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TRACING THE ASHES: UNCOVERING BURNED AREA PATTERNS AND DRIVERS OVER THE BRAZILIAN BIOMES

Maria Lucia Ferreira Barbosa

Doctorate Thesis of the Graduate Course in Remote Sensing, guided by Dr. Liana Oighenstein Anderson, approved in April 02, 2024.

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“The role of the scientist is not to decide between the possibilities but to determine what the possibilities are”.

Lord May, 1990

To Jamile Lessa Ferreira, who always fought for a better education for me.

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ABSTRACT

Year after year fires bring several negative consequences to the environment, society and economy worldwide. Despite advancements in understanding fire dynamics, limitations persist, especially considering the ongoing land use transformations and advancement of climate change. In this sense, remote sensing data and modeling techniques offer valuable tools to monitor and better comprehend fires. The primary goal of this thesis is to analyze the spatiotemporal factors influencing burned area over the Brazilian biomes using remote sensing data and by integrating Bayesian inference and the maximum entropy modeling techniques. The methods were divided into three parts: (1) modeling of uncertainties related to drivers of burning in three categories: all fires (ALL), fires reaching natural vegetation (NAT), and fires in non-natural vegetation (NON) (Chapter 4); (2) identifying the drivers and climate and land conditions associated with increased burning (Chapter 5); and (3) analysis of extreme fires according to climate and land use and land cover (LULC) variables (Chapter 6). First, we developed and evaluated a probabilistic model combining the concepts of Bayesian inference and the Maximum Entropy. The model was applied using remote sensing and historical meteorological and land surface model data from 2002 to 2009 (training phase) and 2010 to 2019 (validation phase). Then, we applied changes in the variables to estimate the spatial variability of controls of burning. Secondly, we optimized a new model with targeted variables and estimated the potential climate and land cover thresholds associated with burning. Moreover, we applied a linear regression model to time series data from 2002 to 2020 to find potential trends in the variables. Finally, we calculated climate and burned area anomalies and the patterns of burning within LULC data and land tenure to evaluate the compound effect of these variables in extreme fires. Our findings indicate that climate is the primary control of burned area across most regions within each biome for the three categories. For NAT, regions with high forest cover in the Amazonia are up to three times less sensitive to variations in climate. Natural lands in Cerrado are more sensitive to fragmentation. Wetland cover below 20% combined with precipitation below 70mm leads to high burning in Pantanal. Moreover, exceptional climate combined with human activities can lead to catastrophic burning. We conclude that the novel method developed as part of this thesis is robust and that despite the importance of climate to fires, the ignition by anthropogenic sources and human changes to the landscape is key. Therefore, the focus on land use regulation is critical to mitigate or prevent future fires.

Keywords: Remote sensing. Bayesian inference. Maximum Entropy. Burned area. Climate change. Wetlands. Natural vegetation.

RASTREANDO AS CINZAS: DESCOBRINDO PADRÕES E FATORES DETERMINANTES DE ÁREAS QUEIMADAS NOS BIOMAS BRASILEIROS

RESUMO

Ano após ano os incêndios trazem diversas consequências negativas ao meio ambiente, à sociedade e à economia em todo o mundo. Apesar dos avanços na compreensão da dinâmica do fogo, limitações persistem, especialmente considerando as transformações em curso no uso da terra e o avanço das mudanças climáticas. Nesse sentido, dados de sensoriamento remoto e técnicas de modelagem oferecem ferramentas valiosas para monitorar e compreender melhor os incêndios. O objetivo principal desta tese é analisar os fatores espaço-temporais que influenciam as áreas queimadas nos biomas brasileiros usando dados de sensoriamento remoto e integrando inferência Bayesiana e o conceito de Máxima Entropia. Os métodos foram divididos em três partes: (1) modelagem de incertezas relacionadas aos fatores determinantes de área queimada em três categorias: o dado de fogo completo (ALL), fogo que atinge a vegetação natural (NAT) e fogo em vegetação não natural (NON) (Capítulo 4); (2) identificação dos fatores e as condições climáticas e terrestres associadas ao aumento do fogo (Capítulo 5); e (3) análise de incêndios extremos de acordo com variáveis climáticas e de uso e cobertura da terra (LULC) (Capítulo 6). Primeiramente, desenvolvemos e avaliamos um modelo probabilístico combinando os conceitos de inferência Bayesiana e de Máxima Entropia. O modelo foi aplicado usando sensoriamento remoto e dados históricos meteorológicos e de modelos de superfície terrestre de 2002 a 2009 (fase de treinamento) e 2010 a 2019 (fase de validação). Em seguida, aplicamos alterações nas variáveis para estimar a variabilidade espacial dos fatores determinantes do fogo. Em segundo lugar, um novo modelo com variáveis específicas foi optimizado e os potenciais limiares climáticos e de cobertura do solo associados ao fogo foi estimado. Além disso, aplicamos um modelo de regressão linear a dados de séries temporais de 2002 a 2020 para encontrar tendências potenciais nas variáveis. Finalmente, calculamos as anomalias climáticas e de área queimada e os padrões de queimadas nos dados de uso e ocupação da terra e posse da terra para avaliar o efeito composto dessas variáveis em fogo extremo. Nossas descobertas indicam que o clima é o principal fator determinante da área queimada na maioria das regiões de cada bioma para as três categorias. Para o NAT, regiões com alta cobertura florestal na Amazônia são até três vezes menos sensíveis às variações climáticas. As terras naturais do Cerrado são mais sensíveis à fragmentação. Cobertura de áreas úmidas abaixo de 20% combinada com precipitação abaixo de 70 mm leva a aumento do fogo no Pantanal. Além disso, o clima excepcional combinado com as atividades humanas pode levar a um fogo catastróficas. Concluímos que o novo método desenvolvido como parte desta tese é robusto e que, apesar da importância do clima para os incêndios, a ignição por fontes antropogênicas e as alterações humanas na paisagem são fundamentais. Portanto, o foco na regulamentação do uso da terra é fundamental para mitigar ou prevenir fogo futuro.

Palavras-chave: Sensoriamento remoto. Inferência bayesiana. Máxima entropia. Área queimada. Mudanças Climáticas. Zonas úmidas. Vegetação natural.

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LIST OF ACRONYMS AND ABBREVIATIONS

AGB	aboveground biomass
ALL	All fires
AMO	Atlantic Multi-decadal Oscilation
C	Carbon
FLAME	Fire Landscape Analysis using Maximum Entropy
ENSO	El Niño Southern Oscillation
EWS	Fire Early Warning System
FUNAI	National Indian Foundation
GRIP	Global Roads Inventory Project
HYDE	History Database of the Global Environment
ILs	Indigenous Lands
ISIMIP	Inter-Sectoral Impact Model Intercomparison Project
JULES	Joint UK Land Environment Simulator Earth System
LIS	Lightning Imaging Sensor
LULC	Land use and land cover
MaxEnt	Maximum Entropy species distribution model
MEI	Multivariate ENSO Index
MMA	Brazilian Ministry of Environment
NAT	Fires reaching natural vegetation
NON	Fires reaching non-natural vegetation
NP	Number of patches
ONI	Oceanic Niño Index
OTD	Optical Transient Detector

PDO	Pacific Decadal Oscillation
PAs	Protected Areas
RPs	Rural Properties
SST	Sea Surface Temperature
TNA	Tropical Atlantic Ocean
TRRM	Tropical Rainfall Measuring Mission

SUMMARY

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1 INTRODUCTION

Fire regimes, the frequency, intensity, and extent, are transforming across the globe (ROGERS et al., 2020). While the global burned area is decreasing, a critical shift is occurring. Regions historically not evolved with fires, such as the Amazon rainforest, are experiencing increased burning (SILVEIRA et al., 2022). Satellite data reveals a decline in burned grasslands, while forested areas witness a concerning rise (ZHENG et al., 2021). Forests are more potent carbon emitters per unit area burned compared to grasslands. Additionally, forest recovery after fire tends to be slower and often incomplete, with some areas succumbing to degradation or deforestation, further hindering their ability to recapture carbon dioxide. Thus, accelerating climate change and increasing extreme fire events along with their negative impacts. UNEP et al. (2022), projected an increase in extreme wildfires, with estimates ranging from 9-14% by 2030 and 31-57% by 2100.

This shift is driven by a complex interplay of factors, including a changing climate with more extreme weather events, land-use changes, human population growth, and altered vegetation distributions (JONES et al., 2022). Several studies have focused on investigating drivers of fires, continually building important knowledge on the subject (FONSECA et al., 2019; LIBONATI et al., 2021; FERREIRA et al., 2023). Nevertheless, fires are inherently stochastic and the mechanisms controlling burning are fraught with uncertainties. In this sense, remote sensing is key in advancing our comprehension of these processes. It provides high-resolution and near real-time data crucial for monitoring and evaluating past events, facilitating the discernment of local patterns. Remote sensing also bridges gaps in the availability of in situ data, which is often challenging to obtain (HERNANDEZ-LEAL et al., 2008; XOFIS et al., 2020). However, remote sensing alone cannot unpick the correlated, interacting, and highly complex relationships between drivers and fire.

Fire modeling has been increasingly used to represent this complexity, understand the drivers of fires and to project future fire changes (FONSECA et al., 2017; UNEP et al., 2022; BURTON et al., 2023). Simulating burning scenarios and their relation with different drivers allows the analysis of historical fire events and the early identification of changing patterns. However, understanding and modeling fires has proven an extremely challenging task. This is particularly true when considering large and complex territories such as Brazil, where models tend to have biases in simulated fire and disagree on the main drivers (KLOSTER; LASSLOP 2017; FORKEL et al., 2017; HANTSON et al., 2020). To be able to better understand fire, we need to combine remotely sensed observations and modeling techniques, either using observations as inputs, for validating models or formally fused with data-driven models with advanced statistics (FONSECA et al., 2019; FORKEL et al., 2016; KELLEY et al., 2019).

In this context, Bayesian inference is a flexible method that integrates prior information about a phenomenon while effectively quantifying the uncertainties inherent in its estimations by modeling probability distributions (VAN DE SHOOT et al., 2021). This prior knowledge is typically derived from historical data, expert insights, or previous experiments. However, given the unpredictability nature of fires, integration of too many assumptions may not be ideal. In this regard, the Maximum Entropy concept emerges as a valuable tool that reconciles the need for prior knowledge with the minimization of assumptions. Maximum Entropy ensures that the model maintains a balance between incorporating existing information and maximizing the entropy or randomness of the distribution. Such tools provide new opportunities to answer complex fire-related questions from local to regional scales. Even though these techniques have been applied to fires individually (KELLEY et al., 2020; FERREIRA et al., 2023), the combination of these two approaches have not yet been tested.

Therefore, the main objective of this study is to analyze the spatiotemporal factors influencing burned area over the Brazilian biomes using remote sensing data and by integrating Bayesian inference and the Maximum Entropy modeling techniques.

The specific objectives (SO) of this research are to:

SO.1 Develop and evaluate a Maximum Entropy-based model to simulate burned area patterns across Brazilian biomes;

SO.2 Estimate the spatial uncertainties of burned area response in the Brazilian biomes to key drivers using the developed model;

SO.3 Generate simulations depicting changes in variables and assessing their impact on burned area in the biomes;

SO.4 Identify critical thresholds of climate and land cover associated with increased burning in the Pantanal;

SO.5 Evaluate the influence of climate conditions and land use and land cover variables on the occurrence of extreme fires in the Alto Paraguay basin.

To achieve these objectives, the thesis is structured into seven chapters:

- Chapter 1 (this chapter) presents a brief introduction to the scope of the work and the objectives to be achieved;

- Chapter 2 presents a literature review on the main characteristics of fires across Brazil and the overall framework of remote sensing and modeling for fire research. The chapter also discusses aspects of fire management in Brazil;

- Chapter 3 presents the general methodology used to achieve the goals of the thesis, which are detailed in the subsequent chapters (4 to 6) in the format of scientific articles;

- Chapter 4 is dedicated to answering SO.1, SO.2 and SO.3 by developing a probabilistic model to simulate and assess burned area response to key drivers;

- Chapter 5 uses the model developed in the previous chapter to answer SO.3 and SO.4 by targeting the Pantanal biome;

- Chapter 6 explores the combined effect of climate and land use and land cover on the occurrence of extreme fires in the Alto Paraguay basin aiming to answer SO.5. This chapter is published in the Global Ecology and Biogeography journal (appendix A).

- Finally, Chapter 7 presents the concluding remarks obtained from the integrated analysis of all results from the three previous chapters.

The development of this thesis goes beyond what is included in this document. The skills and knowledge applied here result from four years of constant learning and collaboration with other researchers, colleagues, and institutions. Other research that I led during this time includes one letter entitled “Time to improve disaster preparedness in Brazil” published by Science in 2022 and one paper which is submitted to the journal Weather and Climate Extremes entitled “Attributing deadly landslide disaster in Southeastern Brazil to human-induced climate change”. The paper resulted from a workshop on Attribution and Impacts of extreme events. Additionally, I have contributed to the paper "Assessment of fire hazard in Southwestern Amazon," published by Frontiers in Forests and Global Change, as well as to other conference papers presented at GEOINFO and the Brazilian Symposium on Remote Sensing (SBSR). Moreover, during my visiting period at the University of Reading, I had the opportunity to improve and present the ongoing results of my thesis during the JULES 2023 annual meeting and the CSSP 2023 annual workshop. This period was essential for developing the model used in this thesis. It led to the opportunity of using the developed code as base for the up-and-coming first addition of an annual report on the global state of wildfires. This report is currently under preparation and is an initiative of the UK Centre for Ecology & Hydrology, UK Met Office, European Centre for Medium-Range Weather Forecasts and the University of East Anglia.

2 LITERATURE REVIEW

2.1 Introduction

In Brazil, catastrophic fires in the Amazon (2019) and Pantanal (2020) and more recently the burning in these biomes due to El Niño have raised the discussion about Brazil's unpreparedness in the face of a fire disaster. Deforestation and the agricultural use of fire led to extreme fires in the Amazon in 2019 (DE MIRANDA et al., 2020). One particular event called “fire day”, gained attention when coordinated fires were criminally set by farmers and land-grabbers in the Amazon on August 10 (SILVEIRA et al., 2020), despite authorities being warned in advance. For the first time in the country’s history military forces were set to lead fire and deforestation suppression in the Amazon (Decree nº 9985/19). Nonetheless, the intervention did not consider the diagnostic and understanding of Amazonia fire seasonality (CARVALHO et al., 2021), reducing its effectiveness. Additionally, despite the deliberate fire use by all types of landowners, the close dependence of fires by small farmers are rarely considered in legal actions leading to the disempowerment of smallholders, food insecurity and highlighting the gap of the laws with the reality (CARMENTA et al., 2018).

Historically, fires were primarily climate-driven, but with the industrial revolution, human factors became dominant (PECHONY; SHINDELL, 2010; LI et al., 2021). The continued deforestation and land use and land cover changes in all Brazilian biomes (ALHO et al., 2019; MENGUE et al., 2020; RODRIGUES et al., 2022; MOHEBALIAN et al., 2022), weakening of environmental laws (VALE et al., 2021), overlooked prevention and poor response capacities reveals that preparedness must be improved in dealing with important fire drivers in the country. On the other hand, the 2023 severe El Niño shows that extreme climate plays a fair part in exacerbating droughts and fires in Brazil (MAP, 2023). In 2023, the Amazon saw its highest peak of active fires in June since 2007, while the Cerrado's fire season was delayed due to above-average rainfall, with an expected increase of fires in the summer (GAMA, 2023). In this context, the interplay of fire weather and human activities is and will severely test Brazil's fire management capabilities.

The civil defense is responsible for preventing and responding to disasters in Brazil. However, fires are managed by different institutions according to land tenure meaning that different strategies and procedures are used across the country (ANDERSON et al., 2019). The absence of a well-structured national framework for fire management prevents the country from advancing in this matter. For this to be achieved, it requires the understanding of fire drivers and its particularities across the country as well as a strong structure involving the civil defense and protection, legislation, reliable data and a proper coordination within and between the local, regional and national levels (MARCHEZINI, 2020).

In this context, Remote Sensing data enable the detection and monitoring of conditions pre-fire, the fire occurrence, severity, and extent over large and remote areas, acting as a primary tool for fire management (CHUVIECO et al., 2020). Through satellite imagery data, it is possible to obtain a comprehensive view of climate dynamics (SILVA-JUNIOR et al., 2019), land cover changes (SOUZA et al., 2020), and other environmental aspects that influence fire (FONSECA et al., 2017; SILVA et al., 2022), empowering authorities to make well-informed decisions. Moreover, Remote Sensing facilitates the development and refinement of predictive models, aiding in the comprehension of fire patterns and controls on both global and regional scales (FONSECA et al., 2019; MORELLO et al., 2020; KELLEY et al., 2021). These integrated tools significantly enhance our capacity to anticipate and effectively respond to fires, contributing to improved wildfire management strategies and the preservation of ecosystems and communities.

The goal of this chapter is to introduce important aspects of fires in Brazil and discuss how Remote Sensing and Modeling can be important tools in this context. Additionally, the chapter aims to delve into some aspects of fire management in Brazil, providing insights and recommendations.

2.2 Structure and methods

This chapter is organized in three sections. In Section 2.3, it is presented an introduction on fire describing their patterns, trends and drivers in Brazil. For this, it was used the Burned area product from the Moderate Resolution Imaging Spectroradiometer (MODIS) and the MapBiomas collection 7 deforestation data from 2002 to 2021 to subside the discussion about fires in the biomes. We calculated the monthly burned area percentage in each Brazilian biome (Amazon, Atlantic Forest, Caatinga, Cerrado, Pantanal and Pampas) for the classes Primary vegetation (Forest formation, grasslands, wetlands, savanna, mangrove and other non-forest vegetation), Secondary vegetation, Anthropic use (agriculture, pasture, forest plantations and urban areas) and others. We also carried out a pixel-by-pixel (10x10km) Mann-Kendall trend analysis using the sum per pixel of the active fires data from MODIS for the same period.

Section 2.4 provides an overview of the use of remote sensing for fire assessment, presenting the main products available in global and national scales. Section 2.5 addresses the potentialities and limitations of fire modeling by comparing two approaches: deterministic and probabilistic modeling. Finally, we offer an overview of fire management instruments available in Brazil, highlighting their key gaps and limitations.

2.3 Fires in Brazil

With the advancement of the climate crisis combined with human activities, fires are considered a threat in many Brazilian regions such as the Amazon, Cerrado and Pantanal biomes. Without people, fires in the Amazon would be a rare event (PIVELLO et al., 2011) which creates an alert to the other biomes that still do not have fires as a primary issue. The Amazon and Atlantic Forest biomes are considered sensitive to fires meaning that fires are not part of their natural dynamics and are associated with negative impacts (GUEDES et al., 2020; FENG et al., 2021). Cerrado, Pantanal and Pampas are considered fire-dependent biomes where fires are an important factor in maintaining native vegetation types and biodiversity (FIDELIS, 2020; FIDELIS et al., 2022). The Caatinga, on the other hand, is considered a fire-independent ecosystem meaning that fires play a minor role in this ecosystem (PIVELLO et al., 2021). This section covers a general description of the burned area patterns in the Brazilian biomes considering the period from 2003 to 2021 followed by a discussion of their main drivers in the country.

2.3.1 Fires in the Brazilian biomes

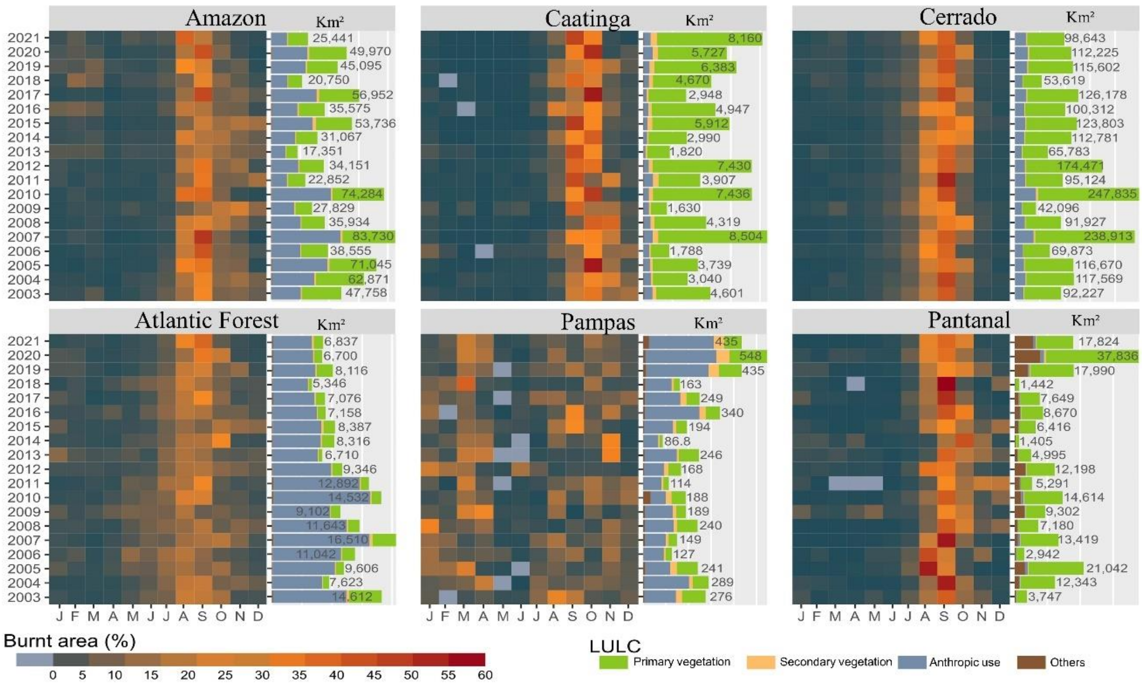
Between 2003 and 2021, extensive areas of natural vegetation in Brazil experienced significant fire activity, as illustrated in Figure 2.1. The Amazon, Cerrado, Caatinga, and Pantanal biomes were notably impacted, with substantial proportions of primary vegetation affected by fires. These fires are mainly concentrated in August, September and October. Conversely, the Pampas and the Atlantic Forest exhibited larger burned areas in regions characterized by anthropic use and a less marked fire season, especially Pampas. According to Rabin et al. (2015), statistical analysis suggests that fire practices in pastures could be responsible for over 40% of the annual burned area in South America. While people might rely on fire for various purposes, these fires often have unintended consequences, impacting the ecosystems regardless of whether they are sensitive to fire or not.

Although both the Amazon and Atlantic Forest are fire-sensitive biomes, their fire patterns can differ significantly due to historical factors. In the Amazon, annual cumulative burned areas are notably extensive, with increasingly frequent extreme fire seasons observed, such as in 2007 (83,730 km^2), 2010 (74,284 km^2), 2019 (45,095 km^2), and 2020 (49,970 km^2). Additionally, large areas of anthropic use have also been affected in the Amazon, where fires are commonly used as a tool to clear areas to introduce or maintain farmlands and pasture. The Atlantic Forest exhibits lower burned areas in its natural vegetation, which may be attributed to the historical degradation of this biome (CARLUCCI et al., 2021). Nevertheless, uncontrolled fires continue to threaten its remnants, including protected areas (DE ASSIS et al., 2022), and impede natural regeneration within the biome (DOS SANTOS et al., 2019). The largest annual burned area in the Atlantic Forest was recorded in 2007, totaling 16,510 km^2. Moreover, the heightened risk of burning in the Atlantic Forest is linked to anthropogenic influences on climate and landscape (DE ASSIS et al., 2022).

The Cerrado, Pantanal, and Pampas have evolved alongside fires, yet the beneficial effects of fire in fire-dependent regions can only occur within their natural regimes, which are disrupted with increased frequency (KEELEY; PAUSAS, 2019). Furthermore, even in these regions, sensitive vegetation remains vulnerable to fire occurrence (SCHMIDT et al., 2018; BARBOSA et al., 2022). The Cerrado experienced its largest burned areas in 2007 (238,913 km^2) and 2010 (247,835 km^2). In 2008, a zero-fire policy was implemented in the Cerrado, shifting the fire regime from the wet season to the late-dry season, leading to more intense fires due to fuel accumulation and the multiplication of ignition sources (DURIGAN; RATTER, 2016; ELOY et al., 2019). Proportionally to its area, the Pantanal is the biome most affected by fires in Brazil, with 51% of its area burned at least once since 1985 (MAPBIOMAS, 2022). Increased burned area is found in Pantanal from 2019 (Figure 1) with 17,990 km^2, 37,836 km^2 and 17,824 km^2 burned in 2019, 2020 and 2021, respectively. In contrast, the Pampas is the least affected by fires, with the maximum annual burned area registered in 2020 (548 km^2).

In Caatinga, the largest cumulative burned area was found in 2007 (8,504 km^2) and 2021 (8,160 km^2). In 2010, approximately 15% of this biome was affected by active fires (SILVA et al., 2017). The authors demonstrated that fires are not evenly distributed across the biome; regions with large areas of forests and savanna vegetation are more susceptible to fire than Caatinga woodlands. Nonetheless, comprehensive studies analyzing historical fires are lacking in this biome.

Figure 2.1. Monthly burned area percentage in each Brazilian biome, between 2002 and 2021, and their respective Land Use Land Cover (LULC) proportion.



In Km² is the total annual burned area.

Source: Author’s production.

2.3.2 Fire trends

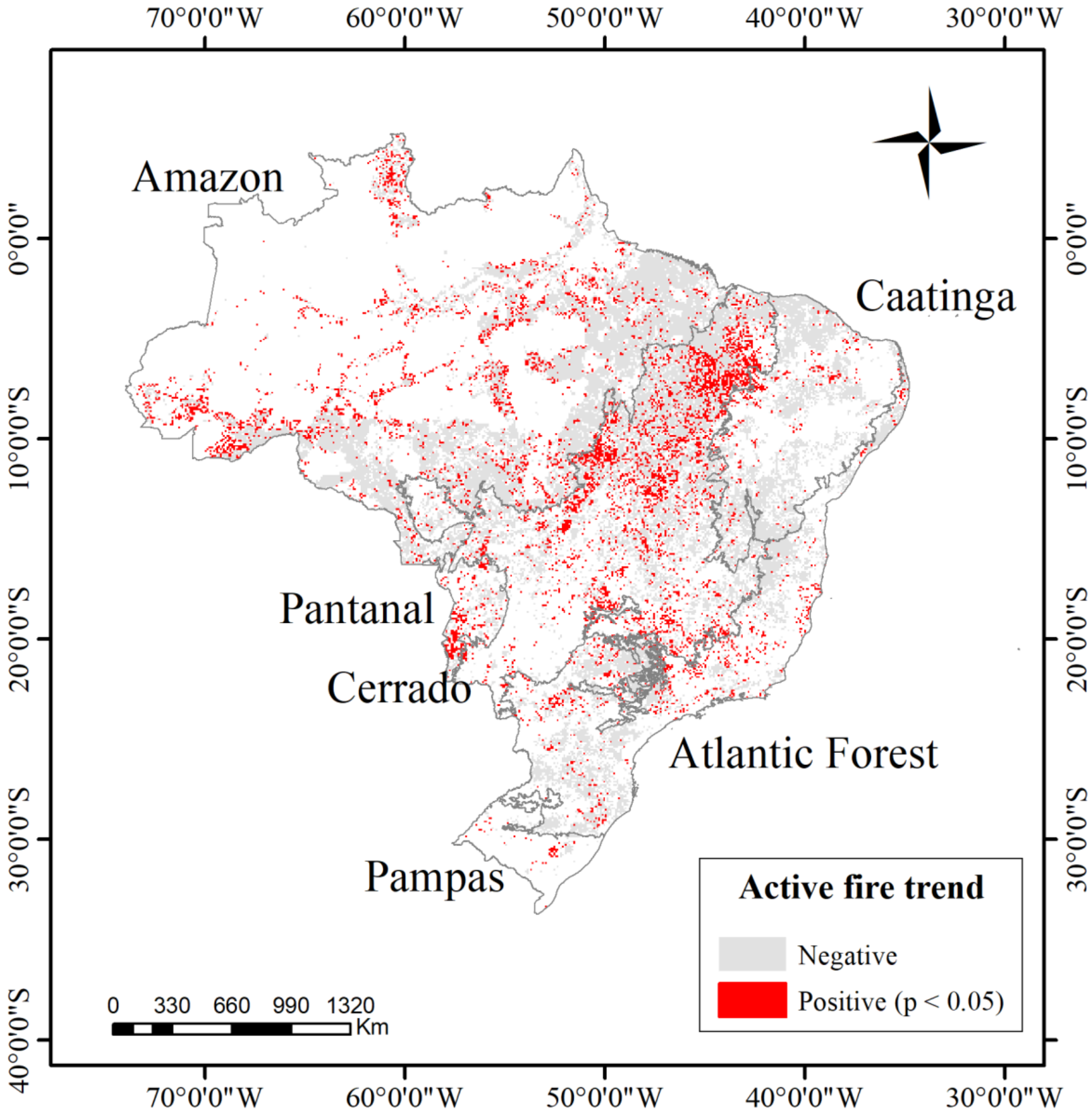
In the past decade, more frequent and intense fires have been observed worldwide, including Brazil. However, other regions have experienced a reduction in fire activity, resulting in an overall decrease in global burned area (ANDELA et al., 2017). Moreover, areas that previously experienced rare occurrences of fires such as the tropical forests are now witnessing a surge in the frequency and scale of extreme fire events. According to Burton et al. (2023), climate change has elevated the global burned area by 16% between 2003 and 2019, contributing to a heightened probability of months with above-average global burned area by 43%.

Brazil stands out as one of the regions most impacted by fires globally (BOWMAN et al., 2009). Several studies emphasize that tropical forests, particularly the Amazonian forest, woody savannah (Cerrado), shrubs, and grasslands, record the highest numbers of fire events, often associated with practices aimed at converting natural vegetation into pasture and agriculture (SCHMIDT; ELOY, 2020; SILVEIRA et al., 2022). Figure 2.2 shows a significant positive fire trend across Brazil, particularly concentrated in the Amazon, Cerrado and Pantanal. Specifically, 14% of the significant trends indicate an increase of fires in natural vegetation and 7% in anthropic areas. In the upcoming decades, Brazil is very likely to face increased extreme weather events (AVILA-DIAZ et al., 2020), accompanied by a transition from moderate to high severity fires.

Oliveira et al. (2022) projected that under a scenario of stabilization of radiative forcing (RCP4.5) and strong environmental governance, high impact fires are likely to increase in Brazil. The authors estimated that in Cerrado these fires would expand from its current 3% to 15%, from 7% to 8% in the Pantanal, and from 0.7% to 1.2% in the Amazon. Furthermore, the impact of fire is expected to intensify in 95% of the Cerrado, 97% of the Amazon, and 74% of the Pantanal region. In the Amazon, Le Page et al. (2017), showed that under a more pessimistic scenario, at least 4 times more forest areas are likely to burn between 2080 and 2100. They emphasize that while land use contraction alone is highly effective under low to moderate climate change scenarios, it provides only limited reduction in fire activity if climate mitigation efforts fail under the most severe climate projections.

Further specific studies are required in the Atlantic Forest, Pampas, and Caatinga biomes to enhance our understanding of the fire trends on these ecosystems. Still, Da Silva Junior et al. (2020), found an upward trend in fires over the Atlantic Forest and Pampa and a potential for high alteration in Caatinga, largely in conserved areas. They highlight that in Caatinga patches of vegetation are more exposed to degradation, potentially increasing the burning.

Figure 2.2 Significant ($p < 0.05$) positive fire trend according to Mann-Kendall trend test (Mann, 1945; Kendall, 1975) in Brazil considering 2002 to 2021.



White regions indicate no burned area trend.

Source: Author’s production.

2.3.3 Key factors affecting fires

The combination of anthropogenic activities with climatic conditions are the main cause of fires in Brazil (CAÚLA et al., 2015; BARBOSA et al., 2022). Yet, fires can also naturally occur in the environment. After being started by either natural sources (VERAVERBEKE et al., 2017) or people (NAGY et al., 2018), fires can be regulated by land use (BUTSIC et al., 2015), vegetation type (FANG et al., 2015), climate (CUNHA et al., 2019) and fire management (ELOY et al., 2019). Therefore, fires are closely related to governance, fuel availability and climatic conditions that favor fires, i.e., drought and high temperatures (LITTELL et al., 2016).

Natural fires play an important role in the dynamics of earth ecosystems, such as in the germination of seeds that needs a thermal shock to break their vegetative dormancy in fire-prone ecosystems, thus acting as a fundamental element in the landscape structuring (DURINGAN; RATTER, 2016). In Brazil, natural fires are mainly ignited by lightning strikes in the rainy season that can be frequent as in Brazilian Cerrado (PIVELLO, 2011) or be rare as in the Amazon region (COCHRANE; BARBER, 2009). Less frequent, natural fires, also occur in the Pantanal and Pampa biomes (MENEZES et al., 2022; FIDELIS et al., 2022). Additionally, lightning and fire seasons are out of synchrony in most parts of Brazil (COUGHLAN et al., 2018; MENEZES et al., 2022). In fact, most lightning fires are fragmented and extinguished primarily by rain (RAMOS-NETO et al., 2000), indicating that natural fires are not associated with fire seasons in the country.

Humans are a key part of the spatial and temporal distribution of fire ignitions. In this sense, anthropogenic activities such as agriculture, cattle raising, road developments, and deforestation, in general, lead to increased fires (CANO-CRESPO et al., 2015; SILVA et al., 2021). Fires are commonly used as a tool to clear areas to introduce or maintain farmlands and pasture. One of the methods traditionally used is the slash-and-burning process that consists of cutting and burning patches of forest to be used for years in agricultural activities and then is left fallow for a variable period (PIVELLO, 2011), aiming to restore the original soil conditions. With the intensification and modernization of agriculture, natural vegetation is removed permanently aided by fire for industrial-scale crop production. In both cases, the use of fire is controlled and they are generally called controlled fire. Nevertheless, these fires can evade from other areas and spread from the edge to the interior of the forest causing the fires to lose control (CANO-CRESPO et al., 2015; SILVA-JUNIOR et al., 2020).

The edge effect plays a particular role in the increase of fires in fire-sensitive biomes. In the Atlantic Forest, the proportion of forest located more than 1 km away from the forest edge has declined from 90% historically to less than 9% in 2015 (HADDAD et al., 2015). Such severe forest fragmentation has significantly influenced the fire dynamics of the Atlantic Forest, making it more susceptible to fires (DOS SANTOS et al., 2019). As a result, areas with increased anthropogenic activities and reduced forest cover generally witness higher frequencies of fire (DE ASSIS et al., 2021). Singh and Huang (2022), analyzed 20 years of data and found together with fragmentation a strong influence of temperature and precipitation in the occurrence of fires in the Atlantic Forest. The authors discussed that fragmentation partly explains fires in the region but due to the poor humidity retention of patches, high temperatures and dry air result in significant fuel load and increase of vulnerability to fires.

In the Amazonia, Silveira et al. (2020), showed that water deficit increases forest susceptibility to fires, however, ignitions depend directly on agricultural activities and deforestation. Forest removal fragments the landscape creating an ideal condition to fire to escape from adjacent agricultural and livestock areas (SILVA JUNIOR et al., 2018). Nevertheless, Aragão et al. (2018) found that despite the decrease in deforestation in the Amazon, the incidence of fire during the 2015 drought was 36% higher when compared to the previous 12 years showing the climatic impact on fire incidence. In fact, the increasing recurrence of droughts makes the Amazonia suffer from drier and prolonged dry seasons (MARENGO; SPINOZA, 2015), making this naturally humid ecosystem more vulnerable to fires. These droughts are mainly linked to positive anomalous sea surface temperatures (SST) in the tropical eastern Pacific Ocean associated with the hot phase of the El Niño–Southern Oscillation (ENSO) and in the tropical North Atlantic Ocean (MARENGO; SPINOZA, 2015).

In the cold phase of the ENSO (La Niña), the opposite effect occurs, the rainfall pattern intensifies in the north and northeast of Brazil, while extended periods of drought and losses in the agricultural sector occur in the south region of Brazil (CIRINO et al., 2015). Andrade et al., showed the active fires and burned area are considerably higher in Pampa during La Niña years, evidencing the relationship between fires and rainfall in the region. Pampas is considered a fire-dependent biome, however, the natural fire dynamics have changed with the reduction of grasslands due to human activities and the use of their remains to cattle raising (FIDELIS et al., 2022). Still, the biome presents a lower risk of fires when compared to other fire-dependent regions such as the Cerrado (OLIVEIRA et al., 2022).

The Brazilian Cerrado also evolved with natural fires, however, anthropogenic fires became common. Cerrado is marked as an agriculture frontier experiencing a loss of 42% of its natural vegetation from 1985 to 2005 (GRECCHI et al., 2014). Anthropic fires in this biome are directly related to deforestation because of conversion to monocultures and lack of fire management in the remaining vegetation. These conditions can be worsened by climatic factors, however, as a natural component of this ecosystem fire suppression may change its structure, biodiversity, and functioning (DURIGAN; RATTER, 2016). While in fire-sensitive biomes suppression policies can help to minimize fire incidence, in fire-dependent biomes can cause the opposite effect, contributing to more intense fires (ALVARADO et al., 2017). A contrasting effect between fire-sensitive and fire-dependent regions is also found regarding landscape discontinuity. Fragmentation can alter the fire regime of fire-dependent biomes by reducing natural fires due to lack of fuel (ROSAN et al., 2022) although this relationship needs further studies in biomes like Pampa and Pantanal.

The fire regime in Pantanal is intricately connected to the annual and pluriannual flood pulse (DAMASCENO-JUNIOR et al., 2021). The biomass generated during the flooding season becomes accessible as fuel for burning in the subsequent dry season. Moreover, the region stands out as a well-preserved biome where historically, native grasslands have been utilized for low-intensity cattle ranching. However, since the 2000s, there has been a shift towards substituting native grasses with exotic varieties in pastures or converting them into croplands, resulting in a high concentration of active fires and an increased risk of fire occurrence (MARQUES et al., 2021). However, grasslands are the primary LULC linked to burning in the Pantanal. Fires serve as an efficient and cost-effective method for managing native pastures (GARCIA et al., 2021). Thus, human activities remain the primary ignition source in the region (MENEZES et al., 2022). Also, the surrounding pressures of land use and land cover changes, coupled with the effects of climate change, may lead to an increased frequency of extreme events such as the one witnessed in 2020 (BARBOSA et al., 2022). In fact, Marengo et al. (2021), demonstrated that Pantanal recorded the worst drought in 50 years in 2019/2020 leading to favorable conditions for fire propagation and the severe fire season in 2020.

In the Caatinga, fires are primarily linked to small agriculture clearings rather than forest fires (SILVA et al., 2017). The biome is located in a dry region of Brazil and may be more vulnerable to fires due to landscape alteration and climate change intensification (DA SILVA JUNIOR et al., 2020). However, there are considerable uncertainties in fire drivers and dynamics in the region.

2.4 Remote sensing for fire analysis

Remote sensing sensors offer global information at various spatial resolutions and spectral regions, making them invaluable tools for multitemporal analysis of the Earth's surface (CHUVIECO et al., 2020). Their systematic observation capability allows for comprehensive data collection without the need for destructive sampling. These characteristics have contributed to the widespread utilization of remote sensing data in fire-related research since the early 1970s. Initially, applications relied on visual analysis of aerial photography. However, since the launch of the Landsat satellite in 1972, satellite data became instrumental in different fields of fire research: assessing conditions before a fire occurs, detecting active fires, estimating fire behavior during the event, quantifying burned area, analyzing fire drivers and impacts and modeling different aspects of fires (MATAVELI et al., 2018; CAMPANHARO et al., 2019; BARMPOUTS et al., 2020; OLIVEIRA et al., 2022).

The detection of active fires with remote sensing has been facilitated by middle- (3–5 μm) and thermal-infrared (centered at 10–11 μm) spectral bands (GIGLIO et al., 2016) from polar-orbiting meteorological satellites. The distinct spectral behavior exhibited by active fire pixels in both bands is the primary characteristic guiding the algorithm's approaches. These satellites have been instrumental in capturing the high thermal contrast between hotspots and the background in the middle-infrared region, initially included for cloud detection purposes. Furthermore, recent algorithms for detecting active fires and burned area mapping from Landsat observations are based on the near-infrared and short-wave infrared bands (SCHROEDER et al., 2016; MAPBIOMAS FIRE, 2023).

Dedicated active fire sensors, particularly after the launch of MODIS on Terra and Aqua satellites, significantly improved the quality of fire detection products. In recent years, the use of these datasets has expanded to geostationary and medium-resolution satellites, even including unmanned aerial vehicles for specific areas. Geostationary sensors offer high temporal resolution, while polar-orbiting sensors provide finer spatial resolution, ensuring higher accuracy in locating and mapping thermal anomalies. Currently, the active fire product from Visible Infrared Imaging Radiometer Suite (VIIRS) on board of the National Polar-Orbiting Partnership (NPP) and NOAA-20 satellites since 2013 and 2017, respectively, strikes a balance between spatial and temporal resolution.

Among the burned area products available, the MCD64A1 is the most widely used (LASKO, 2019; DA SILVA JÚNIOR et al., 2019; ROSSI; SANTOS, 2020). This global product is developed daily at 500 m spatial resolution, combining MODIS active fire data, surface reflectance imagery, and vegetation cover information. The mapping algorithm uses a burn-sensitive vegetation index using short-wave infrared channels, and dynamics thresholds applied to produce the data (GIGLIO et al., 2018). MCD64A1 offers a general improvement in burned area detection when compared to past collections, mainly on detection of small fires, and adjustability to different regional conditions across the world. Even though several remote sensing fire products exist, MODIS burned area have reached high statistical accuracy, compared to other products. For example, Padilha et al. (2015), compared the accuracies of six global burned area products and identified the MCD64A1 as the most accurate product. On the other hand, Santana et al. (2020), found greater limitations in MCD64A1 in detecting fires in Brazilian forests, mainly in fragmented areas associating this difficulty to the low spatial resolution of MODIS sensor.

Other global burned area products include the product Fire Disturbance (Fire_cci), the Global Annual Burned Area Mapping (GABAM), and The Global Fire Emissions Database burned area (GFED). The Fire_cci product was the first to be available in 250 m spatial resolution, yet this product is only available from 2001-2016 (CHUVIECO et al., 2018). The GABAM product is the highest spatial resolution (30m) dataset available, however, its data is yearly provided and it's only available for the years 2000, 2005, 2010, 2015, and 2018. Lastly, the GFED product combines satellite fire activity and vegetation productivity products to estimate gridded monthly burned area and fire emissions accessible from 1997 through the present at a 0.25º spatial resolution (GIGLIO et al., 2013).

In Brazil, an important burned area product is provided by the Mapbiomas project. The product is available annually and monthly from 1985 to 2022 (MAPBIOMAS FIRE, 2023). All mapping was based on image mosaics from Landsat satellites with a spatial resolution of 30 meters, covering the entire Brazilian territory.

In summary, remote sensing is indispensable for the analysis of fires and their effect on the environment. By leveraging satellite imagery, researchers and fire management agencies can gather valuable information on fire dynamics, including fire patterns, intensity, and behavior. It is also key in understanding the complicated interactions of factors influencing fire occurrence by providing data such as vegetation type (HUYLENBROECK et al., 2020), fuel (GALE et al., 2021), climate (JARDIM et al., 2022), and human activities (FONSECA et al., 2021). By integrating data from these various factors, remote sensing enables the development of predictive models for fire assessment, early warning systems, and strategic planning for fire prevention and suppression efforts. The potential for future improvements in remote sensing holds promise for even more advanced techniques and applications in fire analysis and management.

2.5 Enhancing fire understanding through modeling

Given the far-reaching effects of fire in the earth system, there is considerable concern about how fire regimes may respond to projected climate changes in the 21st century. Even though most climate models do not fully include wildfires processes, the IPCC Sixth Assessment Report (AR6) reported that there is a high confidence that they will further increase greenhouse gasses into the atmosphere (LEE et al., 2023). In response, various approaches have been employed and are continuously refined to simulate fire patterns and behavior. This field is essential for understanding the complex dynamics of wildfires and their broader implications for ecosystem health, biodiversity, and human well-being. In the upcoming sections, we will explore the potential benefits and challenges of utilizing modeling for fire analysis, along with their application for assessing fire drivers.

2.5.1 Deterministic versus probabilistic modeling

By employing computational models, we can simulate various fire scenarios, predict their behavior, and comprehend the underlying processes governing fire dynamics. For this, there are two main approaches: deterministic and probabilistic modeling. These approaches offer distinct perspectives on how we simulate fires and predict their behavior. However, it's important to recognize that the boundaries between these methods are often blurred, and there exists a spectrum of models that incorporate elements of both approaches.

Deterministic models represent an important approach in scientific research, offering predictions of system behavior based on well-defined equations and initial conditions (SOARES; CARMO, 2021). They are often simpler to implement, train, and deploy due to their straightforward nature and clear relationships between inputs and outputs. These models operate on the principle that given a specific set of inputs and parameters, the system's evolution follows deterministic rules without inherent randomness or uncertainty. This means that they are based on the concept of causality, which asserts that the current state of the system being examined is primarily influenced by preceding states (HOEFER, 2023). However, we cannot solely depend on our understanding of past events to make simulations because certain events that could occur have not yet been experienced.

Existing models frequently adopt a deterministic approach, yielding a singular output value for each variable. For example, The Joint UK Land Environment Simulator – INteractive Fire and Emissions algorithm for Natural envirOnments

(JULES-INFERNO), like many other vegetation dynamics models, is primarily deterministic in nature. Moreover, their simulations strongly depend on assumptions about the variable's relationship with fires (BURTON et al., 2019). Nevertheless, JULES-INFERNO allows for the explicit representation of complex interactions and feedback loops inherent in Earth system processes such as the impact of fire emissions on cloud formation and future warming. This enables the assessment of the long-term impacts of fires, representing an important advantage of deterministic models.

Oliveira et al. (2022), investigated the determinants of fire impact in the Brazilian biomes by building five predictive models: Spatial Autoregressive Model, Generalized Linear Model, Generalized Additive Model, Support Vector Machine, and Random Forest. The authors used Pearson correlation coefficient to evaluate the models' fitness. They found Random Forest the method with the highest predictive power (76% on average). The authors estimated that 25% of high-impact fires in Amazonia are explained by climate. While providing a broad assessment of the model's performance and the variables' contributions, it overlooks uncertainties and spatial variations in the values. Although Random Forest generates an ensemble distribution, a common practice in probabilistic modeling is to provide a single value, typically the mean. Moreover, Random Forest in particular does not capture the full range of uncertainty, residing somewhere in between deterministic and probabilistic methodologies.

Probabilistic methods assume the inherent randomness in processes and acknowledge that results can vary due to the combination of independent factors affecting the phenomenon under investigation (PIMONT et al., 2021). They are particularly useful in modeling environmental and anthropogenic hazards and simulating complex behaviors and patterns (REFICE; CAPOLONGO, 2002; PAN et al., 2016; ABREU et al., 2022). This approach incorporates historical events, expert knowledge, and theory to simulate physically possible yet unrecorded events. It generates a range of potential outcomes and measures how likely each is to occur, offering a way to assess our confidence level about a process. This better enables the acknowledgment of unaccounted factors within the analysis. Some disadvantages of probabilistic models are the potential complexity in training process and interpretability of the results as they often involve complex distributions and dependencies between variables.

A technique within this framework is the Bayesian inference. In Bayesian analysis, prior information available is encapsulated in a quantitative model or hypothesis known as the prior probability distribution. Bayes' Theorem combines this prior probability distribution with the likelihood of the data to produce a posterior probability distribution (BAYES, 1763). Through Bayesian inference, one obtains a quantitative assessment of the probability of a hypothesis (H) being true given the available data (Y), denoted as P(H|Y). Nonetheless, the priors have a large influence on the posterior distribution, especially when the sample size is small, the priors are strict, and the model is complex (MACNEISH et al., 2016). The utilization of Bayesian estimation is increasing across numerous scientific domains KRUSCHKE et al., 2012; KÖNIG; VAN DE SCHOOT, 2017; VAN DE SCHOOT et al., 2017), and there is a notable surge of studies focusing on fires (SILVA et al., 2015; KELLEY et al., 2019; KELLEY et al., 2021; PIMONT et al., 2021).

Another significant concept employed in probabilistic modeling is the Maximum Entropy. Similar to Bayesian inference, Maximum Entropy utilizes prior knowledge about the data, known as constraints. However, the primary objective is to satisfy these constraints while maximizing entropy or uncertainties based on observed data (SEIDENFELD, 1986). The underlying notion is that real-world phenomena occur in stochastic ways due to dependencies on various factors, making it challenging to account for all in a model. This concept has been largely applied to fire research (YANG et al., 2021; MIRANDA et al., 2023; FERREIRA et al., 2023)

2.5.2 Assessing drivers of fires

The complexity of the interactions and feedbacks between fire, climate, people, and other earth system components makes it challenging to be highly confident about what drives fires in specific locations. Various methods assess the drivers of historical fire events. Some studies correlate individual drivers with burnt area but overlook the interaction of multiple factors (ANDELA et al., 2017; BARBOSA et al., 2019). Fire Danger Indices capture simultaneous drivers to gauge fire risk. However, they overlook human-driven ignition causes (ZACHARAKIS; TSIHRINTZIS, 2023) and typically fail to capture the impact of fuel availability on burning (KELLEY; HARRISON, 2014). Fire-enabled Land Surface Models account for these drivers, simulating observable fire regime measures. However, they often lack precision for year-to-year fire patterns and required accuracy to determine the causes of individual fire seasons (HANTSON et al., 2020). In this sense, research applying Bayesian and Maximum Entropy frameworks can address these gaps.

Kelley et al. (2021) used Bayesian inference to assess whether meteorological conditions contributed to the 2019 Amazonia fires. They demonstrated that the observed June-August fires had a probability of less than 7% of being caused by meteorological conditions alone, which decreased to less than 1% in Paraguay and Bolivia dry forests and at the eastern end of the Amazon's arc of deforestation. It was possible to infer that meteorological conditions alone should have led to a fire season with a 67-89% reduction in burnt area in Bolivian dry forests and a 57-76% reduction for Paraguay dry forests and woodland compared to the August average. This research used the methodology developed by Kelley et al. (2019), which assessed trends in four groups of drivers of burnt area to identify changes in global fire regimes. The authors carried a “potential” analysis, defined as the potential increase in burned area if the influence imposed by that driver is removed in the presence of the remaining factors. Moreover, they show a sensitivity analysis, or rate of change in burned area, given a minor change in the variables. While these analyses have yet to be widely adopted, they offer a valuable approach to analyzing factors influencing burned areas by accounting for uncertainties and estimating changes in burned areas under hypothetical scenarios.

Currently, the Maximum Entropy concept is utilized to estimate the suitability for fire occurrence based on environmental conditions while evaluating significant influencing factors (FONSECA et al., 2017; FERREIRA et al., 2023). To date, this concept has primarily been applied in the context of the MaxEnt (Maximum Entropy) species distribution model (PHILLIPS et al., 2006). These studies treat fires as species due to their strong dependence on environmental factors, enabling the categorization of fires into types or species. For instance, Sari (2023), employed the MaxEnt model to estimate the drivers of fires in a specific region of Turkey, considering various ignition sources such as lightning, agricultural stubble burning, discarded cigarette butts, and power lines. However, the categorization of fires for assessing drivers remains largely unexplored. Moreover, it's worth noting that the binary nature of MaxEnt restricts its use to high-resolution studies of fire, where fire occurrences can be effectively modeled as presence or absence. Despite its importance, the full potential of Maximum Entropy for fire modeling and evaluating its drivers has yet to be fully realized.

2.6 Fire risk management in Brazil

Fire risk management is the process of identifying, monitoring and assessing risk of fires together with the development of procedures to prevent and minimize their impact. It needs to consider interconnected aspects of fire occurrence such as climate change, land use change and sometimes conflicting stakeholders priorities (CAMPBELL et al., 2022). However, from a national perspective, the management is better-established for disasters such as floods and mass movements. Regarding fires, Brazil has advanced in monitoring with several platforms available but still needs to improve its prevention and response strategies. Some of the available instruments and gaps of the fire risk management in Brazil will be discussed in this section.

2.6.1 Fire-related instruments

The fire management efforts in Brazil involve several initiatives, laws and platforms:

1. The Fire Monitoring Program by the National Institute for Space Research (INPE) provides access to the BDQUEIMADAS database, offering near real-time information on active fires, burned areas and fire danger forecasts (SETZER et al., 2019). The interested institutions can receive real-time notifications via email or electronic messages through the Fire Monitoring and Alert System (TerraMA2Q). However, maintenance of the

TerraMA2Q has been halted due to financial constraints;

2. The National System for Prevention and Combating Forest Fires (PREVFOGO) under the Brazilian Institute of Environment and Renewable Natural Resources (IBAMA) focuses on fire prevention and firefighting, particularly in Indigenous Lands, Quilombola territories, and agricultural settlements. Challenges include the need to enhance preventive strategies (OLIVEIRA et al., 2021) while investing in permanent firefighters contracts and increasing the number of personnel;

3. The Mapbiomas project is a collaborative network, formed by NGOs, universities and technology startups. Recently, the project launched the "monitor of fire" which is the monthly mapping of burned areas in Brazil from 2019 onwards. The mapping is based on monthly mosaics of Sentinel 2 multispectral images with spatial resolution of 10 meters;

4. Regionally there is available the Burned Area Alert with Estimated Monitoring by Satellite (ALARMES; https://lasa.ufrj.br/alarmes/) which is a tool for monitoring the advance of the daily extension of the area affected by fires in the Amazon, Cerrado and Pantanal biomes;

5. The Management and Operational Center of the Amazon Protection System (CENSIPAM), under the Ministry of Defense, launched the "fire panel" (https://panorama.sipam.gov.br/painel-do-fogo/) in 2021. This tool tracks active fires in the Amazon region, providing support information for firefighting efforts by grouping active fires into individual events;

6. The MAPFire platform covers the Amazon region, specifically in Acre (Brazil), Madre de Dios (Peru), and Pando (Bolivia) (http://terrama.cemaden.gov.br/griif/mapfire/monitor/). It offers monitoring and alert features to support planning and decision-making regarding fire occurrences. MAPFire enables analysis of active fire locations in relation to land cover, roads, and rural properties. The monthly burned area

mapping present in the platform is produced by the LabGama from the Federal University of Acre, and focuses only in Acre state;

7. The Law project (Nº 11,276/2018) is an attempt to establish the National Integrated Fire Management Policy (PNMIF). The proposed PNMIF aims to integrate fire management efforts and reduce the incidence and damage of forest fires. However, the implementation of PNMIF, including the National Fire Information System (SISFOGO), faces challenges such as outdated data and lack of a national fund for fire prevention and mitigation. The PNMIF was approved by the Chamber of Deputies in October 2021, three years after its presentation, and until this moment is awaiting the Senate appreciation;

8. The State Integrated Fire Management Plan (PEMIF; decree nº 15.654,) of Mato Grosso do Sul is the first integrated plan approved in Brazil, representing an advance in the matter that needs to be expanded across the country;

9. In the Pantanal biome, an Integrated Management Plan organized by IBAMA is in place. However, the plan lacks effective coordination with local institutions, resulting in limited practical implementation and impact;

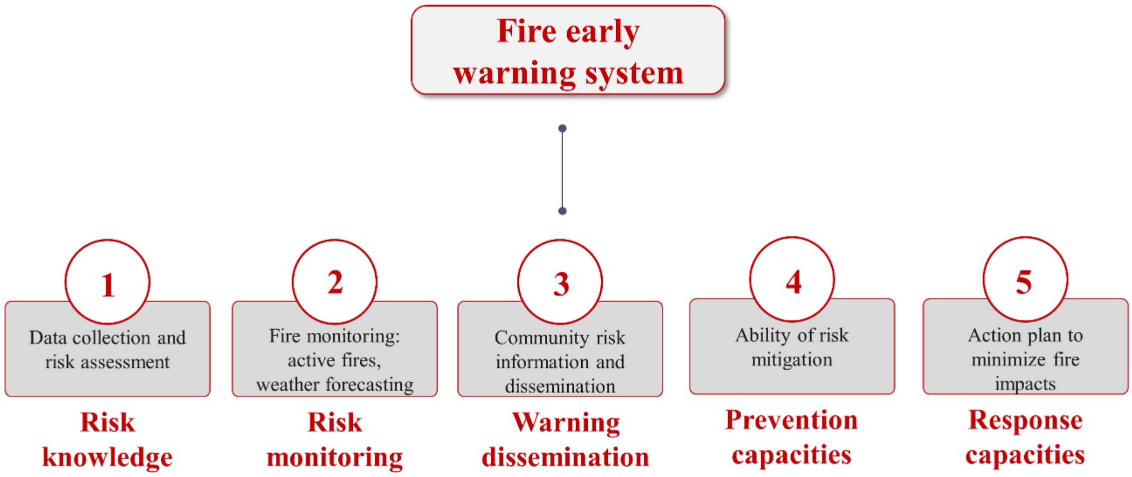
10. Anderson et al. (2021) created a seasonal fire probability forecast for South America Protected Areas to offer alerts for priority regions, up to one month in advance. However, to effectively identify high-risk areas, integration with local and regional conditions is essential.

These laws and initiatives collectively aim to address the challenges of fire monitoring, prevention, and response in Brazil, albeit facing various obstacles in implementation and maintenance.

2.6.2 Main gaps and recommendations

An important tool in the context of fire management is the Fire Early Warning Systems (EWS). EWS are generally based on four axes: risk knowledge; risk monitoring; warning dissemination and communication; and emergency response capacities (UNISDR, 2016) with another element proposed by Anderson et al. (2019) linked to the capacity of prevention (Figure 2.3).

Figure 2.3. The five axes of the Fire early warning system (EWS).



Source: Adapted from Anderson et al. (2019).

For this purpose, EWS are often enhanced with remote sensing data, such as burned area products for risk knowledge, active fires products for early detection, and with data on land cover, climate and fuel conditions (De GROOT et al., 2006). Moreover, improved simulations of fire patterns under changing environmental conditions could potentially improve fire risk management in Brazil. Presently, the utilization of fire simulations in Brazil heavily relies on extrapolations from deterministic global models (DRUKE et al., 2019; BURTON et al., 2022). Yet, the development of models tailored to regional contexts, offering flexibility and minimizing assumptions, coupled with thorough quantification of uncertainties, could represent a major advance into fire risk management in Brazil.

The alert system for seasonal fire probability forecast developed by Anderson et al. (2021) covers all South American Protected Areas and Brazilian municipalities, integrating recent anthropic activity trends with meteorological forecasts. Despite its potential for strategic planning and mitigating fire risks, insufficient engagement of institutions poses a challenge in its utilization. Moreover, regional patterns across South America vary, necessitating tailored approaches, especially considering specific drivers. Furthermore, the system's efficacy is hindered by limited funding released only during emergencies, making it challenging for institutions to implement preventive measures based on forecasts.

Land-use regulation is also critical for fire management (SIL et al., 2019). The government must enhance surveillance to prevent criminal and uncontrolled fires and develop a clear strategy for fire reduction activities. Involving traditional populations is vital to explore their association with fire management and disaster resilience. As we approach the 2030 decade, commitments such as Agenda 2030, and the Sendai Framework for Disaster Risk Reduction require explicit strategies from Brazil. The recent revival of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, extended nationwide, and the reactivation of the Amazon Fund offer hope for future shifts in addressing deforestation and fire management challenges. Nevertheless, despite deforestation reduction in the Amazon in 2023, fires kept rising due to the severe drought experienced in the region (WWF, 2023). This highlights that factors driving fires are dynamic and should be accounted for in strategic planning.

Unlike other hazards like hurricanes and earthquakes, fires lack a standardized scale to measure their magnitude or define extreme events. Tedim et al. (2020), stress the importance of creating such metrics to facilitate fire registration, communication, and strategic planning. Developing standardized metrics for fire intensity and severity will enable better coordination and response strategies to address the growing threat of fires in Brazil.

Efficiently managing fire risk in Brazil requires an integrated national structure, as discussed by Anderson et al. (2019). Challenges arise from differing responsibilities for fire mitigation and suppression at state and municipal levels which often is not addressed by the civil defense. Although primarily focused on response, the civil defense could serve as a centralized body coordinating data and warnings from national centers like CENAD. Collaboration with local communities, firefighters, and brigades is crucial for prevention and response efforts. The involvement of the third sector, which forms brigades and participates in firefighting efforts, is also noteworthy. However, this dynamic has occasionally led to conflicts with the local government institutions. Fonseca-Morello et al. (2017), identified key factors limiting the effectiveness of public policies to reduce Brazilian Amazon fires. These factors include, a predominant budget allocation towards fire suppression at the expense of prevention, geographical limitations in federal action and reduced policymaking capacity at the state and municipal levels, institutional deficiencies and transaction costs associated with fire use licensing, and constraints such as limited access to credit, markets, labor, and rural extension services, hindering the adoption of fire-free agriculture practices.

The Integrated Disaster Information System (S2ID) in Brazil relies on civil defense data, resulting in gaps in monitoring fires' frequency and impacts. Issues include problems in data collection procedures, and an outdated disaster information database (RAMOS et al., 2020). The disaster is recorded within 10 to 15 days after the declaration of emergency situation (BRASIL, 2012) meaning that fires long-term impacts go unregistered. While S2ID adopts the Brazilian Classification and Codification of Disasters (COBRADE) for classification, it overlooks the human-driven nature of fires in Brazil, necessitating a new perspective to emphasize human involvement in fire occurrences and intensification.

2.7 Final Considerations

The Brazilian government must urgently restructure and enhance national preparations for addressing fires and climate change by prioritizing prevention, communication, response, and recovery actions, including the development of long-term policies. Recognizing the complex and varied patterns and drivers of fires across Brazilian biomes, coupled with the concerning increase in the frequency of extreme climate and fire seasons, calls for a unified approach across federal agencies, states, and municipalities throughout all phases of fire risk management.

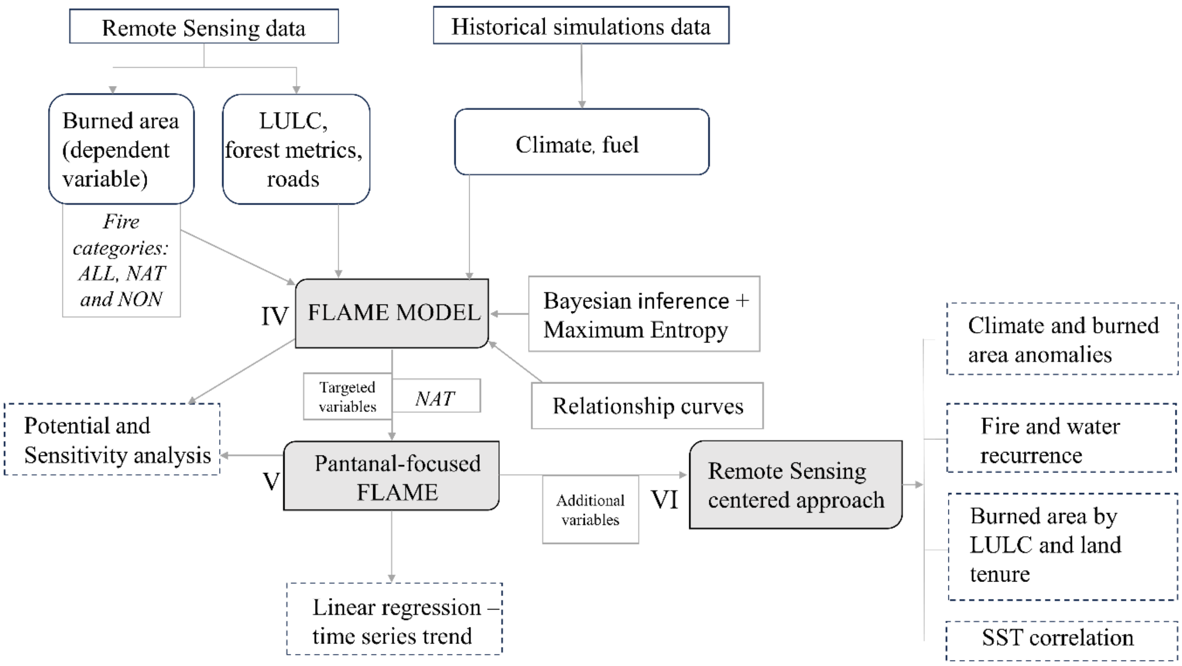
To effectively address these challenges, it is imperative to prioritize the implementation of harmonized data and national data standards considering the uncertainties and spatial variability of them. This entails the development of regional models allied to remote sensing data and common information platforms. While existing platforms focus on monitoring and estimating impacts, they fall short in addressing all aspects of fires in Brazil.

To bridge this gap, the development and implementation of a national Fire Early Warning System is recommended. This system should encompass strengthening civil defense, allocating adequate budgets, fostering qualified human resources, use of scientific knowledge and data, and implementing short and long-term policies to enable successful fire risk management across the country. By embracing interdisciplinary approaches and harnessing scientific advancements, Brazil can enhance its resilience to fires and climate change while safeguarding its natural richness and communities.

3 GENERAL METHODOLOGY

Figure 3.1 summarizes the main methodological steps used in this thesis. In Chapter 4, the Bayesian implementation of the Maximum Entropy concept was applied to the development of the new model FLAME (Fire Landscape Analysis using Maximum Entropy) to simulate burned area. We divided the burned area in three categories of fires: all fires (ALL), fires reaching natural vegetation (NAT) and fires reaching non-natural vegetation (NON). Then, we applied and assessed the model across the six Brazilian biomes. The variables were analyzed through the potential and sensitivity analysis which features modifications in the variables and assess the burned area response.

Figure 3.1 - Flowchart summarizing the main methodological steps of this thesis.



Inputs are represented by black outline white boxes, while the analysis are indicated in dotted line white boxes. The Chapters are outlined in grey boxes.

Source: Author’s production.

In Chapter 5, we conducted a targeted model optimization specifically for the Pantanal biome, focusing on the NAT category. To achieve this, we tailored the variable selection to align with the unique characteristics of the biome. Additionally, we employed a simple linear regression to identify time series trends in climate and land cover variables.

Chapter 6 delved into a comprehensive investigation of burned area in the Pantanal, emphasizing the extreme fire season of 2020. Our analysis involved calculating burned areas and climate anomalies for the rainy and dry seasons of 2019 and 2020. We also assessed the recurrence of burned area and water coverage, and categorized burned area based on land use and land cover (LULC) and land tenure. Furthermore, we explored Spearman's correlation between five oceanic indices (MEI, ONI, AMO, PDO, and TNA) and monthly precipitation anomalies, while also testing temporal autocorrelation across time lags ranging from 0 to 12 months. Additional methodological details will be presented in their respective chapters.

4 FLAME: A NOVEL APPROACH FOR MODELING BURNED AREA IN THE BRAZILIAN BIOMES USING THE MAXIMUM ENTROPY CONCEPT

4.1 Introduction

The Principle of Maximum Entropy states that when trying to estimate the probability of an event and the information is limited available, you should opt for the distribution that preserves the greatest amount of uncertainty (i.e., maximizes entropy) while still adhering to your given constraints (PENFIELD, 2003). These constraints reflect prior knowledge about the probability distribution of a phenomenon of interest (i.e., burnt area) based on its relationship with independent variables. This approach ensures you do not introduce extra assumptions or biases into your calculations. Maximum Entropy has its roots in statistical mechanics (JAYNES, 1957). However, the use of its concept in a species distribution model (PHILLIPS et al., 2006) popularized the approach in several other study areas, including ecology, geophysics, and fires (JIN et al., 2020; LI et al., 2019; FONSECA et al., 2017).

The MaxEnt (Maximum Entropy) species distribution model estimates the probability of target presence for given local conditions (PHILLIPS et al., 2006). Unlike many traditional models, MaxEnt makes minimal assumptions about the relationships between variables, making it more flexible and adaptable to complex ecological interactions. Rather than estimating a single value, MaxEnt models a full probability distribution (ELITH et al., 2011), providing a comprehensive view of potential outcomes. This probabilistic nature enables the incorporation of prior information into the modeling process, enhancing its accuracy. Additionally, MaxEnt enables the quantification of uncertainties (CHEN et al., 2019), providing valuable insights into the reliability and confidence of model predictions.

Recognizing that fires can be treated as a specie due to their strong dependence on environmental factors, utilizing the MaxEnt species model has yielded valuable insights into the field (FERREIRA et al., 2023; FONSECA et al., 2019). However, the MaxEnt model relies on presence-only or presence/absence data, which means it primarily considers locations where the target (in this case, fires) has occurred. This limits fire research using MaxEnt as it does not allow continuous data, such as area burnt over a larger region such as land surface model grid cells. Moreover, the constraints and structure of the underlying model are fundamentally related to species distributions (PHILLIPS et al., 2006) rather than fires, which may not capture the nuances of fire behavior.

Incredibly challenging is the simulation of fires in heterogeneous territories such as Brazil. Wildfires have become a pressing concern in the country, causing significant socioeconomic and environmental losses (CAMPANHARO et al., 2019; BARBOSA et al., 2022; WU et al., 2023). Over 20% (1,857,025 km²) of the country's land area has burned since 1980 (MAPBIOMAS, 2023). Shifts in Land Use and Land Cover (LULC) are frequently linked to fire ignition in Brazil. These changes lead to landscape fragmentation and increased wildfire risk in vulnerable ecosystems (SILVA-JUNIOR et al., 2022). Even changes in the natural fire regime of landscapes which evolved with fires create conditions for more prolonged and severe fires, preventing the original benefits of fires in these areas (SCHMIDT et al., 2018). All these fires pose immediate threats to humans and the environment and contribute significantly to atmospheric carbon emissions, further fueling anthropogenic climate change. However, quantifying the influence of these drivers can be challenging - many interactions between fire and its drivers are non-linear, and drivers heavily interact with each other, making confidently identifying drivers of fire regimes in such diverse landscapes tricky from observations alone (KRAWCHUK; MORITZ, 2014). While traditional fire models provide useful broadscale information on fire, land, and climate interactions, they do not quantify the uncertainty in these relationships and rely on other studies to infer relationships between drivers and burning (HANTSON et al., 2016).

As fire seasons lengthen and intensify in Brazil, the challenges associated with preventing fires, firefighting, and managing their aftermath are growing. Improving fire simulations and understanding the underlying drivers of fires in the country is essential to address these challenges. Here, we present and evaluate a novel fire model, FLAME (Fire Landscape Analysis using Maximum Entropy), based on a Bayesian inference implementation of the Maximum Entropy concept. This combination allows us to incorporate uncertainty and probabilistic reasoning into fire modeling. The model optimizes key driving variables relationship with fires. Here we apply FLAME to the biomes in Brazil, and assess the performance against observations.

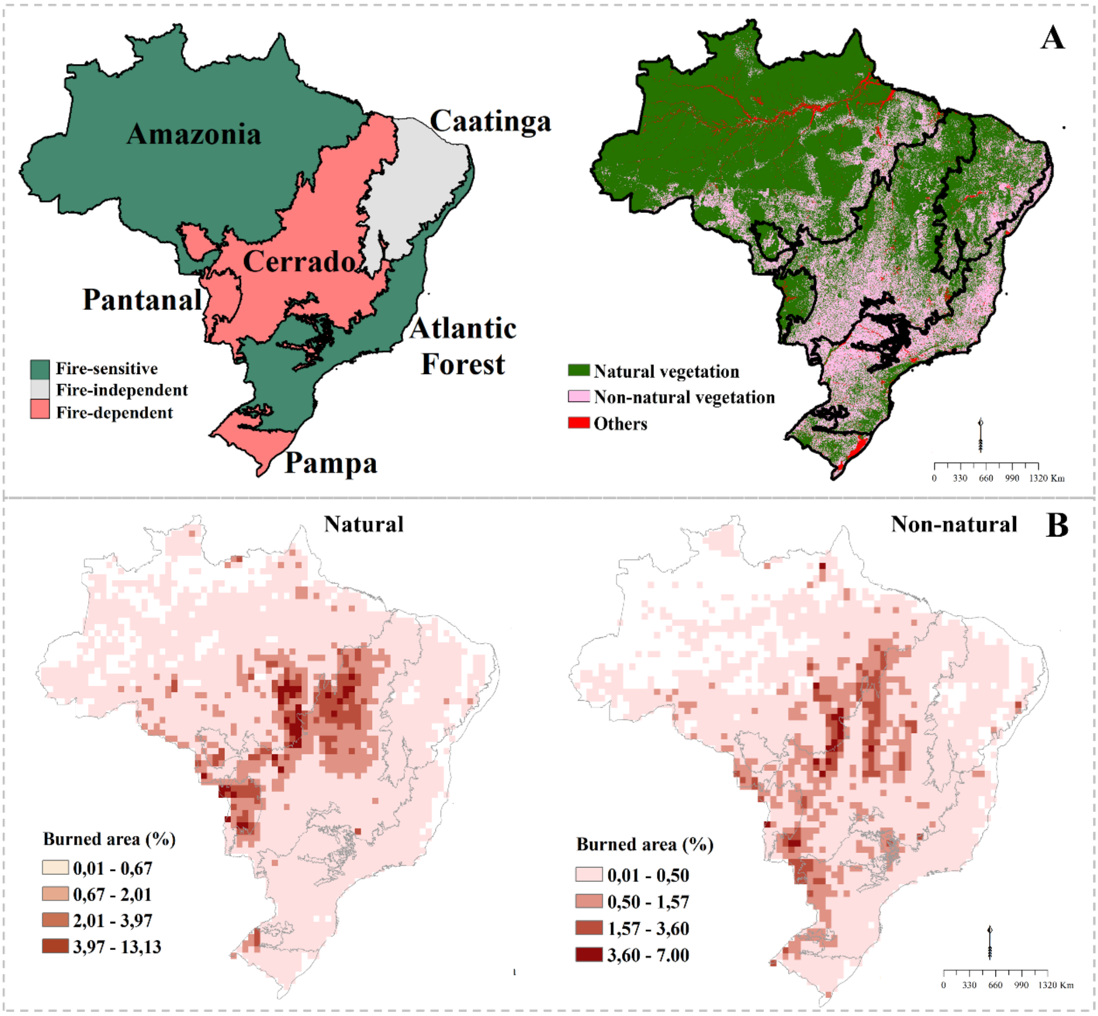
4.2 Methods

4.2.1 Datasets and preprocessing

We used the MODIS collection 6 MCD64A1 burned area product as our target variable (GIGLIO et al., 2018). The burned area data was used in its totality (ALL) and divided into two categories based on the LULC data from the Mapbiomas project (https://brasil.mapbiomas.org/en/): fires reaching natural vegetation (NAT) and fires reaching non-natural vegetation (NON) (Figure 4.1).

We computed all burned areas within forests, grasslands, and savannas for the NAT and the NON within pasture, cropland, and forest plantation, aggregated with croplands. The categorization of fires aims to assess whether there are distinct drivers for NAT and NON and to exemplify the potentialities of the model for assessing more than one fire type across different vegetation types. We adopt a broad approach to encompass the various biomes in Brazil which can be fire-sensitive, fire-dependent or fire-independent (Figure 4.1); however, any type of categorization is permissible. Further studies could focus on even finer stratification, e.g., fires reaching fire-sensitive vegetation and fire-dependent vegetation within each biome.

Figure 4.1. (A) Brazilian biomes classified as Fire-sensitive, Fire-independent and Fire-dependent on the left (HARDESTY et al. 2005) and Natural vegetation (Forests, Grasslands and Savannas) and Non-natural vegetation (Pasture, Cropland and Forest Plantations) in 2019 in Brazil on the right. (B) NAT's mean burned area percentage per pixel is on the left and NON is on the right. The maps show the mean for August, September and October from 2002 to 2019.



Source: Author's production.

The target and independent variables were extracted from August, September, and October from 2002 to 2019, representing the general peak of the fire season in Brazil (Figure 2.1). This time frame is the most extended overlapping period between the datasets which we further divided into a training phase from 2002 to 2009 and a validation phase from 2010 to 2019. The independent variables were divided into five groups (climate, ignition, fuel, LULC and forest metrics) and are described in Table 4.1. We acquired climate variables from the first component of the third simulation round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a, https://www.isimip.org/). ISIMIP is a collaborative effort to compare and evaluate the outputs of various climate and impact models (FRIELER et al., 2023). This data represents the historical simulations using climate-forcings from GSWP3-W5E5, available from 1901 to 2019 at a 0.5° spatial resolution.

We obtained soil, vegetation carbon and soil moisture from the Joint UK Land Environment Simulator Earth System impacts model at version 5.5 (JULES-ES; MATHISON et al., 2023) and driven by ISIMIP3a GSWP3-W5E5 as per Frieler et al. (2023), and is freely available at https://www.isimip.org/impactmodels/details/292/. JULES-ES has previously been used as input for Bayesian-based fire models (UNEP et al., 2022). JULES dynamically models vegetation, carbon fluxes and stores in response to meteorology, hydrology, nitrogen availability, and land use change. JULES-ES has been extensively evaluated against snapshots and site-based measurements of vegetation cover and carbon (MATHISON et al., 2023; WILTSHIRE et al., 2021; BURTON et al., 2022). As per UNEP et al. (2022), vegetation responses to JULES-ES's internal fire model were turned off so as not to double-count the effects of burning. The maps, therefore, represent environmental carbon potential and are applicable to FLAME as the model only assumes that variable variations are correctly ranked – i.e., areas of low/high carbon content correspond with real-world areas of low/high carbon and not that the absolute magnitude is correct.

Regarding ignition variables, Population Density data was also obtained from the ISIMIP3a protocol and based on data from the History Database of the Global Environment (HYDE) v3.3 (VOLKHOLZ et al., 2022). Lightning was prescribed as a monthly climatology from Optical Transient Detector (OTD) and the Lightning Imaging Sensor (LIS) aboard the Tropical Rainfall Measuring Mission (TRMM) data (CECIL, 2006). The LIS/OTD Climatology datasets comprise 0.5º gridded climatologies that document the lightning flash rates. We collected road density data of 2018 from the Global Roads Inventory Project (GRIP) (MEIJER et al., 2018), using total density in m/km², which we regridded from 8 km to the 0.5º grid used by the rest of the data using linear interpolation in the Iris Python package (MET OFFICE, 2023).

We used the collection 7 LULC data from the MapBiomas project, which produces annual LULC mapping for the Brazilian territory. They were regridded from 30m to 0.5º, using the majority class, to match the coarser resolution and interpolated from an annual to a monthly time step.

The forest metrics variables were calculated into the 0.5º grid based on the forest data from the Mapbiomas at 30m resolution using the package 'landscapemetrics' available in R (MAXIMILIAN et al., 2023). The metrics were number of patches (NP) and edge density (ED):

$$NP = n_i \tag{4.1}$$

where n_i is the number of patches belonging to class *i*. NP is an 'Aggregation metric' and describes the fragmentation of a class, in this case, forest formations.

$$ED = \frac{\sum e_i}{A} \tag{4.2}$$

where e_i is the total edge length in meters, and *A* is the total landscape area in square meters. It quantifies edge density by summing up all edges within class *i* in relation to the overall landscape area. This metric provides insights into the landscape's configuration. We incorporated these metrics to integrate fragmentation variables, which studies suggest are linked to fire occurrence in the Amazonia and Cerrado (SILVA JUNIOR et al., 2022; ROSAN et al., 2022) but remain unexplored in the other biomes.

Table 4.1 - Initial list of explanatory variables.

Group	Variable	Abbreviation	Source

to be continued

Table 4.1 - Continuation.

CLIMATE	Maximum Temperature (ºC)	tmax	ISIMIP3a FRIELER et al., (2023
	Precipitation (m/sec)	ppt	
	Vapor pressure deficit (Pa)	vpd	
	Relative Humidity (fraction)	rh	
	Consecutive number of dry days (days)	dry_days	
	Soil Moisture (fraction)	soilM	JULES-ES
IGNITION	Lightning (flashes/km/day)	lightn	ISIMIP3a FRIELER et al., (2023
	Population density (people/1000 km2)	pop	
	Road density (m/m2)	road	GRIP MEIJER et al., (2018)

to be continued

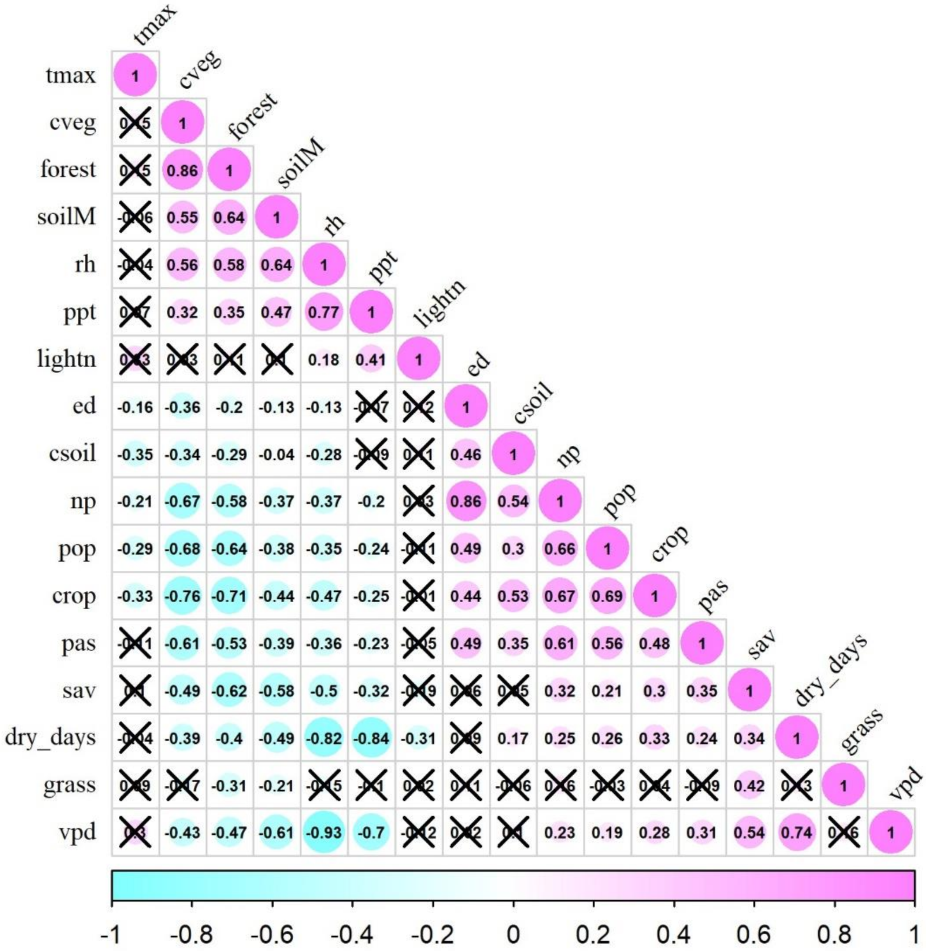
Table 4.1 – Conclusion.

FUEL	Vegetation carbon (kg/m2)	cveg	JULES-ES
	Soil carbon (kg/m2)	csoil	
LULC	Forest (%)	forest	MAPBIOMAS (2022)
	Grassland (%)	grass	
	Savanna (%)	sav	
	Cropland (%)	crop	
	Pasture (%)	pas	
FOREST METRICS	Number of patches	np	Calculated from MAPBIOMAS (2022)
	Edge density (m/m^2)	ed	

4.2.2 Variables selection

In constructing our predictive model, we considered the interrelationships among different variables to ensure a robust and coherent analysis. The selection of variables was guided by their correlation, aiming for a set of features that provided information without redundancy. For this, we calculated the Spearman correlation coefficient (SPEARMAN, 1961) presented in Figure 4.2. We chose Spearman rank over other correlation metrics as our model has a non-linear relationship between drivers and fires (Section 4.2.3), making it a better assessment than parametric comparisons. We identified variables that exhibited strong relationships by examining the correlation matrix, which we removed from the final model. We used a threshold higher than 0.6 from Spearman's coefficient for this. This approach not only helped to avoid multicollinearity issues but also enhanced its interpretability and reduced the risk of overfitting.

Figure 4.2. Spearman correlation of the explanatory variables. Crossed values indicate no correlation, values near 1 [magenta] indicate a strong positive correlation and near -1 [cyan] a strong negative correlation.

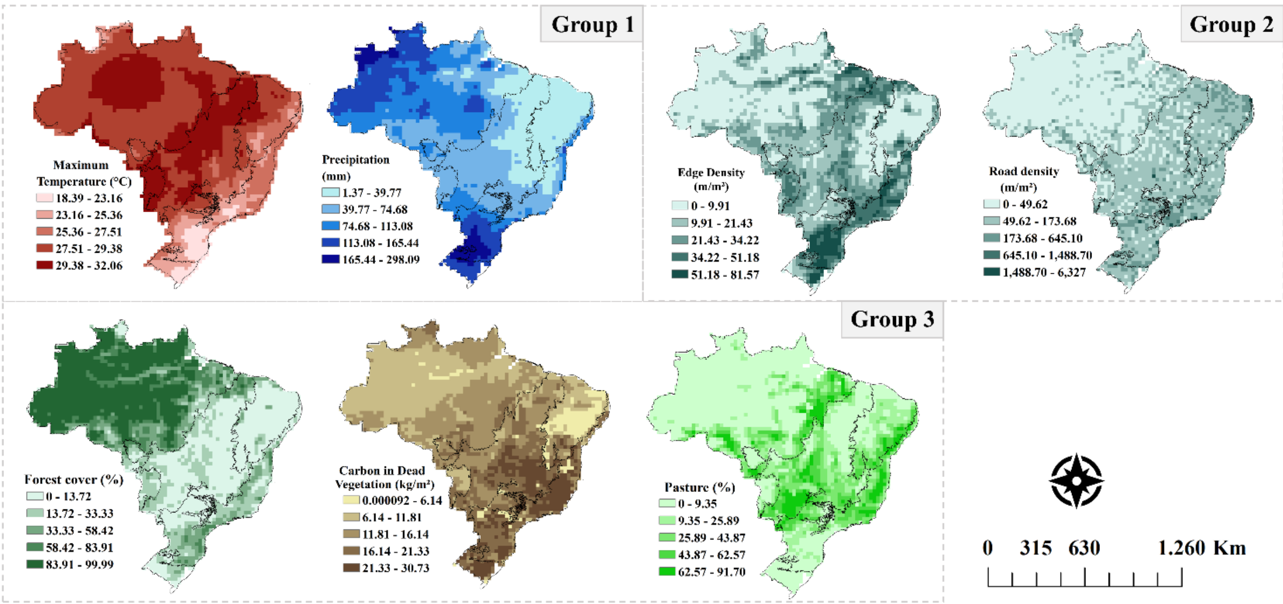


Source: Author's production.

Here, we adopted a more streamlined approach by opting for a shorter list of variables and grouping them in the variables analysis to capture their compound effect. From the 18 initial variables, we selected 7 as input for the final model (Figure 4.3). These variables were chosen based on their correlation, ensuring that at least one variable from each group was selected (Climate, Fuel, LULC, Ignition and Forest Metrics). We divided the variables into three groups: Group 1 is composed of climate variables maximum temperature and precipitation; Group

2 includes the variables edge density and road density, and, finally, Group 3 encompasses forest cover, pasture cover and soil carbon (or carbon in dead vegetation).

Figure 4.3. Mean of the selected explanatory variables for August, September and October from 2002 to 2019.



Source: Author’s production.

4.2.3 Relationship curves

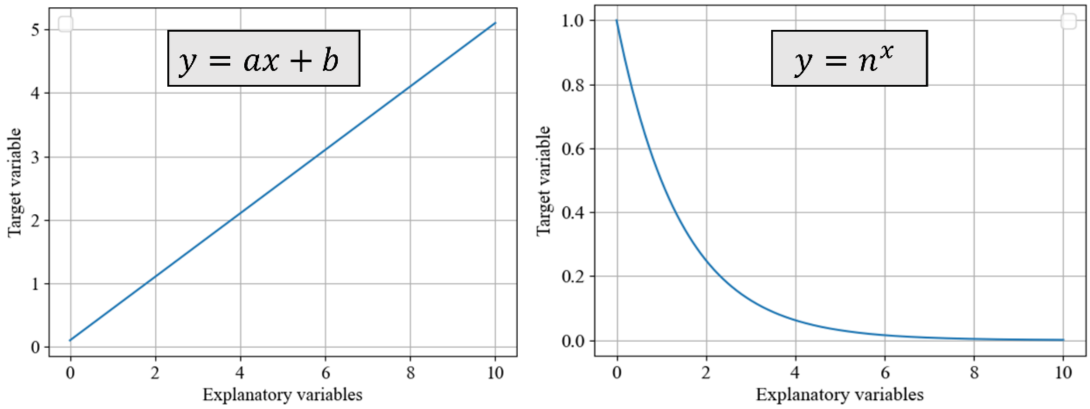
The constraints or priors of the model were added as parameters of different functions, which we refer to here as relationship curves. We included the linear and power functions (Figure 4.4) according to known relationships between fires and environmental variables. This means that some environmental variables, when presenting higher values, are likely to increase fires. In comparison, others have an inverse relationship where lower values of the variable coincide with an increase in burned area. We expect our selected variables to have the following relationship with fires:

1. Maximum temperature, soil carbon and pasture are expected to increase burning with the increase of the variable (CANO-CRESPO et al., 2015; DOS SANTOS et al., 2021; LIBONATI et al., 2022);

2. Precipitation and forest, which we expect to increase burning with the decrease of the variable (ARAGÃO et al., 2008; BARBOSA et al., 2022);
3. Edge density and roads are expected to have more uncertain response across the biomes. High density of edges can lead to more fires into forest ecosystems (ARMENTERAS et al., 2013; SILVA-JUNIOR et al., 2022) but fragmentation can also reduce fires by impeding fire spread (DRISCOLL et al., 2021). Regarding Road Density, while more fires are expected surrounding roads (ARMENTERAS et al., 2017), less fires are expected with increased density due to urbanization.

The model then estimates the contribution of each curve to the final model. Even though it is possible to include more relationship curves, we decided to keep it at a minimum to avoid making too many assumptions and unstable results due to computational efficiency.

Figure 4.4. Graphical representation of the relationship functions implemented in the model. The one on the left is a linear function and on the right is a power function.



Source: Author’s production.

4.2.4 Model optimization

The model was optimized for each Brazilian biome separately using the MCD64A1 product from 2002 to 2009 for Brazil. This process used the PyMC5 Python package (ORIOL et al., 2023), employing 5 chains each over 1000 iterations using the No-U-Turns Hamilton Monte Carlo sampler (HOFFMAN; GELMAN, 2014) while utilizing 20 % of the data or a minimum of 6000 grid cells. While the runs were conducted individually for each biome, subsequently, these results were aggregated to facilitate visualization. The entire code used to develop this model is available on GitHub repository (https://github.com/malu-barbosa/FLAME).

In Bayesian inference, we update our beliefs or knowledge about a system or event by incorporating new evidence or data. It allows us to quantify and update our uncertainty using probability distributions. By maximizing entropy, we aim to achieve the most unbiased, information-rich distribution that satisfies this prior knowledge. In this sense, the likelihood (or posterior probability) of the values of the set of parameters, β, given a series of observations Obs_i and explanatory variables (X_{iv}, from Section 4.2.2) is proportional (∝) to the prior probability distribution of $P(\beta)$ multiplied by the probability of the observations given the explanatory variables and the parameters tested.

$$P(\beta \mid \{Obs_i\}, \{X_{iv}\}) \propto P(\beta) \times \Pi_i P(Obs_i \mid \{X_{iv}\}, \beta) \tag{4.3}$$

Where $\{Obs_i\}$ is a set of our target observations, and *i* is the individual data point and $\{X_{i\,v}\}$ is the set of explanatory variables, *v*, for data point *i*. The pi notation (Π) indicates repeated multiplication. Maximum Entropy in species distribution modeling assumes that individual observations (Obs_i) are either 1 when there is a fire or 0 when there is not, and that:

$$P(1 \mid \{X_v\}, \beta) = f(\{X_v\}, \beta) \text{ and } P(0 \mid \{X_v\}, \beta) = 1 - f(\{X_v\}, \beta) \tag{4.4}$$

Where $P(1 \mid X, \beta)$ is the probability of a fire to occur, $P(0 \mid X, \beta)$ is the probability of no fire. The term $f(X_v, \beta)$ is defined below:

$$f(\{X_v\}, \beta) = 1/(1+e)^{-y(\{X_v\}, \beta))} \tag{4.5}$$

where $y(\{X_v\},\beta)$ = linear function + power function (Section 4.2.3):

$$y(\{X_v\},\beta) = \beta_0 + \Sigma_v(b_{0,i} \times X_v + b_{1,v} n^{X_v}) \quad (4.6)$$

This works for single land points, where a location burns or not burns. We extend this concept to derive the Maximum Entropy solution for fractional area burnt by integrating over a larger grid cell area. Here we consider that when dividing a gridcell indefinitely, the subcell sizes approach infinitesimally small values and the data within each subcell starts to behave like continuous data. We adapted Equations (4.3) and (4.4) to work with continuous data:

$$P(\beta|\{Obs_i\}\{X_{i\,v}\}) \propto P(\beta) \times \Pi_i^n \Pi_j^s P(Obs_{ij}|\{X_{i\,v}\},\beta)^{1/s} \quad (4.7)$$

Where *n* is the observations sample size, *j* is the individual subgrid, and *s* is the subgrid sample size. If, for a given Obs_i, m of the s subgrid cells burn, then we can adapt Equation 4.4 to get:

$$P(m/s \mid \{X_{i\,v}\},\beta) = \Pi_j^s P(1 \mid \{X_{i\,v}\},\beta)^{m} \times P(0 \mid \beta)^{s-m} \quad (4.8)$$

$$= f(\{X_{i\,v}\},\beta)^m \times (1 - f(\{X_{i\,v}\},\beta))^{m-s}$$

and therefore:

$$P(\beta \mid \{m_i/s_i\},\{X_{i\,v}\}) \propto P(\beta) \times \Pi_i^n f(\{X_{i\,v}\},\beta)^{\frac{m}{s}} \quad (4.9)$$

$$\times (1 - f(\{X_{i\,v}\},\beta))^{(m-s)/s}$$

When $s \to \infty$, m/s becomes burnt area fraction (BF). Then:

$$P(\beta \mid \{BF_i\},\{X_{i\,v}\}) \propto P(\beta) \times \Pi_i^n f(\{X_{i\,v}\},\beta)^{BF_i} \quad (4.10)$$

$$\times (1 - f(\{X_{i\,v}\},\beta))^{1-BF_i}$$

This solution assumes that burning conditions at a specific location solely explain the likelihood of burning. In reality, fires spread and, particularly at higher burnt areas, they may overlap. We, therefore, modify Obs_i so that it represents what the burnt fraction of a gridcell would look like if it was one large fire with no overlapping burning:

$$Obs_i = Obs_{i,0} \times (1 + Q) / (Obs_{i,0} \times Q + 1) \quad (4.11)$$

Where $Obs_{i,0}$ is the true observation, and *Q* is a modifier parameter to remove the effects of fire overlap.

Lastly, to account for variations in land cover for assigning between natural and non-natural vegetation which can be very small in some cells, we introduced a weighting factor *w* when assessing fire categories. This weighting factor considers the individual area of each grid cell, ensuring that cells with smaller vegetation cover contribute proportionally to the analysis. To do this:

$$P(\beta \mid \{BF_i\}, \{X_{i\,v}\}) \propto P(\beta) \times \Pi_i^n f(\{X_{i\,v}\}, \beta)^{BF_i \times w} \times (1 - f(\{X_{i\,v}\}, \beta))^{(1-BF_i) \times w} \quad (4.12)$$

We use weak, uninformed prior distributions for our Equation (4.6) parameters. β_0 , $b_{0,i}$ and $b_{1,i}$ priors were set as a normal distribution with a mean of 0 and a standard deviation of 100, and *n* a lognormal with a μ of 0 and a σ of 1.

4.2.5 Model evaluation

The model's main goal is to accurately quantify uncertainties, which we tested by analyzing where the observations fell in the model's posterior probability distribution (Equation 4.10). If more than 20% of the observations fall outside the 10-90th percentile range, the uncertainty range is too narrow. Conversely, if observations cluster around 50%, the uncertainty range is too wide. We aim to minimize uncertainty constraints without compromising accuracy. When evaluating the model against 2010-2019 observations, we also ask how likely the observations are given the optimized model (P(Observed|Simulated)), as per Kelley et al. (2021). Using a different time period from the optimization, we ensure an independent model evaluation. If the out-of-sample observations are more likely given the model, then the model performs well. We use a likelihood of 50% to indicate adequate performance.

We calculate the probability of an observation given our model by integrating the observation’s likelihood across parameter space, weighted by the parameter likelihood given our training in Section 4.2.4:

$$P(\,Y|\,(X,\beta|\,\{BF_0\}\,,\{X_0\}\,))\;=\;\int_\beta P(\beta|\,\{BF_i\}\})\;\times P(Y|\beta)\;d\beta \tag{4.13}$$

which, combined with Equation 4.10, gives us:

$$P(\,Y|\,(X,\beta|\,\{BF_0\}\,,\{X_0\}\,))=\;\int_\beta P(\beta|\,\{BF_i\}\})\times f(X,\beta)^Y\times(1-f(X,\beta))^{1-Y} \tag{4.14}$$

Where *Y* is an observation and *X* corresponds to the model inputs at the time and location of *Y*. We approximate this by sampling 200 parameter ensemble members from each of our 5 chains, providing us with 1000 ensemble members. The frequency of these 1000 in parameter gives us $P(\beta|\{BF_i\})$ in Equation 4.14. We then drive the model with each parameter combination to give us $f(X,\beta)$. We used the iris package (MET OFFICE, 2023) with Python version 3 (Python Software Foundation, https://www.python.org/) for sampling.

We also determine the percentile of our observations within the model's posterior probability distribution. In an unbiased model, we expect the observation position to be essentially random, with the mean over many samples tending towards the middle of the distribution (i.e., a percentile of 50%). We mapped out the mean position of the observations for the 30 (3 months times 10 years) time steps tested (Figure 4.6). The p-value in Figure 4.7 uses the student t-test to ascertain if the mean of the posterior position of the monthly observations for a given gridcell (mean bias) is significantly different of 0.5 (i.e., the model is biased). A mean bias near 0 indicates that observations are consistently smaller than the simulations, and near 1 indicates that the observations are greater than the simulations. Low p-numbers indicate where the model is biased towards a probability distribution, which tends to suggest too low or high burning.

4.2.6 Variables analysis

We assessed the variables' behavior against the burned area simulations by generating response maps for our variable groups in a similar way to Kelley et al. (2019). In the potential maps, we set each variable in the group to their median and kept the others at their original values. The median, representing the middle value in a dataset, was chosen because it is less affected by extreme values compared to the mean. The maps were subtracted from the original simulations (control - potential response) to quantify the influence of the target group on the model's response. This approach enables the assessment of burned area response when the variable deviates from the median and assumes its original values. The agreement maps for the potential response are then the percentage of the modeled distribution that shows an increase in burning in each biome. To compute the sensitivity response, we took the difference between a simulation where we subtracted 0.005 and added 0.005 fraction of the training range of the variable of interest. The goal was to understand how burned area responds to marginal variations in the variables.

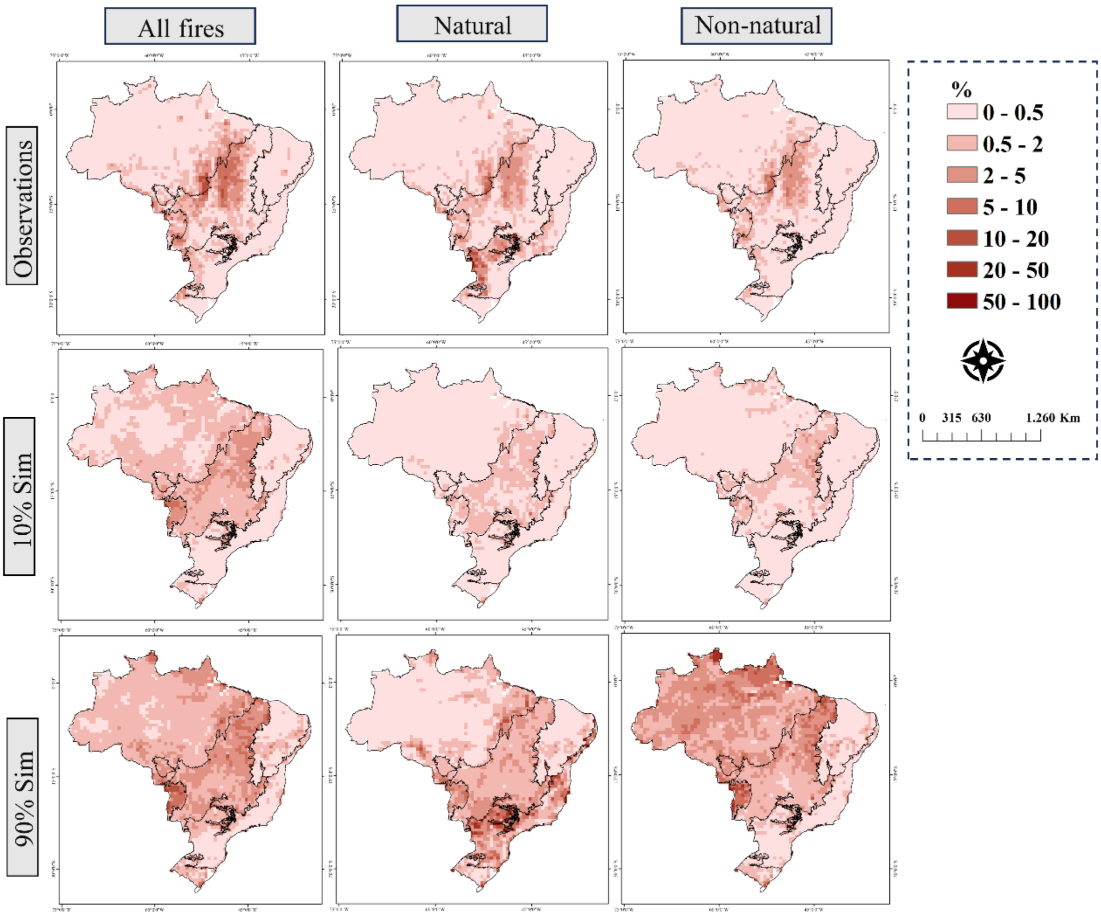
4.3 Results

We present the results in two sections. The first section will focus on the model's performance in simulating the observations, while the second section will delve into the simulation's response to the predictor variables.

4.3.1 Model simulations and performance

We performed simulations of burned area across each Brazilian biome and fire category and the resulting maps are shown in Figure 4.5. The three simulation runs (ALL, NAT, and NON) successfully captured uncertainties in all biomes, with most observations falling within the 10-90th percentile of the model. However, the model exhibits variations in uncertainties based on the simulation category. For instance, in the Amazonia, characterized by a vast expanse of natural vegetation, uncertainties were relatively smaller in NAT simulations, contrasting with larger uncertainties observed in NON simulations, especially in areas where burned areas are small or zero in the observations (Figure 4.5). Similarly, the Pantanal displayed lower uncertainties in NAT simulations, reaching values up to 10%, while NON simulations registered uncertainties up to 20% of burned area. The Atlantic Forest, distinguished by non-natural vegetation, exhibited smaller uncertainties in NON simulations. These findings indicate that the segregation of fire categories substantially impacts the model's response. Conversely, the model struggled to capture large burned areas accurately (> 10%) in the central regions of Brazil across all three simulations.

Figure 4.5. Maps of modeled and observed % burned area.



First row: observed burned area, August-October 2010-2019 annual average for ALL (left), NAT (middle) and NON (right). Second and third row: as top row but simulated by the model 10th and 90th percentiles, respectively.

Source: Author’s production.

In Bayesian inference, the likelihood expresses the probability of observing a particular event given the model's parameters. Our likelihood results imply a strong agreement between the parameters of the model and the observations (Table 4.2), even during the months when the observations were less likely. The mean likelihood during these months was above 90% in all biomes for all simulations, except for the Pantanal, where the likelihood was lower (78% for ALL and 87% for NON) but still satisfactory. The percentiles show that the likelihood of the observations of ALL in the Pantanal varied from 59% to 91% while the other biomes presented a minimum likelihood of 80%. During the best performance months, the alignment with the observations reached its maximum (100%) for most biomes on average, with the lowest value of 97% for Pantanal for ALL and NON.

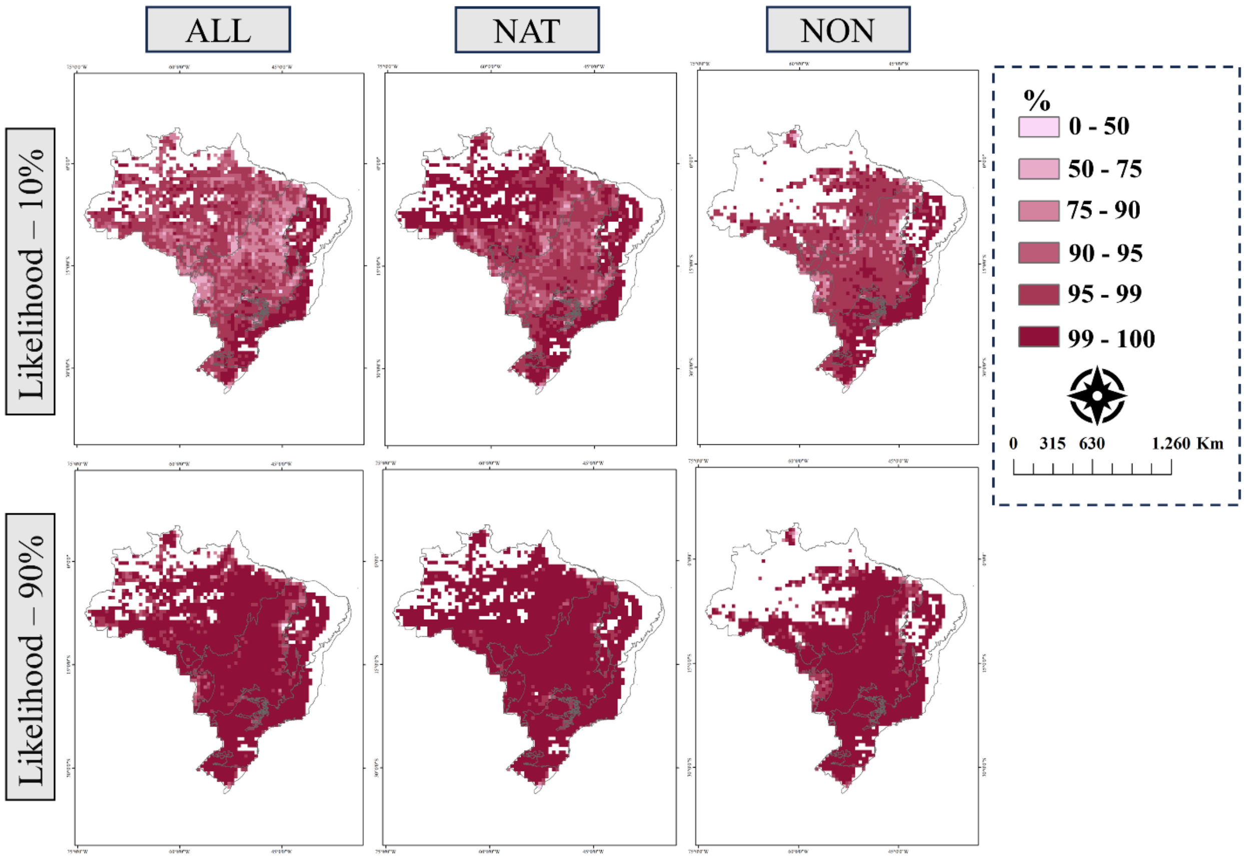
Table 4.2. Likelihood (%) per biome of the observations given the model parameters over all cells and timesteps.

	Worst performance			Best performance		
Likelihood - All fires						
Biome	**Mean**	**10th percentile**	**90th percentile**	**Mean**	**10th Percentile**	**90th Percentile**
Amazon	95	89	99	99	98	100
Caatinga	99	98	100	100	100	100
Cerrado	90	80	97	99	98	100
Atlantic Forest	99	97	100	100	100	100
Pampa	96	92	100	99	98	100
Pantanal	78	59	91	97	93	100
Natural						
Amazon	98	95	100	100	100	100
Caatinga	99	99	100	100	100	100
Cerrado	95	91	99	100	99	100
Atlantic Forest	99	98	100	100	100	100
Pampa	97	95	100	99	98	100
Pantanal	92	86	98	100	99	100
Non - natural						
Amazon	95	91	99	99	98	100
Caatinga	99	99	100	100	100	100
Cerrado	94	88	99	99	98	100
Atlantic Forest	99	98	100	100	100	100
Pampa	97	94	100	99	98	100
Pantanal	87	78	96	97	93	100

10% (left) indicates months/cells with worst performance, while 90% (right) indicates best performance.

Figure 4.6 presents the likelihood per pixel, where areas without values indicate a burned area of zero, making the likelihood incalculable. The spatial likelihood analysis provides additional insights into the model's robustness across different biomes and fire categories. The results across the biomes underscore the model's effective performance. Notably, even in the months and location where observations were less likely, the likelihood remained very high for the Atlantic Forest, Caatinga, and Pampa biomes. A high likelihood is also observed for NAT in Amazonia except for the south and east, which contains most of the non-natural vegetation. A lower performance is evident in the simulations for ALL and NON in this biome indicating that dividing fire categories according to the vegetation can be a good strategy to enhance model performance in the Amazonia, or isolating fire categories where the model has a higher predictive ability. Similarly, the Pantanal showed the best performance for NAT and lower performance for ALL and NAT in almost the entire region. Cerrado, in contrast, performed better in most of the biome for NON during the worst performance months.

Figure 4.6. Spatial likelihood of the observations given the model parameters considering the months with worst performance (top row) and the months with best performance (bottom row).



A satisfactory performance of the model is considered with values above 50%.

Source: Author’s production.

Despite the high likelihood associated with the observations, the model simulations exhibit a certain degree of bias in the three categories. A mean bias near 0.5 indicates no bias as the observations fall in the middle of the model's distribution. The Amazonia and Cerrado presented a mean bias of 0.28 and 0.29 for ALL, respectively, indicating a level of overestimation of the simulations at lower burned areas. The Atlantic Forest presented 0.51 of mean bias, indicating that the model is unbiased overall but can still present some biased pixels. Similarly, Pampa (0.42) and Caatinga (0.61) presented values near 0.5, showing a lower degree of biased values. In contrast, the Pantanal mean bias of 0.17 suggests an overestimating burned area from the model, especially at lower burned areas. However, the model can distinguish between lower and high burned areas for Pantanal (Figure 4.5), indicating the model can still identify times and locations of more extreme burnt areas, even if not exactly at the correct magnitude.

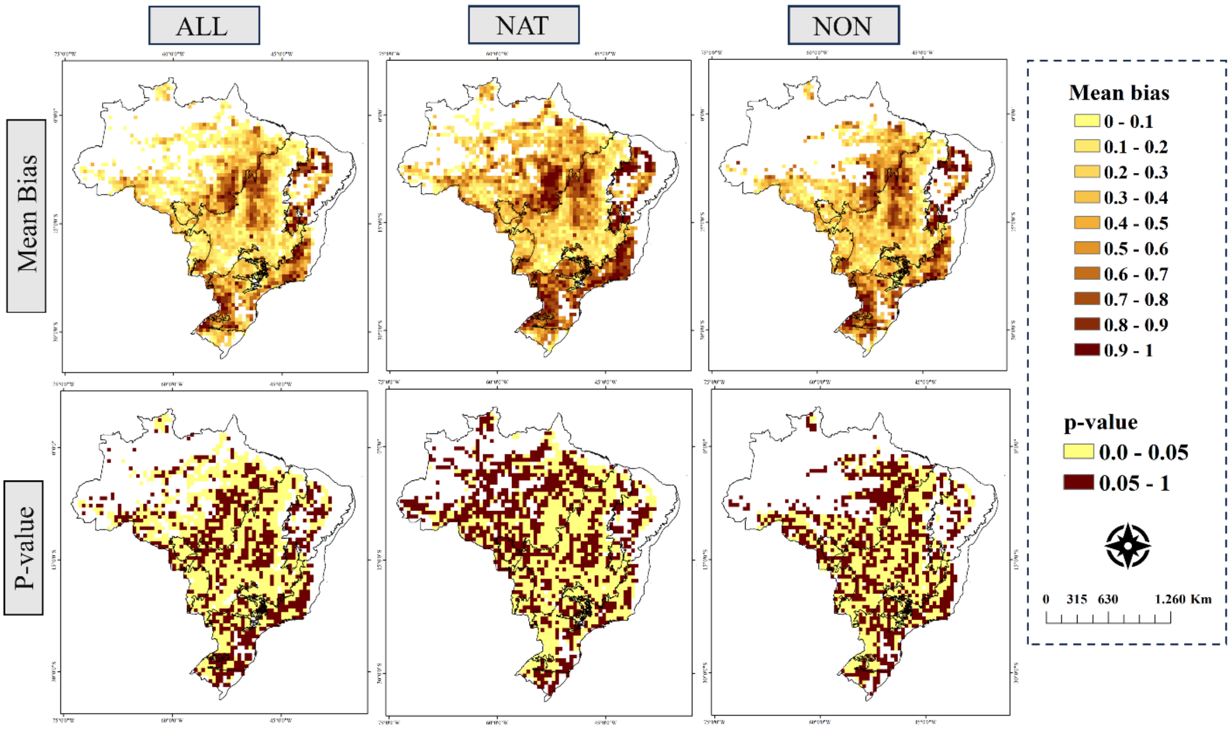
Generally, higher uncertainties are observed for NAT and NON simulations, but a notable improvement in bias is evident when compared to the ALL simulations. In the NAT simulations, the model achieved its most favorable outcomes for Pampa (0.53) and Amazonia (0.40), showcasing an improvement for the Pantanal (0.34). The biases of 0.74 for Caatinga and 0.72 for the Atlantic Forest indicate a tendency toward underestimation in this fire category. In Cerrado, for NAT, a bias of 0.33 was observed, aligning with the pattern seen in the ALL simulations and suggesting a consistent overestimation, particularly for lower burned areas.

In the NON simulations, Amazonia exhibited a bias of 0.38 but overestimated lower burned areas. Cerrado and Pantanal followed a pattern similar to NAT simulations, with mean biases of 0.36 and 0.31, respectively. The model showed a general underestimation of burned areas for the Caatinga (0.81), particularly at higher burned areas. While Atlantic Forest (0.58) and Pampas (0.59) showcased the most unbiased simulations for this fire category, it's worth noting a slight underestimation of burned areas in some instances (Figure 4.7).

The spatial distribution of the mean bias, as depicted in Figure 4.7, exhibits considerable variation. Pixels lacking values indicate zero burned area in the observations, where, by definition, the observation will always fall at the 0th percentile of the model posterior, meaning the bias metric does not provide useful information. The p-values reveal that, in numerous areas, the bias is not statistically different from 0.5 (p-value > 0.05; brown color), suggesting unbiased simulations in these regions. Specifically, lower fires in the Amazonia tend to occur in natural vegetation areas, where NAT simulations exhibit a non-significant bias. In these regions, ALL simulations tend to overestimate burnt area. In southeastern Amazonia, fires are underestimated for the three fire categories, especially for NAT.

Caatinga exhibited similar performance across the three simulations, revealing a significant underestimation of fires, particularly in the northern part of the biome. The Atlantic Forest displayed better results for ALL and NON, with a substantial area exhibiting a non-significant bias. The fragmented nature of this biome contributes to limited data availability for NAT, potentially explaining the comparatively lower performance in this fire category. Cerrado demonstrated a similar pattern across all three fire categories, characterized by an overall overestimation of fires, especially in the south and northeast. While there was some underestimation in the middle of the biome, it was mostly non-significant. In the Pantanal, the simulation consistently overestimated burnt area across all three categories, with ALL simulations showing significant overestimation for most of the biome. Finally, Pampa displayed a non-significant bias for most of the biome, except for the northwest, where the model underestimated burning in all three simulations.

Figure 4.7. Top row: Spatial mean bias of the modeled burned area to ALL (left), NAT (middle) and NON (right). Bottom row: Significance of the mean bias considering a 95% confidence level (p-value < 0 .05).



Pixels with p-value > 0.05 (brown color) are not significantly different from 0.5 mean bias meaning that they are unbiased.

Source: Author's production.

4.3.2 Response of the modeled burned area to the explanatory variables

We assessed the models Potential and Sensitivity responses of the variables (Figures, 4.8, 4.9 and 4.10). The potential response offers insights into burned area changes when the variables deviate from the median, thereby highlighting areas where responses tend to drive or suppress burning. In contrast, the sensitivity response provides information on how marginal changes in the variables affect burned area. Together, they highlight areas that are susceptible to more extreme burnt areas (i.e., where burnt area is sensitive to variables that tend to cause higher potential burning)

For ALL burnt area (Figure 4.8), variations of group 1 (maximum temperature and precipitation) from the median are very likely to lead to an increase in burned area in 62.33% of the Amazonia (likelihood > 80%). This means that in these regions, when these variables assume their actual values, burned area tends to be higher.

The increase was up to 1% in the western edge and 10% in the north, northeastern and southeastern of the biome. Conversely, these variations contributed to a reduced burned area in 33.57% of the Amazonia, predominantly observed in the western and central areas. This indicates that maximum temperature and precipitation tend to suppress burned area in these regions. In 4.08% of the biome, the influence of group 1 is not confidently predictable in terms of whether they will lead to an increase or decrease in burned area (likelihood between 40 and 60%), and the model has strong confidence in the regions where the group is the largest driver and suppress of burning. Our results indicate that the entire Amazon is highly sensitive to minor variations in group 1 for ALL (Figure 4.8). Nonetheless, the middle and western regions tended to be up to three times less sensitive than the rest of the biome.

In the Atlantic Forest, approximately 63.33% of the biome will likely experience an increase in burned areas when temperature and precipitation assume their real vs median values, mostly limited to 1% extra burning. This small increase highlights that these drivers do not have a major influence on driving high levels of total burnt area. However, because it is a fire-sensitive vegetation still could mean a large impact. Reduction of burned area is observed in the western portion, encompassing 31.79% of the biome. Uncertainties linked to group 1 were found in 4.87% of the Atlantic Forest. Moreover, the biome showed overall lower sensitivity to climate.

In Cerrado, group 1 likely drives up to 6% in burned area in 58.30% of the biome, primarily concentrated in the eastern part. Conversely, 37.16% of the Cerrado will likely observe a reduced burned area by up to 10%, showing quite a range in the influence in mean burnt area from the variable group. The remaining 4.53% remains uncertain. Cerrado exhibited high sensitivity to changes in group 1, evident across most areas except for the central region of the biome, which displayed comparatively lower sensitivity. In the Pantanal region, the middle and North areas are likely to experience an increase in burned area by up to 1% due to variations in group 1, accounting for 51.92% of their total area. Conversely, the borders of Pantanal, particularly the South, exhibit a reduced burned area (42.30% of Pantanal). Approximately 5.76% of the Pantanal landscape remains uncertain. The entire biome presented considerable sensitivity for small variations in group 1. Pampa exhibited a high likelihood of increased burned area in 70.14% of their area, mainly limited to 1%. We found a high likelihood of reduction in 26.86% of Pampas, located in the Northwestern and in 2.98% of the biome it is unclear the direction of changes. Pampa's west and southeastern edges showed to be more sensitive to group 1. The southern and eastern portions of Caatinga are likely to face an increase in burned area by up to 4%, which we can attribute to the influence of group 1 (51.23% of the biome). 47.34% of Caatinga is more likely that burned area will diminish, concentrated in the North and Western of the biome while 1.41% is unclear. In general, the biome showed less sensitivity to group 1, with slightly higher sensitivities observed in the middle and Northeast of the biome.

For group 2 (edge and road densities), 47.37% of the Amazonia biome will likely experience an increase in burned area when these variables deviate from the median. This increase is predominantly limited to 1%, concentrated in the western, middle, and northeast regions. Conversely, areas with higher edge and road densities show a reduced burned area of up to 11%, covering 51.82% of Amazonia. Overall, the biome displays moderate sensitivity to minor variations in group 2, with higher sensitivity observed along its borders. The response in the Atlantic Forest exhibited more uncertainty in the 10th and 90th percentiles. Still, the likelihood indicates that 42.30% of the biome will likely experience increased burned areas of up to 2%, primarily located in the north and eastern edges. Small reductions are found in 54.87% of the biome, limited to 0.2%. Regions where increases are more likely also demonstrate greater sensitivity to group 2, showing the potential for these drivers to have a disproportionate influence on extreme levels of burning.

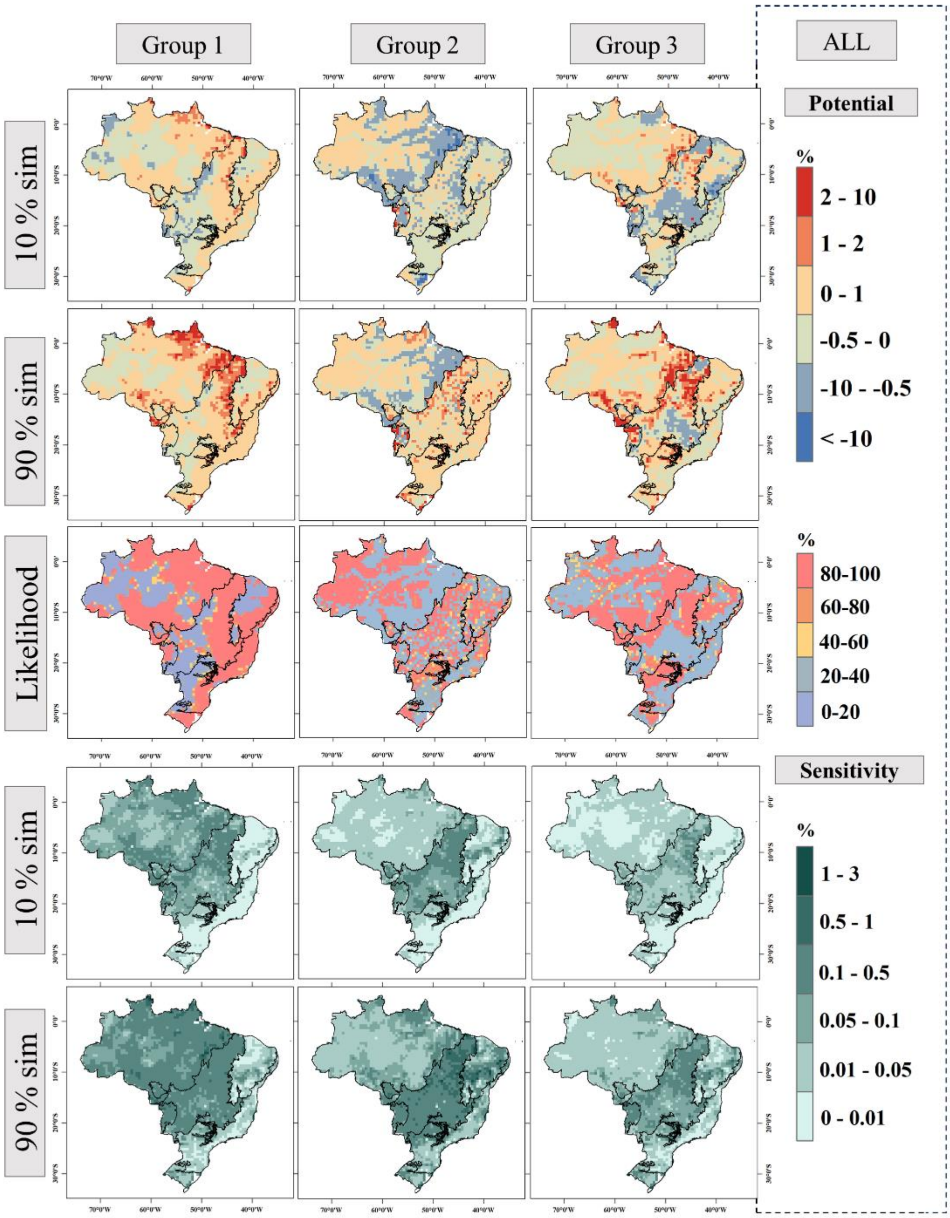
The Cerrado biome exhibited high spatial variability in response to group 2, with a mix of pixels where an increase (47.28%) and decrease (44.56%) in burned area is more likely, both limited to 2.5%. The northeast of the biome displayed higher sensitivity to group 2. In Pantanal's middle and south regions, a decreased burned area is more likely, encompassing 53.84% of the biome. However, an increase is found in 42.30% of Pantanal, limited to 8%. Pantanal demonstrated sensitivity to group 2, especially in the north. Pampa exhibited higher burned areas in 47.76% of the region, with reductions in 47%. Increases reached up to 4%, primarily in the western portion. These regions where an increase is likely also showed higher sensitivities. In Caatinga, a reduction in burned area is likely in 50.17% of the biome, while an increase is expected in 38.86%. Approximately 10.95% remains uncertain about the direction of change, with increases mainly located in the middle of the biome.

In the context of group 3 (forest, pasture, and soil carbon), approximately 53% of Amazonia will likely experience larger burned areas, primarily concentrated in the arc of deforestation, with magnitudes reaching up to 10%. Conversely, reductions are observed in 42% of the biome, with 4.23% remaining uncertain. While displaying less sensitivity to minor changes than other groups, certain areas near the borders with Cerrado and in the north exhibit higher sensitivity within the biome. In the Atlantic Forest, increased burned areas are observed in 41.53% of the region, while reductions are noted in 54.87%. Decreases in the biome are primarily observed in the middle south and eastern areas, with magnitudes reaching up to 0.7%. The sensitivity in this biome is lower overall, although the spatial variation shows heightened sensitivity in the 90th percentile for some pixels across the biome.

In the Cerrado biome, burning in the middle south and northeast edges are likely not driven by group 3, covering 54.83% of the biome. Conversely, the north, northeast, and a portion of the south (39.72% of Cerrado) may experience increased burned areas of up to 10%. Regions with higher likelihood of increase also demonstrate greater sensitivity to small variations in group 3. Pantanal shows approximately 30.77% of its area likely to experience up to a 10% increase in burned areas, mainly in the north and southeastern regions. Conversely, edges and the southern part are more prone to reductions, encompassing 55.76% of the biome, while 13% remain uncertain. Pantanal demonstrates overall high sensitivity to group 3. In Pampas, around 52.23% of the region is more likely to see increased burned areas of up to 3.5%, while reductions are observed in 44.77% of the area. The western part and eastern edges of the biome show greater sensitivity to minor changes in group 3. In Caatinga, approximately

53.35% of the biome is more likely to experience reduced burned area while 38.16% is likely to see up to 3% increases. The middle and Northeast regions, where increases are more probable, also exhibit higher sensitivity to minor shifts in group 3.

Figure 4.8. Response maps to ALL displaying the potential 10h percentile (first row), 90th percentile (second row), likelihood (third row) and sensitivity responses 10th percentile (fourth row) and 90th percentile (fifth rows).



Each column presents the results for one group of variables.

Source: Author’s production.

Similar spatial patterns to ALL were observed for NAT when considering group 1 across all biomes (Figure 4.9). In the Amazon, group 1 will likely increase burned area in 63.79% of the biome. Reductions are found in 29.92%, while 6.27% display an unclear response. This indicates a 2% increase in areas with uncertain responses, particularly in the southeastern region of the Amazon. Sensitivity analysis reveals that the borders of the Amazon are more sensitive to group 1, whereas areas with forest cover < 83% (Figure 4.3) exhibit lower sensitivity. In the Atlantic Forest, group 1 is likely to drive burned area changes in 67.95% of the biome. Conversely, 19.23% is likely unaffected by group 1, with 12.82% remaining unclear, representing an 8% increase compared to ALL. The Sensitivity to group 1 was similar to ALL, generally lower for this biome.

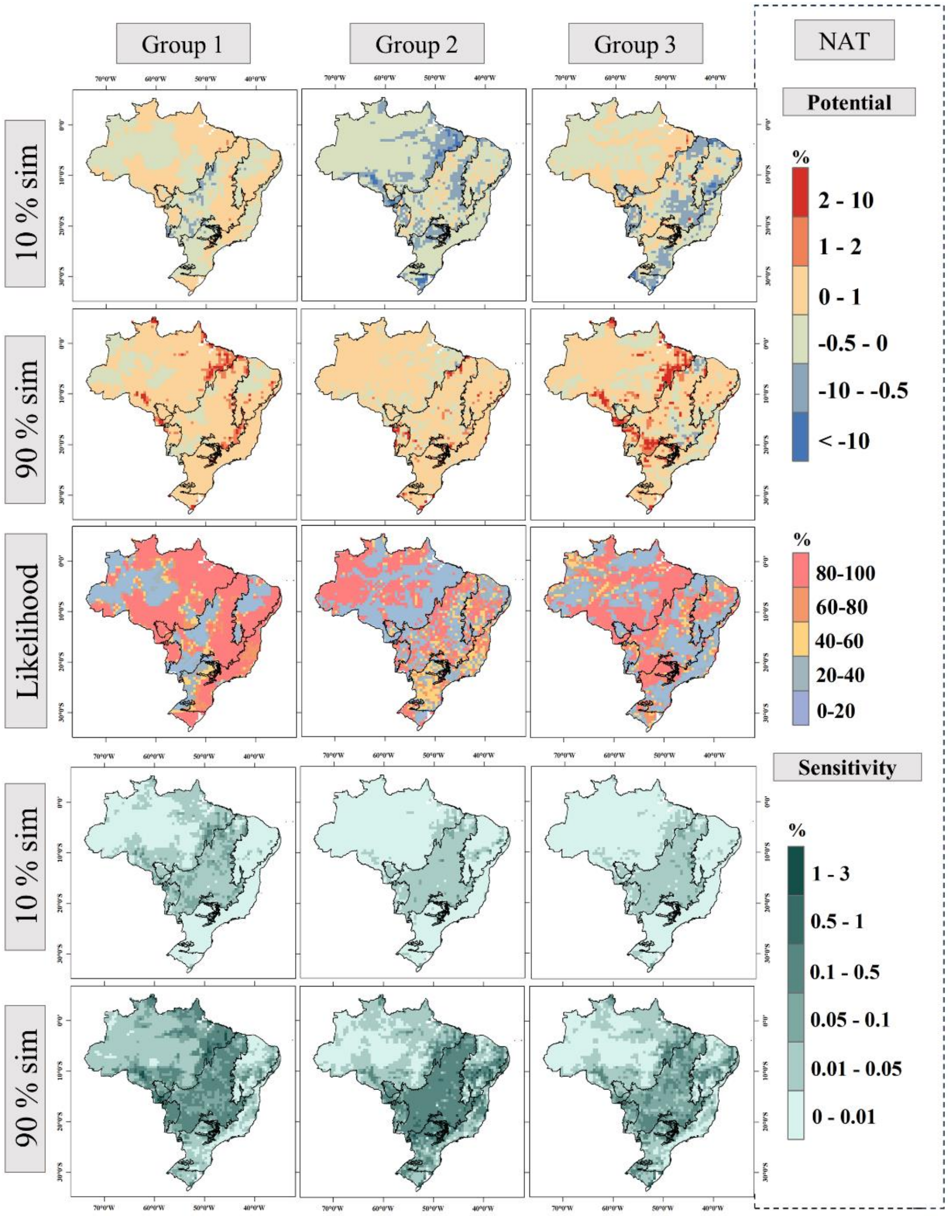
In Cerrado, group 1 contributes to increased burned area in 61.78% of the biome. In 32.78%, group 1 is likely not driving the burned area, while in 4.53%, the response is unclear. The biome also exhibits sensitivity to minor variations in group 1 for NAT, albeit slightly lower in some areas (Figure 4.9) than ALL. In Pantanal, 80.76% of its area likely has group 1 as drivers of burned area in NAT, representing an increase of almost 30% compared to ALL. Areas not influenced by this group decreased by 25% compared to ALL (15.38% of Pantanal), while 3.84% remains unclear. The sensitivity analysis closely resembled ALL, with the entire biome significantly responding to variations in group 1. In Pampas, variations from the median likely lead to increased burning in 70.14% of the biome. Sensitivity is similar to ALL, primarily in the west but generally lower. Caatinga follows a similar pattern to ALL, with group 1 influencing burning in 48.76% of the biome. Uncertainty increased to 4.94% of the biome, and sensitivity is similar, affecting mainly the middle and northeast regions.

For Group 2, Amazon presented a more uncertain response between the 10th and 90th percentiles. However, the likelihood showed a marked pattern very similar to ALL where 47.37% of the biome has group 2 as a driver of burning. Similar to group 1, the sensitivity was lower in highly forested areas. For NAT, the Atlantic Forest showed large areas with an unclear response (Figure 4.9), specifically covering 41.79% of the biome. The areas where burning is likely to be driven by group 2 encompasses 26.41%, a reduction of 15% when compared to ALL. The sensitivity was similar to ALL, with slightly higher values in some pixels. The Cerrado showed a mixed within the biome, with 45.61% of its area identified as potentially driven by group 2 in NAT. While the sensitivity was lower than in ALL, it remained significant within Cerrado. Pantanal exhibited group 2 as a driver of burning in 46.15% of the biome, displaying a spatial pattern for the likelihood very similar to ALL. However, sensitivity was lower in the middle of Pantanal compared to the North and edges. Similarly, Pampas presented a response similar for both potential and sensitivity as in ALL, with 47.76% of areas likely to experience increased burning driven by group 2. In Caatinga, areas likely to experience increased burning accounted for 37.45% of the biome, and the regions with unclear responses were 6.72% higher than in ALL (17.67%). Sensitivity showed the same pattern as in ALL.

Amazonia increased areas with unclear responses for group 3 to 8.10% (4% increase) compared to ALL. Regions susceptible to burning due to this group totaled 54.74% of the biome. Densely forested areas also exhibited lower sensitivity to minor shifts in group 3. In Atlantic Forest, group 3 is likely to be a driver of burned area in 41.02% of the biome, very similar to ALL (41.53%). Similarly, the sensitivity followed the spatial pattern of ALL with an overall lower sensitivity presenting slightly higher in some pixels. Areas prone to burning in the Cerrado due to group 3 reduced by 10.84%, totaling 43.95% compared to ALL. The reduction was concentrated in the northeast while southwest increased the likelihood of burning due to group 3. The sensitivity reduced in the northeast, varying across the biome. Within the Pantanal, regions susceptible to burning due to group 3 comprised 32.69% of the area. Regions with unclear response increased by 4.30%, encompassing 17.30% of the region and concentrated in the eastern edges.

In Pampas, 44.77% of the biome is likely to burn due to group 3, while 17.30% of the biomes showed an unclear response. The sensitivity pattern for NAT followed ALL, concentrated in the western and eastern edges. The Caatinga accounted for 35.68% of areas prone to burning, with higher sensitivities observed in the middle and eastern regions of the biome.

Figure 4.9. Same as figure 4.9 but for NAT.



Source: Author's production.

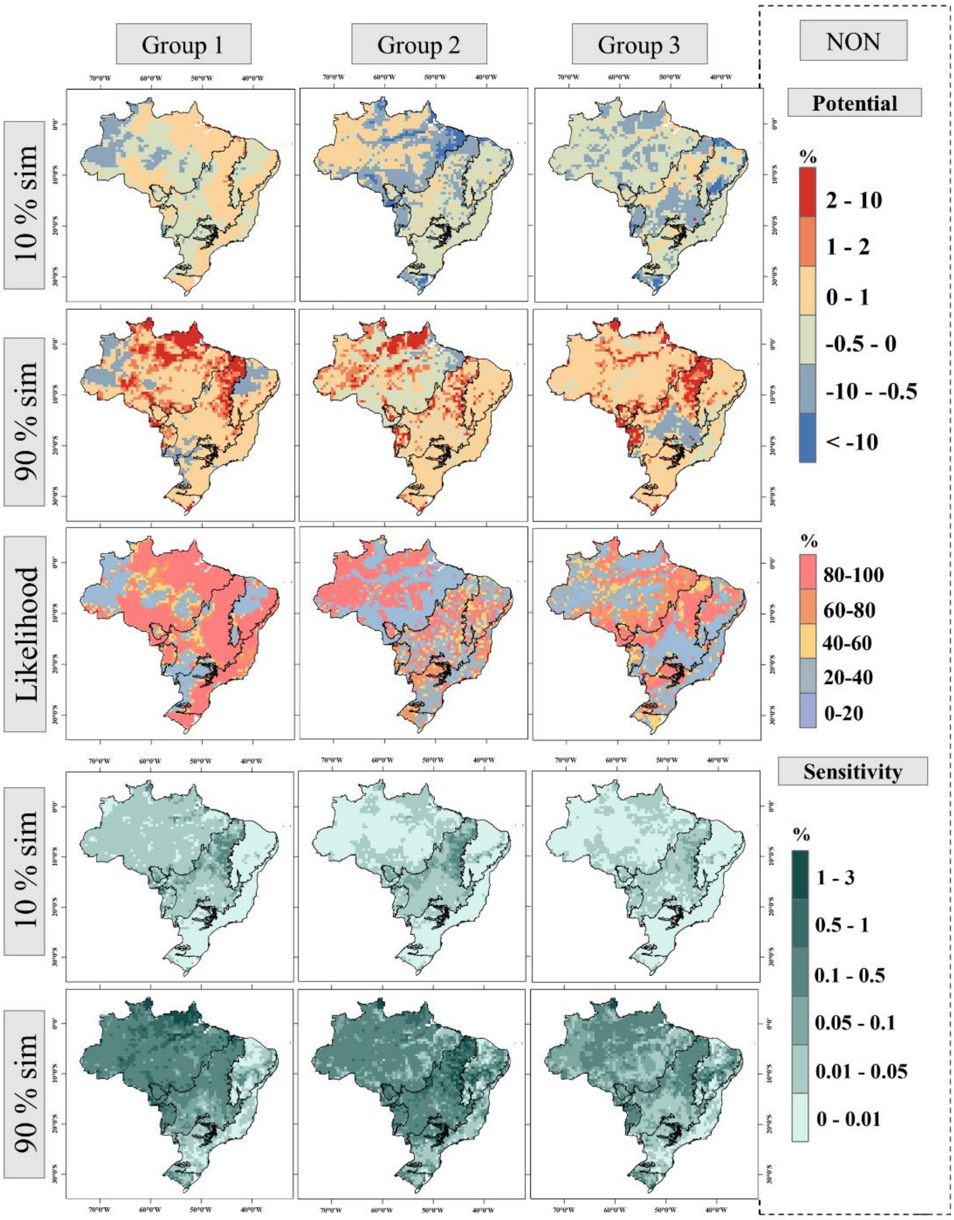
Higher uncertainties were found in the potential response for NON, meaning that the range of possible outcomes was generally larger for this category (Figure 4.10). However, the likelihood showed similar spatial variation, although unclear responses increased. Group 1 acts as a driver of burning in 62.99% of the Amazonia, a similar number when compared to NAT and ALL. The main difference for this category is the magnitude of increase, which is higher in the edges and middle of the biome. Likewise, the sensitivity was higher, especially in the 90th percentile. The potential and sensitivity response of the Atlantic Forest was quite similar for the three categories, with 64.61% likely to have group 1 increasing burning in the biome. Within the Cerrado, a 13.15% and 9.67% % increase in areas susceptible to burning is observed compared to ALL and NAT, respectively (totaling 71.45%). Unclear responses were higher and reached 9.21% of the biome. Sensitivity was higher in the northeast of the biome. For Pantanal, NON comprised 69.23% of areas likely to burn due to group 1. An increase in unclear responses of 7.7% and 9.62% compared to ALL and NAT, respectively was found (totaling 13.45% of the biome). The magnitude of increase was also higher for NON. Sensitivity levels were mostly high across the biome. Within Pampas, 79.10% of the biome was considered likely to burn due to group 1. The sensitivity was larger in the edges of the biome. The potential and sensitivity responses of Caatinga followed a similar pattern between the categories, where 47.70% of the biome is likely to be susceptible to burning due to group 1.

For group 2 again the main difference for this category in the Amazonia was the increase, which reached up to 10% in the North and middle of the biome. Most of the biome shows high sensitivity. Within the Atlantic Forest, there was a notable reduction of 30.51% in regions with unclear responses compared to the NAT, where the proportion was 11.28%. Regions likely to increase burned area due to fragmentation comprise 41.28% of the biome, an increase of 14.87% compared to NAT. Sensitivity showed a similar pattern for the three categories where regions likely to increase burning presented higher sensitivities. In Cerrado, approximately 41.54% of its area is likely susceptible to increased burning due to fragmentation, with 15.70% exhibiting unclear responses. Higher sensitivity was observed in the northeastern region of the biome. Pantanal showed 40.38% likely to increase and a significant sensitivity across the biome. Pampas patterns for potential and sensitivity responses were similar to ALL and NAT, with 49.25% of the biome likely to increase burning. However, the likelihood was comparatively lower (between 60% and 80%). For Caatinga, it is likely to increase burning in 36.39% of the biome, while the regions with unclear response reached 21.90%.

Sensitivity displayed a similar pattern to ALL and NAT with higher sensitivities in the middle and northeast.

Group 3 exhibited higher uncertainties in the Amazonia between the 10th and 90th percentiles. The likelihood of increase encompasses 44.59% of the biome, while areas with unclear responses surpass ALL and NAT, comprising 10.21%. Sensitivity was also higher, especially in the north of Amazonia. The Atlantic Forest showed a similar pattern compared to ALL and NAT with 38.71% of its area likely to increase and generally lower sensitivity to this group. Cerrado exhibited a marked pattern where burning in the north is likely driven by group 3, encompassing 40.78% of the biome. These regions also exhibited higher sensitivity to minor variations in group 3. Unclear responses were identified in 11.48% of the biome. This group exhibited the highest level of unclear response in the Pantanal, totaling 30.77%. Meanwhile, regions with a likelihood of increased burning decreased to 25%. The sensitivity was generally high across the biome. This group also showed to be highly uncertain in Pampas, with 55.22% of the biome presenting unclear responses. The areas likely to increase burning comprised 23.88% of Pampas, a reduction of 28.35% and 20.89% compared to ALL and NAT, respectively. The sensitivity was similar in the three categories with slightly higher sensitivity in the middle for NON. The Caatinga region exhibited a 35.33% portion of its area with a heightened likelihood of increased burning attributed to group 3, displaying a similar pattern across all three categories concerning potential and sensitivity response.

Figure 4.10. Same as figure 4.9 but for NON.



Source: Author’s production.

4.4 Discussion

4.4.1 FLAME's performance in context

Our proposed model combines for the first time two previously distinct approaches employed in the modeling of fires: Bayesian inference and Maximum Entropy (KELLEY et al., 2021; FERREIRA et al., 2023). This combination allows for a more comprehensive understanding of fire dynamics as it models a probability distribution rather than singular values, a departure from conventional models (HANTSON et al., 2016; RABIN et al., 2017). Notably, our approach employs Maximum Entropy to capture the most uncertain outcomes that align with our priors, reflecting the stochastic nature of real-world fires. This concept contributes to a more nuanced and realistic representation of fire behavior. We conducted our analysis by categorizing the burned area into three categories: fires in both natural and non-natural vegetation (ALL), fires reaching natural vegetation (NAT), and fires reaching non-natural vegetation (NON). This classification yielded distinct results for each category with an overall improvement across the biomes for the NAT and NON. Moreover, this approach allows us to make more targeted conclusions.

The results demonstrate the robust performance of our model in capturing observations while providing a range of possible outcomes represented by the 10th and 90th percentiles. Noteworthy is that the model was capable of reproducing the observations in Pampas, Atlantic Forest and Caatinga where other methods have not performed well in previous studies (NOGUEIRA et al., 2017, OLIVEIRA et al., 2022). Despite some level of bias in the results, even during periods of suboptimal performance, the likelihood of the observations remained consistently high, with the majority exceeding 80%. The Pantanal biome presented an exception, displaying a likelihood of 59% for the combined category (ALL), with improvement for specific categories, reaching 86% for NAT and 78% for NON. This biome encompasses a mosaic of vegetation types with very distinct fire dynamics for forest formation and grasslands (BARBOSA et al., 2022), posing a considerable challenge for simulation within the context of our proposed fire categories. However, our framework's adaptability means that future work could look at different explanatory variables, relationship variables and fire categorizations that could target performance in places like the Pantanal.

The MaxEnt species distribution model, which uses the same Maximum Entropy concept applied here, became quite popular in fire modeling studies. However, the MaxEnt software provides default settings, based on average values which are likely to change according to species, study region and environmental data (PHILLIPS; DUDIK, 2008). Additionally, these current settings are estimated to result in excessively complex models, potentially leading to overfitting (RADOSAVLJEVIC; ANDERSON, 2013). When employing MaxEnt, it is crucial to utilize independent evaluation data (PETERSON et al., 2011) such as used in the present study. However, many studies assess performance by randomly partitioning occurrence data into calibration and evaluation datasets (CHEN et al., 2015; GOLTAS et al., 2024). This approach limits the ability to obtain reliable estimates of model performance, generality, and transferability. Finally, the area under the receiver operating characteristic (ROC) curve, commonly known as AUC, is widely used as a standard method to evaluate the accuracy of MaxEnt model. Nonetheless, this measure does not provide information about the spatial distribution of the model's performance (LOBO et al., 2007; JIMÉNEZ-VALVERDE, 2011) which also potentially masks the spatial variability of the explanatory variables contribution to the model.

Currently, global fire models incompletely reproduce the observed spatial patterns of burned area. We found that FLAME captures high burning events, albeit not with the exact magnitude observed. This ability presents an advantage compared to many global fire models. While global fire modeling provides useful information into broad-scale patterns and trends, they are mostly designed to estimate global mean burned area (HANTSON et al., 2016; BURTON et al., 2023). As a result, its applicability to regional scales such as the Brazilian biomes is inherently limited. Furthermore, these models are typically constructed based on assumptions regarding variable relationships, which may not hold true in all locations due to variations in environmental conditions, ecosystem dynamics, and human activities. However, Earth System models integrate feedback mechanisms between burned areas and predictor variables, enabling the evaluation of inter-variable effects. FLAME is not designed to capture these feedbacks, underscoring the need for tailored methodologies to address specific research questions.

4.4.2 Burning controls across the biomes

We combined our variables into three groups to assess their compound effect on the burned area. This is a similar approach than Kelley et al. (2019) which also used a Bayesian framework to assess drivers of global fire regimes. Nonetheless, the research considered only linear responses which is especially challenging when considering the varying responses across the globe. Our results underscored the spatial variability of each variable group's influence on burning within and between each biome. The potential response displayed similar spatial likelihood variation between the ALL, NAT and NON categories. However, differences were still observed, especially for the fire-dependent biomes. Overall, the uncertainties were larger for the NON category, particularly for Pampas and Pantanal.

For example, maximum temperature and precipitation (Group 1) are likely drivers of burning in large portions of each biome during the fires' peak, as demonstrated by the potential and sensitivity results. Our results indicate that climate alone in highly forested areas in Amazonia are not the controls of burning, suggesting that forests can potentially mitigate the effects of climate in burned area. These regions showed up to three times less sensitivity to minor variations of climate for NAT while ALL and NON displayed high sensitivity in the whole biome. However, natural landscapes, especially forests, are highly susceptible during extreme weather conditions (DOS REIS et al., 2021; BARBOSA et al., 2022). This suggests that projected climate change could greatly increase the risk of Amazonia forest fires (FLORES et al., 2024). Moreover, non-natural vegetation in the Amazonia is mainly concentrated in the arc of deforestation, reducing the samples for this category in other parts of the Amazon and potentially influencing the model’s response. An opposite dynamic was found in Cerrado and Pantanal, regions with large areas of natural vegetation were more likely to be influenced by climate. These regions were more sensitive to minor variations in climate for NON in Cerrado while the entire Pantanal displayed similar sensitivity in the three categories. This aligns with prior research showing that fires in Cerrado are linked with meteorological conditions, particularly rainfall and temperature (NOGUEIRA et al., 2017; LIBONATI et al., 2022; LI et al., 2022). Similarly, in Pantanal, the

2020 fire season revealed the connection of increased burning and meteorological conditions in the biome (BARBOSA et al., 2022; LIBONATI et al., 2022b) and once again during the 2023 El Niño. Barbosa et al. (2022), reported that 84% of the 2020 record of fires in Pantanal occurred in natural vegetation with a 514% increase from average within forests. Despite being a combination with land use, the precipitation and maximum temperature anomalies were particularly high in 2020, contributing to the spread of fires into fire-sensitive vegetation.

Group 2 (Edge density and Road density) encompasses variables expected to have uncertain response across the biomes. Within Cerrado, 40.63% of its area will likely decrease burned area for NAT due to group 2. High density of forest edges has been associated with a higher incidence of fires in forest ecosystems (ARMENTERAs et al., 2013; SILVA-JUNIOR et al., 2022). However, fragmentation can also act as a barrier to fire spread, potentially reducing fire occurrences (DRISCOLL et al., 2021). Rosan et al. (2022), revealed that in the Cerrado, fragmentation correlates with a decrease in burned area fraction, while in the Amazonia, it is linked to an increased burning. Nevertheless, we found a decrease in burning where edge densities are concentrated in the Amazon. This could indicate that the edges of the Amazon are reaching a level of fragmentation that fires are impeded of spreading, considering the reduction of aboveground biomass near forest edges (NUMATA et al., 2017). Still, future research is needed to test this hypothesis.

Depending on the landscape, road densities can also exhibit contrasting relationships with fires. While more fires are expected surrounding roads (ARMENTERAs et al., 2017), less fires are expected with increased density due to urbanization. The Atlantic Forest is a very fragmented biome with very high densities of natural edges and roads (Figure 4.3). We found an uncertain response for NAT in 41.79% of the Atlantic Forest and only 26.41% likely to increase. Singh and Huang (2022), suggests that the fragmentation partly explains burned area variation in the Atlantic Forest where small patches are more vulnerable to fires. The majority of Caatinga is likely to decrease burning due to group 2. However, the sensitivity was up to three times higher in the middle and northeast, which is more likely to increase. Antongiovanni et al. (2020), discussed that fires in Caatinga occur at all edge distances, although slightly more frequent at fragment edges. Nonetheless, the limited amount of studies across the different biomes addressing these relationships makes it harder to understand the related uncertainties.

Group 3 is likely to influence burning in 54.74% of Amazonia for NAT, particularly in the arc of deforestation. This suggests that the combination of less forest, increased pasture and more fuel (Figure 4.3) increases burning in natural lands in Amazonia, corroborating previous findings (SILVEIRA et al., 2020; SILVEIRA et al., 2022). The relationship in Pantanal and Pampas showed that these variables increase burning in 32.69% (NAT) and 25% (NON) in Pantanal and 44.78% (NAT) and 23.88% (NON) for Pampas. The regions with unclear responses were the highest for NON, 30.77% of Pantanal and 55.22% of Pampas. These biomes are characterized by lower forest and pasture cover (Figure 4.3) with fires and cattle ranching mainly linked to grasslands (BARBOSA et al., 2022; FIDELIS et al., 2022; CHIARAVALLOTI et al., 2023). Thus, incorporating grassland cover in the model will likely reveal further relationships in these biomes. Caatinga showed increased sensibility where group 3 is likely to increase burning, matching the area of influence of group 2. This area is associated with low forest cover and soil carbon and moderate pasture cover. Araújo et al. (2012), observed that due to the intermittent and scattered characteristics of cattle ranching in the Caatinga, fires tend to occur mainly in natural vegetation, characterized by large cover of savanna vegetation. Although our study provides a general overview of burning dynamics in the biomes, targeting variables is highly recommended in future studies, especially where fires are poorly understood as in Caatinga.

4.4.3 FLAME potentialities

Further developments are recommended to improve FLAME's capabilities. Exploring and incorporating better-informed and additional priors may constrain the variables' response uncertainties. Utilizing alternative metrics to assess drivers, particularly those tailored to specific biomes, could offer a more nuanced understanding of the influencing factors, and help improve biases in biomes such as the Pantanal. Customizing variable selection based on biome characteristics would also contribute to a more biome-focused and contextually relevant analysis. Consideration of different fire categories show how the model could be used in further research. For instance, a more detailed stratification could involve categorizing fires into distinct groups such as forest, agricultural, and deforestation fires. While deforestation data was not incorporated due to its inconsistent availability across all biomes, efforts should be made to integrate this valuable information where possible. Furthermore, accounting for the varying proportions of natural and non-natural lands within each pixel, as demonstrated in this study, provides a more accurate landscape representation, contributing to improved simulations where these areas are very small. It's worth noting that using finer grids and the subdivision of the biomes may uncover local processes, though eventually fire spread between fine-scales would need to be considered. This could be crucial for understanding localized patterns and improving the model's predictive capabilities. Importantly, FLAME is flexible enough to be used in various locations and, through targeted benchmarking, holds the potential to evaluate extreme fires, inter-annual and seasonality variability of fires, project future fire trends, and simulate other hazards. With appropriate adaptations and enhancements, FLAME has the potential to evolve into a robust model capable of simulating terrestrial impacts effectively.

4.5 Final Considerations

The self-reinforcing cycle between fires and climate change makes it fundamental to improving fire simulations. Understanding what drives fires is essential for devising strategies. However, it can be particularly challenging due to the intricate interplay of various factors, especially in a diverse country like Brazil. We propose a novel approach for simulating burned area in the Brazilian biomes that keeps assumptions at a minimum while allowing the quantification of uncertainties. The model performs well in all biomes, and we show that the model enables the assessment of fire categories and the grouped effect of variables. Furthermore, conventional modeling efforts often parameterize on a large region basis. FLAME enables optimization in smaller areas while still providing a means to quantify confidence in the analysis.

The climate is an important factor in burned area in all biomes. Despite several studies showing this relationship, climate-related uncertainties have not been extensively quantified. Groups 2 (road and edge densities) and 3 (forest, pasture and soil carbon) and the NON category showed the highest uncertainties among the responses. This highlights the challenge in modeling human-related factors. Pantanal, Cerrado, and Amazonia showed overall higher sensitivity to minor variations in the variables. Important to note that the sensitivity is more important where burning is already high which is the case of these biomes (ALENCAR et al., 2022). Uncertain responses compound the complexity of burned area drivers, as different variables interact uniquely within each biome. The same vegetation type may show contrasting responses to the same drivers in different locations. Therefore, no universal fire management policies will fit the whole country. Caatinga, Atlantic Forest and Pampas especially require further investigation. Emphasizing regional-scale analysis is crucial for decision-makers and fire management strategies, enabling more informed and effective prevention of fires.

5 BURNING IN PANTANAL DRIVEN BY WETLAND DEGRADATION AND LOWER PRECIPITATION

5.1 Introduction

The Brazilian Pantanal, renowned for its diverse ecosystems, faces escalating threats due to increasingly intense fires. The region is a seasonally flooded biome deeply intertwined with adjacent biomes such as the Cerrado and Amazon, exhibiting a unique blend of fire-prone and fire-sensitive ecosystems. While fire plays a natural role in fire-prone regions, fire-sensitive areas suffer profound biodiversity losses when affected by fires (MIRANDA, 2010; MARTINS et al., 2022). Despite its significant remaining natural vegetation, we should not underestimate the Pantanal's susceptibility to major disasters. Extreme fires ravaged approximately 4 million ha of the Pantanal in 2020 (BARBOSA et al., 2022) and 1.2 million ha in 2023, threatening the ecological processes and the survival of its diverse wildlife, including jaguars and macaws (BARROS et al., 2022; FERREIRA et al., 2023).

Pantanal is a complex environmental system and, thus, also is fire occurrence. The dynamics of the wetlands play a pivotal role in this context. During exceptionally dry years, when the peak water level is too low to inundate the grasslands along the river, a substantial amount of biomass from the previous flooding cycle remains, fueling potential fires. The water surface area of the Pantanal has been continuously decreasing since 2003 when it was 34% greater than the annual average in 2020 (BARBOSA et al., 2022). In 2020, the Pantanal faced an extreme drought, resulting in a wet season with rainfall levels 60% below average (MARENGO et al., 2021). This trend towards extreme dry seasons is anticipated to escalate in frequency due to climate change, influencing inter- and intra-annual flood dynamics (THIELEN et al., 2020), and amplifying the biome's susceptibility to fires. The reduction of wetlands is not only associated with droughts but also with the construction of drainage systems, major roads, and hydropower infrastructure (ANA et al., 2018; DA SILVA et al., 2021; WANTZEN et al., 2023).

Combined with climate change, fires are likely to play a crucial role in shaping the future land-cover types in Pantanal (ARRUDA et al., 2016). They will influence whether these areas can sustain critical habitat types and ecosystem services over the long term or if they will enter a period of degradation.

Considering that fires are rarely a result of one factor alone, the complex interactions among various factors results in inherent uncertainties. Libonati et al. (2022), demonstrated that there is significant spatial variability in the fire-affected areas driven by heatwave and droughts among nine subregions of Pantanal. Moreover, ignitions in Pantanal are mainly linked to human activities which often cause uncontrolled burning over native vegetation (MENEZES et al., 2022). However, further studies are needed to enhance our understanding of the drivers' variability within Pantanal and their land use and climatic dynamics thresholds associated with increased wildfires. In this sense, modeling approaches allow us to quantify burning responses to changes in variables (KELLEY et al., 2021).

Here, we aim to comprehend the Pantanal's vulnerability to changes in climate and land cover. We use the FLAME (Fire Landscape Analysis using Maximum Entropy) model approach to address the following questions: 1. To what extent is the Pantanal biome experiencing an increase in burning due to climate and land cover changes? 2. What are the thresholds of climate and land cover associated with increased burning in Pantanal? Has the exceptional year of 2020 reached these critical thresholds?

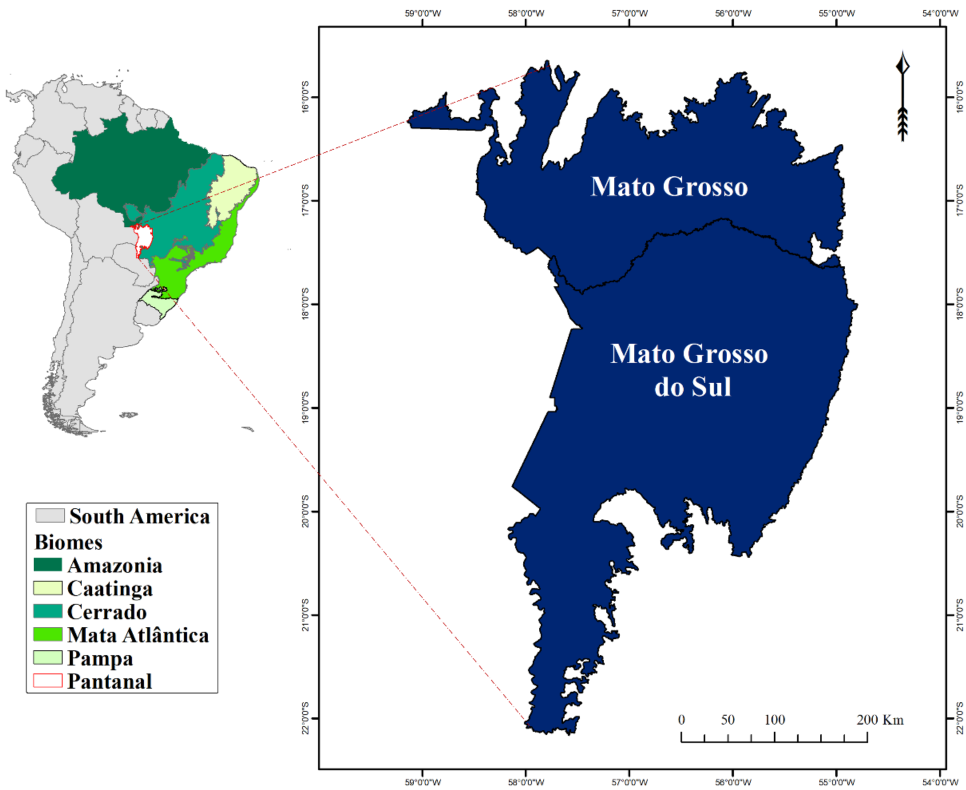
5.2 Methods

5.2.1 Study area

Situated in the central-west region of Brazil, the Brazilian Pantanal spans across the states of Mato Grosso (35%) and Mato Grosso do Sul (65%; Figure 5.1). The biome comprises about 2% of the Brazilian territory, covering approximately 151,000 km² (SORIANO et al., 2020). This unique biome holds particular geographic significance between the Cerrado, Chaco, and Amazon regions. The Pantanal's geographical location influences its climate dynamics and vegetation composition, receiving direct influences from neighboring biomes (MARENGO et al., 2021). The Pantanal is considered one of the largest remaining wetlands of natural vegetation in the world, extending to the countries Brazil (80%), Bolivia (19%) and Paraguay (1%). This biome is located in the Upper Paraguay River Basin, which belongs to the River Plate Basin, the second largest in South America.

The tropical climate in Pantanal is characterized by a distinct rainy season in summer and a dry winter. Annual rainfall varies across the region, with the north-northeast receiving the highest precipitation levels of around 2000 mm, followed by the south (1800 mm) while the central Pantanal records the lowest at approximately 900 mm (LAZARO et al., 2020). This rainfall distribution defines the Pantanal's flooding cycles, with rainy seasons lasting from October to March, accounting for over 80% of the total annual rainfall, and dry seasons from April to September. The wetlands are mainly located in the western and south of Pantanal and flooding is also influenced by rivers that originate in the Plateaus in its eastern half (MARENGO et al., 2021).

Figure 5.1. Geographic location of the Brazilian Pantanal biome.



Source: Author’s production.

5.2.2 Datasets

We used data from the MODIS collection 6 MCD64A1 burned area product (GIGLIO et al., 2018) to derive the dependent variable. We assessed only fires in Natural vegetation (NAT) given the high conservation of natural lands in Pantanal and the reduction of bias for this category found in Chapter 4. For this, we included fires in forests, wetlands, grasslands and savannas. The predictors were selected based on the learnings from Chapter 4, encompassing precipitation (mm), maximum temperature (ºC), soil carbon or carbon in dead vegetation (kg/m²), vegetation carbon (kg/m²), forest (%), savanna (%), cropland (%), pasture (%), wetland (%), and grassland (%). The removal of edge and road densities reduced the bias in the biome. We decided to include wetland, grassland and savanna to better characterize the vegetation linked to fires in the biome. Furthermore, the incorporation of pasture and cropland aimed to capture the dynamics along the borders of the biome where these land uses are concentrated (MAPBIOMAS, 2022). These variables were extracted for August, September, and October from 2002 to 2020, representing the peak of burning in Pantanal (Figure 2.1).

The data used in Chapter 4 was GSWP3-W5E5, the priority one dataset for the third simulation round of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a, FRIELER et al., 2023). However, this dataset finishes in 2019. Here, we therefore use ERA5 dataset instead, also provided by ISMIP3a, which captures the 2020 extreme fire season in Pantanal. The dataset was split into a training phase (2002-2010) and a validation phase (2011-2020). Precipitation and maximum temperature were sourced from ISIMIP3a's ERA5, available at a 0.5° spatial resolution. We derived soil and vegetation carbon data from version 5.5 of the Joint UK Land Environment Simulator Earth System impacts model (JULES-ES; MATHISON et al., 2023), also driven by ISIMIP3a ERA5 data, following Frieler et al. (2023). The Land Use and Land Cover (LULC) data were obtained from the MapBiomas project, collection 7. The LULC variables underwent regridding from 30 m to 0.5° resolution using the most popular value in the filter window and were interpolated from annual to monthly time steps.

5.2.3 Modeling framework

The modeling protocol and optimization framework detailed in Chapter 4 were replicated for the Pantanal region, utilizing FLAME (Fire Landscape Analysis using Maximum Entropy). We obtained the target variable from the MCD64A1 product (GIGLIO et al., 2018). This process employed the PyMC5 Python package (ORIOL et al., 2023), employing 5 chains each over 1000 iterations using the No-U-Turns Hamilton Monte Carlo sampler (HOFFMAN; GELMAN, 2014), while utilizing 20% of the data to train the model. The likelihood of the values of the set of parameters, β, given a series of burned area observations (*BF*) and explanatory variables (X_{iv}) is proportional (∝) to the prior probability distribution $P(\beta)$multiplied by the probability of the observations given the parameters tested:

$$BF_i \ = \ BF_{i,0} \ \times (1 \ + \ Q) \ /(BF_{i,0} \ \times \ Q \ + \ 1) \tag{5.1}$$

Where BF_i is the true Burned Fraction observed, and *Q* is a modifier parameter to remove the effects of fire overlap. Then:

$$P(\ \beta \mid \{BF_i\}\,,\{X_{i\,v}\} \ \propto \ P(\beta) \ \times \ \Pi_i^n f(\{X_{i\,v}\},\beta)^{BF_i \times w} \\ \times \ (1 - \ f(\{X_{i\,v}\},\beta))^{(1-BF_i)\,\times\,w} \tag{5.2}$$

Where *n* is the observations sample size, $\{BF_i\}$ is a set of our target observations, and *i* is the individual data point and $\{X_{i\,v}\}$ is the set of explanatory variables, *v*, for data point *i.* Also, *w* is a weighting factor when assessing fire categories which considers the individual area of each grid cell, ensuring that cells with smaller vegetation cover contribute proportionally to the analysis. The mathematical solution and explanation of each term is fully described in Chapter 4.

We incorporated the linear and power functions as relationship curves of the model, which then estimates the contribution of each curve to the posterior distribution. The assessment of the likelihood of the observations given the optimized model is represented by P(Observed|Simulated). A likelihood of 50%

indicates adequate model performance (KELLEY et al., 2019). To calculate the likelihood of an observation given the model, the likelihood of the observation across parameter space is integrated, weighted by the parameter likelihood given our optimization. This is achieved by sampling 200 parameter ensemble members from each of the 5 chains, yielding 1000 ensemble members. Sampling was conducted using the iris package (MET OFFICE, 2023) in Python version 3 (Python Software Foundation, https://www.python.org/).

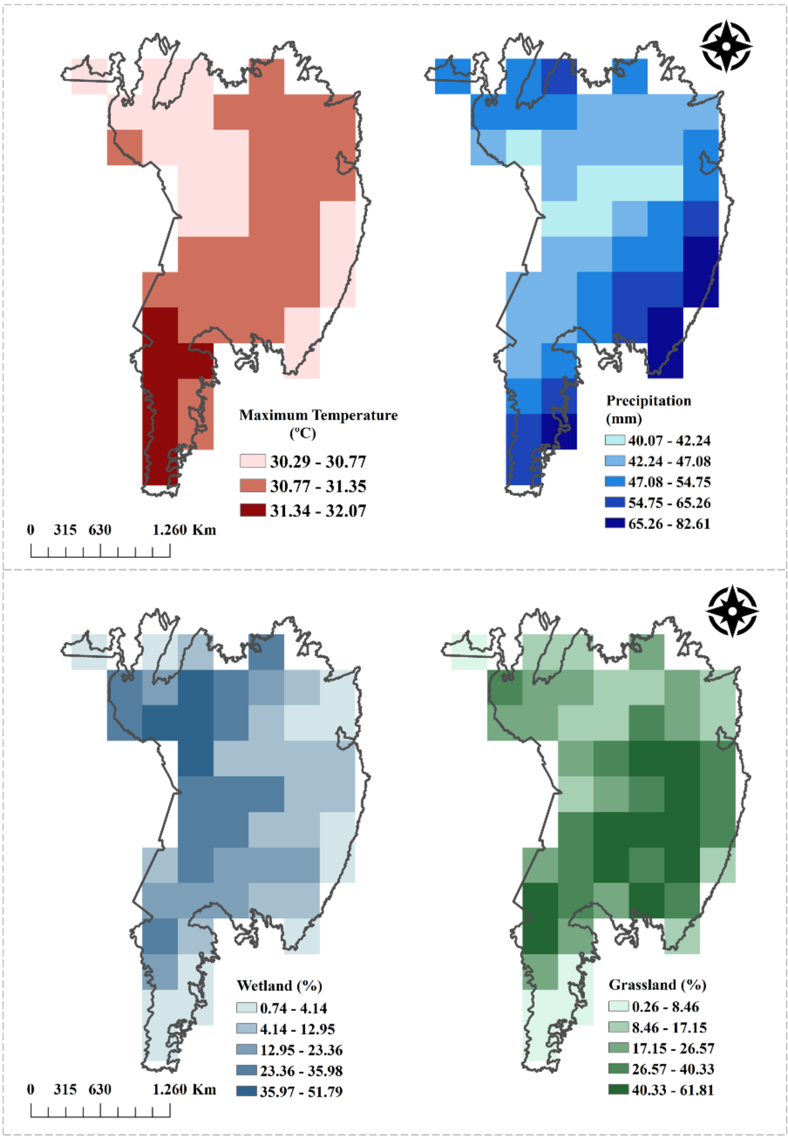
We also evaluate the percentile of observations within the model's posterior probability distribution. In an unbiased model, the observation should randomly fall throughout the distribution, with the mean of the observation position tending towards the middle of the distribution (i.e., a percentile of 50%). The mean position of observations for the 30 (3 months times 10 years) time steps tested. The p-value employs the student t-test to ascertain if the mean of the posterior position of the monthly observations for a given gridcell (mean bias) significantly differs from 50%, indicating model bias. A mean bias near 0 suggests observations are consistently smaller than simulations, while a value near 1 indicates observations are greater than simulations. Low p-values indicate a significant model bias (i.e., the mean observational position is significantly different to 50%), highlighting either too low or high burning.

5.2.4 Variables assessment

From the 10 variables used in the optimization, we decided to analyze in more detail four of them while creating three groups: precipitation and maximum temperature (group 1), wetland and grassland (group 2) and precipitation and wetland (group 3). The four selected variables were the most relevant to the research questions we are investigating as the biome is mainly covered by wetlands and grasslands while very influenced by weather conditions. In the potential analysis, we adjusted each variable within the group to its median value while keeping the other variables at their original values. Subsequently, we subtracted these adjusted maps from the original simulations (control - potential response) to quantify the impact of the target group on the model's response. This approach allows us to evaluate how burned area responds when the variable deviates from the median and returns to its original value. The agreement maps for the potential response represent the percentage of the modeled distribution that indicates an increase in burning within the biome. To compute the sensitivity response, we subtracted the simulations with the group of interest minus 0.005 from those with the group of variables plus 0.005.

Finally, in R Studio version 4.0.4, we utilized the “lm” function to fit a linear regression model to time series data from 2002 to 2020 to identify trends in the variables under evaluation. A trend denotes a consistent movement of the time series in a specific direction. This linear trend model is a simple regression model where the independent variable comprises a time index (in this case, year). Subsequently, we employed the “predict” function to derive predicted values of the dependent variable for each year based on the fitted linear regression model. The function extracts the first and last predicted values, delineating the starting and ending points of the trend line. This trend line represents the singular line that minimizes the sum of squared deviations from the data.

Figure 5.2. Mean percentage of the explanatory variables under assessment for August, September and October from 2002 to 2020.

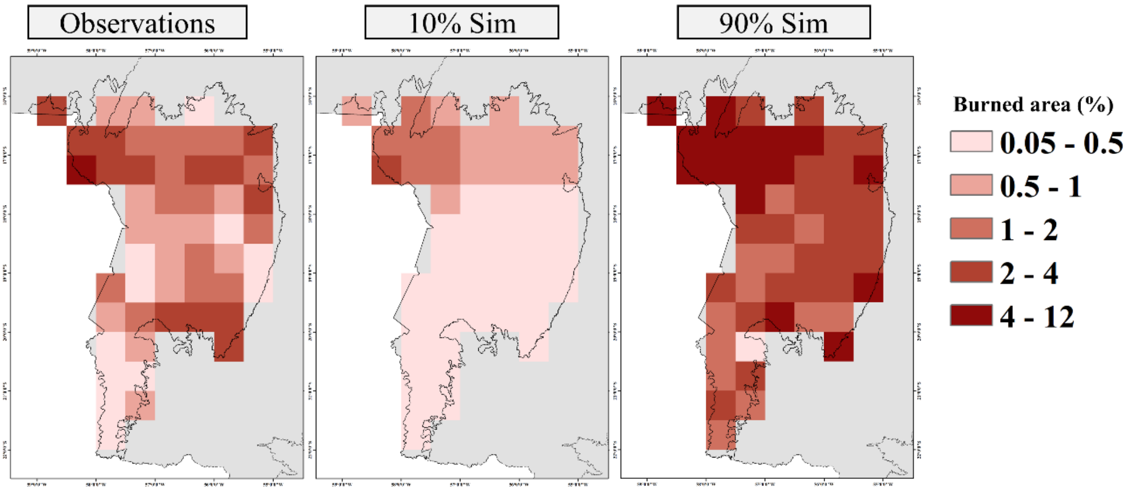


Source: Author's production.

5.3 Results

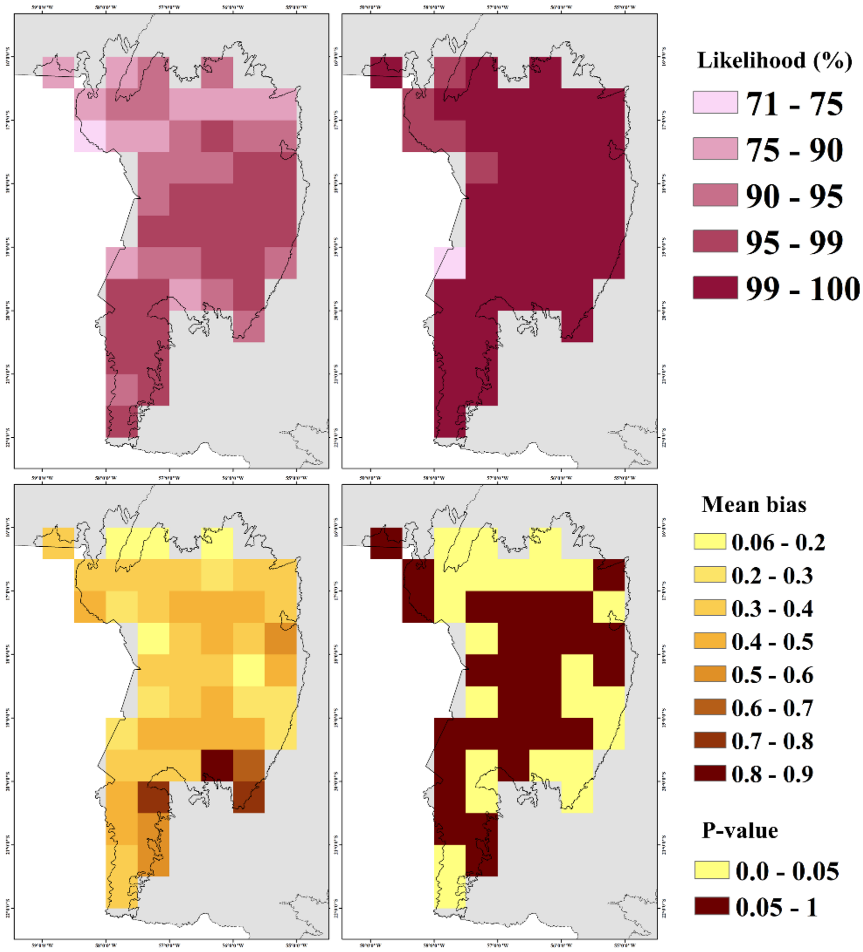
We conducted a new optimization focusing on the Pantanal biome using the FLAME model discussed in Chapter 4. Similarly to our previous optimization, the observations consistently fall between the simulation uncertainties (Figure 5.3), demonstrating the model's adequate performance. By including important variables within the Pantanal dynamics, we kept a high mean likelihood (92%) of the observations while reducing the mean model bias to 0.40. Figure 5.4 shows that the observations are less likely in the north of the biome during months with poorer model performance. Though even in the worst performing months, the likelihood of the observations given model does not go below 0.71 - greater than the 0.5 threshold required to show satisfactory performance. There are some biased pixels concentrated in the edges of the biome with a degree of overestimation in the north and south borders and underestimation in the southeast edge. However, these biased areas are very restricted and the bias for most cells over our study region do not exceed 0.3-0.7. A notable bias reduction is observed in the middle of the biome where most pixels are not significantly different from 0.5 (i.e., unbiased).

Figure 5.3. Maps of the observed (left) and modeled 10th (middle) and 90th (right) percentiles % burned area considering 2011- 2020.



Source: Author’s production.

Figure 5.4. Spatial likelihood of the observations given the model parameters considering the months with worst performance (up left) and the months with best performance (up right).



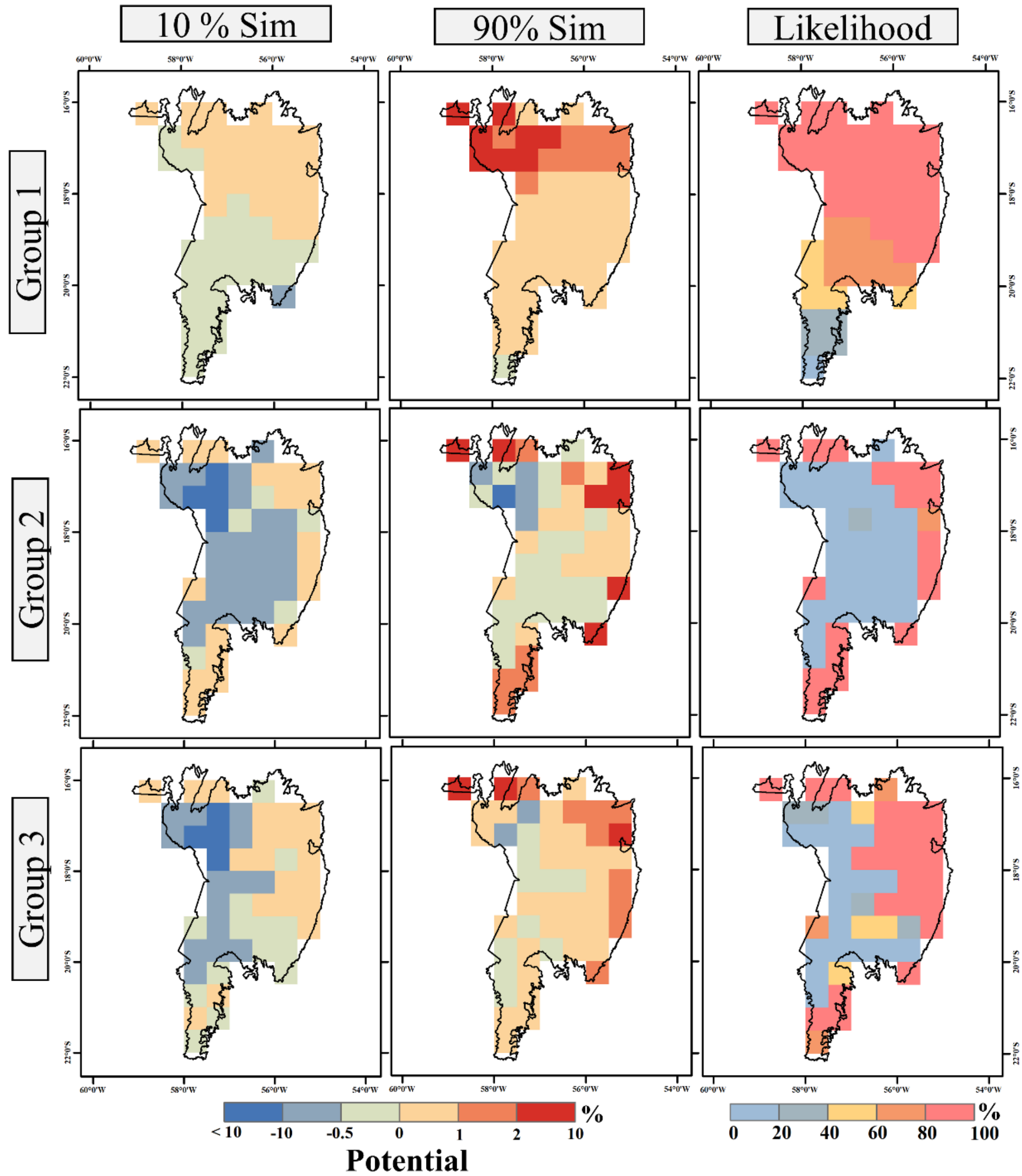
A satisfactory performance of the model is considered with likelihood values above 0.5. Spatial mean bias of the modeled burned area (bottom left). Bottom right: Significance of the mean bias considering a 95% confidence level (p-value < 0 .05). Pixels with p-value > 0.05 (brown color) are not significantly different from 0.5 mean bias meaning that they are not significantly biased.

Source: Author's production.

Our group 1 (maximum temperature and precipitation) potential analysis is displayed in Figure 5.5. The potential response shows climate is likely a driver of higher burned area in 80.8% of Pantanal. Our model shows higher confidence in the middle and north of the biome where the larger increase in burned area (up to 10%) occurs when group 1 deviates from the median. In 9.6% of the biome, located in the south, maximum temperature and precipitation will likely suppress burned area. In the remaining 9.6%, this response is not clear enough to confirm whether climate leads to an increase or decrease of burned area.

Considering wetland and grassland (group 2), 36.5% of the Pantanal biome is expected to experience an increase in burned area due to these factors (Figure 5.5). These areas are primarily situated along the edges of the biome, where increases of up to 10% are associated with group 2. This means that most of the biome, specifically 63.5%, does not have the conditions associated with group 2 that lead to increased burned area during the fire season. Ultimately, 42.30% of the Pantanal area has decreased burning likely explained by wetland and precipitation (group 3). The confidence in this assertion is higher along the western edge, while uncertainties persist in the central region in areas of high wetland but low precipitation. Still, in 50% of the Pantanal, there's a higher likelihood that group 3 contributes to increased burned area when diverging from the median.

Figure 5.5. Potential Response maps displaying the 10% simulations (10% Sim) or 10th percentile (first column), 90% simulations or 90th percentile (second column) and the likelihood of increase burned area (third column).



The first row presents the results for group 1 (maximum temperature and precipitation), the second row for group 2 (wetland and grassland) and the third row for group 3 (wetland and precipitation).

Source: Author's production.

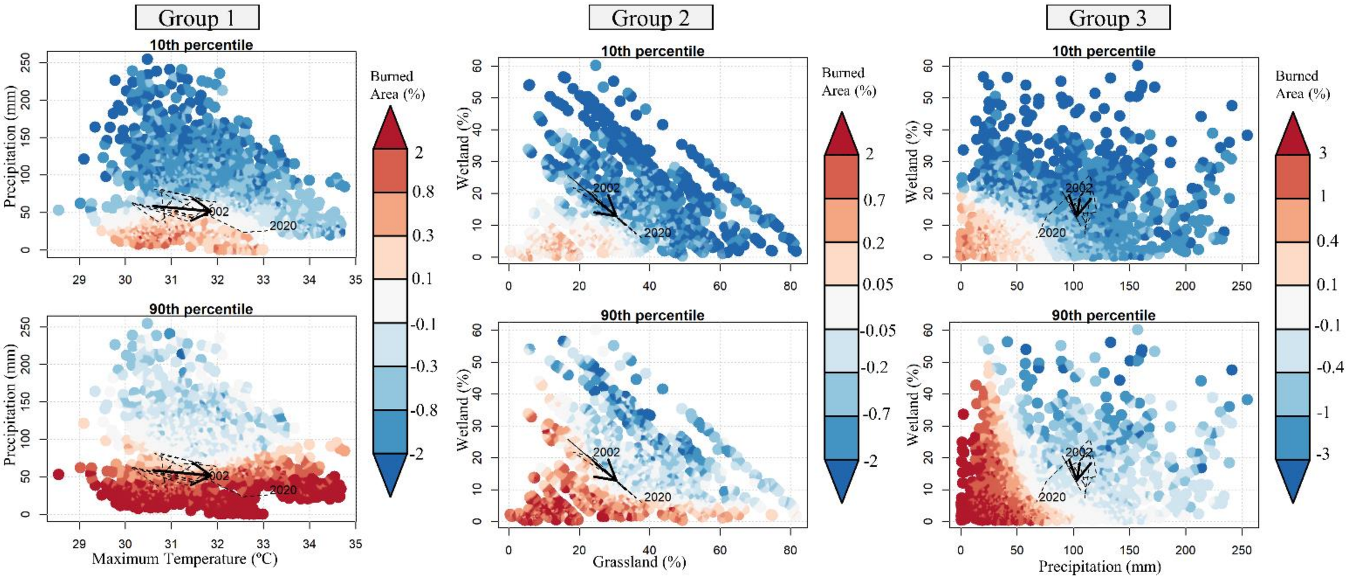
Considering the potential response (Figure 5.6), deviations from the median indicate a propensity for high burning at lower precipitation, becoming particularly susceptible to precipitation below 50 mm. Burnt area is less sensitive to maximum temperature (90th percentile). However, the 10th percentile estimated that a decrease in burned area could be observed as maximum temperatures increase above 31.7 ºC and precipitation < 50 mm. This indicates a level of uncertainty in this response. Given that the analysis encompasses the entire Pantanal, these uncertainties may be associated with other local processes or it is an aspect that should be further refined in the model, potentially through the use of more constrained priors. The Pantanal is showing a trend towards a hotter landscape, although not exhibiting a pronounced signal during the assessed period. The year 2020, however, displayed an exceptionally extreme trend towards lower precipitation and high temperature.

In group 2, the potential response indicates that high burning occurs at lower wetland and grassland coverage. When grasslands exceed 40% and wetlands are less than 8%, there is insufficient confidence to determine whether it increases or reduces burned area. The trend analysis reveals a strong signal indicating that the Pantanal is shifting towards, reduced wetlands while increasing grasslands. This indicates that Pantanal is changing from less to more flammable, though as wetland extent crosses 10% coverage, the degree of this increased flammability becomes more uncertain.

When integrating wetland and precipitation (group 3), there is a high confidence that lower precipitation levels and reduced wetland cover are associated with high burning. Wetland extent offsets some of the increases in burning associated with lower precipitation. Notably, when wetlands are below 20% and precipitation falls under 70 mm, the likelihood of burning is pronounced - equivalent to increases in burning corresponding to at most 40 mm when wetland extent is at 50%. When wetland cover ranges from 20% to 40% and precipitation from 70 mm to 100 mm, a propensity exists for burning, although the response remains uncertain and likely contingent upon additional conditions. The trend indicates a consistent reduction in wetland over time, with a small tendency for a decline in precipitation. Interestingly, in 2020, the average trend approached the critical limits of wetland and precipitation, reaching the region where the Pantanal as a whole increased burning within the response surface.

Examining 2020, which witnessed record levels of burning, we find that when maximum temperature was above 32.5 ºC and precipitation around 25 mm there are conditions for high burning. These fire-prone conditions are also observed when grassland is near 38% and wetlands around 8%. When considering precipitation and wetlands, the thresholds of wetland cover remain the same (8%) while precipitation limit increased to 70 mm. Our findings suggest that reducing wetlands is a critical driver of high burning in the biome.

Figure 5.6. Burned area potential surfaces for group 1 (first column), group 2 (second column) and group 3 (third column).

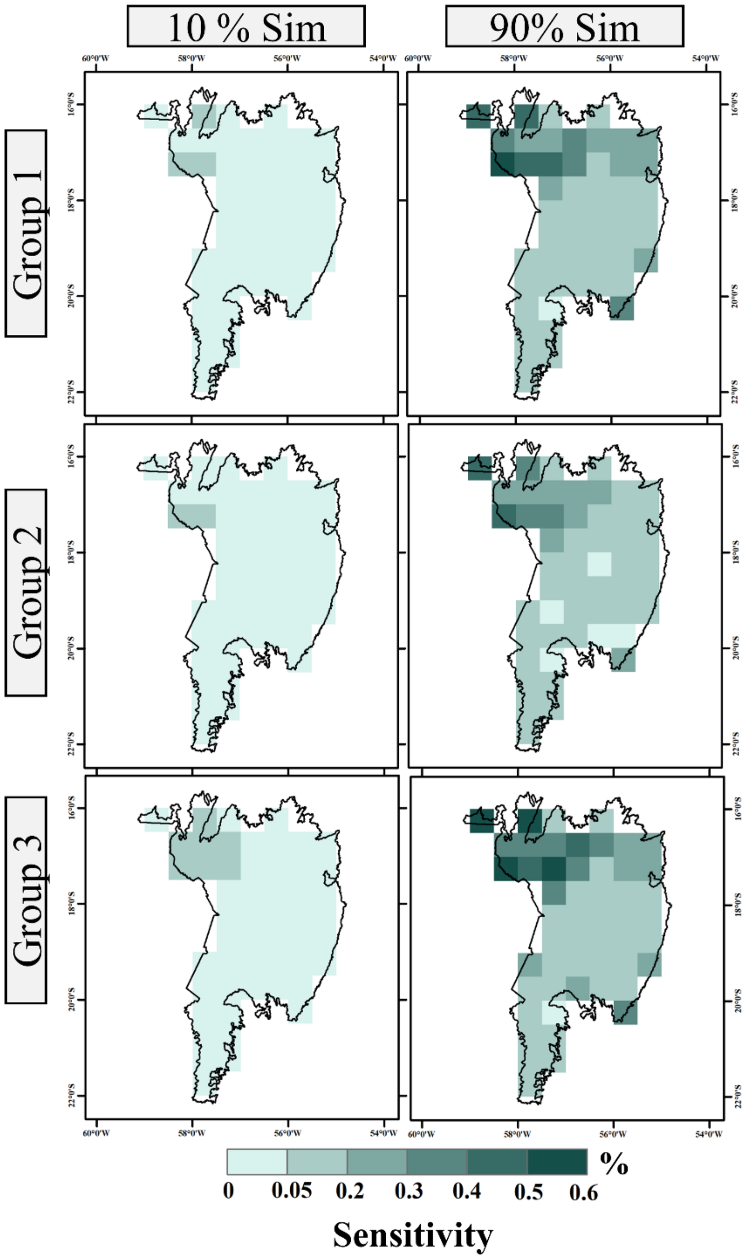


The arrow represents the changes trend of each group considering 2002 to 2020. Source: Author’s production.

The three groups of variables showed a close pattern of areas sensitive to marginal variations of them (Figure 5.7). Burned area in the northern region is particularly sensitive to these variations even though our analysis cannot affirm in which direction. This area is characterized by a significant proportion of wetlands, indicating their vulnerability to environmental conditions. Considering the sensitive surface, burning is likely influenced by minor shifts in precipitation when below 100 mm (Figure 5.8). This sensitivity is the highest when precipitation is below 50 mm. Minor changes in wetland and grassland cover (group 2) can affect burned area across the full range of these variables similarly, but the magnitude of change is not clearly defined. When considering group 3, there is a high confidence that burning is more affected by shifts in these variables when precipitation is below 100 mm. Above this threshold the burned area response becomes more uncertain with a larger range between the 10th and 90th percentiles.

Our findings suggest that minor shifts in climate exert a stronger influence on burning, particularly when reaching critical values, while land cover is likely to impact burning consistently across all ranges. Notably, within group 3, the influence on burning becomes more certain and pronounced when constrained by precipitation levels.

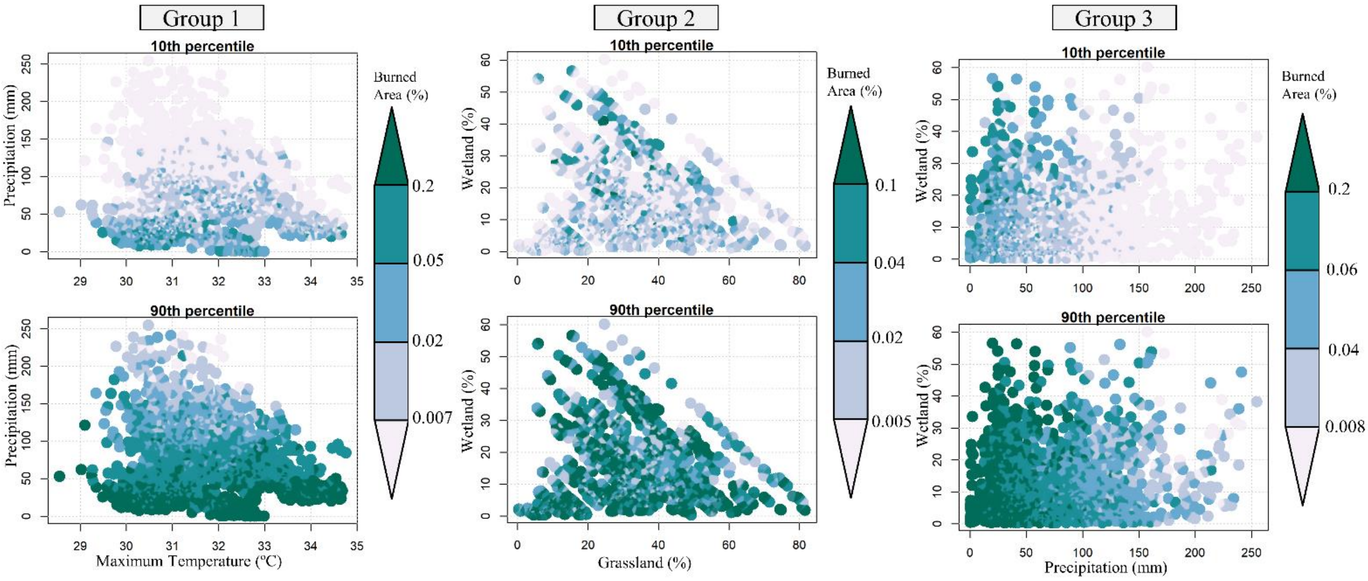
Figure 5.7. Sensitivity response maps displaying the 10h percentile (10% Sim) and 90th percentile (90% Sim).



First row presents the results for group 1, second row for group 2 and third row for group 3.

Source: Author’s production.

Figure 5.8. Sensitivity surfaces for group 1 (first column), group 2 (second column) and group 3 (third column).



Source: Author's production.

5.4 Discussion

Following the extreme fire season of 2020 in the Pantanal, there was a surge of studies showing the close relationship between fires and climate in the biome (MARQUES et al., 2021; LIBONATI et al., 2022; BARBOSA et al., 2022). Our analysis demonstrated that maximum temperature and precipitation are crucial in determining burned areas across most of the Pantanal. We estimated that burning in 80.8% of the biome is likely influenced by the combination of temperature and precipitation, impacting the entire region, except for the southern edge. While the southern Pantanal is normally more susceptible to fires, the 2020 fire season revealed considerable vulnerability in the northern region due to climate anomalies (BARBOSA et al., 2022). In fact, the northern and central regions face a heightened risk of experiencing compounded extreme climate events (COSTA et al., 2023). This aligns with our findings indicating greater sensitivity to climate variations in the north.

Wetland and grassland combined are likely (> 80% likelihood) increasing burning in 36.5% of Pantanal. These areas are located at the edges of the biome, matching the pixels with lower wetland and grassland cover on average (Figure 5.2). Here we isolated the effects of wetland and grassland from the other drivers, particularly moisture. This means that considering only land cover, which would include fuel load, there is an increased likelihood of getting more fires with lower wetland and grassland. The relationship between fire, flood, and vegetation has been explored by Damasceno-Junior et al. (2021). During flooding, biomass production is rapid and substantial, with certain key grass species able to grow up to 5 or 6 meters during this period. As the waters recede, a significant amount of dried biomass remains, serving as abundant fuel for frequent and widespread fires. This pattern is particularly notable in the southern region, although not precisely at the edge where the relationship between these variables was observed. In our analysis, we examine the influence of these variables individually while the reduction of wetlands and, consequently, burning is closely related to summer rainfall and the dynamics of rivers that originate in the highlands around the eastern half of Pantanal (IORIS et al., 2014; MARENGO et al., 2021).

We found that precipitation below 50 mm increases burning in most of Pantanal. However, in areas of reduced wetland extent, the precipitation threshold rises to 70mm. This suggests that even with more rainfall, low wetland coverage still contributes to increased burning. While previously there has been no clear indication of a long-term reduction trend in precipitation in the Pantanal (BERGIER et al., 2016; MARENGO et al., 2021), we show by incorporating precipitation in recent years, there is a tendency to reduce precipitation. However, the wetlands have been diminishing annually (MAPBIOMAS, 2021; BARBOSA et al., 2022), with a much stronger signal than precipitation (Figure 5.6). Our findings suggest that burning is more sensitive to minor wetland changes when precipitation is lower.

Our trend analysis showed that Pantanal is becoming hotter, drier, and more flammable. However, conducting future trend analysis on subregions of the Pantanal may reveal areas where this trend is more or less pronounced. Libonati et al. (2022) estimated that the recent warming trend in this region since 1980 is approximately four times greater than the average global temperature increase. Additionally, studies by Thielen et al. (2020) and Cardoso and Marcuzzo (2010) suggest that drought patterns in the Pantanal are becoming more frequent. The impact of decreasing water surfaces in regions typically characterized by high wetland cover was evident in 2020. The abnormal burning observed in the north was primarily driven by severe drought and exceptionally high temperatures, reaching 6°C above the average (LIBONATI et al., 2022). The ongoing reduction of wetlands combined with climate change may lead to a permanent increase in flammability of Pantanal. This shift, which involves the replacement of wetlands with grassland, poses a threat to the 300 species sensitive to fires (DAMASCENO-JUNIOR et al., 2021), consequently escalating burning in forests, as witnessed in 2020 (BARBOSA et al., 2022). Furthermore, the long-lasting effects of burning on the hydrological cycle and regional climate of Pantanal contribute to a positive feedback loop marked by drier and warmer climate, an increase in open cover types, and elevated fire risk (KUMAR et al., 2022).

Pantanal has been continually burning in the last 20 years, with the majority of the biome burned at least once since 2003 (BARBOSA et al., 2022). Despite that, burning in the biome is mainly associated with small patches (CORREA et al., 2022) due to flooding interannual variability. However, human activities remain the primary ignition source in the biome, accounting for 84% of the burned area during 2012 to 2017 (MENEZES et al., 2022). We learned from the 2020 fire season that when exceptional drought is combined with human activities, a catastrophe can be expected. In this context, estimating critical thresholds associated with burning can yield valuable insights for fire prevention strategies. Anderson et al. (2021) offers a seasonal fire probability forecast for South America, employing a 100 mm precipitation threshold to signify the dry season. Our research indicates that despite capturing the risk of fire, changing the threshold to 70mm could allow more targeted planning. However, it is crucial to incorporate wetland cover information to enhance the forecasting when applied to Pantanal.

Fires are complex phenomena influenced by a multitude of factors, and as such, their occurrence is often subject to random processes. In certain situations, conditions conducive to intense burning may not necessarily translate into increased fires. This highlights the importance of adopting approaches that account for uncertainties inherent in fire assessment and modeling. We reduced the simulation bias by simply including specific variables into the model, however, further research is recommended utilizing better-informed priors. This means to incorporate only physically plausible prior information into the model. By doing so, we can reduce uncertainties associated with fire predictions and improve our assessment of the controls of burning. Additionally, it is essential to explore lagged relationships between the variables and burning to be included into the potential and sensitivity analysis. Furthermore, the influence of the Plateau surrounding the Pantanal on fire behavior warrants thorough investigation. By considering these factors, we can develop more comprehensive fire management planning tailored to the unique characteristics of the Pantanal landscape.

5.5 Final considerations

The Pantanal is shifting towards increased temperatures and grasslands and reduced precipitation and wetlands. Climate alone is a major control of burning in 80.8% of Pantanal, once ignition is present. However, the presence of high levels of wetlands in the western counteracts the effect of lower precipitation. Specifically, wetland cover below 20% combined with precipitation below 70mm leads to high burning in the biome. This is particularly important considering the ongoing reduction of wetlands in the biome which could stimulate the expansion of pasture and agriculture into these areas. Currently, there is already an arc of deforestation taking place in areas of low or no wetland (GUERRA et al., 2020). Comprehending the drivers behind wetland reduction is pivotal for conservation efforts, and fire mitigation strategies in Pantanal must incorporate wetland cover information. We show that burning in the northern portion is more sensitive to changes in these variables which was the case in the 2020 anomalous year. In fact, 2020 reached all critical thresholds associated with high burning. Long-term changes in climate and land cover allied with increased pressure of human activities could mean severe fire seasons on an annual basis. Our approach allows for the rapid assessment of potential scenarios of burning by carrying modifications in the variables. FLAME demonstrated to be an easily adaptable framework to consider the region/ecosystem you are interested in. In practice, very often only a few variables are considered or available to guide response strategies. Thus, isolating its effects can substantially support these responses. This information enables early preparation and the identification of priority areas for monitoring and response.

6 COMPOUND IMPACT OF LAND USE AND EXTREME CLIMATE ON THE 2020 BRAZILIAN PANTANAL'S FIRE RECORD

6.1 Introduction

Pantanal is one of the world's largest wetlands, characterized by a low elevation, flat region that is temporarily and partially flooded by various large rivers that are born in the highlands around its eastern half (IORIS et al., 2014). This dynamic is essential for maintaining the ecosystem services as the flood pulse from upstream regions provides nutrients, sediments and biota, which contributes to abundance, diversity and distribution of fauna and flora, as well as human activities in the area (OLIVEIRA et al., 2019). There is a unique phytogeographic diversity in the Pantanal, a region of convergence of many vegetation types such as Cerrado, Amazonia, Atlantic Forest, and Chaco (POTT; SILVA, 2015). This vegetation mosaic makes fire dynamics in the region highly complex and heterogeneous, with different effects on each vegetation. While fires are a natural component of the Cerrado dynamics, other regions are fire-sensitive, meaning that fire disrupts ecosystem's structure and functions as there is no adaptation to fire (FIDELIS, 2020). Furthermore, changes in the predominant fire regime, such as higher fire frequency and lengthened dry seasons, can cause huge impacts in Pantanal, including the areas with Cerrado species, as it leads to land degradation (PIVELLO, 2011) and higher tree mortality (SCHMIDT; ELOY, 2020).

Pantanal evolved with natural fires as part of its dynamics. High frequency uncontrolled fires that occur in the dry season, caused by humans, however, are not part of this natural cycle. Fires have been used in the Pantanal as a low-cost tool to shift native vegetation into pasture or agriculture and to induce the growth of native grasslands to cattle feeding (SCHULZ et al., 2019). Fires in Pantanal, therefore, are mainly linked to anthropogenic causes, mainly from beef cattle breeding, which is the main form of land use and socioeconomic activity in the region (DICK et al., 2021). Other factors that can exacerbate fires in the region are prolonged dry seasons and increased frequency of extreme weather events such as the 2020 drought, which in combination with known human-activities in the region raises concern about megafires and, thus, increased carbon emissions from this region.

Precipitation is a key driver of the periodicity and the magnitude of upcoming droughts (SPINONI et al., 2020). In the Pantanal, precipitation shows interannual seasonality, which causes either natural floods or droughts in the region. The large natural water storage in the region also affects the occurrence of hydrologic extremes (MARENGO et al., 2021). Precipitation in the Pantanal is also influenced by the carried atmospheric moisture from the Amazonia rainforest, especially the summer precipitation (BERGIER et al., 2018). Lastly, some studies discuss the role of sea surface temperature (SST) on the Pantanal precipitation (DABERNIG et al., 2017; THIELEN at al., 2020; MARENGO et al., 2021), although more research is needed to improve our knowledge as there are uncertainties on the topic. While precipitation trends cannot yet be established for Pantanal (MARCUZZO et al., 2010; BERGIER et al., 2018), the water mass is undoubtedly reducing over the course of the last 35 years (MAPBIOMAS, 2021), which can favor fire occurrence.

In 2020, the Pantanal had almost one-third (nearly four million hectares) of its area affected by unprecedented fires (LIBONATI et al., 2021b; MARENGO et al., 2021). A number of 189,440 active fires were registered in 2020, 508% higher than the annual average from 2012 to 2019 (PLETSCH et al., 2021). The flames invaded Protected Areas and caused contamination of rivers by charcoal and ash, soil erosion, and impacts on the fauna and flora of the region (LIBONATI et al., 2020). This extreme event is linked to the most severe drought registered in the area in the last 60 years (LIBONATI et al. 2020) combined with high temperatures (MARENGO et al., 2021).

Recent studies investigated the hydroclimatic aspects of the 2020 drought (MARENGO et al., 2021) and trends in environmental and climatic variables in Pantanal (MARQUES et al., 2021), and discussed the lack of monitoring and control in the region (LIBONATI et al., 2020; LEAL FILHO et al., 2021; MATAVELI et al., 2021). Despite providing critical information on the real-time status of fire in 2020 in comparison to 2019 (LIBONATI et al., 2020) and on climate

(MARENGO et al., 2021) and land cover change drivers of fire, through a modelling approach in the region (MARQUES et al., 2021), no comprehensive analysis is yet published based on spatially-explicit observations for the whole basin on the influence of long-term climatic changes combined with flooded area, land cover, land use and land tenure upon the extent and frequency of fires and their impacts on natural land covers and forest carbon stocks.

In this paper, hence, we examine the climate, changes in flooded area and land use and land cover (LULC) spatio-temporal patterns of the Alto Paraguay River Basin in order to understand how these variables contribute to explaining the unprecedented fires in the Brazilian Pantanal in 2020. We specifically investigated the consequences of the 2020 fires by asking:1) How the 2020 fires affected each vegetation type in Pantanal ecosystems and how anomalous this event was in the fire history? 2) What is the long-term pattern of fires in Rural Properties (RPs), Indigenous Lands (ILs) and Protected Areas (PAs)? 3) How much carbon was committed to be emitted by the 2020 fires in each LULC? How the combination of these variables played a critical for the occurrence of the 2020 megafires?

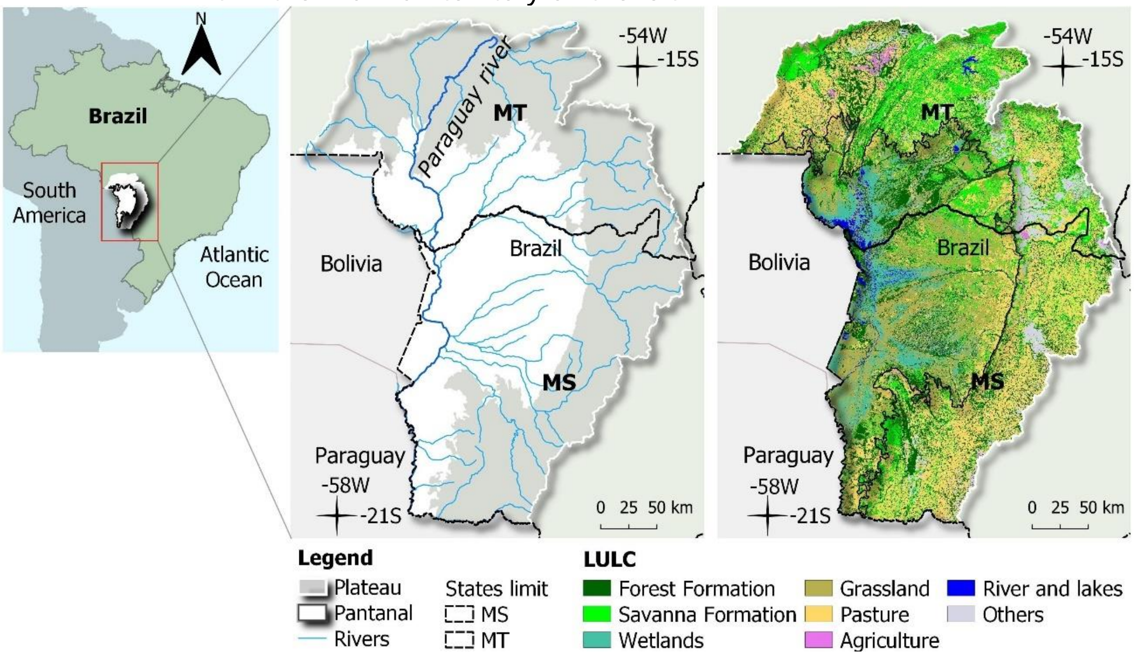
6.2 Material and methods

6.2.1 Study area

This study focuses on the Alto Paraguay Basin located in Brazil (Figure 6.1) which includes two distinct environments: the lowlands (Pantanal Biome) and the highlands (Plateau). The Plateau is located outside the Pantanal boundaries but is geomorphologically and ecohydrologically linked to the biome as part of the Alto Paraguay Basin. Changes in the Plateau area that can affect the water cycle will reflect in changes in the Pantanal. Therefore, considering this region is necessary to understand the causes and consequences of the 2020 event. The Plateau encompasses the Cerrado (50% of the total area) and Amazonia (8%) biomes.

The Alto Paraguay Basin includes part of Mato Grosso (48%) and Mato Grosso do Sul (52%) states, in addition to parts of Bolivia and Paraguay, covering approximately 600,000 km2. The Brazilian portion, studied here, covers an area of approximately 362,380 km² (ANA, 2018). Pantanal is in a tropical and wet climate zone with an average air temperature of 24ºC and annual precipitation of 1000-1250 mm. The region is divided into dry season from April to September and wet season from October to March (MARENGO et al., 2016).

Figure 6.1. Geographical location of the study area (Alto Paraguay Basin), the land use and land cover (LULC) map for 2020 in the right panel and its location within the Brazilian territory on the left.



Source: Author’s production.

6.2.2 Datasets

The climatic data were obtained from TerraClimate (ABATZOGLOU et al., 2018), which is a dataset of global monthly climate that covers the period from 1958-2020, and has a 4km spatial resolution. Here we used data of the following variables: precipitation, soil moisture, maximum air temperature and water deficit. Time series from five oceanic indices (SST data) influencing large-scale atmospheric circulation were also used: Multivariate ENSO Index (MEI; http://www.esrl.noaa.gov/psd/enso/mei/), Oceanic Niño Index (ONI; https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php), Atlantic Multi-decadal Oscilation (AMO; https://climatedataguide.ucar.edu/climate-data/atlantic-multi-decadal-oscillationamo), Pacific Decadal Oscillation (PDO; https://www.ncdc.noaa.gov/teleconnections/pdo/) and Variability Mode in Tropical Atlantic Ocean (TNA; https://stateoftheocean.osmc.noaa.gov/sur/atl/tna.

php/).

We used the burned area product MCD64A1 collection 6 product from the Moderate-Resolution Imaging Spectroradiometer (MODIS) (WEI et al., 2020; DE SANTANA et al., 2021). The product has a spatial resolution of 500x500m, available on NASA's Earth Data platform (https://earthdata.nasa.gov/). The MCD64A1 product takes an approach that uses 500m spatial resolution images together with MODIS 1km active fire observations. This hybrid algorithm applies dynamic limits to composite images generated from a fire-sensitive vegetation index, derived from shortwave channels 5 and 7 (GIGLIO et al., 2016). A good performance of MCD64A1 has been reported for tropical savannas (ALVES et al., 2018), and for the Mato Grosso state, which includes part of the Pantanal biome (SHIMABUKURO et al., 2020).

To represent the land use and water area extent of the study area, we used the MapBiomas water coverage product (Collection 1) and the MapBiomas LULC project (Collection 6) released in 2021. MapBiomas is a multi-institutional project that promotes the annual mapping of LULC in Brazil, and provides data and maps in open access (www.mapbiomas.org) from 1985-2020 with a 30m spatial resolution. The 26 available classes were regrouped into eight classes, to adjust them to the purpose of this study: forest, savanna, wetland, grassland, pasture, agriculture, water bodies and others. The classes water bodies and others were eliminated from the analysis. The carbon loss associated with the fire occurrence in 2020 was estimated according to two aboveground biomass (AGB) datasets. The first dataset was based on the ESA/CCI AGB product for the year 2018 at 100m spatial resolution (SANTORO; CARTUS, 2021) and the second dataset was based on the 4th Brazilian Inventory of Anthropogenic Emissions and Removal of Greenhouse Gases (BI) with vector format (BRASIL, 2020). Lastly, we also analyzed results considering the delimitation of Rural Properties (RPs), Indigenous Lands (ILs), and Protected Areas (PAs) from the Certification System (SNCI; https://certificacao.incra.gov.br/csvshp/exportshp.py), the National Indigenous Foundation (FUNAI; https://www.gov.br/funai), and the Brazilian Ministry of Environment (MMA; https://www.gov.br/mma), respectively.

6.2.3 Analyses

6.2.3.1 Anomalies and SST correlation

To verify whether the climate in 2020 was extreme compared to our study period (2003-2020), we calculated soil moisture, precipitation, water deficit, and maximum temperature monthly standardized anomalies (z-score) for the period between 2003 and 2020, following Equation 6.1:

$$Z_{(p,q)} = \frac{(X_{p,q} - \bar{X})}{\sigma} \tag{6.1}$$

where the coefficients *p,q* means the year (*p*) and month(*q*) in which the anomaly was calculated, *Z* is the anomaly at year *p* and month *q*, *X* is the monthly (*q*) mean at year *p*, $\bar{X}$ is the historical mean and σ is the standard deviation. The mean and standard deviation are calculated for the whole dataset and remains the same for each calculation, whereas *X* represents every month between 2003-2020. The historical mean and standard deviation (s.d., *σ*) were calculated considering the climatology between 1988 and 2018.

We also calculated monthly burned area anomalies following Equation 6.1, but using a different climatology baseline (2003-2019) from the other anomalies due to data availability. The 2020 data were not used for the climatology because of the extreme conditions that could bias the mean. We calculated monthly spatial averages for the Pantanal and the Plateau sub-regions. We analyzed the anomalies considering a 95% confidence level (p-value < 0.05), that is, values lower than -1.96 or higher than 1.96 were considered significant anomalies (ANDERSON et al., 2018). Furthermore, we produced rainy and dry season maps of accumulated burned area and precipitation, and mean maps of water deficit, soil moisture and maximum temperature.

Lastly, the hypothesis that precipitation variability could be explained by anomalies on the SST was tested by carrying out a per pixel Spearman's correlation between the five oceanic indices (MEI, ONI, AMO, PDO, TNA) and the monthly precipitation anomalies. The temporal autocorrelation was tested considering time lags between 0 to 12 months.

6.2.3.2 Mapping fire recurrence

Fire recurrence maps were produced for the rainy season (October-March) and dry season (April-September) using the MCD64A1 product. The accumulated burned area was obtained for the months of the dry and rainy seasons and then the burned area was reclassified in a binary image where the burned areas have values equal to "1" and the unburned, value "0". Subsequently, using map algebra, these data were added year by year between 2003 and 2020 until the two recurrence maps for the year 2020 were obtained. Therefore, the result of the sum is equivalent to the number of times the fire reached each pixel considering the period of 2003 to 2020.

6.2.3.3 Land use and land cover characterization

We produced a water coverage recurrence map from the MapBiomas water product since the basin is characterized by seasonal flooding. The methodology was the same as applied to the fire recurrence, except that the period analyzed was from 2003 to 2018. Lastly, we extracted the areas with water coverage reduction from 2018 to 2020, which depicted the 2020 drought magnitude.

Further, we calculated annual fire recurrence aiming to discern the LULC in each recurrence class. The procedure was the same as explained in Section 6.2.3.2. Then, we divided the fire recurrence, the annual burned areas (2003-2020), and the areas that burned for the first time in 2020 into LULC, RPs, ILs, PAs.

6.2.3.4 Carbon loss from the 2020 fires

We intersected the burned areas in 2020 with two AGB maps, estimated the AGB post-fire following Equation 6.2 (PESSÔA et al., 2020), and then calculated the AGB loss. To convert from AGB to carbon, we used the factor of 0.47 (IPCC, 2006). Before applying the equation, the ESA/CCI map was harmonized from 2018 to 2020 following the methodology from Campanharo et al. (2019) that consisted in (i) reducing the AGB that burned in the period between 2018 and 2020 based on the Equation 6.2, i.e., in this case reducing biomass burned in 2019, and (ii) updating AGB LULC classes, based on locations given by MapBiomas collection 6 (SOUZA et al., 2020; MAPBIOMAS, 2021). Carbon uncertainties were calculated based on the carbon maps standard deviation values. The carbon loss was stratified by the predominant LULC classes of the study area (Figure 6.1): forest, savanna, grassland, agriculture, and pasture.

$$AGB_{post-fire} = 0.05\ x\ (AGB_{pre-fire}{}^{1.47}) \qquad (6.2)$$

where $AGB_{post-fire}$ is the remaining aboveground live biomass (Mg C/ha) after fire, and $AGB_{pre-fire}$ is the initial aboveground live biomass (Mg C/ ha). The coefficients 0.05 and 1.47 are a result of the committed carbon emission model developed by Pessôa et al. (2020), where all values compiled for the development of the equation were derived from measurements of AGB of different vegetation types within 1 year after fire occurrence.

The equation used to estimate the committed emissions is based on measurements of aboveground biomass of different vegetation types but it does not account for belowground emissions. We aimed to account the vegetation committed carbon, nevertheless, the estimation of soil carbon could be interesting for future studies. On the other hand, the soils in Pantanal vary widely in texture and fertility with over half of the Pantanal soil being pure sand because of the transport of sediments from the highlands (POTT; DA SILVA, 2015). Moreover, at least in the north part of Pantanal within the Mato Grosso state there is no significant organic soils even though they present a very low content of organic matter in the A horizon (COUTO; OLIVEIRA, 2011). In this case, belowground emissions may not be significant for the region even though further analysis is necessary to confirm this hypothesis.

6.3 Results

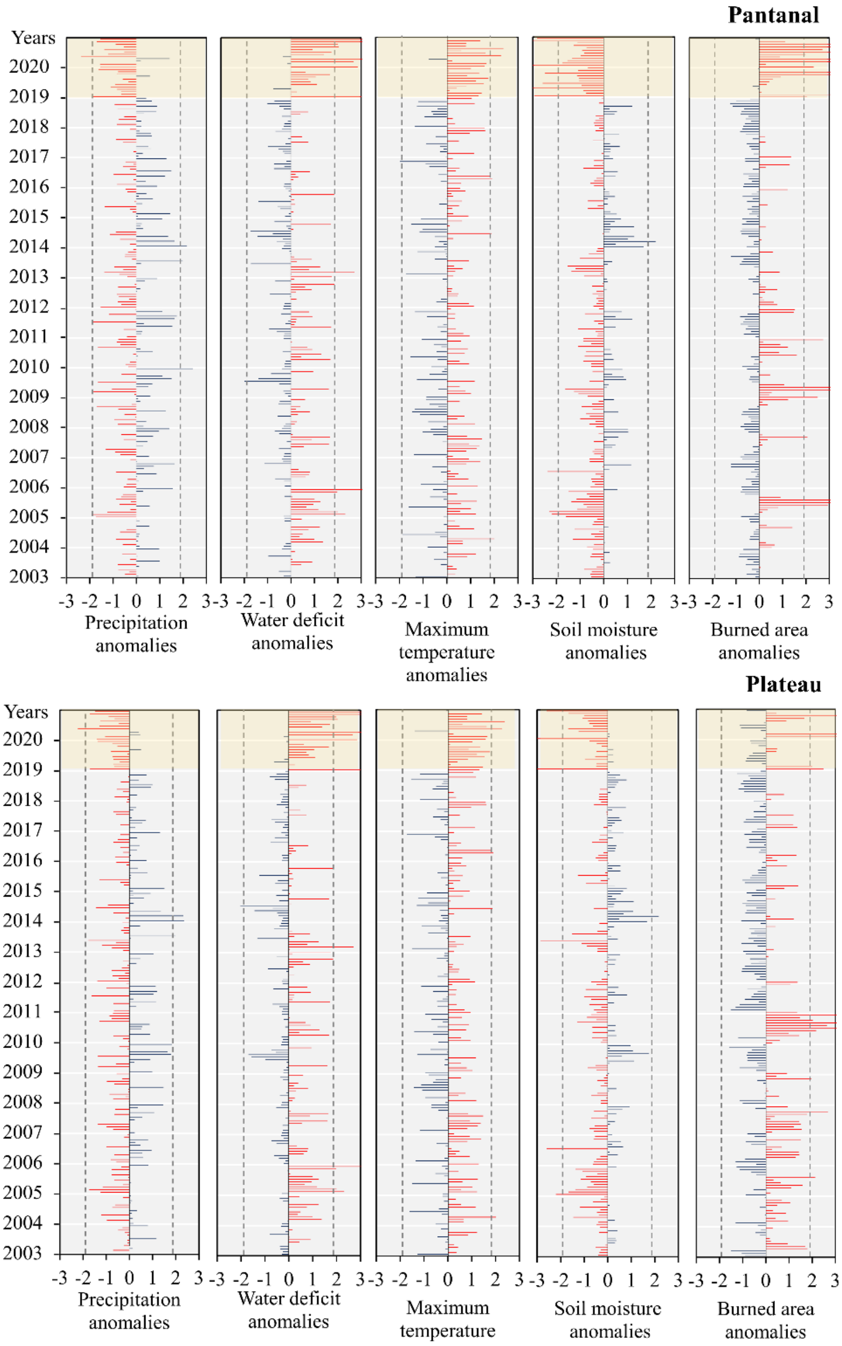
6.3.1 Climate and fires

The atypical climate in 2019 and 2020 were confirmed by our anomalies results (Figure 6.2). We observed consecutive monthly persistent anomalies during these two years associated with drought conditions leading to fire, i.e., negative precipitation and soil moisture anomalies and positive water deficit, maximum temperature, resulting in burned area anomalies; although they were not all significant ($p < 0.05$). It is noteworthy that the largest positive anomalies of burned area were found between 2003 and 2010 both in Pantanal and in the Plateau, while the lowest anomalies were observed between 2012 and 2018.

Overall, within the Pantanal biome limits, significant precipitation anomalies (positive and negative) were found in only 1.85 % of the months analyzed, considering the entire time series (Figure 6.2). Between 2019 and 2020 precipitation only presented a significant negative anomaly in May 2020, despite that, only September 2019, March, and April of 2020 rained above the average, meaning that all other months registered less precipitation than average. Significant anomalous water deficit occurred in 7.87 % of all months analyzed. Moreover, 2020 registered significant water deficit anomalies in eight months with only February and May presenting negative anomalies. Here, assuming only positive values, the higher the value, the higher is the water deficit. Maximum temperature had 5.1 % of the months with significant anomalies, with four months showing positive anomalies in 2019 and five in 2020. Only April 2020 presented temperature below the average. Monthly soil moisture had 11 significant values (5.1 %), four were negative in 2019 and three in the 2020 rainy season (January, November and December). Finally, eight months in 2020 burned above the average and four in 2019 totaling 20 significant values in the series (9.25%), all positive.

Within the Plateau boundaries, precipitation also showed 1.85% of the months with significant anomalies, following the same pattern as Pantanal with only May 2020 presenting a significant negative anomaly but raining below average in several months between 2019 and 2020. Water deficit had 6.48 % of the months with significant anomalies. Also, seven months had positive significant water deficit anomalies in 2020, being consecutive from September to December. The maximum temperature had 1.39 % of the months with significant anomalies and it was positive and significant in May and August of 2020. Soil moisture had 3.24 % of significant anomalies. It was significant (negative) in January of 2019 and 2020, and December of 2020. The burned area was an exception in which five out of 13 significant positive values were in 2010 even though the other variables were not atypical this year. Other two significant anomalies were in 2019, and three in 2020. A total of 6% of the months presented significant burned area anomalies.

Figure 6.2. Variability of monthly anomalies, from 2003 to 2020, for precipitation, water deficit, maximum temperature, soil moisture and burned area.



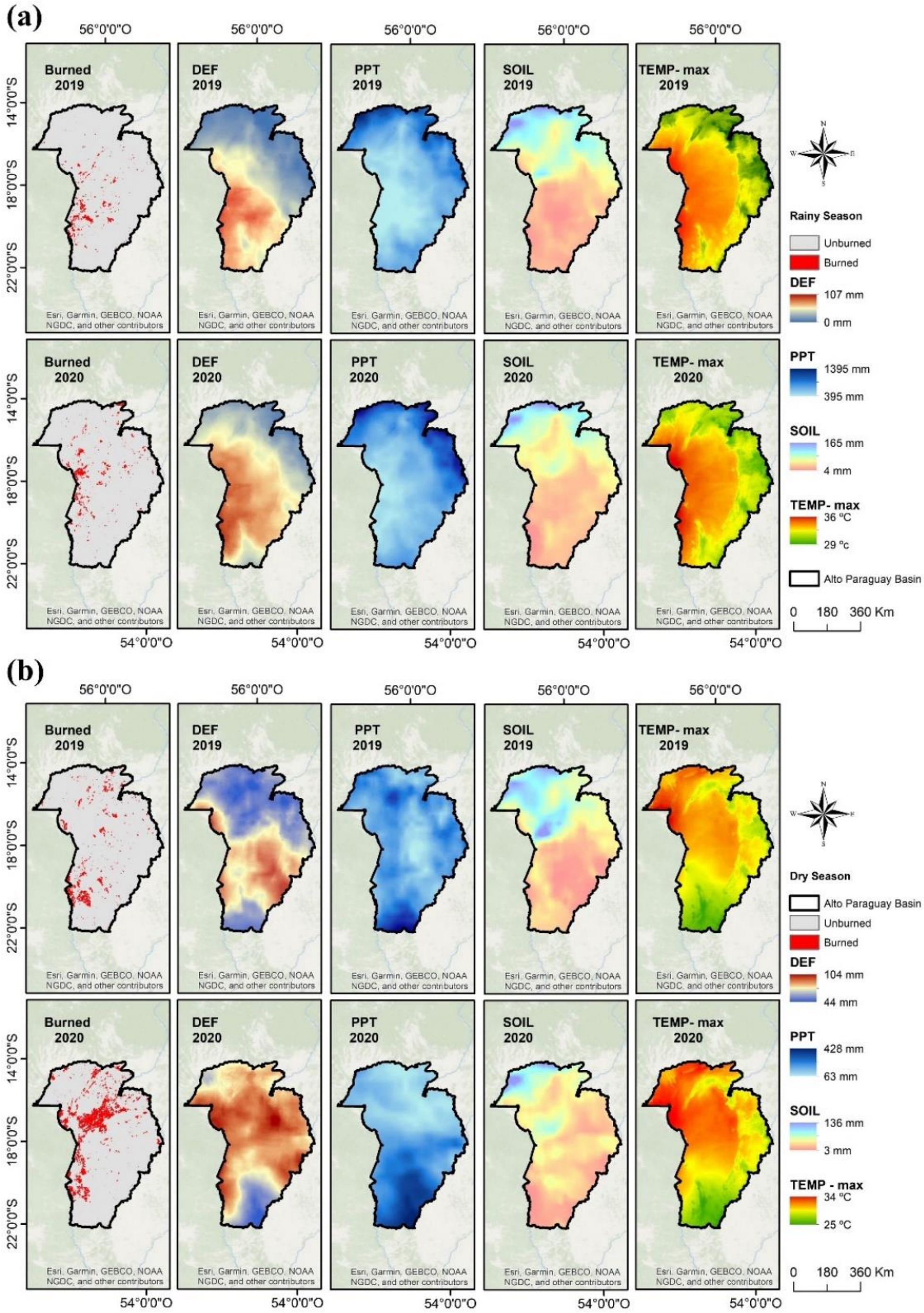
Red bars represent anomalies associated with ideal fire conditions, and the dashed lines indicate significant anomalies ($p < .05$). Shaded areas indicate 2019 and 2020.

Source: Author’s production.

Spatially explicit climatic variables and burned areas during the rainy and dry seasons of 2019 and 2020 are shown in Figure 6.3. During the dry season, the 2020 burned area was 134 % higher than 2019 and 35% of the 2020 fires were concentrated in areas that do not usually burn (Figure 6.3). Significant changes in water deficit from 2019 to 2020 are visible, with an abnormal deficit in the North of the region in 2020. The water deficit reached its peak in September with a minimum of 56 mm in September 2019 and more than double in 2020 (116 mm). The dry season presented water deficits in the whole area. Moreover, in the North of the basin, the dry season reached 64 % less precipitation in 2020 when compared to the last 17 years (2003-2019), with a minimum of 63 mm this year. We found that the precipitation in 2019 was better distributed through the area while in 2020 the Central and North parts experienced low levels of rain. The basin registered low levels of soil moisture in the Central and South portions, however, in 2020, this dryness expanded to the Northern part. High temperatures also extended to the North of the basin (Plateau).

During the rainy season, the burned areas were concentrated near the western edge, mainly in the southwest portion in 2019 and in the middle North in 2020. The water deficit in 2019 was higher in the middle South of the basin and reached parts of the North in 2020. Precipitation in the rainy season was concentrated in the Plateau, with 8 % less precipitation in this area from 2019 to 2020. Soil moisture had a similar spatial pattern to the dry season, with drier soils in the South in 2019 going up to the North in 2020. Maximum temperatures were greater in the Pantanal area and reached their peak during the rainy season (36ºC, $p<0.05$).

Figure 6.3. Climatic distribution in 2019 and 2020 of burned area (Burned), water deficit (DEF), precipitation (PPT), soil moisture (SOIL) and maximum temperature (TEMP-max). (a) Rainy season. (b) Dry season.



Source: Author’s production.

Our analysis of SST showed that there is no consistency between precipitation anomalies and SST anomalies for the Alto Paraguay Basin. We tested five indices (MEI, ONI, AMO, PDO, TNA) within 12-month lags, but the correlations were very weak and mostly not significant ($p > 0.05$) (Figure B.1). The strongest correlation was found between precipitation and AMO with a 11 time lag ($r = 0.23$), being significant only in the middle and northwest portions, but the causes of this correlation are not clear.

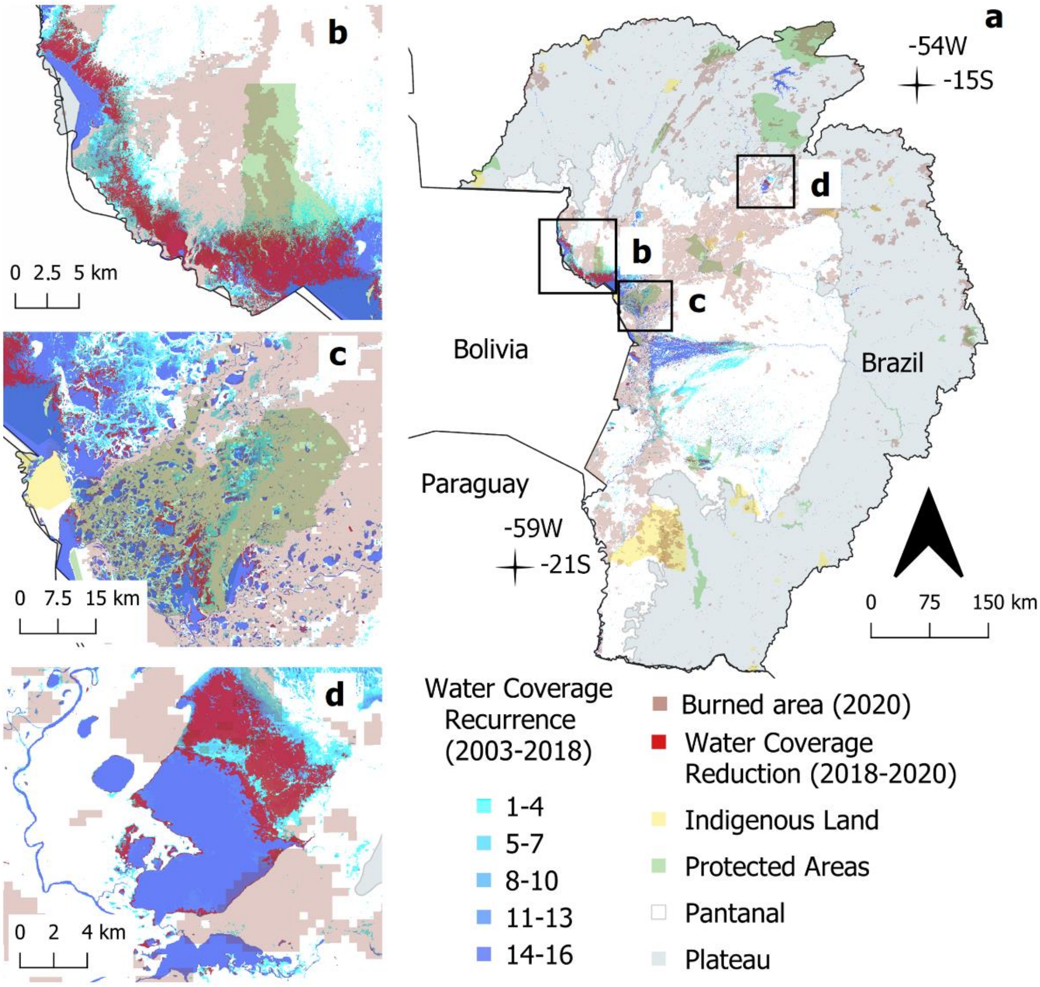
6.3.2 LULC and fires

The drought conditions during 2020 impacted the water coverage in the basin, especially in Pantanal (Figure 6.4). From 2003 to 2019 the basin flooded an average of 8,521 km² per year, while in 2020 this area was 5,592 km², representing a loss of 34 % in flooded area. The maximum flooded area of the series occurred in 2006 (11,230 km²) and the minimum in 2020. In general, the water coverage has been reducing an average of 973 km² per year, with the largest reduction from 2019 to 2020 (1,634 km²) and the least from 2009 to 2010 (744 km²).

The Pantanal lost 1,927 km² of water extent, from which 433.8 km² were lost from 2018 to 2019, and 1,493 km² from 2019 to 2020. Three areas were the most affected by water reduction in 2020 (Figure 6.4). On the plateau, there was a reduction of 26.46 km² and 63.75 km² from 2018-2019 and from 2019-2020, respectively.

The water bodies have been decreasing since 2003, an average of 91 km² per year inside PAs and 3 km² inside ILs. The minimum reduction inside PAs was from 2017 to 2018 (29 km²) and the maximum from 2019 to 2020 (348 km²). While in the ILs, 8.7 km² of water reduced from 2019 to 2020 and no reduction was registered from 2003 to 2004.

Figure 6.4. (a) Water coverage recurrence (2003–2018) in blue shades and water coverage reduction in red from 2018 to 2020. (b–d) The largest water reduction (from 2018 to 2020) is found in these areas.

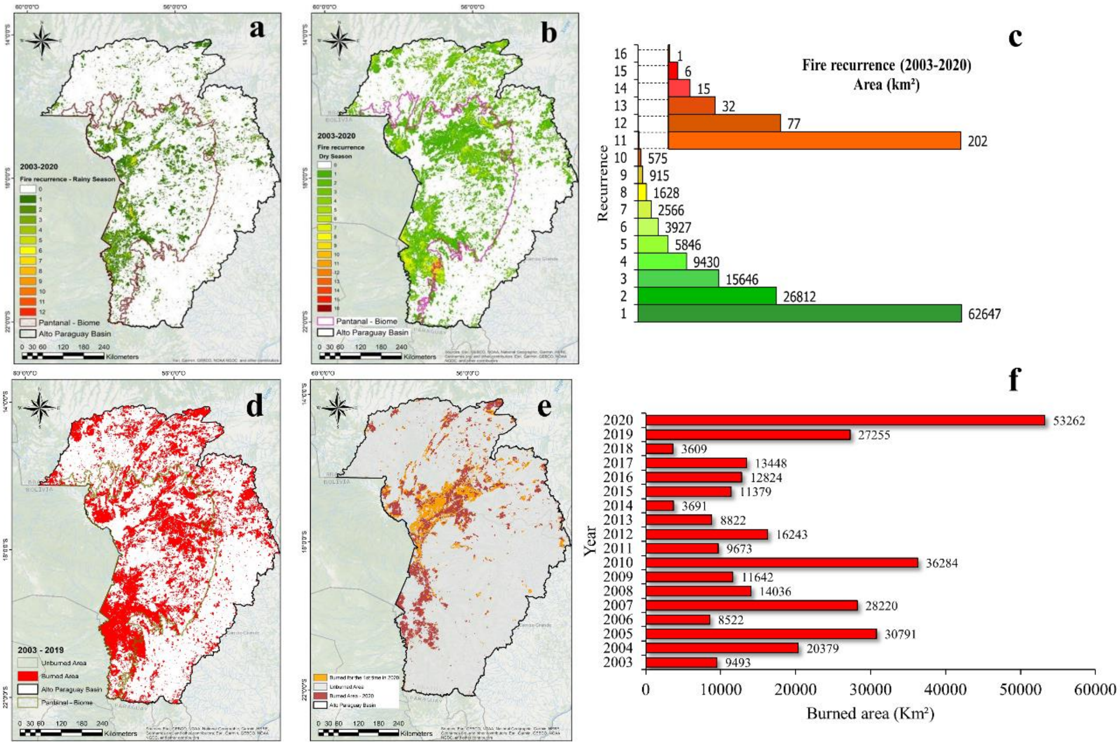


Source: Author's production.

The recurrence of fires during the rainy season (Figure 6.5), reached 12 times even though only an area smaller than 1 km² burned this much. The west portion was the most affected by fire during the rainy season while in the dry season (Figure 6.5) fire spread out through the area concentrating on the north, central and southwest portions. The fire recurrence in the dry season reached 16 times (0.43 km²). Considering all years (Figure. 6.5), 114,535 km² burned less than 5 times, 15,457 km² from 5 to 10 times, and 335 km² burned at least 11 times. This means that the majority of recurrent burned areas do not occur every year.

A total of 18,801 km² burned for the first time in 2020, considering the time-series studied here. This amount represents 35% of the total burned areas, demonstrating how extreme the 2020 fires were. Furthermore, a sum of approximately 53,262 km² burned in 2020, 31% higher than the second largest burned area of the series (2010), almost 50% more than 2019, and 200% higher than average (17,754 km²). Figure 6.5 presents the accumulated burned area from 2003 to 2019 in comparison with burned area in 2020 (Figure 6.5), highlighting the areas that burned for the first time in recent history. Most of the basin burned at least once, however, the 2020 fires impacted natural vegetation that have not burned in the last 18 years. These new burned areas in Pantanal comprise forest formations (5,067 km²), grassland (4,953 km²), and savanna (1,745 km²), while in the Plateau, savanna (1,627 km²), forest (1,190 km²) and pasture (1,073 km²) had the highest new areas burning in 2020.

Figure 6.5. (a,b) Fire recurrence during (a) the rainy season and (b) the dry season. (c) Annual fire recurrence area. (d) Accumulated burned area from 2003 to 2019. (e) Burned area in 2020. (f) Annual burned area (in kilometres squared) from 2003 to 2020.



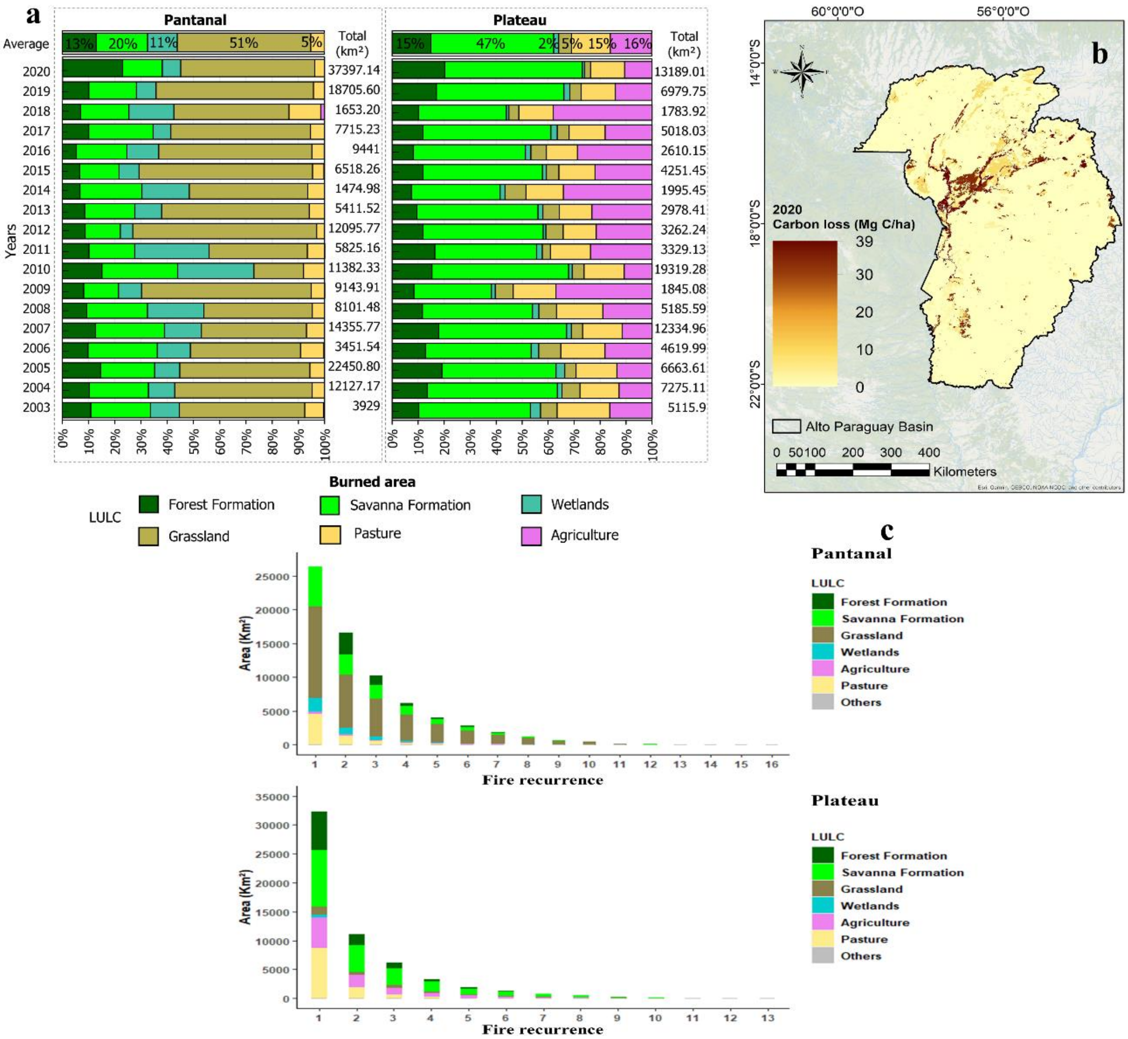
Source: Author's production.

Taking into account the burned area per LULC and the fire recurrence per LULC (Figure 6.6), grassland burns regularly in the Pantanal, and savanna burns regularly on the Plateau. The grasslands represent an average of 49.39% of the total burned areas per year in the Pantanal, and an average of 8.76% of its area has been burning every year, with a maximum area in 2020 (18,561 km²) and a minimum during 2014 (648 km²). Also, the proportion of grassland that burned, starting in 2003, hardly changed over time, except in 2010, when 30% less than average burned, whereas in the wetlands 15% more than average burned. In comparison, forests had the largest burned area in 2020 (8,309 km²), more than double the second largest area burned, which was during 2005 (3,249 km²), and 514% higher than average. Furthermore, the Pantanal has only c. 0.1% of its area used for agriculture, which can explain the modest burned area in this class in 2020 (9.54 km²). Additionally, 5.13% of agricultural areas burn every year on average. Finally, 16% of the Pantanal corresponds to pasture, of which an average of 2.21% burns each year, and in 2020 the burned area was 153% higher than average (1,363 km²).

The Plateau contains extensive areas of pasture and agriculture, representing 41% and 14% of the total area, respectively. However, only 1% of pasture and 3% of agricultural areas burn per year on average. Moreover, these classes constitute 14% (pasture) and 21% (agriculture) of the yearly average burned area on the Plateau. In 2020, 1,722 km² (92% higher than average) of pasture burned, and 1,384 km2 (45% higher than average) burned in agricultural areas. Additionally, 2,660 km² (20% of the total burned area in 2020) of forest and 6,971 km2 (52.85% of the total) of savanna burned on the Plateau in 2020, which were the most affected classes. Normally, 13% of forests burn per year, while 43% of savanna burns, representing 2.20% of forest areas and 6.45% of savanna areas.

The spatial distribution of carbon loss in 2020 is presented in Figure 6.6. The largest losses were concentrated in the Pantanal, matching some of the areas that burned for the first time in this year. We estimated that 70,058,342 Mg C was committed in 2020 (Table B.1) in the Alto Paraguay Basin. We estimated carbon loss per LULC in the 2020 fires, revealing that with both datasets (ESA/CCI and BI) the forests had largest C losses (47% in ESA and 34% in BI), followed by savanna (31% and 25%), grassland (18% and 32%), pasture (3% and 6%) and agriculture (0.5% and 1%). Nevertheless, the datasets presented considerable differences between the carbon losses, whereby ESA estimated more losses for forest and savanna and fewer losses for agriculture, pasture and grassland than the BI dataset.

Figure 6.6. (a) Burned area according to land use and land cover (LULC). (b) Distribution of carbon loss (in megagrams of carbon per hectare) attributable to the 2020 fires, considering the ESA/CCI AGB dataset. (c) Fire recurrence according to LULC.



Source: Author's production.

We should point out that the entire Alto Paraguay Basin is made up of 77.63% RPs, 2.27% ILs and 3.99% PAs. In 2020, a total of 35,438 km2 of burned area was detected inside RPs, representing 12.63% of all RPs, 9.81% of the whole basin and 70.16% of the total burned areas. Moreover, from the total burned in RPs, 4.88% (13,688 km2) did not burn in the last 18 years and constitutes 72.81% of the total that burned for the first time during 2020 (Table 6.1). Regarding ILs, 33.32% (2,747 km2) of its area burned in 2020, yet it is only 0.76% of the basin and 5.41% of the total burned areas. Also, 35.70% (5,144 km2) of PAs burned in 2020, constituting a total of 1.42% of the basin and 10.18% of the total burned areas. Finally, 1.26% and 11.74% of ILs and PAs burned for the first time in recent history, respectively.

Table 6.1. Area burned for the first time in 2020 and total area burned in 2020 divided into rural properties, indigenous lands and protected areas.

	Area (km²)	Area (%)	a) Area basin (%)	b) Burned for the 1st time in 2020 (%)	c) Total burned area in 2020 (%)
Rural Properties					
Burned for the 1st time in 2020	13,688.15	4.88	3.79	72.81	-
Total burned area in 2020	35,461.66	12.63	9.81	-	70.16
Indigenous Land					
Burned for the 1st time in 2020	237.48	2.89	0.07	1.26	-
Total burned area in 2020	2,733.72	33.32	0.76	-	5.41
Protected Areas					
Burned for the 1st time in 2020	2,207.29	15.32	0.61	11.74	-
Total burned area in 2020	5,144.51	35.70	1.42	-	10.18

Abbreviations: IL, indigenous lands; PAs, protected areas; RPs, rural properties. a) Proportion of RPs, ILs and PAs that burned in relationship to the Alto Paraguay Basin total area. b) Proportion of RPs, ILs and PAs that burned for the first time in relationship to the total areas that burned for the first time in the Alto Paraguay Basin. C) Proportion of total burned areas from RPs, ILs and PAs in relationship to the total areas that burned in the Alto Paraguay Basin in 2020.

The fire occurrence per land tenure revealed that on average 3.75 % of RPs, 17.78 % of ILs, and 6.5 % of PAs burn every year. The RPs burned the most in 2020 (35,438 km²), followed by 2010 (23,532 km²) and 2005 (21,061 km²) with a minimum burned area in 2018 (2,504 km²). Regarding the ILs, the peak of burned areas occurred in 2019 (3,541 km²), followed by 2010 (3,067 km²), 2007 (2,982 km²), 2005 (2,945 km²) and then 2020 (2,747 km²). In 2014 the ILs burned 203 km², the smaller amount of the series. Finally, the PAs reached a maximum burned area in 2020 (5,131 km²), followed by 2010 (3,175 km²) and 2007 (1,830 km²). The minimum was in 2018 with 79 km² burned.

To complete our analysis, we looked at RPs, ILs, and PAs within the fire recurrence classes and found that 64.11% of RPs, 23.81% of ILs, and 43.46% of PAs never burned during our period studied. Additionally, 17.85% of RPs burned at least once and 3.76% burned five times or more. Also, 12.14% of ILs and 24.79% of PAs burned one time, and 33.43% of ILs and 10.36% of PAs burned at least 5 times. Lastly, 87% of all burned areas from 2003 to 2020 occurred inside RPs, 5.61% inside ILs, and 0.0005% in PAs.

6.4 Discussion

A linkage between extreme climate and anthropogenic actions appears to be the cause of the record of fires in 2020 in the Pantanal. Our findings corroborate that the whole Alto Paraguay Basin was hotter and drier in 2020 and that the water coverage in the region has been reducing yearly. We estimated that large amounts of carbon were lost by the 2020 fires and are now committed to be emitted to the atmosphere. Our analysis indicates that most fires occur inside private lands, which cover the majority of the basin. Most importantly, in atypical years the protected lands become flammable and, if exposed to ignition sources associated with fires in RPs, can be highly impacted by fires.

Our results show the atypical weather conditions faced by the region in 2020 and 2019, compared with the historical series, showing a reduction in precipitation and soil moisture combined with increased temperatures and water deficit, causing a drastic reduction of water availability and, consequently, drying of vegetation across the region. Interestingly, significant positive anomalies of burned areas were detected in other years (e.g., 2005 and 2010) but associated with less extreme weather, evidencing the importance of human ignition for large fires in the region. In grazing systems such as Cerrado and Pantanal, natural fires used to occur every 3–6 years; nonetheless, anthropogenic burnings have increased fire frequency to 2–3 years (PIVELLO et al., 2021). Another point is that the basin registered low fire activity from 2010 to 2018, which might have caused accumulation of fuel, which, together with drought conditions, can help to explain the atypical fires in 2020.

The northern part of the Pantanal was the most affected by fires in 2020 (Figure 6.3). This region had 13% more days without rain than in the 1960s and 16% less water mass during the drought season (LÁZARO et al., 2020). The largest forest formations of the Pantanal are in this area, pointing to increased vegetation dryness and flammability. Our results confirmed that the highest water deficit in the 2020 dry season was registered in this area (Figure 6.3). Other studies indicate that the annual precipitation in the Pantanal has been intensive during the rainy season, while the dry seasons are becoming longer (MARENGO et al., 2016; OLIVEIRA-JÚNIOR et al., 2020). Our findings show that soil moisture was below the average in all months of 2019 and 2020 (Figure 6.2). Temporal variability in soil moisture is an important indicator of alterations in the water cycle (ROSSATO et al., 2017), a crucial indicator of the potential impacts of climate change on water and land assets. Ribeiro et al. (2021) analyzed the impact of droughts (2009–2015) in soil moisture and suggested that the Pantanal is able to accumulate soil moisture during drought events, because they found an increasing trend in this variable even in 2012, when the biome presented a reduction of 81% of its total flooded area. This fact might indicate a water stress threshold at which the region is capable of maintaining water availability through the soil.

The causes of such an atypical climate in 2020 are still not completely understood. Thielen et al. (2020) associated extreme flood and drought events in the Pantanal with SST variability. Our findings indicate a weak correlation ($r = .23$), with an 11-month time lag, between monthly precipitation anomalies and AMO, whereas Thielen et al. (2020) found a strong correlation ($r = .80$), with a 2-month time lag, between monthly SSTs and monthly precipitation absolute values. The high correlation coefficients in this case reflect the coincident patterns of precipitation and SST seasonality instead of a direct influence of SST on precipitation anomalies. To overcome this problem, our analysis used standardized anomalies (DABERNIG et al., 2017) and did not detect the hypothesized relationship between precipitation anomalies and SSTs. Marengo et al. (2021) also corroborated that correlations between precipitation and oceanic indices were very low, although these authors made a visual interpretation rather than a statistical analysis. Other previous studies (e.g., ARAUJO; OBREGÓN, et al., 2018; SILVA et al., 2016) found different results depending on the methodology, suggesting a lack of consensus on the matter. Although the direct effects of SST on precipitation in the Pantanal are not clear, several studies have demonstrated the influence of SST on the occurrence of extreme weather events in Amazonia (ARAGÃO et al., 2007, 2018; CIEMER et al., 2020; MARENGO et al., 2011; VILANOVA et al., 2021). Moreover, the Amazonia plays a significant role in controlling summer rainfall in the Pantanal, with water security in the region being critically linked to conservation of the Amazonian rain forest (BERGIER et al., 2018). With the increase in deforestation and drought events in Amazonia, there is less evapotranspiration and moisture to be carried elsewhere. However, more studies are needed to clarify this and other dynamics, because future climate in the Pantanal remains a puzzle.

Our findings regarding the reduction in water coverage shed light on a worrying trend in the region. As reported by Mapbiomas (2021), the Pantanal has lost 68% of its water mass since 1985 and is the biome with the greatest reduction its water area in Brazil. Furthermore, in 2020 the Pantanal showed the smallest flooded area in the period (83% lower when compared with the period-based average) when analyzing data between 2000 and 2020 (PEREIRA et al., 2021). The 2020 drought contributed to this decrease, but other local causes should be accounted for, such as the construction of drains and other infrastructure built (e.g., paving and grounding of the MT-040 road) (DA SILVA et al., 2021). In this sense, the construction of hydropower facilities within the Alto Paraguay Basin is another worrisome factor. According to ANA (2018), there are 47 hydropower plants in operation in the region and 124 projects under construction or planned, most of them categorized as small. National policies often encourage this type of energy production, with the premise that small hydropower is a clean method of energy production and has minimum environmental impacts. In contrast, studies discuss how small dams can also have large impacts on reducing flood peaks (ZANATTA; MACIEL, 2021), decreasing habitat availability (AGUIAR et al., 2016), causing instability of river channels (LIAGHAT et al., 2017) and massive tree mortality (RESENDE et al., 2019), and that their expansion is largely unregulated in Brazil (ATHAYDE et al., 2019).

Other human activities, such as beef cattle and crop production, combined with poor conservation policies have also been modifying the Alto Paraguay Basin substantially. Our results show that native grasses burn the most in the Pantanal, suggesting that fire might be used for pasture maintenance in areas that do not flood. Native grasses are the primary food for the cattle in the Pantanal, with cattle production characterized by the movement of animals according to grassland availability, which is renewed seasonally by the temporarily flooded areas (ARAUJO; MONTEIRO, et al., 2018). Cattle production is considered to be the main economic activity in the Pantanal, whereas owing to the flood season, only a small portion of the area is designated for crop production (SOS-PANTANAL, 2021). On the Plateau, savannas have the largest burned areas, followed by agriculture (Figure 6.6). Savannas have evolved with natural fires; nonetheless, humans and climate change have been altering savanna fire regimes from wet-season fires (mostly caused by lightning) to dry-season fires (SCHMIDT; ELOY, 2020). Although the Plateau is very anthropized and composed of large areas of agriculture and pasture, the Pantanal still has 80% of its native vegetation (MAPBIOMAS, 2021). However, the conversion rate of natural vegetation to anthropic use in the Pantanal has jumped from 0.64% in 1976 to 16% in 2017 (PADOVANI, 2017), following a tendency of increased pressure on natural areas in the region (ROQUE et al., 2016). In comparison, by 2016 the Plateau already had 53% of its natural areas converted to anthropic use (WWF, 2017).

The combination of climate change and land use conversion, such as for sugarcane for biofuel production (ANDRADE-JUNIOR et al., 2019), can cause an escalation in fires, hence in carbon loss in the Alto Paraguay Basin. In fact, an “arc of deforestation” is already taking place in the basin, starting on the Plateau in the direction of the Pantanal borders, where land-use conversion is projected to increase at a rapid rate (GUERRA et al., 2020). Our estimation of carbon loss (Table 6.1) corroborates that the burning of forests contributes to more committed carbon emissions than the low carbon content of natural or anthropic pastures. In addition, with the grasslands burning every year, the carbon is being captured and emitted in an annual cycle, with little impact on atmospheric accumulation. Conversely, burning of forests and other types of vegetation that have higher carbon residence time and are fire sensitive releases carbon that stays in the atmosphere, and increased forest burning indicates the anthropic pressure on the ecosystem. Despite variations between the estimates of carbon loss from ESA and BI maps, which are attributable to the different methodologies used for these two datasets, the patterns of loss across different land uses were consistent. These results are important to subsidize planning of actions to support the recently approved Law Project 1539/2021 by the Brazilian senate, which institutes a reduction of 43% of carbon emissions by 2025 and 50% by 2030. The present observed patterns of increased deforestation (GUERRA et al., 2020) are in disagreement with current Brazilian legislation, and there is an urgent need to mitigate them efficiently to achieve the proposed targets.

Our findings show that PAs and ILs are key for the conservation of native vegetation remnants. Today, together, they cover only 6.27% of the basin. In 2020, 35% of PAs and 33% of ILs burned (Table 6.1). This shows that even PAs are vulnerable to surrounding fires in hot and dry years, such as 2020. ILs did not burn the most in 2020, when the majority of the fires were within private properties, refuting anecdotical information blaming indigenous people and other traditional inhabitants for the fire events (RECUERO; SOARES, 2020). Alho et al. (2019) discuss how in the Pantanal, farmers often set fire to the vegetation during the dry season to clear areas for pasture and that some farmers burn garbage produced by tourism. As a result, fires frequently propagate uncontrollably, reaching adjacent forest environments. The effectiveness of the small number of PAs and ILs is jeopardized by their fragmentation and anthropogenic pressure. Therefore, the enlargement of PAs in combination with a long-term strategy to mitigate fires are essential to prevent future disasters.

To prevent and fight fires better in natural areas of Brazil, the National Policy for Integrated Fire Management (Law project no. 11276/18) was an initiative recently approved by the Chamber of Deputies and is now waiting to be approved by the

Senate. Even so, there is a need to improve this policy and to develop regional policies to ensure efficiency in disaster risk management. One crucial component that can contribute with strategies for prevention is the seasonal fire probability forecast (ANDERSON et al., 2021). This anticipated information on areas more likely to face wildfires in the following months might contribute with strategic planning. Particularly in the Pantanal, there has been launched the Burned Area Alert with Estimated Satellite Monitoring (ALARMES; https://lasa.ufrj.br/alarmes/) which provides near-real-time information on fire occurrence and the burned area, contributing to the response capacity. Together, these two pieces of data might contribute to fire prevention and combat, but operational plans, such as those formulated by Guerra et al. (2021), must be developed and implemented in the region. These initiatives are important, but they require national coordination, capacity building, further technical development and long-term commitment to make advances in the fire prevention investments.

6.5 Conclusions

The reduction in rainfall, exacerbating the water deficit, drying soils and reducing the extent of flooded areas, combined with an increase of 8% in fires on private lands in a region with a small area of protected lands favored the spread of fires in 2020. The interconnection between the Plateau and the Pantanal requires analysis of the whole basin to understand these anomalous periods, because their LULC dynamics are different, but with a combined influence on burned area. Beef cattle production in the Pantanal strongly influences fires, because farmers use native grasslands as a source of food for the cattle, as in the Plateau, together with the expansion of agriculture. The Pantanal depends on the Plateau to maintain its flooded areas; therefore, fire mitigation and conservation strategies must include the highlands. Forests were particularly vulnerable in 2020, with substantial burning in areas that do not usually burn, committing large amounts of carbon to the atmosphere that would otherwise be kept stored in the wood biomass. We showed that most of the fires were within private properties, but public properties, such as protected areas and indigenous lands, were also affected, to a smaller degree, by fire in 2020. These public areas are endangered by fire used for the management of land in private properties. This fact raises the need for pasture practices that eliminate the use of fire on farms around preserved lands. A strategy focused on fire mitigation and LULC regulation inside the Alto Paraguay Basin with the increase of protected areas is recommended, but yet to be developed in Brazil. The incorporation of educational practices that disseminate the importance of natural areas is also essential. Furthermore, our results also emphasize that in a hotter and drier future, megafires might not be an anomalous event in the Pantanal. The devastation of the Brazilian Pantanal by fires in 2020 showed how the combination of extreme weather, fire-related activities (e.g., beef cattle and agriculture) and ineffective governance create an ideal scenario for large wildfires. Finally, researchers need to strengthen our knowledge about fires and the impacts of climate change in the region to enhance effective actions and decision-making.

7 CONCLUDING REMARKS

The model developed in this thesis, FLAME, is the first of its kind for fire modeling. Combining Bayesian inference and an overhaul of Maximum Entropy methods also required new evaluation techniques that demonstrated its ability to effectively simulate burned area patterns across the Brazilian biomes. The model is flexible enough to be adapted to different locations, time periods and hazards accordingly with specific characteristics. By modeling a probability distribution, it is possible to simulate likely “worse” (90th percentile) and “better” (10th percentile) scenarios of burning based on the relationship between the variables. Moreover, it is possible to isolate the effects of groups of variables. The potential evaluation confirmed the high uncertainties related to controls of burning, with areas exhibiting conflicting trends across the percentiles. However, it remains possible to determine the most likely scenarios based on the likelihood maps. Moreover, integrating additional and contextualized priors may help constrain the uncertainties in the variables' responses. In conclusion, this approach is valuable for pinpointing knowledge gaps that future research can address to reduce these uncertainties in burned area responses.

The model application for Brazil revealed some interesting results. For instance, the interactions between the variables are spatially different. While many studies address this issue by subdividing their study areas into subregions or conducting local-scale analyses, our approach allows us to account for this variability without needing separate analyses of subregions. Our findings indicate that highly forested areas mitigate the impact of climate variability on burned area, as demonstrated by the Amazonia potential response. However, the response of the Atlantic Forest suggests that once fragmented, this resilience is compromised. Future studies could further focus on this hypothesis. The division into fire categories reduced the bias of the simulations. Nevertheless, it increased the regions with unclear patterns in the potential responses. The sensitivity analysis showed that NAT and NON have different sensitivities to the variables for Amazonia, Cerrado and Pantanal. This indicates that the analysis of ALL can potentially mask some relationships even though it is recommended to customize the division of fires according to local characteristics. Based on these results, I conclude that policymaking must account for burning dynamics' spatial variability. Further research should focus on customizing the analysis for each biome or vegetation type in Brazil.

In Chapter 5, our biome-focused analysis showed how FLAME effectively minimized model bias and identified additional relationships. Changes in climate and land cover are closely associated with burning in Pantanal. The 2020 extreme fires crossed all the thresholds estimated in this research, a worrisome finding considering the estimated trend of hotter and drier landscapes in the biome. Interestingly, wetland cover compensates for the effect of climate in increased burning. However, burning is likely to occur even with higher precipitation levels, especially when combined with wetland degradation. This methodology holds promise for identifying critical transitions to higher burning of other variables and in subregions of Pantanal and other biomes. Incorporating thresholds associated with burning into planning efforts can bolster response strategies and strategic planning initiatives. Here, I conclude that this novel approach is adaptable to other biomes and regions. This tool may be useful to support early warnings, generate future scenarios and identify priority areas for monitoring and prevention.

In Chapter 6, we employed a centered remote sensing approach to further detail the conditions underlying the 2020 extreme fire season and to delve into additional relationships within Pantanal and its surroundings. The findings corroborated the trend of wetland reduction identified in Chapter 5 and highlighted how these areas became susceptible to fires. Our assessment of the human factor underscored the significant role of increased human pressure in driving the occurrence of extreme fire seasons. While Pantanal has historically experienced fires, extreme fires in 2020 have severely impacted the biome. The 2020 season took everyone by surprise, raising concern for two points: firstly, the potential for intense fire seasons to become an annual occurrence in Pantanal given the observed trends and the challenges in mitigating human factors; and secondly, should we expect severe changes in other biomes? Are they already on course? To adequately prepare for long-term monitoring of fire within the biomes and design effective prevention strategies, it is essential to develop further burning scenarios that could potentially enhance Brazil's institutional and social capacities and the design of public policies. Moreover, focused research is needed for Caatinga, Pampas and Atlantic Forest where burned area dynamics are poorly understood and documented compared to other areas.

Remote sensing offers a finer analysis scale than most simulation data for fire modeling. Furthermore, integrating certain data inputs, such as information on land tenure types, into models is not always straightforward. However, some critical data, such as monthly soil and vegetation carbon levels, remain unavailable through remote sensing. Therefore, recognizing the strengths of both approaches and leveraging their combined use whenever feasible is vital. To enhance preparedness in Brazil, it is imperative to leverage and fuse these tools effectively while also advocating for government restructuring and increased investment. By addressing these aspects comprehensively, we can better mitigate the impact of fires and safeguard communities and ecosystems alike.

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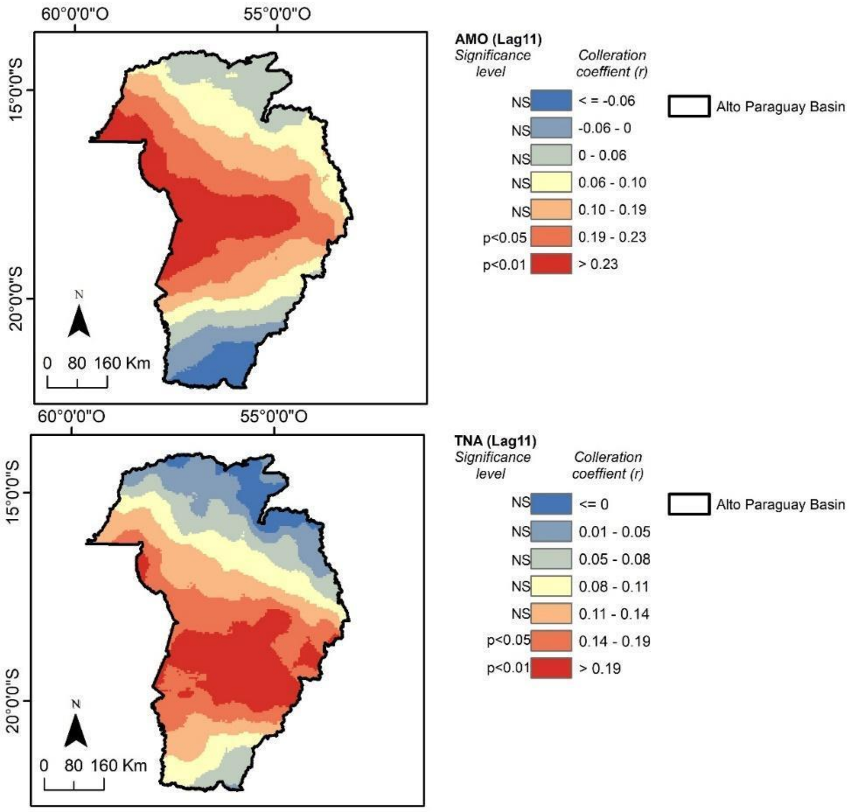
APPENDIX B - SUPPLEMENTARY FIGURES AND TABLES

Figure B.1. Spearman's correlation coefficient between precipitation and AMO (upper) and precipitation and TNA (bottom) indexes with a 11-time lag.



Source: Author's production.

Table B.1 - Carbon loss (Mg C) by fire in the year 2020 for each LULC type.

LULC	ESA (Mg C)	SD*	BI (Mg C)	SD*
Forest formation	32,980,189	150,92055	24,933,671	18,700,253
Savanna formation	22,033,139	9,340834	18,461,846	13,846,384
Agriculture	343,360	263,353	734,693	551,019
Pasture	1,961,950	1,513,596	4,627,726	3,470,794
Grassland	12,739,704	9,828,365	23,670,993	17,753,244
Total	70,058,342	36,038,203	72,428,929	54,321,694

*Standard deviation.

Source: Author’s production.