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Research article

Long temporal trend and seasonal variation analysis of forest fires in Brazilian biomes: A stochastic approach

Tendencia de largo plazo y variación estacional de los incendios forestales en los biomas brasileños: Un enfoque estocástico

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Abstract

This study uses a Bayesian Structural Poisson model to address the increasing frequency of wildfires in Brazilian biomes. Long-term trends, seasonal behavior, and the impact of certain meteorological variables on the occurrence of forest fires were identified in the following biomes: Amazon, *Caatinga*, *Cerrado*, Atlantic Forest, *Pampa*, and *Pantanal*. Nonlinear temporal trends were observed in all biomes, with varying annual increments between 1999-2020: 5.5 % in *Pampa*, 4.9 % in *Pantanal*, 3.0 % in *Caatinga*, 2.3 % in Amazon, 2.2 % in Atlantic Forest, and 2.2 % in *Cerrado*. Seasonal patterns were present in all biomes, with similarities among the Amazon, *Caatinga*, *Cerrado*, and Atlantic Forest, while the *Pampa* and *Pantanal* displayed a bimodal pattern. Environmental factors such as evapotranspiration, precipitation, and temperature had significant effects on fire occurrence in different biomes. The findings of this study contribute valuable insights into fire patterns and their relationships with environmental factors in Brazilian biomes, helping to inform fire management and prevention strategies.

Keywords: Bayesian modeling, Brazilian biomes, long-term trends, Poisson model, stochastic variation, wildfires.

Resumen

Este estudio aborda la creciente frecuencia de los incendios forestales en los biomas brasileños; para ello, se utilizó un modelo Bayesiano Estructural de *Poisson*. Se identificaron las tendencias a largo plazo, el comportamiento estacional y el impacto de determinadas variables meteorológicas en la ocurrencia de incendios forestales en los siguientes biomas: Amazonía, *Caatinga*, Cerrado, Bosque Atlántico, Pampa y Pantanal. Se observaron tendencias temporales no lineales en todos los biomas, con incrementos anuales variables entre 1999-2020: 5.5 % en Pampa, Pantanal 4.9 %, Catinga 3.0 %, Amazonía 2.3 %, Bosque

Atlántico y Cerrado 2.2%. Los patrones estacionales estuvieron presentes en todos los biomas, con similitudes entre Amazonía, Catinga, Cerrado y Bosque Atlántico, mientras que la Pampa y el Pantanal mostraron un patrón bimodal. Factores ambientales como la evapotranspiración, las precipitaciones y la temperatura influyeron significativamente en el surgimiento de incendios en distintos biomas. Los resultados de este estudio aportan información valiosa sobre los patrones de incendios y su relación con los factores ambientales en los biomas brasileños, lo cual ayudará en el desarrollo de las estrategias de gestión y prevención de incendios.

Palabras clave: Modelado bayesiano, biomas brasileños, tendencias a largo plazo, modelo de *Poisson*, variación estocástica, incendios forestales.

Introduction

The frequency and extent of wildfires are increasing worldwide (Li *et al.*, 2020). Enhanced fire regimes result in more severe events that release a large amount of energy over vast areas in a short period, affecting both public and private lands (Li *et al.*, 2020; Schmidt and Eloy, 2020). These fires strongly impact ecosystem services, reduce water and soil quality, impoverish habitats and biodiversity, affect agricultural productivity and the carbon cycling, and the climate (Brando *et al.*, 2020; de Oliveira-Júnior *et al.*, 2020), thereby compromising the resilience of terrestrial ecosystems (Pellegrini *et al.*, 2021).

Wildfires also cause substantial economic losses by damaging infrastructure, agriculture, and forestry, compromising water resources and recreational activities (da Silva *et al.*, 2020). Additionally, air pollution from fires poses a serious health hazard (Tedim *et al.*, 2018).

Fires, particularly those that affect hundreds or thousands of hectares, are generally triggered by human activities (Cullen *et al.*, 2021). Usually, these fires ignite in agricultural or peri-urban regions, subsequently extending their reach into encompassing forests and shrublands. Thus, the proximity to agricultural land, roads, villages, and urban areas influences the occurrence of forest fires, particularly when the use of fire for managing agricultural areas is a cultural practice (Ganteaume *et al.*, 2013; de Oliveira *et al.*, 2019).

Brazil has the highest frequency of fires in South America (SA) (Li *et al.*, 2020). Among the Brazilian biomes, *Cerrado* is the only one whose ecosystems have evolved in association with fire (Schmidt and Eloy, 2020). However, historically, large fires have devastated wide areas not only in the *Cerrado* but also in the Amazon (Schmidt and Eloy, 2020) and the *Pantanal* biomes (Libonati *et al.*, 2020). These three biomes experienced significant fires during the dry seasons of 2019 and 2020: *Cerrado* had 127 693 forest fire ignitions, Amazon 320 036 forest fire ignitions, and *Pantanal* with 32 141 forest fire ignitions, although the dry seasons in the Amazon were not as exceptional as the droughts of 2005, 2010, and 2015 (Schmidt and Eloy, 2020; Carvalho *et al.*, 2022). In 2019, for the first time on record, smoke from forest fires in the Amazon reached *São Paulo*, the largest city in SA, due to the burning of more than 2.7 thousand kilometers Southeast of the burned regions. In 2020, one-third of the *Pantanal* biome was burned (Libonati *et al.*, 2020; Oliveira *et al.*, 2022).

To date, the studies conducted within the Brazilian biomes have taken various approaches, including descriptive utilizing remote sensing products (Moreira *et al.*, 2012; de Oliveira-Júnior *et al.*, 2020), inferential modeling with Generalized Extreme Values (GEV) distributions (Carvalho *et al.*, 2022), as well as the application of machine learning techniques and non-parametric analyses based on IPCC projections (da Silva *et al.*, 2020). However, it is noteworthy that none of the reviewed studies have delved into the analysis of fire data from the perspective of the Structural Poisson Model, which encompasses elements such as level, latent trend, seasonality, and stochastic terms. This model framework posits that wildfire counts within the same region over time exhibit correlated patterns.

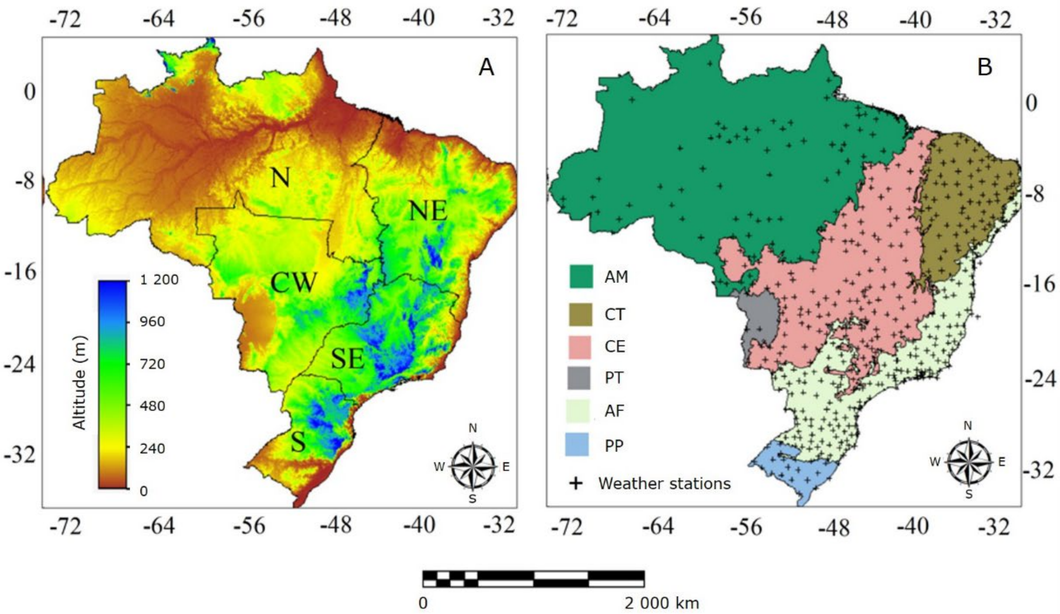
The level component accounts for the effects of environmental covariates in the natural logarithm of expected fires. Trend identification assists in comprehending whether the number of hotspots is increasing, decreasing, or remaining stable over time. This information can have significant implications for fire management and policy. The seasonality component provides valuable insights for fire preparedness and resource allocation, enabling the prediction of periods with higher or lower fire risk based on historical patterns. Finally, the stochastic or error term includes everything not accounted by the other terms including random fluctuations.

The goal of this work is to comprehend the long-term trend and seasonal behavior of the time series corresponding to wildfire records in Brazil's biomes, as well as to estimate the effect of certain meteorological variables that potentially could increase or decrease the associated wildfire risk.

Material and Methods

Study Area

This study covered the entire Brazilian territory, spaning 8.52 million km^2. We focused on the analysis of six Brazilian biomes: Amazon, *Caatinga*, *Cerrado*, Atlantic Forest, *Pampa*, and *Pantanal* (Figure 1).



A = Brazilian geographic regions; B = Terrestrial biomes (AM = Amazon; CT = *Caatinga*; CE = *Cerrado*; PT = *Pantanal*; AF = Atlantic Forest; PP = *Pampa*) according to the official Brazilian classification and meteorological stations locations (Teixeira *et al.*, 2023).

Figure 1. Distribution of the Brazilian biomes described in this study and the elevation model across the territory.

Brazilian biomes

The Amazon biome is the largest in Brazil, occupying about 49.3 % of the national territory (IBGE, 2004). It experiences significant expansion in the Northern region and is characterized by vast, towering forests, making it the largest tropical timber reserve globally (da Silva *et al.*, 2020). Additionally, the Amazon hydrographic basin is noteworthy, with the Amazon River being the largest in the world, flowing through a network of 1 100 tributaries and covering approximately six million km^2 (MMA, 2022).

The *Cerrado* biome, the second largest in South America, occupies approximately 22 % of the national territory. It can be found in the North, Northeast, Southeast, and Midwest regions of Brazil (MMA, 2022). The *Cerrado* comprises various physiognomies, including *Campo Limpo*, *Campo Sujo*, *Campo Rupestre*, *Cerradão*, *Matas Secas*, *Ciliares e Galeria*, and *Veredas* (da Silva *et al.*, 2020).

The *Caatinga* biome covers around 11 % of the national territory. It extends across a significant portion of the Northeast Brazil region and a smaller portion in the North of Southeast Brazil (da Silva *et al.*, 2020; MMA, 2022). The vegetation in this biome thrives in environments with limited water availability, resulting in aridity for seven to nine months, between June and December.

The Atlantic Forest stretches along the majority of the Atlantic coastal strip in Brazil. It occupies 15 % of the national territory and currently retains only about 29 % of its original coverage. The Atlantic Forest is composed of Dense Ombrófila Forest, Mixed Anthropophilic Forest, Open Ombrófila Forest, Semidecidual Seasonal Forest, as well as associated ecosystems such as mangroves, *restinga* vegetation, altitude fields, inland swamps, and forest enclaves in the Northeast (da Silva *et al.*, 2020; MMA, 2022).

The *Pampa* biome, characterized by temperate zone fields, is situated in the Southern region of Brazil, confined to the state of *Rio Grande do Sul*. It covers an area equivalent to 2.1 % of the national territory (da Silva *et al.*, 2020).

The *Pantanal*, although the smallest biome in Brazil, is considered one of the largest continuous wetlands on the planet. It occupies 1.8 % of the national territory (da Silva *et al.*, 2020). This biome is directly influenced by three significant Brazilian biomes: the Amazon, *Cerrado*, and Atlantic Forest. The Amazon Basin contributes significantly to the *Pantanal's* annual rainfall, making it a vast wetland. Many rivers that flow into the *Pantanal* originate in the *Cerrado*, bringing sediment and nutrients crucial for the *Pantanal's* ecosystem.

Lastly, the Atlantic Forest, a lush biome along Brazil's coast, influences the *Pantanal's* biodiversity. Bird species, in particular, migrate between these two regions, enriching the *Pantanal's* avian diversity during certain seasons (Batista *et al.*, 2017). As an alluvial plain, it is also impacted by rivers draining the Upper *Paraguay* basin and the *Chaco* biome (which refers to the *Pantanal* located in Northern *Paraguay* and Eastern *Bolivia*) (de Oliveira-Júnior *et al.*, 2020).

Data

In this study, we analyzed meteorological variables extracted from the meteorological database of the National Institute of Meteorology (Inmet, www.inmet.gov.br) covering the period between 1999 and 2020 (Figure 1B). Fire data was obtained from the National Institute of Space Research (INPE, 2021), specifically the Imaging Division (DGI), which collects and processes satellite images from NOAA-12 and NASA AQUA satellites. The images are captured by AVHRR and MODIS sensors.

Bayesian Structural Poisson model

We fitted to data a Structural Poisson model used in similar studies (Villar-Hernández *et al.*, 2022). The variable Y_t that represents the number of fires at a given time (t) (month) for a specific biome, can take values Y_t=0,1,2,…, and so on. The exogenous variables in our analysis were the following meteorological variables: maximum (*Tmax*; °C) and minimum (*Tmin*; °C) monthly temperature, average monthly wind speed (*WS*; m s^{-1}), monthly precipitation (*PP*; mm), average monthly vapor pressure (*VP*; hPa), and monthly evaportranspiration (ET_0; mm).

The following two equations form the foundation of our modeling approach:

$$Y_t|\lambda_t \sim Po(\lambda_t), t = 1,2,..., \quad (1)$$

$$ln(\lambda_t) = x_t^T\beta + m_t + s_t + u_t \quad (2)$$

Where:

Y_t = Number of fires at a given time (t)

λ_t = Expected number of fire focis at time t

Po = Poisson distribution

x_t^T = Vector of standardized environmental covariates

β = Vector of regression coefficients

Model formulation in Equation 2 consists of four parts: $x_t^T\beta$ represent the contribution of environmental variables into the natural logarithm of expected fires spots, m_t represents the latent trend (long-term variation), s_t representing the seasonal variation, and u_t represents the stochastic term.

The latent trend helps analysts and researchers understand whether the data is increasing, decreasing, or following a specific trajectory over time. Seasonal variation refers to the recurring patterns or fluctuations in the data that follow a regular, predictable cycle. The stochastic term represents the random or unpredictable component of the time series data. It includes noise, irregular fluctuations, or unexpected events that cannot be attributed to environmental variables, trends, or seasonality (Harvey and Koopman, 2014).

We fitted the aforementioned model from a Bayesian perspective using the Integrated Nested Laplace Approximation (INLA) methodology (Rue *et al.*, 2009) implemented in the R programming language (R Core Team, 2022). The specific details of each component of Equation 2, priors and hyperpriors used, and example code can be consulted at https://github.com/bjesusvh/LTTSVABrazil.git.

Results and Discussion

Fires in Brazilian Biomes

The Amazon and *Cerrado* biomes in Brazil exhibited the highest number of fire hotspots throughout the analyzed time period, with more than 100 000 hotspots recorded in some months almost every year (Figure 2). The *Pantanal*, *Caatinga*, Atlantic Forest, and *Pampa* biomes also experienced higher hotspot values (>60 000), particularly in 2019 and 2020.

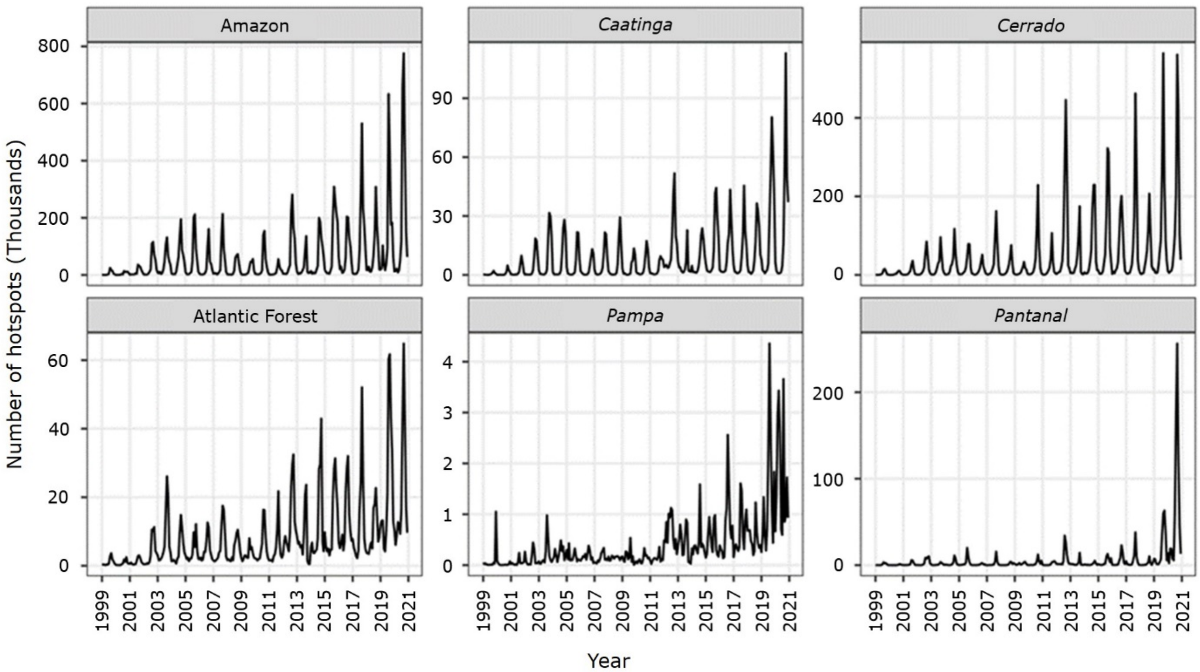


Figure 2. Number of monthly fire spots in the biomes of Brazil (period 1999-2021).

The fire hotspots recorded in 2019 and 2020 coincide with specific phases of the *El Niño*-Southern Oscillation climate variability mode (ENSO), which significantly impacts rainfall, temperature, and humidity patterns. These climatic influences, along with their subsequent effects such as dry spells and severe drought, vary across regions and contribute to the intensification of fires in Brazil's biomes (de Oliveira-Júnior *et al.*, 2020; Carvalho *et al.*, 2022). Ecosystems like the *Cerrado* are prone to fires due to dry conditions, fire-adapted vegetation, and human activity, while wetlands like the *Pantanal* are less susceptible due to moist conditions, dense vegetation, and limited human impact. Fire adaptation and management practices also influence susceptibility (Pereira *et al.*, 2014).

Effects of meteorological variables

The meteorological variables statistically related to fire outbreaks are monthly precipitation, monthly evapotranspiration, maximum and minimum monthly temperature, and vapor pressure (Table 1) indicated by the 95 % Highest Posterior Density Interval (*HPDI*) not containing the zero. Positive values indicate an increase in the logarithm of the mean of fire outbreaks, while negative values indicate a decrease. For instance, precipitation exhibits a Regression coefficient of -0.11, with a 95 % credible interval ranging from -0.2 to -0.02. To interpret the coefficient more intuitively, we take the exponential: *exp*(-0.11) equals 0.89. This implies that for everyone standardized unit increase in precipitation, the Amazon biome experiences an 11 % reduction in the risk of wildfire occurrence, calculated as $(1 - 0.89) \times 100$, while keeping all other variables constant. Similar interpretations apply to the other coefficients.

Table 1. Summary statistics for regression coefficients associated with statistically significant (95 % probability) variables in each biome.

Biome	Environmental variable	Coefficient	95 % *HPDI* interval	*Exp* (Coefficient)
Amazon*	*PP*	-0.11	[-0.2, -0.02]	0.90
Amazon*	*ETo*	0.38	[0.16, 0.6]	1.46
Caatinga+	*ETo*	0.31	[0.01, 0.6]	1.36
Caatinga+	*VP*	0.21	[0.02, 0.4]	1.24
*Cerrado***	*ETo*	0.37	[0.26, 0.48]	1.45
Atlantic Forest*	*ETo*	0.28	[0.01, 0.56]	1.33
Atlantic Forest*	*Tmax*	0.39	[0.02, 0.76]	1.48
*Pampa***	*PP*	-0.16	[-0.24, -0.07]	0.85
*Pampa***	*VP*	-1.17	[-1.9, -0.45]	0.31
*Pampa***	*Tmax*	1.33	[0.69, 1.98]	3.78
*Pantanal***	*PP*	-0.27	[-0.44, -0.11]	0.76
*Pantanal***	*ETo*	0.46	[0.22, 0.7]	1.58
*Pantanal***	*Tmax*	0.68	[0.08, 1.28]	1.98
*Pantanal***	*Tmin*	-1.06	[-2.04, -0.08]	0.35

*Fire sensitive; **Fire dependent; +Fire independent.

Monthly evapotranspiration exhibited a statistically significant positive effect in five out of the six biomes (excluding the *Pampa* biome); while precipitation had statistically significant negative effects in the Amazon, *Pampa*, and *Pantanal* biomes. Maximum monthly temperature had positive effects in Atlantic Forest, *Pampa*, and *Pantanal* biomes; vapor pressure had a positive effect in the *Caatinga* biome and a negative effect in the *Pampa* biome, and *Tmin* had a positive effect only in the *Pantanal* biome.

Singh and Zhu (2021) highlight that in the Amazon, a decrease in precipitation and an increase in temperature strongly impact fire dynamics, with this impact being much more significant in years with the presence of *El Niño*. In the case of biomes located in Southern Brazil, there is also evidence of the correlation between lower precipitation and vapor pressure and a higher incidence of forest fires (de Andrade *et al.*, 2020). Another crucial variable is evapotranspiration; as it increases, it implies greater water loss from vegetative cover, leading to an increase in fuel that facilitates fire ignition and propagation. The only inconsistent sign is observed for the coefficient associated with vapor pressure in the *Caatinga* biome, but this might be due to its effect being masked by evapotranspiration.

Long-term trends

Our model suggested that the latent trends in the six biomes exhibit nonlinear increments over time (Figure 3). The annual average increments in the long-term (period 1999-2020) were as follows: 5.5 % for *Pampa*, 4.9 % for *Pantanal*, 3.0 % for *Caatinga*, 2.3 % for Amazon, 2.2 % for Atlantic Forest, and 2.2 % for *Cerrado*.

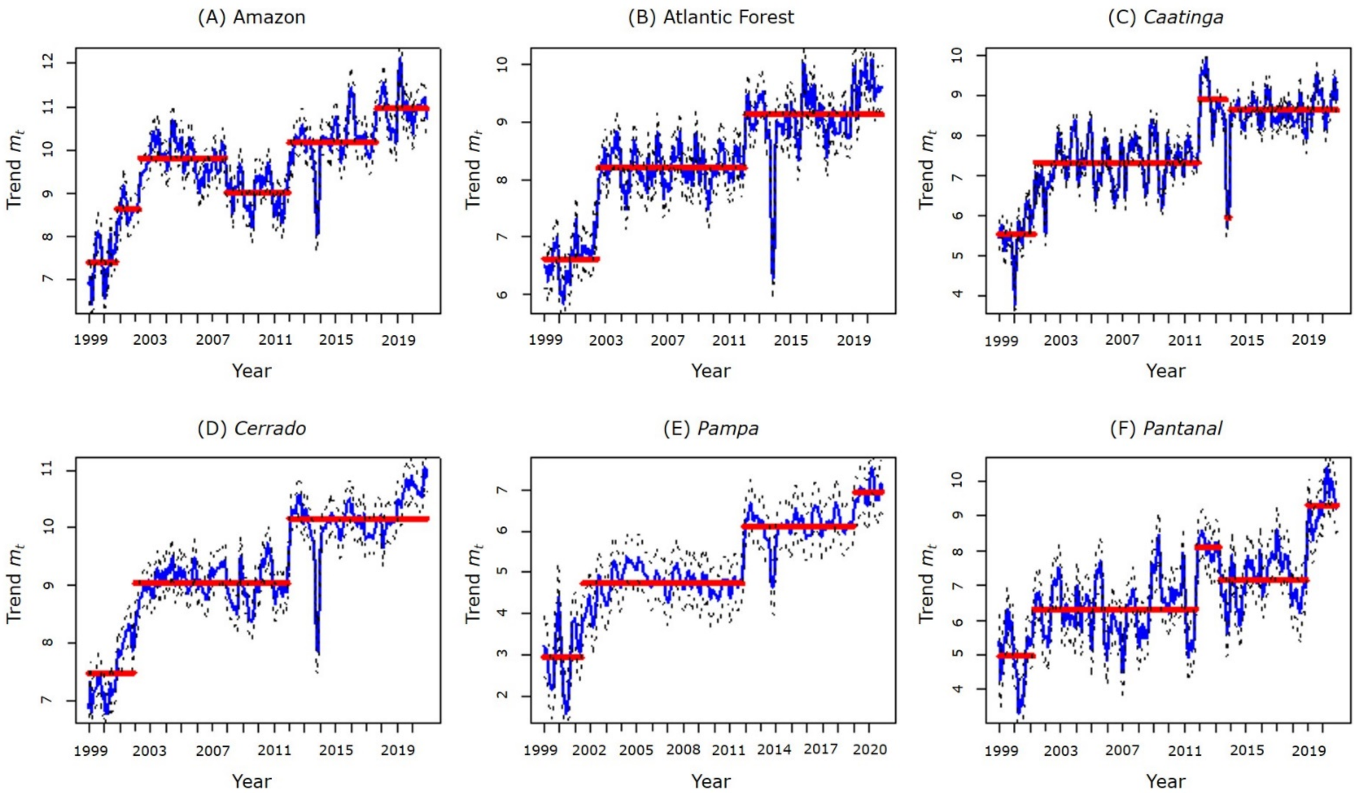


Figure 3. Posterior mean of the latent trend (m_t; blue), its 95 % Highest Posterior Density Interval (*HPDI*, dotted lines), and time periods (red lines) with similar trends based on breakpoints for the six biomes in Brazil.

According to ecological role that fires plays in Brazilian ecosystems, biomes can be classified into fire-sensitive, fire-dependent, and fire-independent. Fire-dependent biomes are coevolved with fire and are characterized by ecosystems dominated by grasses-grasslands and savannas. Conversely, fire-sensitive biomes are not adapted to fire, and not easily burn. When these forest do burn, fire can cause severe impacts, as is the case with tropical forests. Finally, in fire-independent biomes, fire is not an essential feature of their functioning (Pivello *et al.*, 2021).

The Amazon (fire-sensitive biome) exhibits six periods of relative homogeneity in long-term trends. The final period extends from August 2018 to December 2020. The difference in average trend (per period) between the last and the first was 48 %. When conducting the same analysis for the other biomes, we observe that the Atlantic Forest (fire-sensitive) and *Cerrado* (fire-dependent) have three periods. For both biomes, the latest of these begins in 2011 and extends to December 2020, with differences of 37 and 36 %, respectively, between the first and last periods. *Pampa* (fire-dependent) and *Caatinga* (fire-independent) share similarities, each displaying four periods in the trend. The difference between the last and the first period were 137 and 53 %, respectively. Finally, *Pantanal* (fire-dependent) exhibits four breakpoints, generating five periods in the long-term trend, with the last period spanning from late 2018 to the end of the study series, featuring an 86 % difference compared to the first period.

In general, all biomes experienced substantial increases in long-term trends from 1999-2004. Following this, the trend stabilized due to efforts made by the Brazilian government to combat deforestation (Pivello *et al.*, 2021). Even in the Amazon and the *Pampa*, the trend decreased for a decade. However, by 2014, a new period of significant increases began, reaching new highs in 2020 by combination of dry weather, human activities and lack of adequate environmental policies and surveillance (Pivello *et al.*, 2021).

The substantial increases in the long-term trend inferred by the model are complemented by previous research from a distinct inferential perspective. For example, Carvalho *et al.* (2022) found that there is a strong correlation between fire occurrences and agricultural activities, especially in *Cerrado*, *Pantanal*, and Atlantic Forest biomes. This leads us to suggest that antropogenic effects play a key role in the increase of the long temporal trend in these biomes. This is inline with Franco *et al.*

(2020) that suggest that 50 % of the original *Cerrado* has been converted for other purposes.

The scenario is grim for the *Pantanal* biome; our work and other studies (Pivello *et al.*, 2021; Marengo *et al.*, 2022) indicates a recent increase in the number and extension of fires, leading to significant vegetation loss and fauna impacts. According to de Magalhães and Evangelista (2022), human activities near roads and waterways triggered fire events, while a dryer climate episode provided conditions for the fire to spread in this biome.

Despite the fact that some biomes have evolved such that the biodiversity within them has developed fire-dependent adaptation mechanisms, the increasing levels in the long-term temporal trend are alarming. If this trend continues to rise in the coming years, the impacts on biodiversity, ecosystems, and human health will continue to worsen.

Seasonal variation

The seasonal patterns are provided for the log expected fire outbreaks and the 95 % Highest Posterior Density Interval (*HPDI*) captured by the Poisson model (Figure 4). According to da Silva *et al.* (2020), there is a similarity in the seasonal component between the Amazon and *Cerrado* biomes. However, this study also observes that the *Caatinga* and Atlantic Forest biomes exhibit similar seasonal patterns to those of the Amazon and *Cerrado*. The majority of fire hotspots throughout the year for the Amazon are concentrated from August to October, accounting for 61 % of the total, being September with the highest incidence. For the *Caatinga* biome, the period of peak incidence (amplitude) extends from September to November, constituting 68 %, with the highest peak occurring in October.

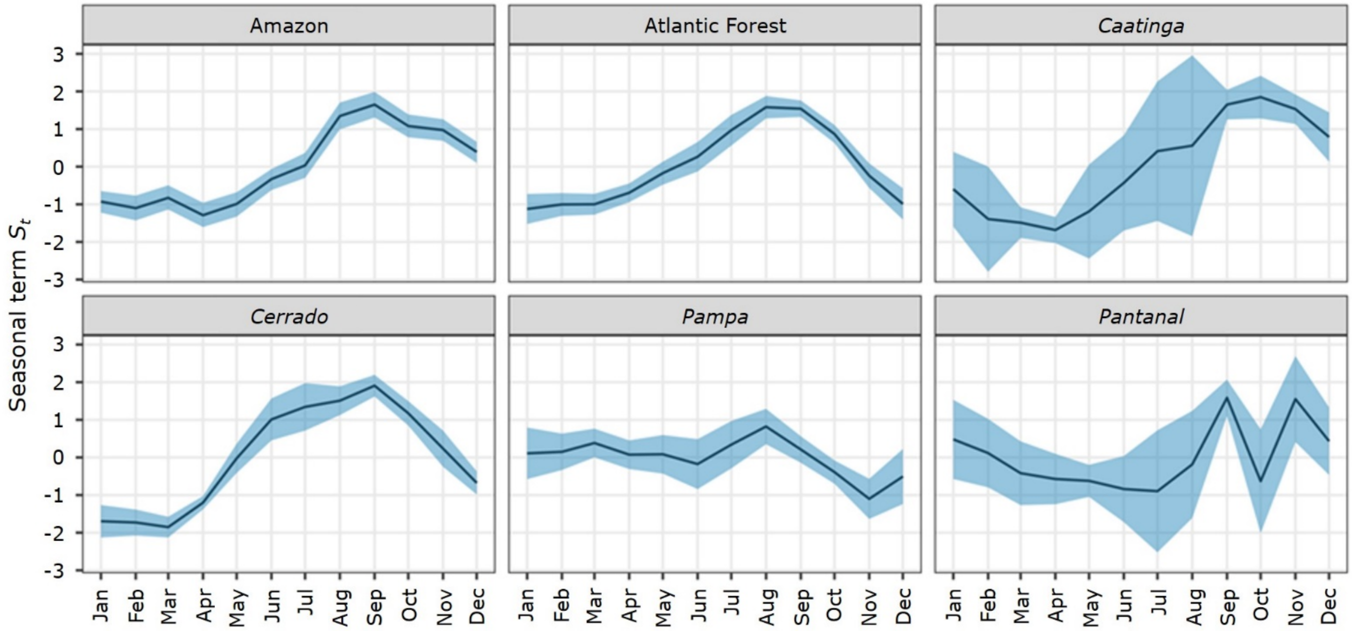


Figure 4. Posterior mean of the seasonal component (S_t; black solid line) and its 95 % Highest Posterior Density Interval (*HPDI*; blue shade) for the six biomes in Brazil.

In the *Cerrado* biome, the period spans from July to October, comprising 74 %, with the peak in September. In the Atlantic Forest, the period is from July to October, making up 75 %, with the peak in August. On the other hand, the *Pampa* and *Pantanal* biomes showcase distinct seasonal patterns. The *Pampa* experiences a period from July to September, contributing to 37 %, with the peak occurring in August. Lastly, for the *Pantanal*, the period extends from August to December, accounting for 70 %, featuring two peaks in September and November. The first peak is driven by reduced rainfall and natural and human factors. The second peak, coincides with the driest vegetation conditions, mainly due to human activities like land clearing. Broadly speaking, peaks in all biomes occurred at the end of the dry season, just before the onset of the rainy season. Seasonality of forest fires accros biomes is influenced by the Intertropical Convengence Zone that migrate seasonally following the sun, and its position influences the onset and cessation of the rainy season in Brazil.

The uncertainty associated with seasonal patterns captured by the *HPDI* (Figure 4) is higher in *Caatinga* and *Pantanal* compared with the rest of the biomes. The cause of this uncertainty would be linked to the natural conditions under which these biomes have evolved or if it is attributed to anthropogenic effects or climate change.

Finally, it is important to note that high-amplitude seasons lead to intense fires with severe ecological, economic, and human risks, requiring extensive resources. In contrast, low amplitude seasons result in milder, more manageable fires, benefiting ecosystems and reducing the threat to communities. The period from August to November need the greather attention on from the public authorities regarding the implementation of prevention and control fire programs, as emphasized by Lopes *et al.* (2020).

Conclusions

Among the Brazilian biomes, the Amazon and *Cerrado* consistently harbor the highest number of fire hotspots in Brazil, often exceeding 100 000 annually. These hotspots coincide with specific phases of the *El Niño*-Southern Oscillation (ENSO).

Some meteorological variables are statistically related to fire outbreaks. When precipitation increases by one standardized unit, the risk of wildfires decreases by 11 % in the Amazon biome (a fire-sensitive biome). Evapotranspiration increases the risk by 33 % when it increases by one unit in the Atlantic Forest biome (also fire-sensitive), and maximum temperature increases the risk of wildfires by 48 % when it increases by one unit in the same biome.

In future research, it will be crucial to assess the potential impact on the expected number of forest fires under adverse scenarios of climate change, such as temperature and evapotranspiration increases, as well as precipitation decreases, based on projections from the Intergovernmental Panel on Climate Change for the Brazilian regions.

The analysis of long-term trends reveals nonlinear increases in fire occurrences across all biomes, with annual average increments ranging from 2.2 to 5.5 % over the period from 1999 to 2020. Notably, the Amazon, Atlantic Forest, and *Cerrado* biomes have experienced periods of relative stability followed by significant increases in recent years.

Amazon, Atlantic Forest, and *Cerrado* biomes exhibit distinct periods in long-term fire trends, with significant differences between first and last periods. Amazon saw a 48 % difference, while Atlantic Forest and *Cerrado* experienced differences of 37 and 36 %, respectively. Other biomes like *Pampa* and *Caatinga* also show varied trends, with differences of 137 and 53 %. *Pantanal* displays notable breakpoints, with an 86 % difference compared to first period.

The Amazon, *Cerrado*, *Caatinga*, and Atlantic Forest biomes exhibit similar seasonal patterns, with peak incidences typically occurring at the end of the dry season. In these biomes, more than 60 % of fire hotspots are concentrated from July to October. The *Pampa* biome does not exhibit a remarkable seasonal pattern, while in the *Pantanal* biome, two peaks occur in September and November, coinciding with reduced rainfall and dry vegetation conditions.

These findings highlight multifaceted wildfire dynamics in Brazilian biomes, emphasizing integrated management. Leveraging evidence and proactive measures can mitigate impacts and promote resilience. Future research should employ space-time modeling for identifying high-incidence zones and delineating protected areas.

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Conflict of interests

The authors declare that they have no conflict of interest.

Contribution by author

Bartolo de Jesús Villar-Hernández: original idea, coding and fitting the statistical model; Paulino Pérez-Rodríguez: revision of the fitted statistical model; Amaury de Souza: accessing and cleaning datasets. All authors wrote, discussed, and revised the manuscript.

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