extremely wet periods. According to Ribeiro et al. (2018), Recurrent burning outbreaks in the Cerrado are due to environmental characteristics such as high air temperature, long-term drought, and highly flammable vegetation, as the Cerrado is mainly composed of grasses, shrubs and small palm trees. In addition, the Cerrado biome in Mato Grosso has been undergoing a strong change in land use due to agricultural expansion (Gomes et al., 2019) which contributes to the higher occurrence of fires (Durigan & Ratter, 2016).

The patterns of error variability observed in the Pantanal biome are related to heterogeneity in the temporal and spatial distribution of land use/land cover. The Pantanal has an annual oscillation between dry and flooding periods (Junk et al., 2005) and this feature is the main driver of biodiversity patterns and ecological processes in wetlands (Junk, Bayley, & Sparks, 1989). Other factors such as; Topography and soil result in different levels
of flooding (Nunes-da-Cunha & Junk, 2004) which contributes to the heterogeneity of spatial distribution of land use.

3.2. Principal component analysis – PCA

The results obtained by the principal component analysis (PCA) method, the eigenvalues, percentage of variance illustrated are shown in Table 1. The data show that the first two main components (CPs) represented 78.8% of the total proportion, on the
value of the gross primary production (GPP) of some points in the biomes in the state of Mato Grosso, with PC1 representing 64.8% and PC2 by 14.1% of the proportion of the data.

In determining how many major components would be relevant in the study, it was noted that the first two PCs obtained from the analysis having eigenvalues $> 1$ ($\lambda_i > 1$) using the Kaiser criterion, 1958 (Fraga, et al., 2015; Hongyu, Sandanielo & De Oliveira Junior, 2016) and representing 78.8% of the total data variance, both CPs were retained by the scree plot (Figure 7) and represented in Table 2. Thus, we can consider the first two main components effectively explaining the total sample variance and for the study of the data they can be used.

Table 2 shows the correlation between the original data and the main components, in order to understand the relevance of each variable in the construction of two separate components in the analysis. This table also shows the correlations with the
first two main components and their weighting coefficients of each characteristic. With the reduction of 12 points from original variables to 2 main components, it is considered acceptable for the composition of Equations (5) and (6) to explain the behavior of the data. For Equations (5) and (6) it was considered that: X1:Point 1 Amazon biome with burning; X2:Point 2 Amazon biome with burning; X3:Point 1 Amazon biome without burning; X4:Point 2 Amazon biome without burning; X5:Point 1 Cerrado with burnt biome; X6:Point 2 Cerrado with burnt biome; X7:Point 1 Cerrado biome without burning; X8:Point 2 Cerrado biome without burning; X9:Point 1 Pantanal biome with burnt; X10:Point 2 Pantanal biome with burnt; X11:Point 1 unburnt Pantanal biome; X12:Point 2 unburnt Pantanal biome.

![Figure 6. Annual average of the burned area (Km²) on the biomes in Mato Grosso state, Brazil.](image)

| Principal Component | Eigenvalues | Proportion | Accumulated Proportion (%) |
|---------------------|-------------|------------|----------------------------|
| PC1                 | 7.772       | 0.648      | 64.760                     |
| PC2                 | 1.686       | 0.141      | 78.820                     |
| PC3                 | 0.804       | 0.067      | 85.514                     |
| PC4                 | 0.366       | 0.030      | 88.563                     |
| PC5                 | 0.255       | 0.021      | 90.684                     |
| PC6                 | 0.212       | 0.018      | 92.450                     |
| PC7                 | 0.204       | 0.017      | 94.151                     |
| PC8                 | 0.174       | 0.015      | 95.605                     |
| PC9                 | 0.163       | 0.014      | 96.963                     |
| PC10                | 0.139       | 0.012      | 98.124                     |
| PC11                | 0.135       | 0.011      | 99.251                     |
| PC12                | 0.090       | 0.007      | 100.000                    |
Figure 7. The scree plot of the eigenvalues of the principal components.

Table 2. Weighting and correlation coefficient with the first two principal components.

| Biome                                           | Weighting Coefficient | Correlation |
|-------------------------------------------------|-----------------------|-------------|
|                                                 | CP1       | CP2      | CP1      | CP2      |
| Point 1 Amazon biome with burning                | 0.751     | −0.505   | 0.269    | −0.389   |
| Point 2 Amazon biome with burning                | 0.827     | −0.355   | 0.297    | −0.273   |
| Point 1 Amazon biome without burning             | 0.490     | −0.680   | 0.176    | −0.523   |
| Point 2 Amazon biome without burning             | 0.791     | −0.438   | 0.284    | −0.337   |
| Point 1 Cerrado with burnt biome                 | 0.888     | −0.055   | 0.318    | −0.043   |
| Point 2 Cerrado with burnt biome                 | 0.854     | 0.049    | 0.306    | 0.038    |
| Point 1 Cerrado biome without burning            | 0.839     | 0.069    | 0.301    | 0.053    |
| Point 2 Cerrado biome without burning            | 0.867     | −0.005   | 0.311    | −0.004   |
| Point 1 Pantanal biome with burnt                | 0.794     | 0.454    | 0.285    | 0.350    |
| Point 2 Pantanal biome with burnt                | 0.844     | 0.377    | 0.303    | 0.291    |
| Point 1 unburnt Pantanal biome                   | 0.807     | 0.366    | 0.290    | 0.282    |
| Point 2 unburnt Pantanal biome                   | 0.832     | 0.397    | 0.298    | 0.306    |

\[
CP1 = 0.751X1 + 0.0827X2 + 0.490X3 + 0.791X4 + 0.888X5 + 0.854X6 + 0.839X7 + 0.867X8 + 0.794X9 + 0.844X10 + 0.807X11 + 0.832X12
\]

\[
CP2 = -0.505X1 - 0.355X2 - 0.680X3 - 0.438X4 - 0.055X5 + 0.049X6 + 0.069X7 - 0.005X8 + 0.454X9 + 0.377X10 + 0.366X11 + 0.397X12
\]
Based on Equation (5) and data from Table 2, we can highlight in relation to the first main component (PC1) the values contained in the Cerrado biome that stood out the values X5, X8, and X6, however if we take and verify between the three biomes the which stood out in CP1 were the values X5, X10 and X2. In the analysis of Equation (6), in the second principal component (PC2), the contrast between X9 and X3 is evident.

Variables, when separated by biomes, have high correlations between them, as they form sharp angles between them, but, however, in the Amazon biome when we use the variable X1 between X2, X3 and X4 there may be no correlation because it forms an angle close to 90 degrees. We can highlight that when we analyze the variables between biomes there may not be a correlation because they form an angle near/equal/greater than 90 degrees, as shown in Figure 8.

A dispersion of values during the GPP time series as a function of the first major component, as it is the best indicator among all the points sampled in the analysis, in Figure 9 some relevant dates were indicated since in the total of 826 analyzed dates in each point. In the sample, we can highlight some dates such as 25/05/2018 that presented the largest dispersion and the one with the smallest dispersion was on 16/05/2016 during the entire time series of the study.

### 3.3. Effects of the fires on the gross primary productivity (GPP)

In order to verify the effect of burning on GPP (kg/C m$^2$), two representative points (P1 and P2) were selected for each biome in areas with burning and without burning. The
average annual values for each biome are shown in Figure 10. In the Amazon biome (Figure 10(a)), the years 2001 and 2016 were highlighted by presenting the smallest and the highest GPP peaks, respectively. For 2001 the averages were $3.299 \pm 0.323$ kg/C m$^2$ (P1) and $4.307 \pm 0.382$ kg/C m$^2$ (P2) in areas with presence of burn, while for areas without presence of burn the average values were of $5.722 \pm 0.446$ kg/C m$^2$ (P1) and $4.720 \pm 0.377$ kg/C m$^2$ (P2). In 2016, where the maximum GPP peak was observed for the period studied in the Amazon biome, the averages were $5.525 \pm 1.048$ kg/C m$^2$ (P1) and $6.884 \pm 1.677$ kg/C m$^2$ (P2) at the points with $9.902 \pm 1.711$ kg/C m$^2$ (P1) and $7.585 \pm 1.826$ kg/C m$^2$ (P2) at the points without burning.

In the Cerrado biome (Figure 10(b)) the maximum GPP peaks were observed in 2016 and 2018 and the lowest peak in 2001. The maximum GPP peak for the burned points was observed in 2018 with average values of $4.261 \pm 0.343$ kg/C m$^2$ (P1) and $3.834 \pm 0.345$ kg/C m$^2$ (P2), while in areas without presence of burnt the maximum peak was observed in 2016 to $4.097 \pm 0.854$ kg/C m$^2$ (P1) and 2018 to $5.481 \pm 0.390$ kg/C m$^2$ (P2). The lowest GPP peaks for burned areas were $1.859 \pm 0.210$ kg/C m$^2$ (P1) and $1.857 \pm 0.235$ kg/C m$^2$ (P2) and for non-burned areas of $1.962 \pm 0.233$ kg/C m$^2$ (P1) and $2.351 \pm 0.261$ kg/C m$^2$ (P2).

For the Pantanal biome (Figure 10(c)) the highest GPP peaks were observed in 2016 and 2018, as well as in the Cerrado. In the area with the presence of burning the average values were $4.574 \pm 1.130$ kg/C m$^2$ (P1) and $3.056 \pm 0.692$ kg/C m$^2$ (P2) in 2018 and $4.355 \pm 1.109$ kg/C m$^2$ (P1) and $6.914 \pm 1.573$ kg/C m$^2$ (P2) for areas without burning for 2016 and 2018, respectively. The lowest GPP peaks for the Pantanal were also observed in 2001, similar to other biomes. The mean values of GPP in 2001 for the area with burning presence in the Pantanal were $1.090 \pm 0.144$ kg/C m$^2$ (P1) $0.891 \pm 0.118$ kg/C m$^2$ (P2) and for the area without burning of $1.200 \pm 0.141$ kg/C m$^2$ (P1) and $2.301 \pm 0.210$ kg/C m$^2$ (P2).

According to Figure 10, the points without the presence of burning presented higher values of GPP for all studied biomes. In some points with the presence of burning the GPP
Figure 10. Annual average GPP for two points with fire and two without fire on the biomes in Mato Grosso state, Brazil: (a) Amazon biome, (b) Cerrado biome and (c) Pantanal biome.
even decreased by 44.20%, 30.04% and 55.78% for Amazonia, Cerrado, and Pantanal, respectively.

The impact of burning on GPP is basically due to the loss of plant biomass since after fire the affected plants decrease or even lose their ability to assimilate carbon through photosynthesis (Biswas et al., 2015; Rap et al., 2015). According to Li, Zhang, Yang, Ding, and Zhao (2018) burns significantly affect canopy structure and leaf area index, which ultimately causes changes in energy balance and forest evapotranspiration.

Change in forest structure has direct impacts on the regional and global carbon cycle (Chagas et al., 2019; Yang et al., 2018). Studies conducted in the Amazon indicate that increased fires in this biome will be more frequent during extreme droughts and this will affect the carbon sink capacity of the Amazon (Silva & Junior et al., 2019; Yang et al., 2018). Other studies also point to the decrease and uncertainties of forest carbon sink capacity following fires in some parts of the world (Dore et al., 2008; Yue et al., 2016). For example, in US pine forests carbon losses may persist for several years due to the slow recovery of gross primary production after fires (Dore et al., 2008).

Some research points to the ability of the Cerrado biome as a carbon sink (Morais et al., 2017; Pellegrini, Socolar, Elsen, & Giam, 2016). Interestingly, fires in the Cerrado biome may be beneficial to the biome, according to Pilon, Hoffmann, Abreu, and Durigan (2018) fire triggers important ecological processes in Cerrado grasslands, such as seed production and the genetic diversity of many species. However, it is noteworthy that this only applies to areas where the biome maintains its natural conditions, in degraded areas or where land use has changed in the Cerrado, the effect may be the opposite.

To evaluate the monthly variability of GPP (Figure 11), two years were chosen, one with a low burn rate (2009) and one with a high burn rate (2010) (Figure 3). In 2010 GPP values fell in all biomes from May to November at the points with burning. As for the monthly variability, in the Amazon biome (Figure 11(a)) the values of GPP have a fall between June to September, the Cerrado (Figure 11(b)) and the Pantanal (Figure 11(c)) have a fall between months. May and October.

Some studies highlight rainfall as one of the main factors responsible for GPP temporal variability (Kanniah, Beringer, & Hutley, 2013; Petrie et al., 2016). The work carried out by Delgado et al. (2018) with the objective of this study is to analyze seasonally the Gross Primary Production and compare with the meteorological variables in the Itatiaia National Park. These authors observed that between the rainy and dry seasons GPP presents changes in their values.

The months with the highest GPP values presented here (Figure 11) coincide with the state’s rainy season, according to Paiva Sobrinho et al. (2014). According to these authors, the state of Mato Grosso presents a significant spatiotemporal variability of rainfall throughout the state, with the highest precipitation averages between November and March.
Figure 11. Monthly average GPP for points with and without fire considering only the years 2009 (low fire cases) and 2010 (high fire cases) on the biomes in Mato Grosso state, Brazil: (a) Amazon biome, (b) Cerrado biome and (c) Pantanal biome.
4. Conclusions

Considering the studied period, the Cerrado biome presented more susceptibility in burning, taking into account the affected area in Km², this is mainly due to the savanna features of this biome. However, it is important to highlight that in second place was the Amazon Biome, where the causes that occur in the fires are other, such as drought years. The dynamics of the burns follow the intensity of the drought years since, in the driest years, higher values of the burned area were observed.

Our results highlight that burning has a negatively impacts on gross primary productivity (GPP) in all biomes in the state of Mato Grosso, Brazil. The results also suggest a standard GPP seasonality for the studied biomes. The years 2007 and 2010 stand out for presenting the highest values of the burned area. The dynamics of the burns follow the intensity of the drought years since, in the driest years, higher values of the burned area were observed.

The use of cluster analysis techniques, such as principal component analysis (PCA), is an alternative to bigdata analysis when the objective is to evaluate the presence of forest burning in more than one biome. In our case, PCA presented a good performance, wherewith the PCA it was possible to explain ≅ 80% of the variation of the analyzed data. It was also possible to distinguish areas with the presence of burned from areas without burned, thus reinforcing their use in studies involving rainforest fires in different biomes at the same time.

The state of Mato Grosso, has three different types of biomes, with a rich biodiversity of fauna and flora, with the presence of endemic species that need to be conserved, with chances of providing important ecosystem services for regional development. From the perspective of conservation of both the Amazon forest and the other biomes that make up the state of Mato Grosso, it’s important to understand the dynamics of burning in the state of Mato Grosso and its relationship with the carbon cycle, future studies should involve a wider range of variables, including analysis of how fire affects the vegetation canopy of the studied biomes. Besides that, we suggest the use of advanced machine learning algorithms for forest fire forecasting, this technology could be used to developing models that can predict the occurrence of fires. Studies such as these are important for decision-making in public environmental conservation policies.

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Data availability statement

Data generated at a central, large-scale facility. Raw data were generated at State University of Mato Grosso large-scale facility. Derived data supporting the findings of this study are available from the corresponding authors F.R.S and G.A.A.S on request.

Disclosure statement

No potential conflict of interest was reported by the authors.
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