

# Impact of climatic and anthropogenic drivers on spatio-temporal fire distribution in the Brazilian Amazon

Dissertation  
zur Erlangung des akademischen Grades  
doctor rerum naturalium  
(Dr. rer. nat.)  
im Fach Geographie  
eingereicht an der  
**Mathematisch-Naturwissenschaftlichen Fakultät  
der Humboldt-Universität zu Berlin**

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Disputation: 11.07.2022

<https://doi.org/10.18452/25844>

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## Abstract

The Amazon region has experienced an intensification of human activities in the last decades, which combined with frequent severe droughts has led to an environment more susceptible to fire. Fires have been altering ecosystem structure, biogeochemical cycles and atmospheric composition with unprecedented rapidity in the Brazilian Legal Amazon (BLA). In this dissertation, remotely sensed data is employed to comprehensively analyse the spatio-temporal fire distribution in the BLA over the past 20 years in order to disentangle the diverse fire drivers in the region. Special focus is given to burned tropical evergreen forests.

Three research papers constitute the chapters of this dissertation and provide the evidence for the following main findings. First, the evaluation of the burned area distribution revealed that most of it occurred in pastures and tropical evergreen forests, supporting the claim that fire incidence responds strongly to anthropogenic land-use changes ([Chapter II](#)). The results also showed that neither deforestation nor degradation correlated with forest fires, but escaping fires from pastures and agriculture do - up to 52% and 22% of the burned forests, respectively. Second, the analysis of individual fires identified by the complex networks-based FireTracks algorithm led to the characterization of six different land cover-dependent fire regimes ([Chapter III](#)). The integrated size, duration, intensity, and rate of spread of those spatio-temporal fire clusters in the different land uses uncovered how evergreen forest fires have escalated from being naturally rare to showing characteristics more typical of savanna fires. Third, the analysis of extreme, i.e. the most intense, individual fires in evergreen forests showed their large contribution to the total forest burned ([Chapter IV](#)). While global climate change has the potential to increase drought conditions, anthropogenic drivers of forest degradation (deforestation, roads, logging, mining, farming, etc.) provide the ignition sources that determine extreme fire distribution in the sensitive tropical forests of the BLA.

In conclusion, the findings call for the development of control and monitoring plans to prevent fires from escaping from managed lands into forests. Better training in management techniques should be promoted to support effective land use and ecosystem management. In addition to this, targeting forest degradation in addition to deforestation becomes crucial. The results also highlight the relevance of properly assessing the synergistic effects of continued anthropogenic pressure, ongoing climate change and fire. Outcomes of the fire regimes assessment provide detailed information to be considered when parametrising the human factor in fire ignition and spread in Dynamic Global Vegetation Models in order to reduce uncertainty in fire regime projections, future emissions scenarios and fire interactions with socioeconomic drivers.

## Zusammenfassung

Das Amazonasgebiet hat in den letzten Jahrzehnten eine Intensivierung der menschlichen Aktivitäten erfahren, die in Verbindung mit häufigen schweren Dürren die Umwelt anfälliger für Brände gemacht hat. Brände haben die Ökosystemstruktur, die biogeochemischen Kreisläufe und die Zusammensetzung der Atmosphäre im brasilianischen Amazonasgebiet (BLA) mit beispielloser Geschwindigkeit verändert. In dieser Dissertation wurden Fernerkundungsdaten analysiert, um die räumlich-zeitliche Verteilung der Feuer in den letzten 20 Jahren im BLA umfassend zu untersuchen und die verschiedenen Brandursachen in der Region zu entschlüsseln. Besonderes Augenmerk gilt dabei den verbrannten immergrünen Tropenwäldern.

Drei Forschungsarbeiten bilden die Kapitel dieser Dissertation und liefern Evidenz für die folgenden Hauptergebnisse. Die erste Forschungsarbeit wertete die Verteilung der verbrannten Fläche aus und zeigte, dass die meisten Brände auf bewirtschafteten Weiden und in den immergrünen Tropenwäldern auftraten, was die Behauptung stützt, dass ihr Auftreten stark auf anthropogene Landnutzungsänderungen reagiert ([Kapitel II](#)). Die Ergebnisse zeigten auch, dass weder Entwaldung noch Walddegradierung mit Waldbränden korrelierte, wohl aber Feuer, die auf Weiden oder Ackerflächen gelegt wurden und in den angrenzenden Wald überggesprungen sind (bis zu 52 % bzw. 22 % der abgebrannten Wälder). Die zweite Forschungsarbeit analysierte einzelne Brände, die durch den auf komplexen Netzwerken basierenden FireTracks-Algorithmus identifiziert wurden. Der Algorithmus wurde verwendet, um Feuerregime für sechs verschiedene Landnutzungsklassen zu ermitteln ([Kapitel III](#)). Die integrierte Größe, Dauer, Intensität und Ausbreitungsrate dieser räumlich-zeitlichen Brandcluster in den verschiedenen Landnutzungstypen zeigte auf, wie seltene Waldbrände, die natürlicherweise nicht in immergrünen tropischen Wäldern vorkommen, sich zu einem Feuerregime entwickelten, das für Savannenbrände typisch ist. Die dritte Forschungsarbeit analysierte extreme, d. h. die intensivsten Einzelfeuer in immergrünen tropischen Wäldern, und zeigte deren großen Anteil an der insgesamt verbrannten Waldfläche ([Kapitel IV](#)). Während der globale Klimawandel das Potenzial hat, die Trockenheit zu verstärken, sind die anthropogenen Ursachen der Waldzerstörung (Entwaldung, Straßen, Holzeinschlag, Bergbau, Landwirtschaft usw.) die Zündquellen, die die Verteilung extremer Brände in den empfindlichen tropischen Wäldern der BLA bestimmen.

Abschließend fordern die Ergebnisse die Entwicklung von Kontroll- und Überwachungsplänen, um zu verhindern, dass Brände von bewirtschafteten Flächen in die Wälder übergreifen. Eine bessere Ausbildung in Managementtechniken sollte gefördert werden, um eine effektive Landnutzung und Ökosystemmanagement zu unterstützen. Darüber hinaus ist es von entscheidender Bedeutung, neben der Entwaldung auch die Walddegradierung zu bekämpfen. Die Ergebnisse zeigen auch, wie wichtig es ist, die Synergieeffekte des anhaltenden anthropogenen Drucks, des fortschreitenden Klimawandels und der Feuer richtig zu bewerten. Die Ergebnisse der Bewertung der Feuerregime liefern detaillierte Informationen, die bei der Parametrisierung des anthropogenen Faktors bei der Entzündung und Ausbreitung von Bränden in dynamischen globalen Vegetationsmodellen zu berücksichtigen sind, um die Unsicherheit der Projektionen von Feuerregimen, künftigen Emissionsszenarien und Wechselwirkungen von Bränden mit sozioökonomischen Faktoren zu verringern.

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# Chapter I

## Introduction

## **1 Fire in the Earth system**

Fire is an integral Earth system process that has been influencing regional and global biogeochemical cycles, ecosystem structure, vegetation dynamics, and atmospheric composition for millions of years (Ryan, 1991; Mouillot and Field, 2005; Archibald et al., 2018). Fire occurrence and behaviour depend on the convergence of the appropriate fuel conditions, weather patterns, and ignition sources (Lavorel et al., 2007; Marlon et al., 2008; Flannigan et al., 2009). Vegetation attributes, structure and continuity determine fuel characteristics and flammability (Anderson, 1970; Schwilk, 2015). Climate and weather control fires' behaviour, severity, and the conditions for fire ignition and spread. Climate influences the spatial distribution of the different vegetation types, and hence, fuel characteristics, whereas local weather regulates fuel moisture and physical conditions for fire propagation (Benson et al., 2008; van der Werf et al., 2008; Jolly et al., 2015). In turn, fires influence climate by a series of complex and non-linear interactions. Fires released a global average of 2.1 Gt C/year over the period 1997-2020 (from 1.4 Gt C from savanna, grassland and shrubland fires, to 0.06 Gt C from temperate forest fires), which directly contribute to global warming (van der Werf et al., 2017; GFED4.1s, 2021). Savanna-type vegetation, and tropical deforestation and degradation fires released most of the global carbon emitted over that 24-year period (65% and 15% of the global emissions, respectively) (GFED4.1s, 2021). Light absorbing aerosols emitted by fires also affect global climate by altering the radiation balance and taking part in the aerosol-cloud-radiation-circulation feedbacks (Tosca et al., 2013; Landry et al., 2017; Jiang et al., 2020). Thus, fires increase the concentration of radiatively active gases and aerosols in the atmosphere, which leads to changes in atmospheric heating and composition (Rogers et al., 2020). The post-fire increase in surface temperature impacts the radiative budget and the biophysical feedbacks that depend on the dynamic interactions between evapotranspiration and albedo (Randerson et al., 2006; Bonan, 2008; Liu et al., 2019). Fires affect global vegetation patterns and species composition too by favouring selected species and plant traits (Eva and Lambin, 2000; Lawes et al., 2016; Giorgis et al., 2021). Nowadays, fire-climate feedbacks are amplified by anthropogenic drivers of climate change, specially by those processes that involve land-cover changes.

Where fuel loads and conditions are sufficient to sustain a fire, ignition sources for the fire to start are provided by humans and lightnings (Bistinas et al., 2013; Kelley et al., 2019). Ignition sources changed in extent and frequency over time, from mostly natural origin to become mainly human-induced. Humans have been using fire to manage the landscape for millennia (Marlon et al., 2008; Bowman et al., 2011; Lewis et al., 2015). Centuries of experience in managing fuel to lower fire risk and maintain a diverse landscape is captured in traditional and often indigenous knowledge (Hoffman et al., 2021). However, over the past decades, multiple land-use change (LUC) processes driven by anthropogenic fires have increased considerably (Curtis et al., 2018; Li et al., 2018; Rogers et al., 2020). Humans modify fuel types, structure and continuity throughout deforestation, road construction, logging, mining, farming, fragmentation, etc., and provide most of the ignition sources (Laurance, 2001; Hantson et al., 2017; McLauchlan et al., 2020). Emissions from land use, LUC and forestry contributed 18% of the global anthropogenic emissions, that more than doubled in the last sixty years (Friedlingstein et al., 2022). Highest LUC emissions occur in the tropical regions, including the arc of deforestation in the Amazon basin (Friedlingstein et al., 2022). Brazil is one of the most important countries in terms of emissions associated with LUC (Bustamante et al., 2018). According to the last Brazilian report on annual estimates of GHG emissions (MCTI, 2020), 22% (ca. 291 GHG CO<sub>2</sub>e) of the total GHG emissions in 2016 occurred as a consequence of emissions from LUC, which reveals the severe anthropogenic pressure the region is enduring, specially the Amazon. For this reason, improved mitigation policies in the region require a better understanding of the characteristics of the diverse land-covers and the complex land conversion patterns.

Under a warmer and drier climate and increasing anthropogenic pressures, future projections of fire activity show a more severe fire weather, increased ignitions and burned area, and longer fire seasons (Flannigan et al., 2006; Pausas and Keeley, 2014; Brando et al., 2019).

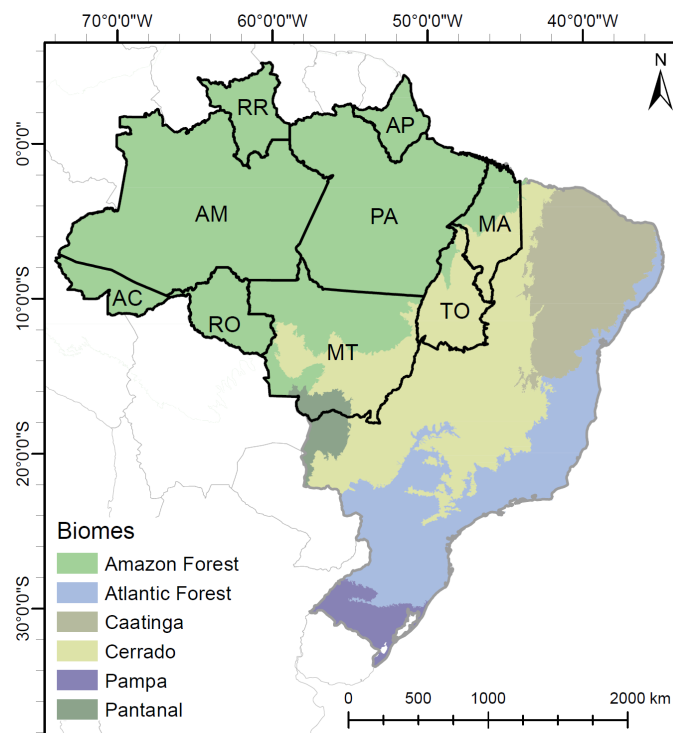
## **2 Study area**

Brazil is the most biologically diverse country in the world, the second in terms of species endemism, and one of the world's 17 mega diverse countries - comprising

70% of the world's catalogued animal and plant species - (BIOFIN, 2021; SiBBr, 2021). Especially, the Amazon ecosystems host a large proportion of global biodiversity (Barlow et al., 2007; Cardoso et al., 2017; Feng et al., 2021), which makes them a conservation priority in order to maintain all of their environmental functions and services. The Amazon regulates water (Arraut et al., 2012; Zemp et al., 2014; Casagrande et al., 2021), energy (Longo et al., 2020; Stark et al., 2020), and carbon (Brienen et al., 2015; Covey et al., 2021; Gatti et al., 2021) cycling. Feedbacks between them have the capacity to alter regional and global climate patterns (Sampaio et al., 2007; Lejeune et al., 2015; Leite-Filho et al., 2020).

The intrinsic value of the Amazon region, however, has been heavily disturbed in the last decades by the increasingly frequent extreme weather events, as the consequence of climate change and anthropogenic pressures. The most severe droughts registered in Amazonia in the twenty-first century were linked to anomalously warm phases of the tropical eastern Pacific (related to the El Niño Southern Oscillation, ENSO) and/or the northern Atlantic oceans (related to the Atlantic Multidecadal Oscillation, AMO). The year 2005 witnessed an extensive AMO-associated drought identified as a 1-in-100-year event in the BLA (Marengo et al., 2008; Lewis et al., 2011). In these cases, anomalously warm Sea Surface Temperature (SST) in the tropical North Atlantic weakens northeast trade wind moisture transport during the summer resulting in reduced rainfall during the dry season especially in western and southwestern Amazon (Zeng et al., 2008). When the warm SST anomalies occur in the equatorial Pacific, convection is suppressed and subsequently, also rainfall over the northern, central and eastern Amazon (Jimenez et al., 2018; Panisset et al., 2018; Silva Junior et al., 2019). A combination of eastern Pacific and tropical north Atlantic warming may cause more severe, prolonged and/or widespread droughts (Yoon and Zeng, 2010; Marengo et al., 2011; Zou et al., 2016), which is what happened in 2010. The 2010 drought started during an El Niño event and then became more intense with the anomalous warming of the tropical north Atlantic (Espinoza et al., 2011; Lewis et al., 2011). The combination of both phenomena caused the 2010 drought to be more severe and remain for longer than the 2005 drought (Jimenez et al., 2018). At the end of the year 2015 and beginning of 2016, one of the greatest El Niño events of the last decades - combined with the regional warming trend - struck the region with unprecedented warming and

the most extensive area under extreme drought severity (Cunha et al., 2019; Silva Junior et al., 2019). As the mentioned studies reported, those extreme events were associated with increased mean temperature, decreased levels of rainfall, and/or an extended dry season. Ongoing global warming is projected to increase the frequency and intensity of extreme events, therefore increasing the risk to the integrity and functionality of the Amazon ecosystems (Fu et al., 2013; Marengo et al., 2018; Cunha et al., 2019).



**Figure I-1** Biomes distribution in Brazil in the year 2019 (IBGE, 2019). The states within the Brazilian Legal Amazon appear delimited in black: Acre (AC), Amapá (AP), Amazonas (AM), Maranhão (MA), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR) and Tocantins (TO)

Climatic drivers operate simultaneously and synergistically with anthropogenic drivers in the Amazon (Le Page et al., 2010; Nobre et al., 2016; Staal et al., 2020). Anthropogenic drivers related to LUC - fragmentation, deforestation, degradation, logging, mining, ranching and farming, agricultural expansion - increase fire susceptibility as the result of changes in ignitions, fire season and fuels - type, moisture, structure and continuity - (Gutiérrez-Vélez et al., 2014; Le Page et al., 2017; Fonseca et al., 2019). Humans are almost entirely the cause of fires in the

region (Cochrane and Laurance, 2008; Nepstad et al., 2008; Barlow et al., 2020), often even in the absence of suitable climatic conditions (Le Page et al., 2010; Pivello, 2011; Carmenta et al., 2013). Human activities have introduced fires into the tropical forests, where the moist understory and the scarce natural ignition sources precluded them from significant burning (Ray et al., 2005, Le Page et al., 2017). Forest fires are caused not only by activities taking place inside the rainforests but also by escaping fires from managed lands in their vicinity (Silva Junior et al., 2018; Cammelli et al., 2020).

Since fires were infrequent, plant species in evergreen forests are poorly adapted to fire (Brando et al., 2012; Hoffmann et al., 2012). In contrast, in fire-prone savanna-type ecosystems, fire is a natural component and woody plants and grasses have developed traits to cope with it over thousands of years (Bowman et al., 2009; Simon et al., 2009; Keeley et al., 2011). Fire suppression, a measure of vital importance for the conservation of the tropical forests, has devastating effects in savanna-type communities (Berlinck and Batista, 2020; Durigan, 2020). Reduced fire frequency increases woody encroachment and the accumulation of grassy fuels, which increases the risk of catastrophic large-scale wildfires jeopardising biodiversity conservation (Moreira, 2000; Higgins et al., 2007; Pellegrini et al., 2016). Therefore, to understand the specific impacts of fires and the potential measures to apply in order to minimise damages, it is crucial to capture the regional heterogeneity and to determine the fuel characteristics and condition in each case.

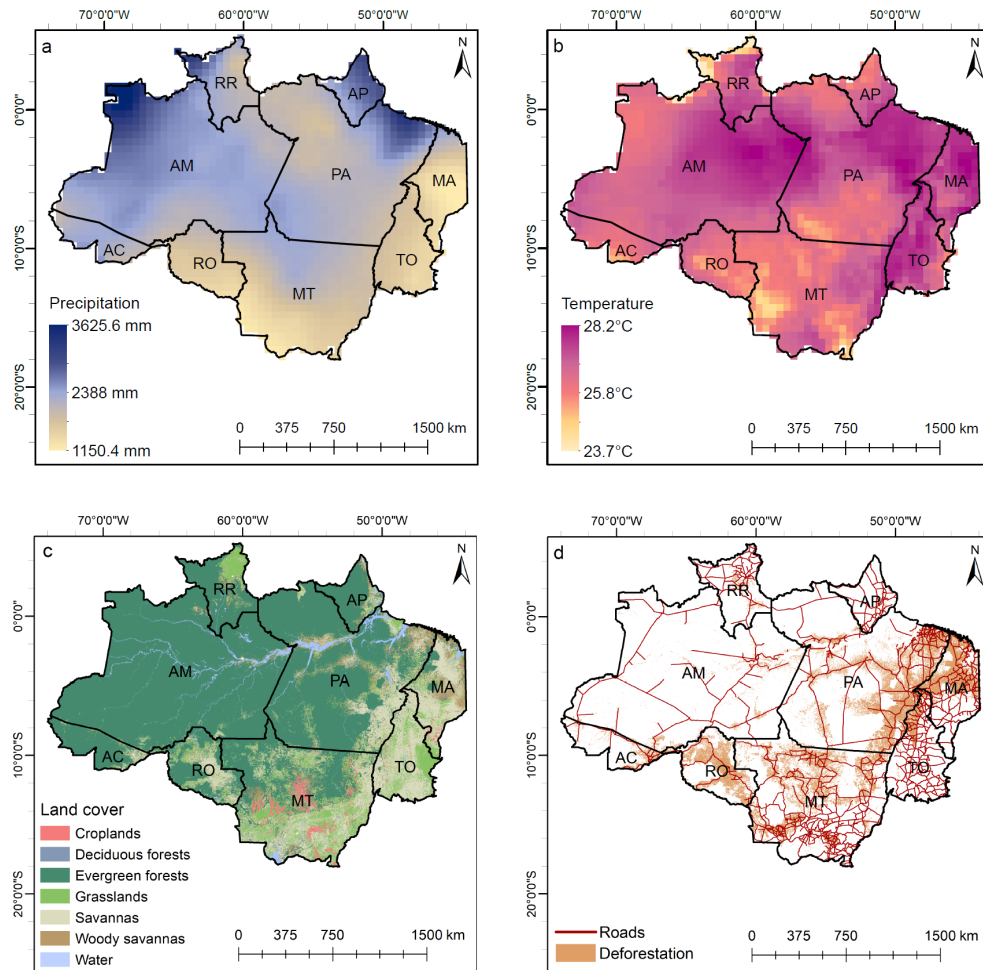
Specifically, the study area is defined following the boundaries of the Brazilian Legal Amazon (BLA), a geopolitical delimitation first established by law in 1953 and last updated in 2007 (*Lei Complementar n° 124*, 03-01-2007). The BLA was constituted for the purpose of social and economic planning of the region under the jurisdiction of the Superintendence of the Amazon Development (SUDAM). This institution promotes the progress of the region in order to integrate the local production to the national and international economy. The BLA encompasses the states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA), occupying ca. 5 million km<sup>2</sup> - nearly 60% of the Brazilian territory -. Most of the region is covered by the Amazon biome (84% of the BLA in 2019), and also includes part of the Cerrado

biome (15%) - along southern MT, TO and southern MA -, and part of the Pantanal biome in southwestern MT (1%) (Fig. I-1).

The Amazon biome is covered predominantly by dense moist tropical forest consisting of tree species, shrubs, lianas, epiphytes and herbaceous species, with small inclusions of other types of vegetation (IBGE, 2019). The climate is classified as tropical rainforest or monsoon climate (Beck et al., 2018), without a biologically dry period throughout the year and exceptionally with two months of scarce humidity. The Cerrado biome is characterised by scattered trees and shrubs, small palms, and a ground layer of herbaceous species. It has a typical tropical savanna climate with well-defined dry and wet seasons that strongly influence the vegetation composition (IBGE, 2019). Pantanal ecosystems, which are submerged 80% during the rainy season, are formed by sandy terrains with various subregions depending on their hydrological, geological and ecological characteristics (IBGE, 2019). Although some heterogeneity exists within the biomes, dominant vegetation traits, species composition, and regional climate exert a direct effect on fire activity across those zones (Benson et al., 2008; van der Werf et al., 2008; Jolly et al., 2015).

The BLA experiences an annual rainfall gradient from 1000 mm in the south to more than 3600 mm in the northwest and northeast of the region (Fig. I-2a), with most of the precipitation occurring during the rainy season of the austral summer (CCKP, 2021). In general, the drier regions in the BLA are found in the southern and southeastern areas. Higher temperatures are experienced in the northern region of the BLA south of the equator, and in its eastern flank, whereas the lowest temperatures are concentrated in southern BLA, and in the portion north of the equator of the states of Roraima and Amapá (Fig. I-2b) (CCKP, 2021).





**Figure I-2** a Spatial distribution of the observed annual precipitation (in mm), and b mean annual temperature (in °C) at a 0.5°×0.5° resolution in the BLA. Values correspond to the average over the period 1991-2020 (CCKP, 2021). c Land-cover spatial distribution in the BLA in 2019 (Friedl and Sulla-Menashe, 2019). d Main roads in 2014 (IBGE, 2014) and cumulative deforestation over the period 1988-2020 (INPE, 2021a)

The nine states encompassed by the BLA were mainly covered by evergreen forests (66%), open and woody savannas (20%), and grasslands (10%) in 2019, whereas croplands and deciduous forests were less present (around 1.3% and 0.3%, respectively). There are remarkable differences in the spatial distribution of the different land-cover types. Woody savannas are mainly concentrated in northeastern PA and MA, while savannas are distributed along southeastern BLA in the states of RO, MT, TO and MA (Fig. I-2c). Grasslands appear more interspersed between tropical forests and savannas. Northeastern RR and eastern TO also host a significant grassland extent. Most croplands and deciduous forests spread over MT, and to a lesser extent in TO and MA (Fig. I-2c). Land use weighs heavily on the type of fire regime due to both the vegetation characteristics at the site and the amount of

anthropogenic ignition sources. Fire is used intensively in LUC processes such as deforestation, not only during the process itself but also for the management of the subsequent anthropogenic land uses, e.g. agriculture or cattle pastures (Cochrane et al., 1999; Barona et al., 2010; Barlow et al., 2020). Most of the deforestation is distributed along the southern and eastern borders of the BLA (Fig. I-2d), in the so-called arc of deforestation (along the states of AC, RO, MT, PA, TO MA), and it is generally associated with roads (Fig. I-2d) that increase forest accessibility and occupation (Nepstad et al., 2001; Alves, 2002; Fearnside, 2007; Armenteras et al., 2017).

### **3 Research objectives**

The aim of this work is to comprehensively analyse the spatio-temporal distribution of fire activity in the BLA over the period from 2002 to 2020, with special focus on tropical evergreen forests, and disentangle the various fire driving forces in the region. Thus, the investigation, based on quantitative and model studies, of the specific causes behind fire occurrence in areas where it would not naturally happen - specially tropical forests - and the increase in fire severity and extent, outlines the background of this dissertation.

The broad research questions successively addressed by the three studies detailed below are:

1. What are the anthropogenic drivers of tropical forest fires in the Amazon?  
(Chapter II)
2. How do fire regimes differ between the land-cover types in the Amazon?  
(Chapter III)
3. How do changing climatic conditions and other anthropogenic drivers impact the spatio-temporal distribution of high-intense fires in the Amazon tropical forests? (Chapter IV)

These broad questions motivate the development of the following research and their more specific objectives and methodological approaches.

### **3.1 Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures (Chapter II)**

Fires have always accompanied deforestation and degradation processes in tropical Amazonian forests. However, some regions witnessed increases in fire occurrence with reduced deforestation rates. I explore how in those regions the continuous enlargement of forest edges and fire-involving management techniques in already deforested areas appear to be primary drivers of forest fires. In this study, I use high-resolution land-cover satellite imagery combined with remotely sensed fire data to analyse the burned area distribution in the various land-cover types in three states of the Brazilian Amazon that are under large-scale anthropogenic pressure (PA, MT and RO). Here, I compare fire occurrence in 2008, an average year, with those in 2010, a drought year, to investigate the role of deforestation and forest degradation processes as potential drivers. Moreover, I develop an algorithm to quantify the proportion of burned forests associated with fires escaping from managed lands, i.e., agricultural lands and cattle pastures. Thus, I provide a comprehensive analysis on the relationship between fire occurrence and anthropogenic activities such as deforestation, forest degradation, and LUC, with a specific focus on fires occurring along the frontier between rainforests and the rapidly expanding agricultural frontier. Finally, I highlight the strong influence that LUC has on fire occurrence and distribution, and support the assumption that most of the forest fires in the region in those years were caused by escaping fires from managed lands, while deforestation and forest degradation were secondary drivers.

Research objectives:

1. Analyse the burned area distribution in the different land-cover types of three states of the BLA using high-resolution satellite imagery in the years 2008 and 2010
2. Assess the amount of burned forests associated with deforestation and forest degradation processes
3. Quantify the proportion of burned forests resulting from managed fires in the proximity

### **3.2 Characterization of land cover-specific fire regimes in the Brazilian Amazon** (Chapter III)

Satellites provide remotely sensed data such as single-pixel fire detections or burned area. However, information about individual fires and their behaviour over time is required in order to understand current changing fire regimes in response to climate and anthropogenic land-cover changes. In addition to global fire trends or total burned area, the individual fires approach allows the analysis of the dominant fire features in the different fire regimes. Based on this approach, a novel distributed network clustering algorithm is implemented to identify local formations of spatio-temporal fire clusters from remotely sensed fire and land-use data in the BLA from 2002 to 2020. The individual fires approach enables tracking the progression of fires over space and time from their ignition point/s. Thus, several single active fires are grouped if they are considered to belong to the same fire cluster. I determine the integrated size, duration, intensity, and rate of spread of the individual fires to analyse fire behaviour and dynamics in the different land-cover types. This research provides the first estimates of individual fires integrated intensity in the Amazon, which is crucial to assess socio-ecological impacts of fires as well as burned biomass and fire-induced emissions. Specific combinations of the four fire variables characterise different fire types in the region and make it possible to define six land-cover specific fire regimes resulting from the interactions between climate and human actions. As prominent changes in fire regimes are attributed to anthropogenic activities, this study remarks the urge of incorporating LUC in fire modelling.

Research objectives:

1. Examine the spatio-temporal distribution of individual fires in the BLA over the period 2002-2020
2. Estimate the size, duration, intensity and rate of spread of individual fires to explore fire dynamics at local scales
3. Identify and describe six different land-cover-specific fire regimes based on the attributes of fires

4. Supply detailed information on fire features that can be used in fire modelling to parametrise different fire regimes and better represent fire activity and impacts

### **3.3 Spatio-temporal patterns of extreme fires in Amazonian forests (Chapter IV)**

The number of high-intensity fires has increased in the Amazon tropical forests in recent years, usually associated with extreme droughts and/or intensified human influence. Fire intensity controls the amount of biomass consumed, combustion ratios, and amount and composition of the emissions. The same individual fires approach used in [Chapter III](#) is implemented in this research to identify individual fires in tropical forests of the BLA over the period 2002-2019 and track their evolution over space and time. The approach allows the estimation of the individual aggregated intensity of those fire clusters, and the selection of the 5% most intense fires, i.e. extreme fires. I interpret fire spatio-temporal variability in relation to large-scale climate events such as the anomalously warm phases of the tropical eastern Pacific - related to the ENSO - and the northern Atlantic oceans - related to the AMO -, that cause more severe, prolonged and/or widespread droughts in the region. I also evaluate the impact of anthropogenic-driven forest fragmentation by deforestation and road development on fire activity. Thus, fire spatial patterns in years with diverse meteorological conditions and different degrees of anthropogenic pressure are compared to disentangle the effects of the climatic and anthropogenic drivers and the synergies between them.

Research objectives:

1. Evaluate the spatio-temporal dynamics of extreme intense fires in evergreen forests of the BLA from 2002 to 2019
2. Compare the spatio-temporal distribution of extreme forest fires in severe drought years associated with the ENSO and AMO phases as well as in average years
3. Investigate the effect of forest fragmentation by deforestation and road construction on the spatio-temporal variability of extreme forest fires

## 4 Data and methods

### 4.1 Datasets

As ground-based long-term information on fire occurrence and impact on vegetation is scarce in the extensive Amazon region, high-resolution remote-sensing derived products become the most suitable source of data. Remotely sensed datasets enable us to fill the ground-data gap and explore large and diverse areas such as the BLA of ca. 5 million km<sup>2</sup> in size. However, uncertainties associated with the detection may occur as a consequence of persistent cloud cover and vegetation canopy, particularly in tropical closed-canopy forests. In this section I describe the datasets used throughout this research. The precise geographical extent, study period, and data particularities are specified in each chapter for the different studies that constitute this research.

#### 4.1.1 Burned area

The Moderate Resolution Imaging Spectroradiometer (MODIS) on board the polar-orbiting Terra and Aqua satellites maps fire-affected areas since the year 2000. The MODIS Burned Area Monthly 500 m product (MCD45A1 v051) employs surface reflectance imagery to provide per-pixel burned area (Roy et al., 2002). The validation of the product (Roy et al., 2008; Roy and Boschetti, 2009) revealed some uncertainties in the detection, such as burned area underestimation owing to persistent cloud cover and vegetation canopy, particularly in tropical closed-canopy forests, that may obscure the surface. Other uncertainties arise from the difficulty in accurate mapping of burned areas that are small, fragmented or transient (Roy et al., 2008; Tulbure et al., 2011). The MCD45A1 collection 5.1 used in Chapter II has been substituted by the MCD64A1 collection 6 product (Giglio et al., 2015) available at the Land Processes Distributed Active Archive Center (LP DAAC) within the NASA Earth Observing System Data and Information System (EOSDIS), <https://lpdaac.usgs.gov/products/mcd64a1v006/>

#### 4.1.2 Active fires

In the MODIS Global Monthly Fire Location 1 km product (MCD14ML v05) the thermal anomalies represent the geographic coordinates of the centre of those 1-km pixels that are flagged by the MODIS algorithm as containing one or more fires.

Limitations in the detection are likely to be due to cloud cover, topographic shadows, or highly reflective surfaces. Patchy, irregular-shaped, short, small or low-intensity fires may be underestimated (de Klerk, 2008; Hawbaker et al., 2008). The MCD14ML algorithm was developed by Giglio et al. (2003) - using swath products (MOD/MYD14) rather than tiled products (MOD/MYD14A1) -, and validated by Morisette et al. (2005). The MCD14ML collection 5 used in Chapter II was distributed by the University of Maryland. This version of the data was superseded by collection 6.1 provided by the Fire Information for Resource Management System (FIRMS), [https://firms.modaps.eosdis.nasa.gov/active\\_fire/](https://firms.modaps.eosdis.nasa.gov/active_fire/)

The MODIS Terra (MOD14A1 v06) and Aqua (MYD14A1 v06) Thermal Anomalies/Fire Daily L3 Global 1 km SIN Grid datasets (Giglio and Justice, 2015) have been registering daily hot pixels since the year 2000, and have been extensively validated (Morisette et al., 2005; Csiszar et al., 2006; de Klerk, 2008; Hawbaker et al., 2008). The collection 6 of the data addresses previous limitations such as frequent false alarms caused by small clearings in the Amazon forests (Friedl et al., 2010), which is particularly helpful for our purpose. The data present low levels of commission errors, but omission errors, which decrease as fire size increases, might occur with fires of short duration, small size or low intensity (Schroeder et al., 2008; Hantson et al., 2013). Also, burnings under dense vegetation cover, heavy smoke or on very cloudy days may go undetected (Giglio et al., 2016). The product is available at the LP DAAC within the NASA EOSDIS, <https://lpdaac.usgs.gov/products/mod14a1v006/>

#### *4.1.3 Individual fires*

The Global Fire Atlas (GFA) dataset (Andela et al., 2019b) has been used in this research for comparison purposes. It is derived from the MODIS MCD64A1 v06 Burned Area product (Giglio et al., 2018) and the data spans from 2003 to 2016. The algorithm tracks daily progression of individual fires at 500-m resolution to produce a set of metrics on fire behaviour such as fire size, duration, daily expansion, fire line length, speed, and direction of spread. The dataset is available at <https://www.globalfiredata.org/fireatlas.html>

The FireTracks (FT) Scientific Dataset (Traxl, 2021) is derived from two MODIS products, i.e. the 1-km MOD/MYD14A1 datasets (Giglio and Justice, 2015), and the 500-m Land Cover Type MCD12Q1 product (see 4.1.4 below). The FT dataset contains the individual fires identified by the FT algorithm and registers the location, date, characteristics - size, duration, intensity and rate of spread - and dominant land cover of the fires. The FT dataset was first produced for the year 2002 to present day, and it is regularly updated as new MODIS data are released. The FT dataset is available at <https://zenodo.org/record/4461575>

#### *4.1.4 Land cover*

The TerraClass Project mapped the dynamics of land use and occupation that follow deforestation in the BLA. By interpreting Landsat 5 Thematic Mapper images, very detailed 30-m resolution land-cover maps of previously deforested areas are produced. The product was generated every two years starting at 2004 (de Almeida et al., 2009; INPE and EMBRAPA, 2015). Despite its high resolution, the TerraClass dataset was reported to have commission errors from 8.3% (agriculture) to 33.8% (degraded pastures) and omission errors from 2.9% (for agriculture) to 57.8% (areas in regeneration) (Coutinho et al., 2013). The product is available at [http://www.inpe.br/cra/projetos\\_pesquisas/dados\\_terraclass.php](http://www.inpe.br/cra/projetos_pesquisas/dados_terraclass.php)

The MODIS Land Cover Type Yearly L3 Global 500 m SIN Grid data (MCD12Q1 v06) is derived using supervised classifications of MODIS reflectance data with additional post-processing to further refine specific classes (Sulla-Menashe et al., 2019). The data collection 6 includes new gap-filled spectro-temporal features and refinements of the algorithm, which improves the accuracy in the classifications. However, some limitations are known, e.g. grassland areas might be misclassified as savannas, and small agricultural fields in tropical regions may be underrepresented. In this research, two of the six provided classification schemes are used, i.e. the International Geosphere-Biosphere Programme (IGBP), and the University of Maryland (UMD) schemes. The product is available at the LP DAAC within the NASA EOSDIS, <https://lpdaac.usgs.gov/products/mcd12q1v006/>

#### *4.1.5 Deforestation*

The PRODES Project has been monitoring the deforestation of the BLA since 1988, providing a spatially explicit version since 2000 (INPE, 2021a). Maps of clearings



where clear-cutting deforestation has occurred are produced annually at 30-m resolution (aggregated to 60 m) by combining data from the sensors on the Landsat, Disaster Monitoring Constellation, and China-Brazil Earth Resources satellites. The official minimum mapping unit of 6.25 ha may omit small-scale deforested patches (Griffiths et al., 2018), whereas persistent cloud cover, always a challenge for optical remote sensing, becomes an important constraint in the selection of imagery for forest change detection (Giglio et al., 2006). The dynamic behaviour of vegetation over time may also introduce additional errors when monitoring deforestation. The datasets are available at <http://terrabrasilis.dpi.inpe.br/downloads>

#### *4.1.6 Forest degradation*

The DEGRAD Project registered degraded forests by logging or recurrent fires (INPE, 2021b). In this case, the forest areas have not been totally removed by clear-cutting but they are in a deforestation process. The DEGRAD datasets employed data from the Landsat and China-Brazil Earth Resources satellites at 30-m spatial resolution (aggregated to 60 m) to create annual maps for the period 2007-2016. Significant forest degradation may remain undetected by satellites due to the quick regeneration of the forest canopy that obscures changes in vegetation. Additional limitations on the assessment of degraded forests are related to the misinterpretation of natural phenological changes as actual land-cover changes (Barlow and Peres, 2008; Matricardi et al., 2010). The DEGRAD maps are available at <http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/degrad>

#### *4.1.7 Roads*

The road network in the BLA for the years 2005 and 2014 is retrieved from the Brazilian Institute of Geography and Statistics (IBGE) at <https://www.ibge.gov.br/geociencias/organizacao-do-territorio/redes-e-fluxos-geograficos/15793-logistica-dos-transportes.html?edicao=24589&t=acesso-ao-produto>

#### *4.1.8 Meteorological variables*

Mean temperature and annual precipitation series (1991-2021) in the BLA at 0.5° spatial resolution are provided by the World Bank Group's portal at <https://climateknowledgeportal.worldbank.org/country/brazil/climate-data-historical>

## 4.2 Methods

Throughout the analysis I used the geographic information system ArcMap 10.4.1 (ESRI) software to perform various types of spatial and temporal digital analyses, together with R (R Core Team, 2021) for statistical computations. Apart from that, a specific computational procedure was developed in [Chapter II](#) to identify and quantify the burned forests caused by escaping fires from managed lands. In addition to this, in [Chapters III](#) and [IV](#) I used a novel dataset of individual fires that has been generated by combining the individual fires approach with network theory to identify spatio-temporal fire clusters that can be tracked.

For the study in [Chapter II](#) (Cano-Crespo et al., 2015), I developed an algorithm to test the influence of escaping fires from managed lands in tropical forest fires. Fires are set on pastoral and agricultural lands to mobilise nutrients, promote resprouting, control pests, remove litter accumulation or remnants after harvests, avoid woody encroachment, etc. I assumed that it was likely that these management fires go out of control and escape into the surrounding forests. The assumption was based on the large amount of burned forests that concentrates along forest edges, the poor correlation between burned forests and deforestation and degradation processes, and the large amount of burned area found in managed lands, specially in pastures. The algorithm is developed to combine the information contained in the datasets on burned areas, active fires, and land-use. The results obtained by the implementation of this algorithm are the first precise estimates of the contribution of managed lands to forest edge burning in the Amazon.

I used the novel FireTracks Scientific Dataset (Traxl, 2021) in [Chapters III](#) (Cano-Crespo et al., 2022) and [IV](#) (Cano-Crespo et al., 2021). This dataset has been produced by combining the individual fires approach with network theory to represent complex systems. In this way, the individual parts of the system, i.e. active fires, are represented by the graph's nodes, and their pairwise relations by edges. This methodological approach aggregates the data and represents fires as spatio-temporal clusters of fire events that evolve over space and time and can be tracked. As fires can be treated separately, their integrated fire variables - size, duration, intensity and rate of spread - can be computed with the information held by their constituent events. The results in [Chapter III](#) represent the first estimates of

integrated intensity of individual fires for the characterization of fire regimes. Fire intensity has a major role in the amount of biomass burned, the magnitude and type of the emissions, and the socio-ecological impacts.

In the study in [Chapter IV](#), only extreme individual fires occurring in the rainforests are selected from the FT dataset for the analysis. Unlike in other studies where burned areas or single-pixel hotspots are employed, the individual-fires approach enables to classify the fires into different categories according to their integrated intensity. Fires whose intensity was greater than or equal to the 95th percentile of the variables' distribution, i.e. the most intense 5%, are identified as extreme fires. The fact that 70% of the extreme fires are also within the 5% largest fires in the sample, and that they contribute to almost 30% of the total integrated burned area in the BLA tropical forests over the study period, reveals the significant part played by the most intense fires in Amazonian forest dynamics.

## Chapter II

# Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures

Cano-Crespo A, Oliveira PJC, Boit A, Cardoso M, Thonicke K (2015)

An edited version of this chapter has been published in the Journal of Geophysical Research: Biogeosciences 120, 2095-2107

## **Abstract**

Understanding to what extent different land uses influence fire occurrence in the Amazonian forest is particularly relevant for its conservation. We evaluate the relationship between forest fires and different anthropogenic activities linked to a variety of land uses in the Brazilian states of Mato Grosso, Pará, and Rondônia. We combine the new high-resolution (30 m) TerraClass land use database with Moderate Resolution Imaging Spectroradiometer burned area data for 2008 and the extreme dry year of 2010. Excluding the non-forest class, most of the burned area was found in pastures, primary and secondary forests, and agricultural lands across all three states, while on average only around 3% of the total was located in deforested areas. The trend in burned area did not follow the declining deforestation rates from 2001 to 2010, and the spatial overlap between deforested and burned areas was only 8% on average. This supports the claim of deforestation being disconnected from burning since 2005. Forest degradation showed an even lower correlation with burned area. We found that fires used in managing pastoral and agricultural lands that escape into the neighbouring forests largely contribute to forest fires. Such escaping fires are responsible for up to 52% of the burned forest edges adjacent to burned pastures and up to 22% of the burned forest edges adjacent to burned agricultural fields, respectively. Our findings call for the development of control and monitoring plans to prevent fires from escaping from managed lands into forests to support effective land-use and ecosystem management.

## **1 Introduction**

Over the past 30 years the Amazon has undergone an intensification of human activities in the forest, such as deforestation and logging (Laurance et al., 2001; Cochrane, 2003; Asner et al., 2005), and in particular at the forest edges due to the increasing expansion of agricultural and pasture lands (Morton et al., 2006; Armenteras and Retana, 2012; Davidson et al., 2012). Amazonian fires have become much more frequent and widespread (Barreto et al., 2006) due to the intensive use of fire to convert natural vegetation into agricultural and pasture fields and for the subsequent maintenance of deforested areas (Cochrane et al., 1999;

Barona et al., 2010). During extreme droughts occurring in El Niño-Southern Oscillation years or as a consequence of the warming of the tropical North Atlantic, the frequency of forest fires upsurges (Aragão et al., 2007; Alencar et al., 2011; Chen et al., 2011), sometimes increasing the area burned by an order of magnitude, as in 1998 (Alencar et al., 2006). Such interactions between climate, land use change, and fire are of high relevance not only for understanding and predicting their environmental impact on the Amazon biome but also for regional and global climate feedbacks (Cochrane and Laurance, 2008; Liu et al., 2013).

Advances in governance, through an increase in protected and indigenous areas and establishing the soy and beef moratoria, contributed to the reduction of deforestation since the mid-2000s (Godar et al., 2014; Nepstad et al., 2014), whereas fire activity seems to follow a different trend. Between 2000 and 2006, Aragão and Shimabukuro (2010) found increasing fire trends in 59% of the area that experienced reduced deforestation trends in the Brazilian Amazon, which they ascribed to slash-and-burn activities in secondary forests and to an increased fire risk with landscape fragmentation. Although only reported for 31% of the Brazilian Amazon, Chen et al. (2013) confirm the positive trend of annual active fires in areas where the deforestation rate concurrently decreased during 2001-2012. Specifically, the contribution of deforestation fires to the total number of detected fires has been declining since 2005 (Ten Hove et al., 2012). At the same time, fires set to maintain agricultural and pastoral lands in previously deforested areas that may escape into the forests have gained importance (Achard et al., 2002; Nepstad et al., 2008; Bonaudo et al., 2014). With droughts increasing in frequency and areal extent, fire leaking into fire-prone forests may be the main force of biome conversion (Alencar et al., 2004; Aragão et al., 2007). The significance of understorey fires which escape from managed land into neighbouring forests was noticed already in earlier studies (Sorrensen, 2000; Nepstad et al., 2008). Recent analysis has shown that understorey fires continue to occur unabated despite reduced deforestation calling for a fire-free land use management along the forest edges (Morton et al., 2013).

To understand why occurrence and interannual variability of fires remain high despite decreasing deforestation in the Amazon, potential drivers of land conversion need to be analysed. This requires high-resolution land-cover maps to specify in which

land-cover type fires occurred and where the new hot spots of fire activity are. Since most of burned forests are located 1 km or less from the forest boundary (Armenteras et al., 2013; Morton et al., 2013), it is important to specify from which land-use type these fires originate if we are to improve our understanding of fire causes and to elaborate options for their control. If these fires indeed escape from neighbouring managed land, it can only be evaluated by using high-resolution temporal information of fire occurrence to identify which of the neighbouring burned areas burnt first. In the absence of on-ground monitoring of fire causes for the entire Amazon, an option for such attribution analysis is by combining fire events information with burned area and land-cover data of the region from remote sensing.

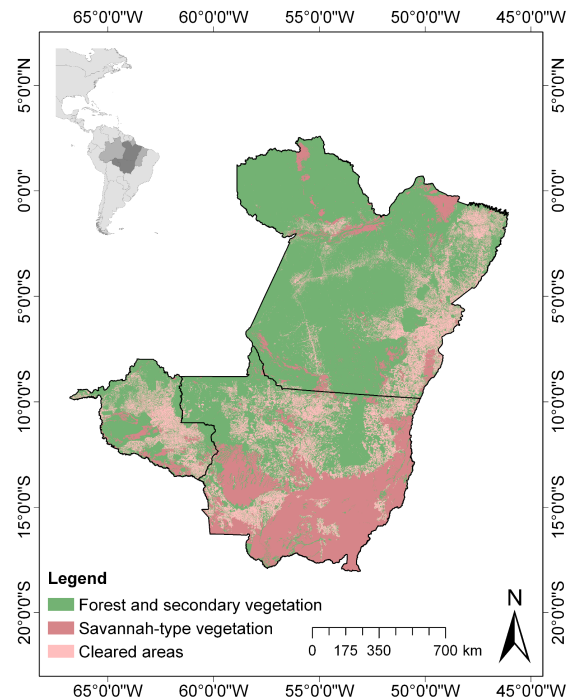
In this study, we use high- and moderate-resolution satellite imagery for land cover and burned area, respectively, to evaluate how much area burned occurred in each land-cover type in the Brazilian Amazon. We investigate how deforestation and degradation processes are related to fire occurrence and quantify the proportion of forest fires related to fires escaping from managed lands. We provide a comprehensive analysis on the relationship between fire occurrence, deforestation, degradation, and land use with a specific focus on fires occurring along the interface between forest and managed land. These analyses contribute important insights on fire regimes in recent years in the Amazon and support the assumption that most fires in the forest no longer originate from deforestation itself, but from fires that escape from managed lands under agropastoral activities, which have implications for management and monitoring of fires in the region.

## **2 Methodology**

### **2.1 Area of interest**

We selected the Brazilian states of Mato Grosso (MT), Pará (PA), and Rondônia (RO) in Amazonia for our data analyses (Fig. II-1), as they share large-scale anthropogenic pressure patterns and characteristics. They concentrated 84% of all deforestation detected in the Brazilian Amazon between 2000 and 2012 (INPE, 2021a). Between 1999 and 2002, selective logging was concentrated in the states of MT and PA, where logged areas matched or exceeded deforested areas (Asner et

al., 2005). In MT, tropical forest covers the northern part of the state, while the southern part features predominantly woodland savanna (*cerrado*) (Fig. II-1).



**Figure II-1** Map showing land cover in the states of Mato Grosso, Pará, and Rondônia in 2008 (INPE and EMBRAPA, 2015). Savannah-type vegetation includes *cerrado*, *campinas*, and *campinaranas*. Cleared areas include agricultural and pasture lands, urban areas, deforested areas, mines, and bare soil. The inserted map shows the location of the states of Mato Grosso, Pará, and Rondônia (in dark grey) within Brazilian Amazonia (in light grey)

The state has undergone a rapid expansion of mechanised agricultural production (DeFries et al., 2008), which has altered the dynamics of deforestation since the early 2000s (Morton et al., 2006). MT is now an important producer of soybean, corn, and cotton (Brown et al., 2013). According to TerraClass (INPE and EMBRAPA, 2015), three quarters of PA were covered by forest and secondary vegetation in 2010. A smaller percentage of land was dedicated to agriculture compared to MT. However, ranching has shifted from northern MT to southern PA leading to greater cleared area (Barona et al., 2010), especially in southeastern PA (Fig. II-1). RO has a smaller proportion of its territory covered by forest and secondary vegetation than PA (60% in 2010 according to TerraClass). This is in part due to the rapid advance of soybean cultivation during the late 1990s in southeastern RO as part of a rapid



northward expansion of soybeans in Brazilian Amazonia that started in the 1970s (Fearnside, 2001).

## **2.2 Data**

### *2.2.1 Fire*

The Moderate Resolution Imaging Spectroradiometer (MODIS) on board the polar-orbiting Terra and Aqua satellites maps fire-affected areas since 2000 (Giglio et al., 2015). We used the reprojected monthly Geotiff version available from the University of Maryland of MODIS collection 5 burned area product (MCD45A1) (Roy et al., 2002) from 2001 to 2010 (500-m resolution), of which Windows 5 and 6 cover the study area. The validation of the product (Roy and Boschetti, 2009) revealed some uncertainties associated with the detection, such as burned area underestimation owing to persistent cloud cover and overstorey vegetation, particularly in tropical closed-canopy forests where leaf area index and percent tree cover are high and obscure the surface. Other uncertainties arise from the difficulty in accurate mapping of burned areas that are small or spatially fragmented relative to the satellite's spatial resolution, as well as transient burned areas, for example, agricultural fields that are burned and then ploughed (Roy et al., 2008; Tulbure et al., 2011).

We also employed the MODIS collection 5 global monthly fire location product (MCD14ML) developed by Giglio et al. (2003), which has been extensively validated (Morissette et al., 2005), for identifying the temporal sequence of burned area along the forest edges in the year 2010. Every 1 km spatial resolution active fire observation holds information about the location and time when it was detected by the sensors. Limitations in the detection are likely to be due to cloud cover, topographic shadows, or highly reflective surfaces. Patchy- and irregular-shaped fires or short-, small-, and low-intensity fires may be underestimated (de Klerk, 2008; Hawbaker et al., 2008).

### *2.2.2 Land use*

Land-cover maps of the Legal Amazon were produced by the TerraClass project showing a very detailed land-use classification at 30-m resolution with data generated from the interpretation of Landsat Thematic Mapper 5 images (de Almeida

et al., 2009; INPE and EMBRAPA, 2015). We employed the maps for 2008 and 2010 (see Text S.II-1 for the description of land-use classes). The non-forest class was excluded from the burned area distribution analysis because we are interested in the influence of anthropogenic activities associated to LUC on fire occurrence and extent within the forest biome, while the non-forest class covers natural vegetation with characteristics of savanna-type ecosystems with a different fire regime. Despite the high resolution of the land-cover product, the information provided by TerraClass was reported to have commission errors from 8.3% (for annual agriculture) to 33.8% (for degraded pasture) and omission errors from 2.9% (for annual agriculture) to 57.8% (for areas in regeneration) during the mapping process (Coutinho et al., 2013). This validation of the data set was done using high-resolution (2.5 m) SPOT satellite images and field observations in 535 locations.

### *2.2.3 Deforestation*

Annual deforestation maps for the period 2001-2010 were obtained from the PRODES project, which has been monitoring the deforestation of the Brazilian Amazon since 1988 (INPE, 2021a). PRODES combines data from the Landsat Thematic Mapper, DMC (Disaster Monitoring Constellation Satellite), and CCD (China-Brazil Earth Resources Satellite (CBERS)) sensors (and their successors for recent years) and detects clearings of at least 6.25 ha where deforestation by clear-cutting has occurred. The spatial resolution is high (30 m, although it is aggregated to 60 m in the database), but the temporal frequency is low with one map each year. An important constraint in the selection of imagery for forest change detection when using a bitemporal approach is the lack of data due to the limitations imposed by cloud cover. Many areas of the Amazonia present an extremely persistent cloud cover, which prevents the satellites from obtaining cloud free observations (Giglio et al., 2006; 2010). When cloud-free images are not available for the desirable dates, methods exist to fill the gaps with data derived from other scenes or even other sensors, but this can introduce errors into the processing chain. The dynamic behaviour of vegetation over time may introduce additional errors in the detection of forest changes. Besides, extensive deforestation monitoring in tropical forests by the PRODES project does not incorporate all the possible deforestation pathways because it is limited to deforestation associated to the original forest area, without taking into account degradation and deforestation of

secondary forest. Once an area has been labelled as deforested by PRODES, it is not further revisited in subsequent years, which implies that forest regeneration is not assessed by the current method. In spite of all that, PRODES is the most advanced remote sensing-based forest monitoring system in tropical countries (DeVries et al., 2015).

#### *2.2.4 Degradation*

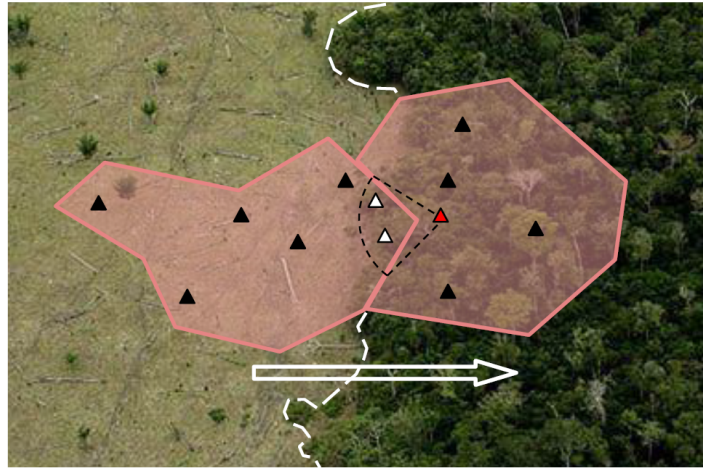
Areas in a deforestation process where the forest has not been totally removed (areas that are neither detected as forest nor as deforested) are classified as degraded by the DEGRAD project, which monitors the degradation of the Brazilian Amazon forest caused by wood extraction or by recurrent fires (INPE, 2021b). DEGRAD employs data from the Landsat Thematic Mapper and CCD (CBERS) sensors to detect clearings of at least 6.25 ha. Annual maps for the period 2007-2011 at the same spatial resolution as PRODES (60 m) were employed for the analysis. Limitations of the degradation assessment in satellite imagery exist related to the interpretation of natural phenological change as actual land-cover change and to the quick regeneration of the forest canopy that obscures changes in vegetation (Barlow and Peres, 2008; Matricardi et al., 2010). Thus, significant forest degradation may remain undetected by satellite images and large-scale monitoring of forest cover. Additional limitations come from the fact that it neither makes a distinction between degradation by fire and by logging nor quantifies degradation in secondary forest. Nevertheless, it is the only data set that covers the entire study region at a relatively high spatial resolution.

### **2.3 Data analysis**

We worked with the geospatial processing program ArcMap 10.1 (Environmental Systems Research Institute) to conduct all spatial and temporal digital analyses. After preprocessing the data, the amount of burned area in the different land-use types in 2008 and 2010 was quantified by intersecting burned area and land-use maps. The same method was applied to the maps of deforested and burned areas detected in the same year to quantify the amount of deforested area that burned. To determine the amount of forest degradation following upon burnings, degradation maps were superimposed with burned area maps of the previous year (see Text

S.II-2 for additional details on data processing). Linear regression analysis was used to correlate the burned and deforested areas at monthly and annual time scale.

To estimate the proportion of burned forests adjacent to burned managed lands, we selected burned area polygons in forests which share boundaries with burned area polygons in agricultural fields and pastures, respectively. Adjacency in this context quantifies the amount of burned forests that may have been driven by escaping fires from managed lands, but only those adjacent fires that burned on managed land first can be included. We developed an algorithm that combines the information held in the burned area, active fires, and land-use datasets. We selected burned areas larger than 2 km<sup>2</sup> which matched at least two active fire pixels to improve certainty in the active fires location in relation to burned areas at the forest edge (Hawbaker et al., 2008). To identify if a forest burned area was driven by an escaping fire from neighbouring managed lands, three requirements had to be fulfilled. First, burned areas in the forest had to be adjacent to burned areas in managed lands (fire perimeters must be spatially connected). Second, potential escaping fire events from managed lands must occur within a 1 km buffer zone created around fire events in the forest as the majority of forest burnings occurs within the first kilometre of the forest edge (Armenteras et al., 2013; Morton et al., 2013). Third, the forest fire under study had to happen on the same day or up to 2 days later than the potential escaping fire in the managed lands (Fig. II-2). After examining if the first two conditions were met, forest fires with their corresponding burned area that also met the third requirement were selected and considered as forest fires driven by managed lands' fires. We tested the sensitivity of the temporal threshold being longer than 2 days and found that it did not change the proportion of burned forest caused by escaping fires from managed lands, indicating that most of the fires do not last more than 2 days.

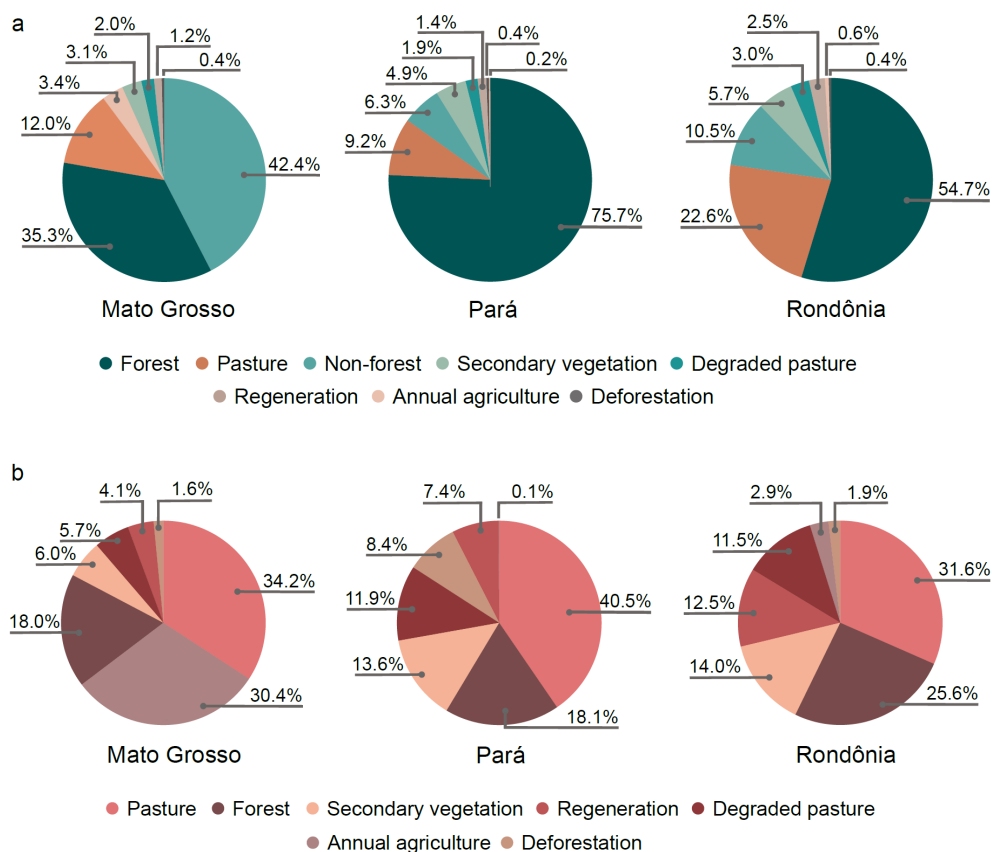


**Figure II-2** Schematic illustration of a burned area in the forest adjacent to a burned area in a managed land (red polygons), which is a pasture in this case. Black triangles indicate active fires within the burned areas. The red triangle denotes the active fire in the forest currently under study. A 1 km buffer zone is created around it, and active fires in the pasture within the buffer are selected (white triangles). If the forest fire under study (red triangle) occurred up to two days later than any of the active fires in the pasture within the buffer (white triangles), the burned area in the forest can be attributed to escaping fires from the pasture

## 3 Results

### 3.1 Fire distribution by land use

The proportion of the different land-cover types showed large variation between the states (Fig. II-3a). Forty-two percent of the territory of MT was covered by savanna-type vegetation, which is classified as non-forest in TerraClass, followed by forests (35.3%) and pastures (12%). Annual agriculture and secondary vegetation extended over 3% of the state each (Fig. II-3a) (see Text S.II-1 for the description of the land-use classes). PA was mostly covered by forests (75.7% of the area) followed by pastures (9.2%). The large forested area in PA leads to a high cloud cover (Asner, 2001), preventing the satellite from observing the ground in some areas. PA showed fewer non-forest (6.3%) and annual agriculture (0.2%) than MT. Around half of RO was covered by forests (54.7%) with pastures accounting for 22.6%. RO had 10.5% of its area occupied by non-forests, with smaller proportions of secondary and regenerating vegetation. Deforested areas made up 0.4% of the territory in each of the three states (Fig. II-3a).



**Figure II-3 a** Land-use distribution, and **b** burned area distribution in Mato Grosso, Pará, and Rondônia in 2008. The non-forest class has been excluded in b

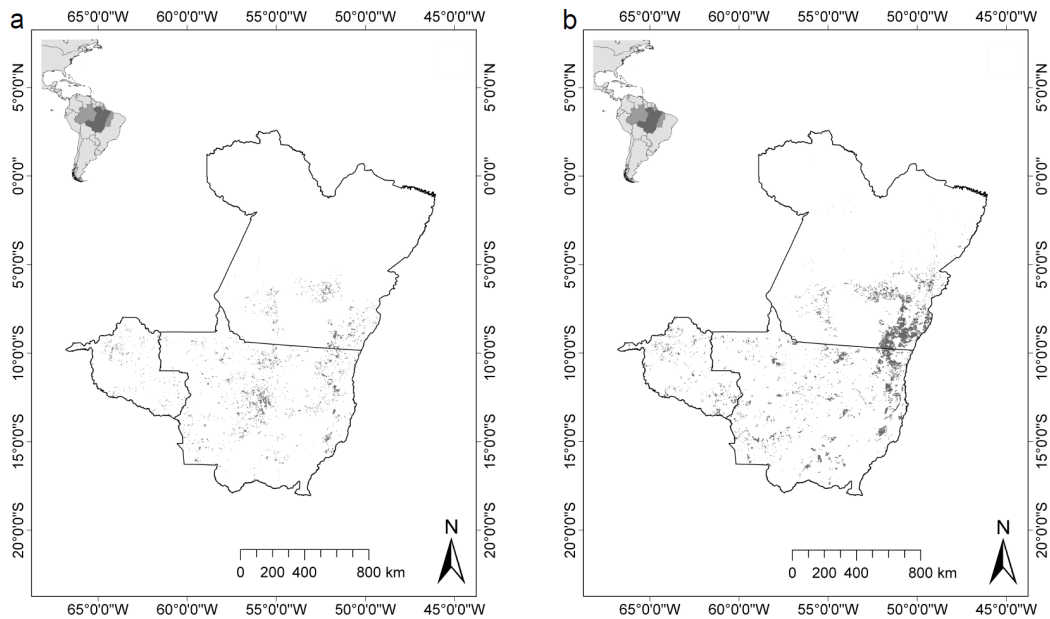
Most of the burned area in all three states was found in pastures in 2008, when non-forest class was excluded (Table II-1 and Fig. II-3b). According to MODIS, the annual burned area accounted for 5269 km<sup>2</sup>, 2245 km<sup>2</sup>, and 463 km<sup>2</sup> in MT, PA, and RO, respectively, for the year 2008 with burned area located in the non-forest class excluded. While the burned area in PA was concentrated in the southern half of the state, it did not show any distinctive spatial pattern in RO (Fig. II-4a). In MT, several clusters of burned areas were distributed in the central and eastern parts of the state in 2008. Fires occurred mostly in pastures (PA: 40.5%, MT: 34.2%, and RO: 31.6%) in the three states (Fig. II-3b). In MT, a major centre of agricultural production, 30.4% of the burned area occurred in annual agriculture, compared to only 2.9% in RO and 0.1% in PA. A substantial amount of burned area was found in forests (RO: 25.6%, PA: 18.1, and MT: 18%), while a smaller amount was located in secondary vegetation, degraded pastures, and regenerating areas. It is important to note that fire in deforestation made up only 8.4% (PA), 1.9% (RO), and 1.6% (MT) of the total burned area (Fig. II-3b). Our results show that the land-use classes that contain the

highest frequency of fires are pasture, forest, and agriculture, when the non-forest class is excluded (Fig. II-3b).

**Table II-1** Burned area distribution in the different land uses (excluding non-forest) in Mato Grosso, Pará, and Rondônia in the years 2008 and 2010 (in percentage)

	Mato Grosso		Pará		Rondônia	
	2008	2010	2008	2010	2008	2010
Annual agriculture	30.4	3.3	0.1	0.0	2.9	3.0
Deforestation	1.6	0.9	8.4	1.5	1.9	2.2
Degraded pasture	5.7	6.3	11.9	10.2	11.5	11.4
Forest	18.0	38.2	18.1	21.6	25.6	30.8
Pasture	34.2	35.3	40.5	43.2	31.6	33.0
Regeneration	4.1	5.6	7.4	12.5	12.5	8.0
Secondary vegetation	6.0	10.5	13.6	11.0	14.0	11.6

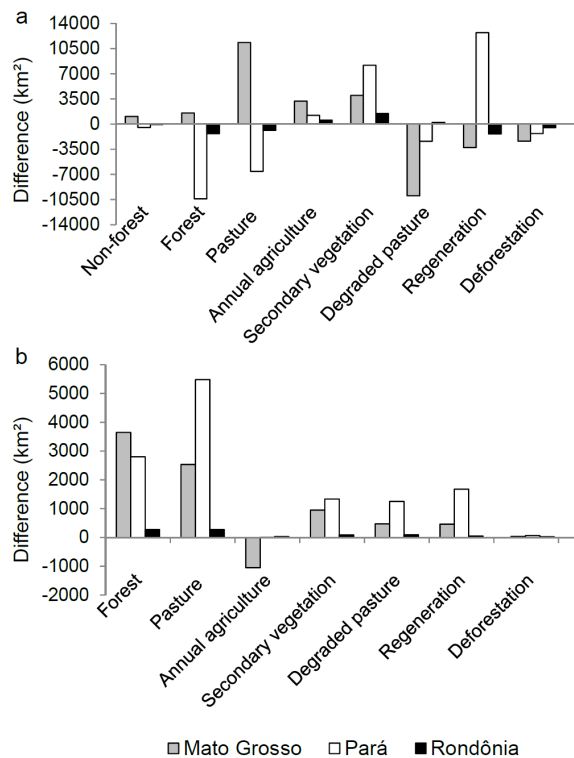
In all three states, land-cover distribution remained widely unchanged in 2010 compared to 2008 (Fig. II-5a), indicating that differences in burned area distribution in 2010 were not a consequence of significant changes in land-cover class proportions but likely of climate variations and/or changes in fire use as a management technique in specific land uses. In MT, secondary vegetation (+14%), pastures (+11%), and annual agriculture (+10%) increased at the expense of degraded pastures (56%) and areas in regeneration (29%) (Fig. II-5a). In PA we observed a different situation, where pastures (6%) and forests (1%) decreased, while areas in regeneration (+78%) and secondary vegetation (+14%) increased. RO experienced the smallest change compared to 2008, where areas in regeneration (23%), pastures (2%), and forests (1%) decreased while annual agriculture (+38%) and secondary vegetation (+11%) increased. Deforestation decreased despite the relatively drier year of 2010 in all three states (between 74% and 28%) (Fig. II-5a).



**Figure II-4** Spatial burned area distribution in **a** 2008 and **b** 2010 in Mato Grosso, Pará, and Rondônia (burned areas in the non-forest class have been excluded). The inserted map shows the location of the three states (in dark grey) within Brazilian Amazonia (in light grey)

In 2010, the burned area increased significantly to 13,177 km<sup>2</sup>, 16,571 km<sup>2</sup>, and 1636 km<sup>2</sup> in MT, PA, and RO, respectively, accounting for an increase of 638% in PA, 253% in RO, and 150% in MT in comparison to 2008. Burned area was concentrated in southeast PA, while no characteristic pattern was observed in RO (Fig. II-4b). The northeast of MT showed a large concentration of burned area, although several clusters were also observed unevenly distributed across the state. The amount of burned area increased in all land-use classes in 2010, except in annual agriculture in MT (1051 km<sup>2</sup>, which translates to 73% of decrease compared to 2008 values) (Fig. II-5b). The largest increase in burned area was found in forests in MT (+3645 km<sup>2</sup> or +424%) and in pastures in PA (+5478 km<sup>2</sup> or +719%) and RO (+272 km<sup>2</sup> or +195%) (Fig. II-5b). Burned area detected in deforested areas also increased in 2010 (PA: +63 km<sup>2</sup> or +40%, MT: +32 km<sup>2</sup> or +42%, and RO: +19 km<sup>2</sup> or +235%), but the increase was small in comparison to the changes in the rest of the land-cover classes. These results provide important insights into the association between fires and anthropogenic activities, showing that most of the burned area is not associated with deforestation but rather with the use of fire for land management, especially in pastures.





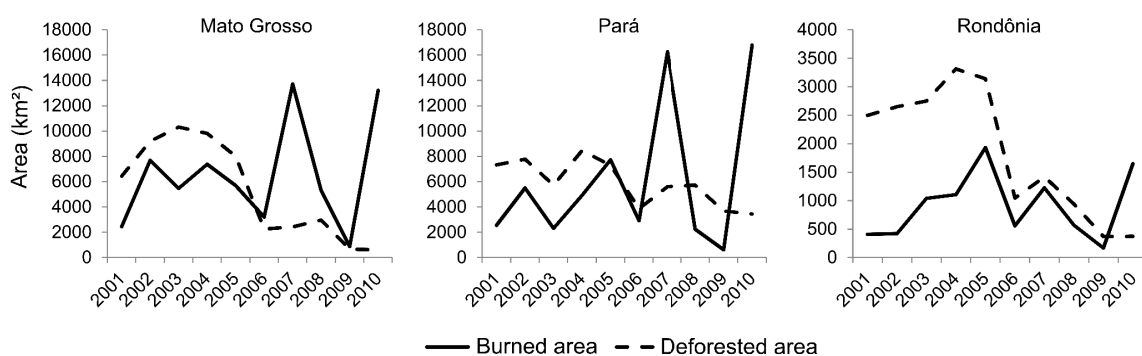
**Figure II-5** Differences in the areal extent distribution of the **a** land-cover classes and **b** burned area between 2010 and 2008 (in km<sup>2</sup>, based on 2008 values) in Mato Grosso (grey bars), Pará (white bars), and Rondônia (black bars). The non-forest class has been excluded in b. Note the different scales on the vertical axis

## 3.2 Fire in the forest

### 3.2.1 Dissociation between deforestation and fire

Burned and deforested area showed a remarkable variability between 2001 and 2010 (Fig. II-6). On the annual time scale, no significant relationship was found between the annual amount of burned area (excluding burned area located in the non-forest class) and deforested area (mapped by PRODES) over the 2001-2010 period in MT ( $r^2 = 0.01$ ,  $p > 0.05$ ), PA ( $r^2 = 0.03$ ,  $p > 0.05$ ), and RO ( $r^2 = 0.06$ ,  $p < 0.05$ ). Notably, deforestation fires were higher in the first half of the decade, when 73% of the total deforestation took place. Similar levels were only reached in the dry years of 2007 and 2010. The annual percentage of deforested area that burned across the three states remained below 13% (2776 km<sup>2</sup>) in the period 2001-2010 (8% on average) (Fig. II-7). The disconnection found between burned area and deforestation would still be valid taking potentially burned areas within small deforested areas that may go unnoticed into account (see Text S.II-3 on the effect of potentially undetected burned areas in the results).

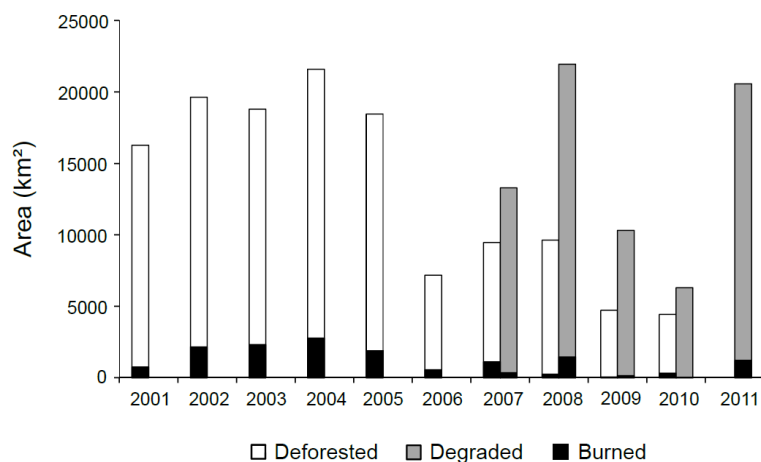
Fires did not show a lagged effect after deforestation took place. One year after deforestation, fires occurred on average in only 4% of the deforested area across the three states between 2001 and 2010 (Fig. S.II-1), which means that forests which were not burned in the dry season following deforestation were also not burned in the following year. After 10 years, 31% (PA), 27% (MT), and 13% (RO) of the deforested area accounted for in 2001 had burned. Most recurrent burns, linked to managed lands, are known to occur 3 to 4 years after the initial deforestation activity (Lima et al., 2012). We divided deforested area into two categories: old deforestation (deforested area detected between 2001 and 2006) and recent deforestation (deforested area detected between 2007 and 2010), in order to recognise fires connected to management of cropland and pastures (old deforestation) or the conversion processes of deforestation (new deforestation). Of the burned area mapped in 2010, 7684 km<sup>2</sup> (74% on average of the total) occurred in areas that were deforested between 2001 and 2006 (old deforestation) (Fig. S.II-2). The evidence shows that the processes of deforesting per se lead to only a slight increase in burned forest area, whereas fires used for land management in previously deforested areas have the largest effect on forest burning.



**Figure II-6** Annual area burned (solid line, with burned areas in the non-forest class excluded) and deforested area (dashed line) in km<sup>2</sup> over the period 2001-2010 in Mato Grosso, Pará, and Rondônia. Note the different scales on the vertical axis for Rondônia

Considering the low correlation found between deforestation and fire, we also explored the relationship between forest degradation and fire in order to explain the high proportion of burning occurring in the forests. However, we found low values of degraded area in areas mapped as burned during the previous year, making up 3186

km<sup>2</sup> across the three states between 2007 and 2011 (4% on average of the total degraded area in the period) (Fig. II-7). The highest percentages of burned degraded area were found in 2008 and 2011, following dry years, respectively. The results suggest a small influence of forest degradation in forest fires, but given the limitations of the MODIS sensor in mapping small burnings or detecting burned areas below the canopy, the amount of forest degradation driven by fire may be larger. Therefore, these results present a lower bound estimate of burned degraded area.

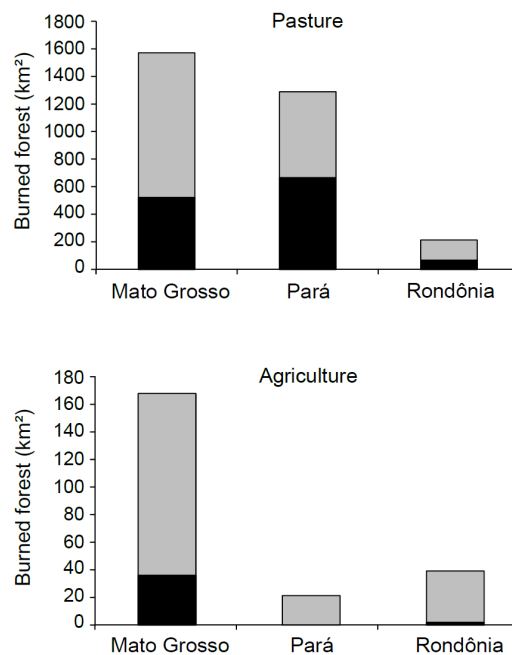


**Figure II-7** Annual deforested area (in white), degraded area (in grey), and the proportion burned each year (in black) in km<sup>2</sup> over the period 2001-2010 for deforestation data and 2007-2011 for degradation data. Annual values are summed over Mato Grosso, Pará, and Rondônia. Deforestation was superimposed with burned area detected in the same year, while forest degradation was superimposed with burned area detected in the previous year

### 3.2.2 Strong influence of fires escaping from managed pastures

Considering the low temporal and spatial correlation between deforestation and fire in the forest (Fig. II-6 and Fig. II-7, respectively), other processes must strongly influence forest fire occurrence. The large amount of burned area found not only in pastures and agricultural lands but also in forests (Fig. II-3b) suggests that forest fire occurrence is linked to fires set on pastoral or agricultural lands in the vicinity of the forests as a cheap, labour-saving way of clearing and managing land. Fires used for nutrient mobilisation, pest control, and removal of brush and litter accumulation may go out of control and escape from managed lands into forests; therefore, the majority of burned forests are located along the forest boundaries.

We found that in 2010, the year with the highest amount of burned area in the study period, 1571 km<sup>2</sup> (MT), 1289 km<sup>2</sup> (PA), and 212 km<sup>2</sup> (RO) of the burned area in the forests, was touching the boundaries of burned areas in pastures (Fig. II-8a), making up 69%, 87%, and 68% of all the burned forests, respectively. Smaller amounts of burned forests were located adjacent to burned agricultural fields: 168 km<sup>2</sup> (MT), 39 km<sup>2</sup> (RO), and 21 km<sup>2</sup> (PA), making up 7%, 12%, and 1% of all the burned forests, respectively (Fig. II-8b). These values indicate not only that most of the forest fires concentrate along the forest edges but also that their majority is found in close vicinity to pastoral lands. RO showed the largest proportion of the total burned forests spatially connected to burned agricultural lands, whereas PA showed the greater amount of burned forests spatially connected to burned pastures.



**Figure II-8** Annual burned forest which is located along the forest edge adjacent to burned **a** pastoral and **b** agricultural fields (grey bars, in km<sup>2</sup>) in Mato Grosso, Pará, and Rondônia in 2010. The amount of burned forest edges attributed to escaping fires from these managed lands is shown in black

To prove that burned areas in forests are the continuation of burned areas in managed lands, it is required to check the dates of the fire events that originated the burned areas. Investigating the temporal sequence of the fire events along the forest-managed land interface (see section II-2.3 and Fig. II-2), we found that 666 km<sup>2</sup> (PA), 523 km<sup>2</sup> (MT), and 68 km<sup>2</sup> (RO) of the burned forest edge adjacent to

burned pastures (shown in grey in Fig. II-8a) originated from fires that escape from those adjacent pastures (shown in black in Fig. II-8a). That translates to 52% (PA), 33% (MT), and 32% (RO) of the burned forest edge adjacent to burned pastures. The proportion of burned forest driven by fires which escaped from agricultural lands was smaller with 36 km<sup>2</sup> for MT and 2 km<sup>2</sup> for RO, which translates to 22% and 5% of the burned forest edge adjacent to burned agricultural fields, respectively (Fig. II-8b). The amount of burned forest connected to escaping fires from agricultural lands is negligible in PA because only 0.1% of the territory is covered by that land use (Fig. II-3a). These results provide the first estimate of the contribution of managed lands to forest edge burning showing the substantial amount of burned forests driven by fires that escape from pastures. This demands escaping fires to be included in the plans and policies aiming forest fires reduction in the region.

#### **4 Discussion**

Our study supports the assumption that fire incidence responds strongly to anthropogenic LUC and introduces new information about the contribution of specific land-use types to forest edge burning. We can now specify the land-use type from where the fires originated and escaped into the forests filling the data gap by combining diverse remote sensing data sets in the absence of extensive on-ground data. A large proportion of burned forests was adjacent to burned pastures (76% on average across the three states). Of this amount, 41% (1257 km<sup>2</sup>) on average of the burned forests can be attributed to escaping fires from pasture fields (Fig. II-8a). This highlights the high risk of fires escaping from these sites into contiguous forests. Since most of forest conversion is destined for cattle pasture (Morton et al., 2006) and the conversion process has accelerated over the last four decades (Nepstad et al., 2006), management plans to reduce the accidental spread of fires into neighbouring forests should come into focus. In Amazonia, the use of fire for land management is one of the major sources of carbon emissions, being involved in the vegetation-atmosphere interactions (Morton et al., 2008). For this reason, we need to have a good understanding of the dynamics of fires occurring in pastures to develop initiatives to minimise edge-driven fire processes and for policy development targeting reduced carbon emissions. Additional studies are required to quantify the effect of changes in burned area in the respective land uses on total fire-related

emissions, as small fires burning in high biomass forests can release as much carbon as large-scale fires burning in low-biomass land-cover types.

The largest proportion of burned area was found in pastures (40.5%-31.6%, depending on the state), while only a small amount was found in deforested areas in 2008 (Fig. II-3b). The situation changed in 2010 when the amount of burned area located in most of the land uses strongly increased, especially in forests and pastures (Fig. II-5b), while the proportion of the different land-use types in the states showed only small variations in 2010 compared to 2008 (Fig. II-5a). This indicates that differences in the amount of burned area between the two years can be a consequence of the widely reported severe drought of 2010 which increased fire risk (Lewis et al., 2011; Marengo et al., 2011). In particular, the large increment in burned area in pastures in 2010 may be due to a more extensive use of fire for clearing and managing pastoral lands taking advantage of the drier conditions. As a result, fires escaping from pastures into the forests may have increased in that year inducing a larger amount of burned forests.

The small amount of burned area encountered in deforested areas (Fig. II-3b) supports the claim that from 2005 onward, most of the burned area is not associated with new deforestation (Aragão and Shimabukuro, 2010; Chen et al., 2013) but instead with the use of fire to clean and renew pastures, to convert secondary forests, and to burn crop residues. It explains why annual burned area did not follow the same trend as deforestation (Fig. II-6), which declined from 2005 onward, possibly as a consequence of policy changes such as the implementation of the Action Plan to Prevent and Control Deforestation in the Brazilian Legal Amazon (PPCDAM) in 2004. Even though Lima et al. (2012) reported values of 32% on average for annual deforested area burned between 2001 and 2005 at local scale in a deforestation hot spot, we found lower values at the state scale (10% on average for the same period). These results provide evidence that anthropogenic pressure is very heterogeneous in the region due to the large ecological, socioeconomic, political, and institutional differences.

Burned areas in deforestation spots are not obscured by the canopy; thus, in the absence of clouds the potential underestimation of burned areas in deforested areas lies in the spatial resolution of the MODIS sensor (see section II-2.2.1 and Text S.II-3

on the effect of potentially undetected burned areas in the results). Including potentially undetected burned areas from small-scale fires incorporated in the Global Fire Emissions Database (GFED4) (Randerson et al., 2012) would increase the total annual amount of burned area. However, there is no information about the location of the burned polygons within each grid cell, which prevented us from directly comparing between the amount of annual deforested area that burned using the MCD45A1 and GFED4 burned area products (see Text S.II-3). High spatial resolution burned area products with spatially explicit information at global scale would allow to perform finer analyses on forest edge processes as well as on the environmental impact of fires. The low proportion of annual degraded area that was detected as burned area in the previous year suggests that fire would play a minor role in forest degradation (Fig. II-7). As the only drivers contemplated by the DEGRAD product are fires and logging, forest degradation would be mainly controlled by logging. However, more effective remote sensing techniques to improve the detection of burned areas inside the forests would be desirable in order to account for all the burnings occurring below the canopy (see Text S.II-3). Despite the difficulties in mapping forest degradation due to the quick regeneration of the forest canopy (Barlow and Peres, 2008; Matricardi et al., 2010), targeting forest degradation in addition to deforestation is crucial because degraded area often exceeds deforested area in the Brazilian Amazon (Peres et al., 2006; Souza et al., 2013). Finer temporal resolution of the large-scale degradation products would advance the degradation assessment through satellite imagery.

## **5 Conclusions**

The high-resolution land-cover data allowed us to ascribe detected burned area to specific land-use classes (excluding wildfires in savanna-type areas). We found that most of the burned area occurred in pastures in the three states, followed by forests, secondary vegetation, and annual agriculture. In addition, only a small amount of the burned area occurred in deforestation, which supports the claim that fires are used predominantly as a land management tool and less in deforestation processes nowadays. This is supported by the high interannual variability in burned area despite the declining deforestation trend during the study period and the low spatial overlap between burned and deforested areas. Spatial correlation between burned

and degraded areas was even lower. On the contrary, our study confirms that fires that escape from managed lands largely contribute to forest fires, especially those originating in pastures. Considering the large amount of burned area found in those managed lands and the notable number of fires escaping from there into the forest, more research is required on the role of policy, management practises, and human behaviour. To prevent fires from escaping into neighbouring forests, an effective fire management and monitoring system becomes crucial. Better training in management techniques should also be promoted. Also, this poses a new challenge for fire models, sometimes embedded in dynamic vegetation models, to consider the human factor in fire ignition and spread in order to reduce uncertainty in fire regime projections and their interaction with socioeconomic drivers.

## Acknowledgments

AC-C acknowledges the support by the IRTG 1740/TRP 2011/50151-0 funded by the DFG/FAPESP and received funding by the European Commission's FP7 project ROBIN (283093). MC was funded by the European Commission's FP7 projects COMBINE (226520) and AMAZALERT (282664). ArcMap software license was provided by the German Research Centre for Geosciences (GFZ, Potsdam). We specially wish to thank the two anonymous reviewers and an Associate Editor for their valuable suggestions that significantly improved the paper. We also thank Achtzehn D, Simón A, Prat-Ortega G, Ciemer CA, Randerson J, and Chen Y for their contribution to this manuscript.

## Supplementary material

### Text S.II-1 Description of land-use classes

Land-cover maps produced by the TerraClass project (de Almeida et al., 2009; INPE and EMBRAPA, 2015) include 15 land-use classes in 2008 and 16 in 2010 (reforestation class was introduced), from which we employed the eight classes listed below for the land-use spatial distribution analysis. The non-forest class, where most of the species are fire tolerant or dependent (Coutinho, 1990), was excluded from the burned area spatial distribution analysis:

- *Non-forest* covers natural vegetation with characteristics of savanna-type ecosystems: *cerrado*, *campinas* or *campinaranas*, that has been mapped by the PRODES project (INPE, 2021a).



- *Forest* refers to native tree vegetation with no or little disturbance and continuous canopy.
- *Pasture* refers to areas currently in use for grazing where there is a predominance of herbaceous vegetation and 90-100% of grass-coverage.
- *Degraded pasture* refers to areas with predominance of herbaceous vegetation, 50-80% of grass-coverage and presence of scattered bushes covering 20-50%.
- *Annual agriculture* refers to large areas with predominance of annual crops that use certified seeds, pesticides and mechanisation, among others.
- *Secondary vegetation* refers to areas that after a total removal of the tree vegetation are in an advanced stage of shrub and/or tree vegetation.
- *Regeneration* refers to areas that after a total removal of the tree vegetation and after having been used as pastures or agricultural lands, are in an initial stage of native vegetation regeneration dominated by bushes and pioneer trees.
- *Deforestation* refers to the deforested areas mapped by PRODES in that year.

The definition of the savanna-type ecosystems (non-forest class in TerraClass) and their delineation from pastoral areas is known to be difficult (Harris, 2000). Medium to high agreement in the mapping of pastures (68%) and non-forests (63%) was found when TerraClass land-use information was evaluated against pictures taken on the ground during field work in the analysed region (INPE and EMBRAPA, 2015).

### **Text S.II-2** Additional data analysis material

The TerraClass, PRODES and DEGRAD files are provided in Esri shapefile format. Burned area files are in raster format and were transformed into polygon shapefiles in ArcMap 10.1, while the active fires product is distributed as a plain ASCII file. We defined the South American Datum 1969 as the geographic coordinate system of the files. It was then transformed to the projected coordinate system Goode Homolosine, when working with Amazonia, or to the state corresponding projected coordinate system according to the Universal Transverse Mercator system so that the data align in ArcMap and accurate spatial analysis and area calculations can be performed.

### **Text S.II-3** Effect of potentially undetected burned areas on the results

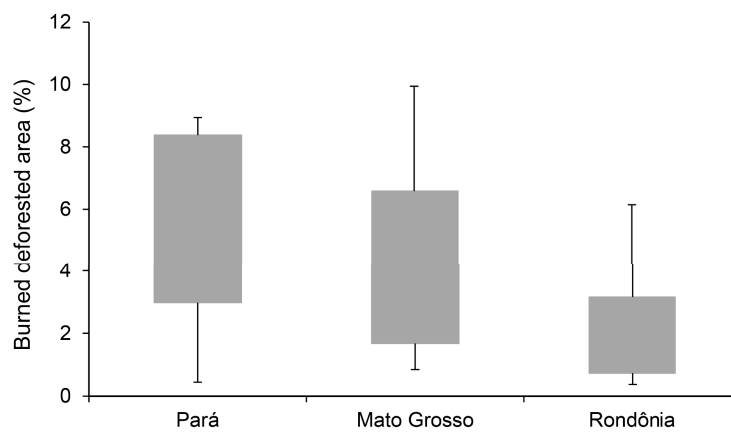
#### a) Burned areas below the canopy

Considering that the deforested areas reported in the PRODES dataset represent open areas (INPE, 2021a), the potential omission errors in the MODIS detections of burnings occurring under the forest canopy may be substantially minimised.

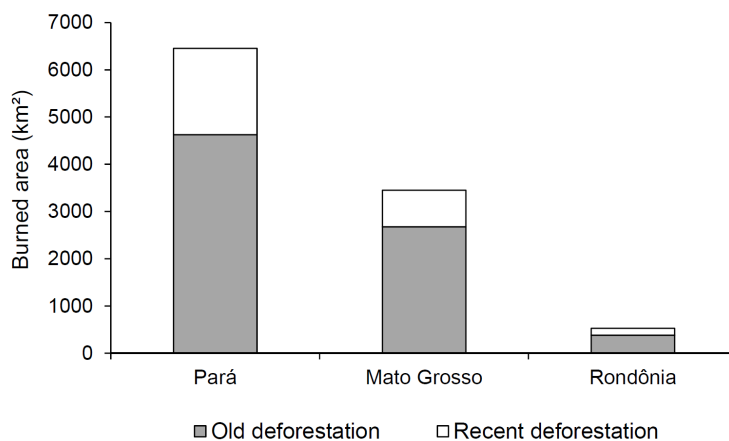
Therefore, it is unlikely that the small amount of deforested areas burning in the same year we found is the result of omission errors in the detection of subcanopy fires. In connection with this, Sorrensen (2000), Giglio et al. (2006) and Aragão et al. (2008), explained that forest felling is usually followed by fire to make land clearance as complete as possible. In particular, Aragão et al. (2008) described the chronological sequence of deforestation and fire in Amazonia, where deforestation reaches its annual maximum approximately three months after the peak of the rainy season. When the fallen wood is desiccated, it is burned on the ground during the following peak of dry season. According to that investigation, fire is set once the forest area has been opened, which is in accordance with the PRODES definition and allows MODIS burned area product to be used in the fire-deforestation analysis. On the other hand, in the fire-forest degradation analysis, burned areas may be obscured by the overstorey vegetation because in the degraded areas the forest has not been totally removed. Therefore, the contribution of fires to forest degradation may be higher than the reported in this study.

#### b) Small burned areas

Burned areas generated when burning the residuals from the cut trees and debris in small deforested areas may go unnoticed because of the spatial resolution of the sensor. Including burned area from small-scale fires from the Global Fire Emissions database (GFED4) (Randerson et al., 2012) burned area increased by 84% (sum for the three states). However, because the GFED4 algorithm to detect small-scale fires does not allow sub-grid cell attribution, the spatial comparison between the MODIS and the GFED4 burned area products is not possible. GFED4 provides only the amount of burned area in each quarter-degree cell (in km<sup>2</sup>) but there is no information about the location of individual burned area polygons within each grid cell. Most of the deforested areas are smaller than the size of a burned area pixel of 0.25 km<sup>2</sup> (MT: 66%, RO: 83%, PA: 87%), contributing 19%, 41% and 45% to the total amount of deforestation in MT, PA and RO, respectively, in the period 2001-2010. The proportion of small deforestation areas that contain active fires, but no burned areas, can be used as a measure of the potentially undetected small burned areas. It could be that some fires were large enough to be detected as hotspots, but not large enough to trigger the burned area algorithm. However, in the year 2010, when the highest amount of burned area was detected in the study period, we found that the potential missing burned areas could only occur in 5% on average of the small deforested areas. This would contribute very little to the total overlap between deforestation and burned areas and hence, does not question the disconnection found between these two variables.



**Figure S.II-1** Amount of deforested area that burned in the following year over the period 2001-2010 in Pará, Mato Grosso and Rondônia (in percentage)



**Figure S.II-2** Amount of the burned area detected in 2010 located in old (areas deforested between 2001 and 2006) and recent (areas deforested between 2007 and 2010) deforested areas in Pará, Mato Grosso and Rondônia (in km²)

## Chapter III

# Characterization of land cover-specific fire regimes in the Brazilian Amazon

Cano-Crespo A, Traxl D, Prat-Ortega G, Rolinski S, Thonicke K (2022)

An edited version of this chapter has been published in the journal *Regional Environmental Change* 23, 19

## **Abstract**

Humans profoundly alter fire regimes both directly, by introducing changes in fuel dynamics and ignitions, and indirectly, by increasing the release of greenhouse gases and aerosols from fires, which can alter regional climate and, as a consequence, modify fuel moisture and availability. Interactions between vegetation dynamics, regional climate change and anthropogenic pressure lead to high heterogeneity in the spatio-temporal fire distribution. We use the new FireTracks Scientific Dataset that tracks the spatio-temporal development of individual fires to analyse fire regimes in the Brazilian Legal Amazon over the period 2002-2020. We analyse fire size, duration, intensity and rate of spread in six different land-cover classes. Particular combinations of fire features determine the dominant and characteristic fire regime in each of them. We find that fires in savannas and evergreen forests burn the largest areas and are the most long lasting. Forest fires have the potential for burning at the highest intensities, whereas higher rates of spread are found in savannas. Woody savanna and grassland fires are usually affected by smaller, shorter, less-intense fires compared with fires in evergreen forest and savanna. However, fires in grasslands can burn at rates of spread as high as savanna fires as a result of the easily flammable fuel. We observe that fires in deciduous forests and croplands are generally small, short and low intense, although the latter can sustain high rates of spread due to the dry post-harvest residuals. The reconstructed fire regimes for each land cover can be used to improve the simulated fire characteristics by models and, thus, future projections.

## **1 Introduction**

Humans influence fire occurrence and distribution decisively in the Brazilian Amazon, where fires are almost entirely ignited by humans associated with fire-driven logging, mining and deforestation processes (Aragão et al., 2008; Cochrane and Barber, 2009; Curtis et al., 2018). Fire is also subsequently used for the maintenance of cattle pastures and shifting agriculture established in deforested patches, where it stimulates grass resprouting, removes shrubs and harvest remnants, controls pests, etc. (Cochrane and Laurance, 2008; Nepstad et al., 2008; Lewis et al., 2015). Thus, humans have modified the spatial and seasonal niche of

fire for millennia (Le Page et al., 2010; Pivello, 2011; Fu et al., 2013; Marengo et al., 2018). Additionally, the Amazon region experienced frequent severe drought conditions in the last years (2005, 2010, 2015-2016), which were often associated with an extended dry season and anomalously low levels of precipitation (Marengo and Espinoza, 2016; Cunha et al., 2019). Drier environmental conditions increase flammability and promote fire spread, boosting fire emissions and carbon release into the atmosphere, which accelerate warming (Brando et al., 2014; Fonseca et al., 2017; Jimenez et al., 2018). This positive fire-climate feedback loop, exacerbated by increasing anthropogenic disturbances, leads to an environment more susceptible to fire (Gutiérrez-Vélez et al., 2014; Nobre et al., 2016; Le Page et al., 2017).

Fire regimes are a generalised description of the typical fire characteristics in a particular place and time (Pausas et al., 2004; McLauchlan et al., 2020). A deviation from eco-climatic fire regimes towards anthropogenically driven regimes is being observed globally (Le Page et al., 2010; Pausas and Keeley, 2014). Specifically, patterns of fire seasonality driven by climate or weather become greatly influenced by anthropogenic activities due to alterations in species composition and plant functioning, which induce changes in fuel loads, structure and dryness (Hantson et al., 2015; Barlow et al., 2016). This, in turn, may introduce changes in ecosystem dynamics and future biome shifts when local changes persist (Davidson et al., 2012; Boit et al., 2016). As a result, the incorporation of variables representing anthropogenic fire practices in Dynamic Global Vegetation Models (DGVMs) becomes essential to reproduce diverse fire regimes and estimate their impacts and future activity (Silvestrini et al., 2011; Mann et al., 2016; Teckentrup et al., 2019).

To analyse fire distribution and dynamics in an extensive area such as the Amazon, where ground data is scarce, remote sensing provides an opportunity to study regional patterns. Here, we employ the FireTracks (FT) Scientific Dataset (Traxl, 2021, v1.0.0), which has been generated by combining network theory and the individual fires' approach. Network theory-based techniques have proven to be effective tools to examine systems in climate and geoscience by modelling the relations between their features (Goswami et al., 2013; Traxl et al., 2016a). The individual fires approach that separates large burned clusters that contain multiple fire events into individual fires, has recently demonstrated its potential to provide

insight into global fire behaviour and dynamics (Andela et al., 2019a; Artés et al., 2019). The FT algorithm aggregates remotely sensed fire and land-cover data to produce local formations of spatio-temporal fire clusters that evolve over space and time, and computes their aggregated size, duration, intensity - for the first time in the region - and rate of spread. As the fires in the FT dataset contain information about the land cover where they occur, we characterise six land cover-specific fire regimes in the Brazilian Legal Amazon (BLA) over the period 2002-2020: croplands, deciduous forests, evergreen forests, grasslands, savannas and woody savannas. The 1-km spatial resolution of the fire data enables us to capture the heterogeneous vegetation composition at the regional scale, while the long study period makes it possible to filter out transient dynamics and focus on the long-term fire patterns that determine fire regimes. We additionally provide a comparison of the FT's fire variables in the different land-cover types with those estimated by the Global Fire Atlas (GFA, Andela et al., 2019b).

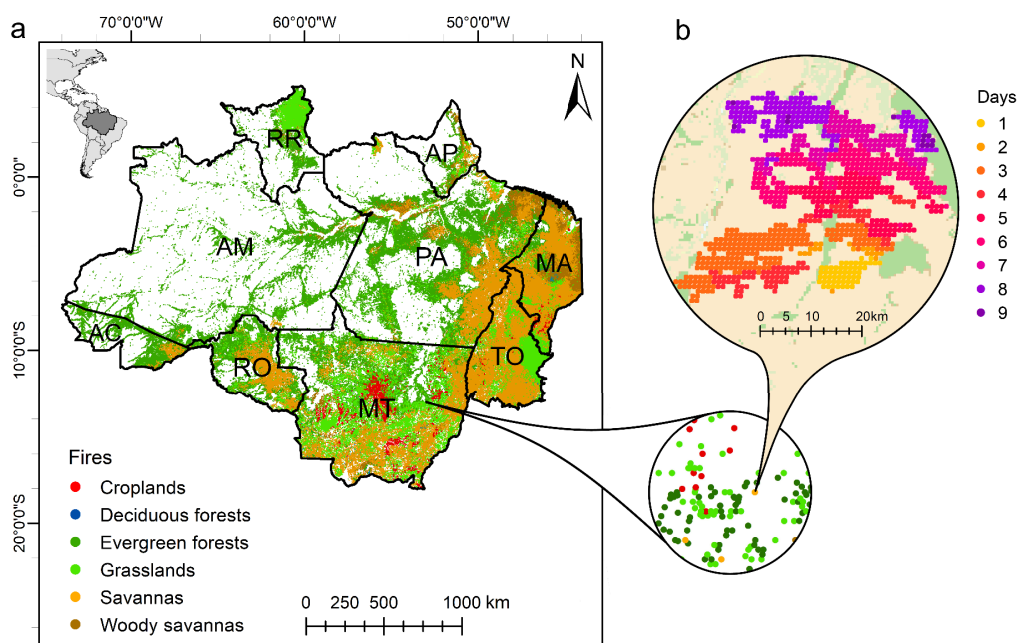
In this study, we address the following specific objectives: (1) report the spatial distribution of individual fires in the BLA over the period 2002-2020; (2) examine and evaluate properties of individual fires: size, duration, intensity and rate of spread and the relation between them to explore fire dynamics at the local scale; (3) identify and describe six land cover-specific fire regimes based on the attributes of individual fires; (4) assemble comprehensive statistical tables of key fire characteristics in different land covers that contribute to the efforts to parametrise different fire regimes in fire models.

## **2 Methodology**

### **2.1 Area of interest**

Our study area is the BLA region, which comprises the Brazilian states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA) (Fig. III-1a). Together, they cover approximately 60% (ca. 5.1 million km<sup>2</sup>) of Brazil's area. The Amazon biome spreads over two-thirds of the BLA, while smaller portions of Cerrado and Pantanal biomes are located along the southeast flank, and in the most southern part of the BLA, respectively (IBGE, 2019). In 2001 - at the beginning of the study period -, the

BLA was mainly covered by evergreen forests (70%), open and woody savannas (19%) and grasslands (8%), while croplands and deciduous forests were less present (less than 1%) (Friedl and Sulla-Menashe, 2019).



**Figure III-1** **a** Fire spatial distribution in the Brazilian Legal Amazon over the period 2002-2020 (FireTracks,  $n = 857,942$ ). The inserted map shows the location of the region (in dark grey) within South America. The study area comprises the states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA). Black lines are political boundaries. Each point in the map marks a location where a fire occurred during the 19-year period. The type of land cover where fires take place is denoted by colour. In locations when repeated burning occurs, the map shows the last land-cover information. The small number of deciduous forest fires are not visible at the scale of the map. **b** High-resolution illustration of one of the largest fires in the FireTracks dataset. Dots represent active fires within the individual fire, and colours indicate the time steps of the fire development. Background land-cover colour coding is the same as in Fig. S.III-2 (MCD12Q1, UMD)

## 2.2 Data

We use the novel FireTracks (FT) Scientific Dataset (Traxl, 2021) of individual fires. The FT algorithm employs network theory and the individual fires approach to aggregate fire events into spatio-temporal fire clusters that are tracked over space and time (Fig. S.III-1). Individual fires are defined as the union of nearest neighbours of active fires in the discrete spacetime grid given by the spatial and temporal resolution of the Moderate Resolution Imaging Spectroradiometer (MODIS) 1-km MOD/MYD14A1 Thermal Anomalies and Fire dataset (Giglio and Justice, 2015) that



feeds the algorithm. Two fire events are considered neighbours if they are in the same 3-dimensional (latitude, longitude, time) Moore neighbourhood with no spatial or temporal gaps (Fig. III-1b). The MOD/MYD14A1 fire product offers an indication of fire activity and has been extensively validated (Morissette et al., 2005; Csiszar et al., 2006; Hawbaker et al., 2008; de Klerk, 2008). The collection 6 of the data addresses previous limitations such as frequent false alarms caused by small clearings in the Amazon forests (Friedl et al., 2010), which is particularly helpful for our purpose. The data present low levels of commission errors, but omission errors, which decrease as fire size increases, might occur with fires of short duration, small size or low intensity (Schroeder et al., 2008; Hantson et al., 2013). Also, burnings under dense vegetation cover, heavy smoke or clouds may go undetected (Giglio et al., 2016). The FT algorithm combines the MODIS fire data with land-cover information from the previous year. We use the UMD classification scheme of the 500-m Land Cover Type MCD12Q1 product from MODIS (Sulla-Menashe et al., 2019). The collection 6 of the land-cover data includes new gap-filled spectro-temporal features and refinements of the algorithm, which allows a more accurate classification. However, some limitations are known, e.g. grassland areas might be misclassified as savannas, and agriculture can be underrepresented in tropical regions where agricultural fields are small (Friedl et al., 2010). Since the land-cover data has a spatial resolution twice as high as the active fires data (0.21 vs. 0.86 km<sup>2</sup>), the FT algorithm associates four values of land cover with every MODIS active fire within a particular individual fire. Fires are assigned a dominant land cover when at least 80% of all the land-cover values within them belong to the same land-cover type. Fires that do not fulfil this criterion are discarded from the analysis. In this way, we ensure that the FT's fire characteristics estimated for each land-cover type are not a combination of values from different land covers.

The FT dataset registers location, time and land cover of individual fires at daily time step, as well as their estimated size, intensity, duration and rate of spread (see Text S.III-1 for the definition of the fire variables). The smallest identifiable fire size and duration is imposed by the spatio-temporal resolution of the MODIS fire data, 0.86 km<sup>2</sup> and one day, respectively. Fires with sizes smaller than one fire-data pixel are attributed a size of 0.86 km<sup>2</sup> regardless, which may generate some overestimation of

burned area. Fires of a single fire-data pixel size ( $0.86 \text{ km}^2$ ) are not considered for the calculation of rate of spread - the ratio between size and duration. We select those fires within the BLA over the time period from 2002 to 2020 in six land-cover types: croplands, deciduous forests, grasslands, evergreen forests, savannas and woody savannas (see Text S.III-2 and Fig. S.III-2 for the description and spatial distribution of the different land covers, respectively).

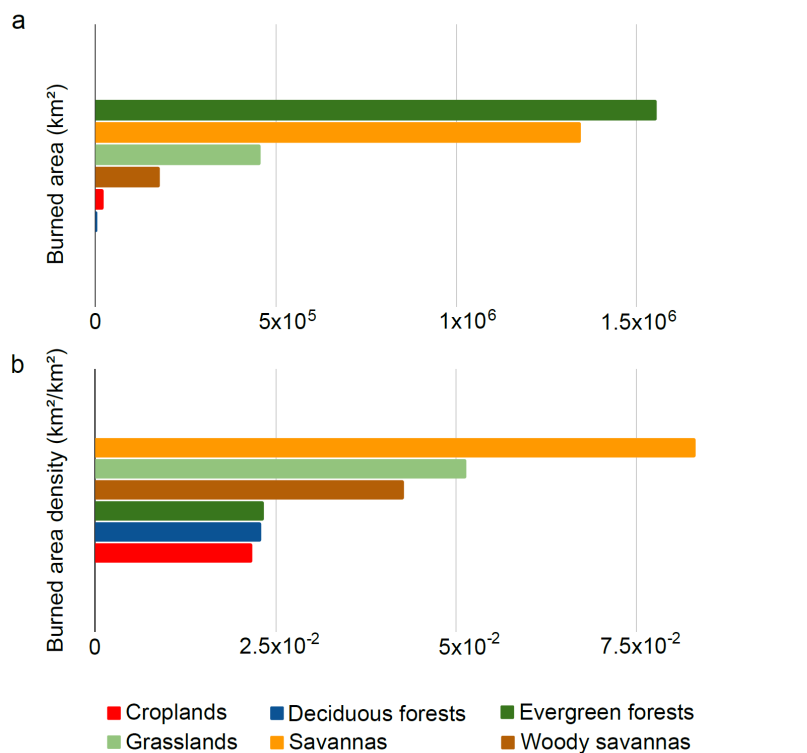
We employ the GFA dataset (Andela et al., 2019b), the most extensive study on individual fires covering the BLA so far, to perform a comparison of our estimated fire characteristics. The GFA is derived from the MODIS collection 6 500-m Burned Area MCD64A1 product (Giglio et al., 2018) and spans from 2003 to 2016. The quality of the algorithm, as for the FT's, highly depends on the inherent limitations of the data that serve as input. Fires of  $0.21 \text{ km}^2$  - the smallest identifiable fire size - are not taken into account when calculating rate of spread. The GFA algorithm tracks the daily progression of individual fires to produce a set of metrics on fire behaviour such as fire size, duration, daily expansion, fire line length, speed and direction of spread. We select from the FT dataset the fires identified in the BLA over the period 2003-2016 - the same 14-year time window when data from the GFA is available - and compare fire size, duration and rate of spread - the variables present in both datasets - occurring in croplands, forests, grasslands and savannas (Text S.III-2).

## **3 Results**

### **3.1 Fire distribution**

Of the total number of fires that FireTracks identifies in the BLA over the period from 2002 to 2020, 52% were assigned a dominant land-cover type and selected for the analysis ( $n = 857,942$ ). The total burned area of these fires covers approximately  $3.6 \times 10^6 \text{ km}^2$ . Most of the burned area is found in evergreen forests (44%) and savannas (38%) (Fig. III-2a). Smaller amounts are located in grasslands (13%) and woody savannas (5%), while we find less than 1% in croplands (0.6%) and deciduous forests (0.1%). When considering the extent covered by the different land-cover types in the BLA region, in order to ensure that the results are not consistent with homogeneous distribution, the annual fire density over the period shows a contrasting perspective, especially for evergreen forests. Although the

amount of burned area is the largest in evergreen forests, fire density is one of the lowest ( $0.02 \text{ km}^2$  burned area per  $\text{km}^2$  land cover, average of the annual values over the period) (Fig. 2b), together with deciduous forest and cropland densities. We register the highest burned area density in savannas ( $0.08 \text{ km}^2/\text{km}^2$ ), followed by grasslands ( $0.05 \text{ km}^2/\text{km}^2$ ) and woody savannas ( $0.04 \text{ km}^2/\text{km}^2$ ).



**Figure III-2** **a** Absolute amount of burned area (in  $\text{km}^2$ ), and **b** burned area density (in  $\text{km}^2$  of burned area per  $\text{km}^2$  of land cover, average of annual densities over the period) in the six land-cover classes analysed in the Brazilian Legal Amazon over the period 2002-2020. Land-cover types are ordered by the magnitude of their values

Spatially, we observe a high concentration of forest fires (dark green points in Fig. III-1a) on the northern side of the so-called arc of deforestation (the tropical forest-savanna frontier in Fig. S.III-2), mainly in the states of AC, RO, AM, PA and the northern half of MT. We estimate that these states account for 92% of the total deforestation registered in the BLA over the study period (INPE, 2021a), and 95% of the total amount of burned area identified in evergreen forests. PA and MT are the states with the largest amount of burned area in tropical forests (37% and 20% of the total amount, respectively). The spatial aggregation of forest fires along roads and rivers can be observed in Fig. III-1a, especially in the states of PA and AM, where

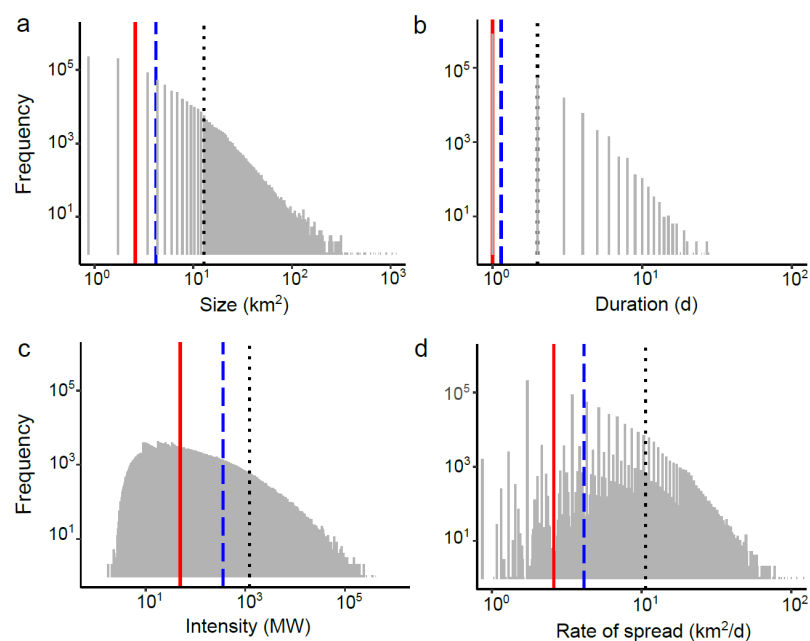
fire distribution patterns following straight lines can be easily recognised (see the road network in Fig. S.III-2). We find that savanna fires (orange points in Fig. III-1a) occur mainly along the southeastern border of the BLA, where the states of MA, TO and PA accumulated 79% of them over the 19-year study period. Fires in woody savannas (brown points in Fig. III-1a) concentrate in the most northeastern flank of the BLA, where the states of MA and PA hold 87% of them. We observe that grassland fires (light green points in Fig. III-1a) are prevalent in MT, northeastern RR and eastern TO. Seventy-seven percent of the grassland fires are located in these three states. The vast majority of the agricultural fires (red points in Fig. III-1a) that we identify over the study period are located in MT (83%). Lastly, we find that the few fires identified in deciduous forest (blue points in Fig. III-1a) occurred predominantly in the state of MT (81%).

Temporally, we found that 71% of the total burned area registered in the BLA over the study period occurs during the dry season (April-September). The largest amounts of burned area are observed in August in evergreen and deciduous forests, while the burned area peak occurs in September in savannas, woody savannas and grasslands (Fig. S.III-3). Burned croplands reach its maximum in April. Almost three-quarters of the burned area identified in savannas, evergreen and deciduous forests, and grasslands is detected during the dry season. Lower values were found in croplands and woody savannas (60% and 47%, respectively).

### **3.2 Fire variables**

We compute four key characteristics of fires that control the impacts on vegetation and emissions: size, duration, intensity and rate of spread. The frequency distribution of fire sizes is best described by a truncated power law according to a maximum likelihood estimation and maximum likelihood ratio tests (Clauset et al., 2009), a power law with an exponential cutoff at the largest fire sizes (Fig. III-3a). The lowest values show the highest frequencies (mode of the distribution at 0.86 km<sup>2</sup>), and few fires substantially larger than the rest result in mean values larger than median values. Fire size ranges from 0.86 to 1453.7 km<sup>2</sup> with a median of 2.6 km<sup>2</sup> over the 19-year period (Fig. III-3a, Table S.III-2). We find that 25% of the total number of fires are small and do not exceed 1 km<sup>2</sup> in size. Most of the 5% largest fires - those at the 95th percentile for size - are mostly located in evergreen forests (46%) and

savannas (39%). The fire duration frequency distribution follows a power law with few dominant low values (Fig. III-3b). We observe that the majority of the fires last only 1 day (91% of the sample) (Fig. III-3b, Table S.III-2), while the median value of the remaining 9% of the fires is 2 days. More than half of the 5% longest fires are identified in evergreen forests (55%), lasting up to 27 days. Fire intensity and spread show a positively skewed log-normal frequency distribution (Fig. III-3c, d) that peaks at 10 MW and 1.72 km<sup>2</sup>/day, respectively. Fire intensity varies between 1.7 and 418,976 MW with a median of 50 MW (Fig. III-3c, Table S.III-2). The 5% most intense fires are predominantly registered in evergreen forests (50%). Fire rate of spread ranges from 0.4 to 131 km<sup>2</sup>/day, with a median value of 2.6 km<sup>2</sup>/day (Fig. III-3d, Table S.III-2). Most of the 5% of fires with the highest rates of spread are found in savannas (41%) and evergreen forests (37%), with a considerable presence also in grasslands (17%).



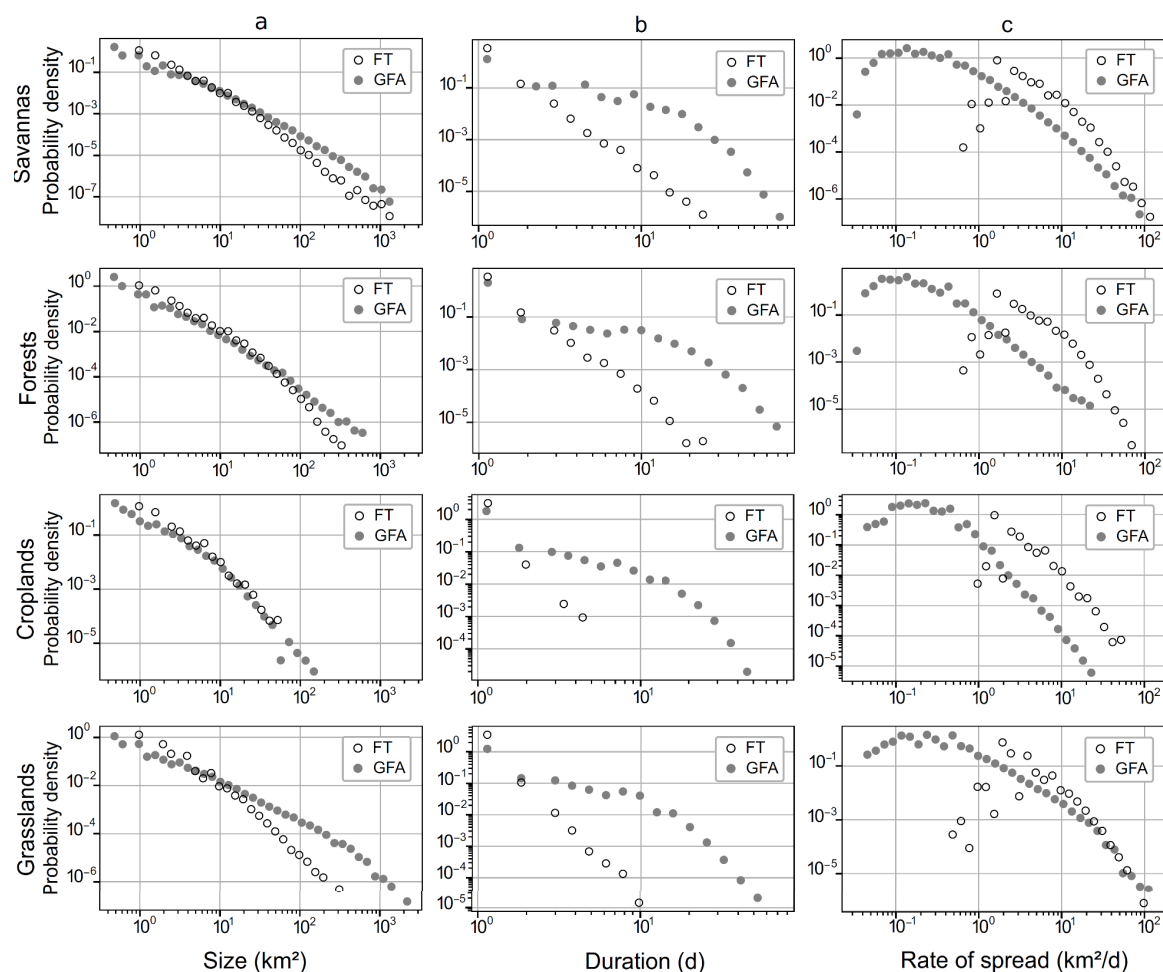
**Figure III-3** Frequency distribution of **a** fire size (in km<sup>2</sup>), **b** duration (in d), **c** intensity (in MW), and **d** rate of spread (in km<sup>2</sup>/d) in the Brazilian Legal Amazon over the period 2002-2020 ( $n = 857,942$ ). Rate of spread is computed for fires larger than 0.86 km<sup>2</sup> ( $n = 639,579$ ). Both axes and bins are in logarithmic scale. The red solid line, blue dashed line, and black dotted line indicate the median, mean, and 95th percentile values of the distribution, respectively

We find a moderate positive and significant correlation between fire size and intensity ( $R = 0.69$ ,  $p < 0.05$ ), size and rate of spread ( $R = 0.68$ ,  $p < 0.05$ ) and size

and duration ( $R = 0.63$ ,  $p < 0.05$ ) (Fig. S.III-4), which evinces the interrelations between the fire variables. By selecting the extreme fires, i.e. those whose size, intensity, duration and rate of spread are greater than or equal to the 95th percentile of the variables' distribution, we find the highest relationship between fire intensity and size since 74% of the most intense fires are also within the 5% largest fires. Size and duration - 68% of the longest fires are also the largest - and size and spread - 68% of the fires with the highest rates of spread are also the largest - also show a notable relationship.

### 3.3 Comparison FT vs. GFA datasets

We identify 32% more fires ( $n = 652,892$ ) and 35% more cumulative burned area (2,714,021 km<sup>2</sup>) in the FT dataset than the GFA in the BLA over the period from 2003 to 2016. The fire size probability density distribution is best described by a truncated power law for both datasets (Fig. III-4a), according to a maximum likelihood estimation and maximum likelihood ratio tests. The lower median value of the GFA's size distribution indicates a higher proportion of small fires (Table S.III-1), although the contribution of the lower half of the dataset to the cumulative burned area is very low in the GFA (6% of the total burned area) compared with the FT dataset (23%). The subset of the 5% largest fires make up 30% and 60% of the cumulative burned area over the study period in the FT and GFA datasets, respectively, which demonstrates the strong effect the largest fires have on the total burned area estimated by the GFA. Regardless of the land-cover type, the FT's size distribution displays a steeper drop in the probability density with increasing size compared with the GFA (Fig. III-4a). Thus, the size distribution in the GFA dataset is more skewed towards larger sizes, and it identifies the largest fires. At the lower end too, the range is usually higher in the GFA, except in savannas, where it is similar in both datasets (Fig. III-4a). The largest difference in the range of fire size is found in grasslands.



**Figure III-4** Probability density distribution of fire **a** size (in km<sup>2</sup>), **b** duration (in d) and **c** rate of spread (in km<sup>2</sup>/d) in the FireTracks ( $n_{FT} = 652,892$ ) and Global Fire Atlas ( $n_{GFA} = 443,863$ ) datasets in the Brazilian Legal Amazon over the period 2003-2016. The plots show the distribution of the fire variables in savannas ( $n_{FT} = 280,885$ ,  $n_{GFA} = 295,504$ ), forests ( $n_{FT} = 278,095$ ,  $n_{GFA} = 79,613$ ), croplands ( $n_{FT} = 4547$ ,  $n_{GFA} = 49,010$ ) and grasslands ( $n_{FT} = 89,365$ ,  $n_{GFA} = 19,736$ ). Rate of spread is computed for fires larger than 0.86 km<sup>2</sup> ( $n_{FT} = 487,347$ ) and 0.21 km<sup>2</sup> ( $n_{GFA} = 315,648$ ) in the FT and GFA datasets, respectively. Both axes and bins are in logarithmic scale

Both datasets have the same temporal resolution, and therefore, the lower end of the duration range coincides at one day (Table S.III-1). The majority of fires are very short in the FT dataset, where fires that last only for one day make up 91% of all fires. The same subset constitutes 39% of all fires in the GFA dataset, which shows higher fire duration variability. For longer lasting fires, the probability density decreases as duration increases, describing a power law distribution in the FT, and a truncated power law in the GFA datasets (Fig. III-4b), where durations as long as 80 days are reached (Table S.III-1). Longer fires are identified in the GFA dataset in all

the land covers. The largest disparity in the duration range is found in croplands (Fig. III-4b).

In the FT dataset, the probability density distribution of rate of spread is best described by a positively skewed log-normal distribution (Fig. III-4c). Fires with the highest spreads are usually identified in the FT, except in grasslands, where the maximum value of the range is similar in both datasets (Fig. III-4c, Table S.III-1). It is not clear if the spread distribution of the GFA dataset is best described by a stretched exponential or a truncated power law distribution, a maximum likelihood ratio test finds no significant difference between the two models. The GFA dataset exhibits a wider range at the lower end of the distribution in all the land covers (Fig. III-4c).

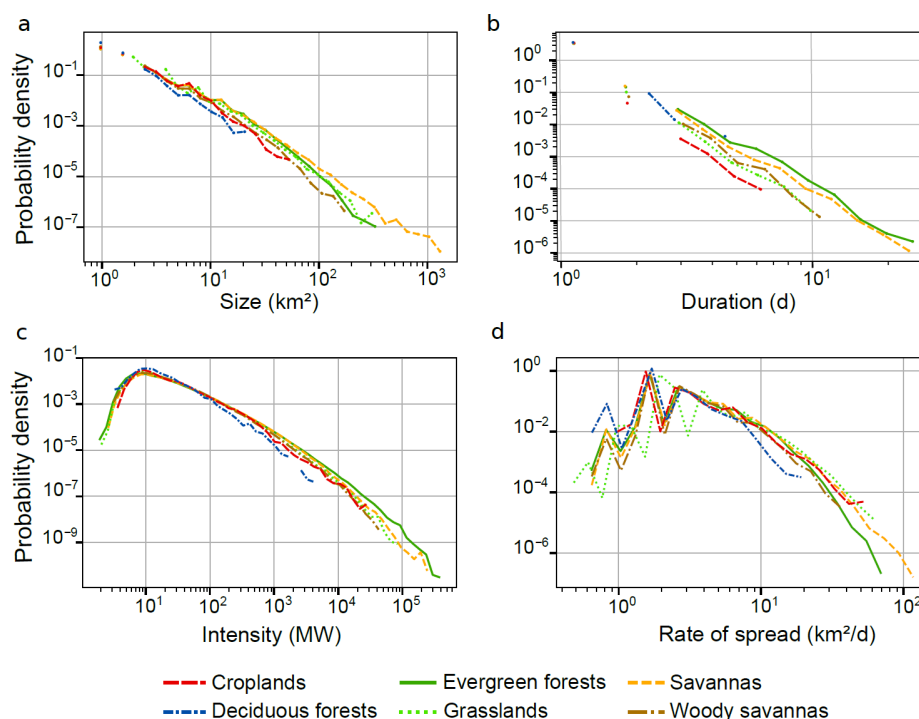
We find 44% of the FT-burned area in forests and 43% in savannas in the BLA over the study period. The amount of burned area in grasslands makes up 13% of the total, and less than 1% is located in croplands. In the GFA dataset, there is a higher proportion of burned area in savannas (75%), and seven times more burned area in croplands. Conversely, we identify almost five times more fires in forests with the FT algorithm than the GFA dataset.

### 3.4 Characterization of fire regimes

We observe that the probability density distributions of the fire variables follow a similar pattern regardless of the land cover, although probabilities differ between them (Fig. III-5). The size probability density distribution shows the highest probabilities concentrated at the lowest sizes in all the land covers (Fig. III-5a, Table III-1a). Savanna fires show the widest upper range, being the only land cover with fires that exceed 400 km<sup>2</sup> in size, followed by evergreen forests and grasslands. We observe the most limited range in deciduous forests, while croplands and woody savannas take an intermediate position (Fig. III-5a). In the same way as size, the fire duration probability density results in a distribution where we find the highest probabilities at the shortest durations (Fig. III-5b, Table III-1b). Deciduous forests and croplands hold the shortest duration ranges, while long fires are most likely to be sustained by evergreen forests and savannas. Only fires that take place in these two land-cover types may exceed 14 days in length (Fig. III-5b). The probability density



of fire intensity shows a distribution whose mode is a value between 8.7 and 12.6 MW, depending on the land cover (Fig. III-5c, Table III-1c). From that point onwards, the distribution presents a long tail to the right in which the probability decreases as the intensity values increase. Evergreen forests display the widest intensity range, followed by savannas and grasslands. Similar to fire intensity, the spread distribution shows the highest probability densities at low to intermediate values, from where the probability continuously drops to find only few large values within the right tail (Fig. III-5a, Table III-1d). The highest probability density is found at 1.72 km<sup>2</sup>/day in all the land covers. Fires in savannas present the broadest range of all the land covers. Fires in grasslands and evergreen forests also reach high rates of spread, while croplands and woody savannas present more limited ranges (Fig. III-5d, Table III-1d).



**Figure III-5** Probability density distribution of fire **a** size (km<sup>2</sup>), **b** duration (d), **c** intensity (MW), and **d** rate of spread (km<sup>2</sup>/d) in croplands ( $n = 6882$ ), deciduous forests ( $n = 2466$ ), evergreen forests ( $n = 369,932$ ), grasslands ( $n = 121,310$ ), savannas ( $n = 300,777$ ), and woody savannas ( $n = 56,575$ ) in the Brazilian Legal Amazon over the 19-year period (2002-2020). Rate of spread is computed for fires larger than 0.86 km<sup>2</sup> ( $n = 639,579$ ). Both axes and bins are in logarithmic scale

Our results describe fires in savannas as large, long, intense and with high rates of spread (Fig. III-5, Table III-1). In evergreen forests, fires tend to be large, long and intense too, but they usually have much lower rates of spread than savanna and

grassland fires. Compared to fires in savannas, fires in woody savannas are usually smaller, shorter, less intense and with slower rates of spread (Fig. III-5, Table III-1). Although grassland fires are smaller, shorter and less intense than savanna and evergreen forest fires, they may reach rates of spread close to those in savannas. Fires in croplands and deciduous forests are likely to be small and short, and spread at low rates, although cropland fires can sustain higher intensities (Fig. III-5, Table III-1).

**Table III-1** Distribution of fire variables in the FireTracks dataset per land cover in the Brazilian Legal Amazon (2002-2020)

**a) Fire size distribution (km<sup>2</sup>)**

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Croplands	0.86	0.86	1.72	3.19	3.44	8.6	58.39
Deciduous forests	0.86	0.86	1.72	2.16	2.58	6	74.7
Evergreen forests	0.86	1.72	2.58	4.2	4.29	13.7	365.78
Grasslands	0.86	0.86	1.72	3.77	4.29	12	342.6
Savannas	0.86	1.72	2.58	4.47	4.29	13.7	1453.67
Woody savannas	0.86	0.86	1.72	3.13	3.44	10	190.62

**b) Fire duration distribution (d)**

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Croplands	1	1	1	1.03	1	1	7
Deciduous forests	1	1	1	1.09	1	2	8
Evergreen forests	1	1	1	1.17	1	2	27
Grasslands	1	1	1	1.08	1	2	14
Savannas	1	1	1	1.15	1	2	27
Woody savannas	1	1	1	1.07	1	1	12

**c) Fire intensity distribution (MW)**

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Croplands	3.2	15.8	40.2	209.7	125.5	628.4	62,139.8
Deciduous forests	2.9	12.8	25.3	78.06	59.4	311.6	4655.6
Evergreen forests	1.7	18.4	51	434.9	181.3	1420.2	418,976.1
Grasslands	1.8	16.1	41.1	254.0	135.6	901.2	93,356.1
Savannas	2.3	20.2	53.8	334.9	183	1243.6	343,431.7
Woody savannas	2.8	17.7	43.8	224.1	1305.2	827.7	75,763.0

**d) Fire rate of spread distribution (km<sup>2</sup>/d)**

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Croplands	0.86	1.72	2.58	3.94	5.15	9.45	58.39
Deciduous forests	0.57	1.72	1.72	2.78	3.44	6.87	21.47
Evergreen forests	0.57	1.72	2.58	4.01	5.15	10.3	77.28
Grasslands	0.43	1.72	2.58	4.27	5.15	11.59	109.05
Savannas	0.57	1.72	3.44	4.26	5.15	11.16	130.51
Woody savannas	0.57	1.72	2.58	3.55	4.29	8.59	50.66

$n_{\text{CROPLANDS}} = 6882$ ;  $n_{\text{DECIDUOUS FORESTS}} = 2466$ ;  $n_{\text{EVERGREEN FORESTS}} = 369,932$ ;  $n_{\text{GRASSLANDS}} = 121,310$ ;  $n_{\text{SAVANNAS}} = 300,777$ ;  $n_{\text{WOODY SAVANNAS}} = 56,575$

## 4 Discussion

Regional land-cover changes play a critical role in future fire regimes and their resulting impacts on ecosystems since fires behave differently depending on the land cover where they burn. Recurrent fires are a natural component in tropical savanna-type ecosystems, where they contribute to define vegetation composition and structure (Mistry, 1998; Pivello, 2011). As a result, woody plants and grasses have developed traits to cope with it over thousands of years (Bowman et al., 2009; Simon et al., 2009; Keeley et al., 2011). We interpret the fact that almost three-quarters of the burned area occurred during the dry season (Fig. S.III-3), when lightning are scarce, as fire activity in savannas being largely of anthropogenic origin. Although there are important regional variations within the BA (Carvalho et al., 2021), fires caused by lightning are usually detected during the rainy season or during change-of-season storms (Ramos-Neto and Pivello, 2000; Morgan et al., 2019). The herbaceous vegetation desiccated over the dry season is ignited for land clearing and soil restoring purposes (Higgins et al., 2000; Klink et al., 2020; Schmidt and Eloy, 2020). This highly flammable fuel facilitates high rates of spread in open savannas, which usually result in large, long and intense fires, according to our findings (Fig. III-5, Table III-1). When the climate is dry enough, fires can spread freely in the absence of moist areas acting as barriers, only limited by the spatial pattern of fuel resulting from earlier fires or grazing (Archibald et al., 2012). Fire suppression has devastating effects in fire-prone savanna-type ecosystems (Berlinck and Batista, 2020; Durigan, 2020) since the accumulation of grassy fuels increases the risk of catastrophic large-scale wildfires jeopardising biodiversity conservation.

Woody vegetation cover may increase in savannas as the result of various local anthropogenic disturbances - livestock, management interventions, fire frequency, etc. (Bond and Keeley, 2005; Baggio et al., 2021). Usually, increased grazing intensity and/or fire frequency promote the growth of woody vegetation by removing competitor grasses and fine fuels (Scholes and Archer, 1997; Archer et al., 2017; Coelho et al., 2020), although the ecosystems' response can be different (Moreira, 2000; Rosan et al., 2019). In woody savannas, we find smaller, shorter, less intense and slower spreading fires than in open savannas (Fig. III-5, Table III-1) since more scattered woody patches and individual trees contribute less than grasses to the total amount of fuel (Archibald et al., 2018).

Unlike in savannas, most plant species in evergreen forests are poorly adapted to fire (Hoffmann et al., 2012) since fire events have been rare in their evolutionary history (Barlow and Peres, 2008; Balch et al., 2015). The moist understory and the scarce natural fire ignition sources preclude significant burning in dense primary forests (Kauffman and Uhl, 1990; Ray et al., 2005). However, forest degradation and fragmentation caused by agriculture and ranching expansion, logging, overexploitation, etc., expose forest edges to drier conditions that favour tree mortality, canopy openings and grass invasion (Laurance et al., 2011; Silva et al., 2018; Silvério et al., 2019; Montibeller et al., 2020). In particular, increases in dry grassy vegetation beneath the trees make the forests more flammable and provide the fuel to sustain understorey fires of higher intensity and rates of spread (Silvério et al., 2013; de Faria et al., 2017). Most of the burned area happens during the dry season (Fig. S.III-3), when natural ignition sources are rare, which points to anthropogenic pressure on evergreen forests as the most likely cause (Ramos-Neto and Pivello, 2000; Morgan et al., 2019). Nevertheless, as in the case of savannas, reduced forest connectivity and fuel continuity caused by humans may contribute to a decrease in the amount of burned forest (Brando et al., 2020). Our analysis aligns with previous literature documenting the strong impact of anthropogenic activities on fire activity in tropical forests. For example, Archibald et al. (2013) identified global pyromes using satellite imagery and stated that fires in the tropical moist broadleaf forest biome fell predominantly into the pyrome with the largest Human Impact Index. The profound human-induced changes in fire regimes are also illustrated in the review of twenty-seven studies on the multiple interacting global change drivers by

Rogers et al. (2020). According to our findings, we characterise forest fires as large, long, intense and with high rates of spread, although savanna fires can reach higher rates (Fig. III-5, Table III-1). These fire features reflect how evergreen forest fires have escalated from being naturally rare to showing characteristics more typical of savanna fires. As forest fires can spread through the ground, surface, crowns or all three together, it is important to consider that slow-moving understorey fires, which can burn for days in forests (Alencar et al., 2006; Morton et al., 2013; dos Santos Prestes et al., 2020), may go undetected if the tree canopy precludes the satellite from capturing the signal from the surface (Eva and Lambin, 1998; Giglio et al., 2016; Boschetti et al., 2019).

As opposed to evergreen forests, deciduous forests shed their leaves during the dry season. They are usually interspersed with savannas (Fig. III-1a) but while grasses are the predominant fuel in savannas, leaf litter constitutes the main fuel in deciduous forests (Goldammer, 1993). This seasonal, surface flammable layer may be ignited by lightning or, most likely, by pastoralists and farmers towards the end of the dry season in order to remove non-desirable plant material, stimulate grass growth or facilitate the harvest of other forest products (Goldammer, 2016). Just as it happens in evergreen forests, fires can escape into the deciduous forests from those shifting agricultural lands and cattle pastures. Fires in deciduous forests have been described generally as surface fires of moderate intensities (Stott et al., 1990; Nepstad et al., 1999), which may leave shrubs and trees unaffected. This is the result of a more frequent consumption of the available dry fuel in deciduous communities, e.g. the same area may sustain a grass fire at the beginning of the dry season and a leaf-litter fire in the late dry season. In agreement with that, we find smaller, shorter, less intense and less consuming fires compared to fires in evergreen tropical forests (Fig. III-5, Table III-1), basically as a consequence of the differences in fuel amount, structure and humidity.

Currently, all grasslands show some degree of human interference (FAO, 2020). Tropical grasslands in the BLA are mostly managed grasslands, i.e. pastures (Text S.III-2), that occur when anthropogenic and climatic disturbances trigger a change of the vegetation from forest to savanna to pasture (Pivello, 2011), although also the direct clearing of tropical forests for cattle pastures has been recognised as a continuous

process in the Amazon (Arvor et al., 2012; Armenteras et al., 2013; Navarrete et al., 2016), and across Latin America (Wassenaar et al., 2007). Pastures in the Brazilian Amazon may also be the result of abandoned agricultural lands (Carmenta et al., 2013). Grassland fires are sustained by the grass fuel accumulated during the growing period that desiccates from the beginning of the dry season (Soares, 1990; Brunel et al., 2021). As a result of the high fire frequency to improve soil fertility and control pests, we find grassland fires to be of moderate size, duration and intensity, which are controlled by fuel availability, and to have high rates of spread associated with the easily flammable fuel (Fig. III-5, Table III-1). Our results are in line with the findings by Archibald et al. (2013), who described fires in tropical grasslands as frequent with variable size and duration, which we assume depends on the anthropogenic treatment of the land. It is important to note that, as it occurs in savannas, where the balance between grasses and woody vegetation can be altered by anthropogenic and climatic drivers, grasslands can also experience those shifts. Depending on the severity and frequency of burning and grazing, pasture composition and development can vary to a great extent (Rufin et al., 2015). Gutiérrez-Vélez et al. (2014) revealed how different vegetation stages in Amazonian pastures can lead to changes in fire regimes from promoting to inhibiting burnings, e.g. fires can spread rapidly in homogeneous pastures without firebreaks, while pasture heterogeneity with scattered patches of less flammable vegetation may decrease fire spread. However, if those patches are fallows or secondary forests, fire spread in that same location may increase during dry years (Schwartz et al., 2015). Intensification of livestock activity is slowly bringing along management techniques where fire is less present (Parente and Ferreira, 2018; Vale et al., 2019).

The prominent human signature of the fire regime in agricultural lands was underlined by Archibald et al. (2013), who identified a pyrome characterised by small and cool fires under high human influence that occurred in regions of deforestation and agriculture. Small-scale farmers and indigenous people ignite fires regularly in the slash-and-burn cultivation technique (Sorrensen, 2000; Bowman et al., 2011; Thomaz and Rosell, 2020), which involves the clearing of forests or woodlands, the subsequent burning of the removed vegetation once it is dry and the exploitation of the field for several years (Junqueira et al., 2016). Regular fires provide a nutrient-rich layer of ash and control weed and pest invasion (Metzger, 2002;

Bonaudo et al., 2014). However, the plot's productivity decreases over time due to the progressive depletion of soil nutrients (Holscher et al., 1996), forcing farmers to move to another cultivable area systematically eroding forests inward from the forest-agricultural edges (Nobre et al., 2016; Coe et al., 2017). Thus, the ancient form of land management becomes unsustainable with intensification (Jakovac et al., 2017; Villa et al., 2018; Rebola et al., 2021). Especially in dry years, land management fires both in agriculture and grasslands may escape beyond the field limits and cause damages in the surrounding forests (Aragão et al., 2018). In this line, Uriarte et al. (2012) stated that drought severity can double the fire risk in areas predominantly covered by agricultural fields in western Amazonia. We find that the fire regime in agricultural areas consists of fires of small size, short duration, moderate intensity and low rates of spread (Fig. III-5, Table III-1). Fire sizes and rates of spread are similar to those in deciduous forests, while intensities are usually higher in agriculture, sometimes reaching values similar to grassland fires if large amounts of dry agricultural material are burned. Nowadays, just as in cattle pastures, more intensive fire-avoiding agriculture is expanding to support growing populations by increasing production (Gollnow and Lakes, 2014; Zalles et al., 2019).

The larger number of fires and amount of burned area identified by the FT dataset compared with the GFA is the result of three main factors: (1) the GFA algorithm does not allow the same pixel to burn twice in the same year, limitation that does not exist in the FT algorithm; (2) due to the lower spatial resolution of the FT's fire-data input, fires with sizes smaller than one fire-data pixel are attributed a size of 0.86 km<sup>2</sup> regardless; (3) the detection of active fires used by the FT algorithm poses an advantage over burned areas under relative cloudiness or overstorey vegetation since the former is triggered by temperature anomalies (Giglio et al., 2016) that may sometimes be captured under those circumstances (Humber et al., 2019). Our conservative approach in the delimitation of individual fires can partly explain the smaller number of large and/or long fires identified by the FT algorithm. Since it considers MODIS fire data pixels with missing data or obscured by clouds as non-fire pixels, individual fires are prevented from growing into the direction of adjacent pixels labelled as "unknown" or "clouds". This may limit potential fire expansion when clouds obscure existing fire pixels on the ground. Both the GFA's underestimation of burned area and the overestimation of fire duration, as conceded by the authors of

the GFA algorithm (Andela et al., 2019a), lead to a tendency towards identifying lower rates of spread than the FT algorithm. The same behaviour was observed in the comparison Andela et al. performed between the GFA's rates of spread and those by the US Forest Service.

The larger amount of burned area detected in agricultural lands in the GFA is a result of its higher spatial resolution, which clearly poses an advantage in detecting small cropland fires. Conversely, we identify a higher number of forest fires due to the detection process of the active fires used by the FT vs. the burned areas used by the GFA. The thermal channels of the sensor may still capture active fires in the presence of canopy cover, while changes in surface reflectance are easier to be obscured. Apart from the limitations derived from the input fire data, uncertainties in the number of fires in the different land-cover types may have partly originated from the input land-cover data as well. The same land-cover product is used in both algorithms (MCD12Q1, UMD scheme), but while the GFA uses collection 5.1, FT uses collection 6. The latter includes refinements and new features that may cause significant changes in the land-cover classification maps. Moreover, the specifics of the decision process to assign a dominant land cover to the individual fires is not described in the work by Andela et al. (2019a) and may vary from the one that is applied in the FT algorithm, contributing to discrepancies in the proportion of burned area in the different land-cover types. Additional validation of our results with future individual fire datasets will contribute to a better understanding of the goodness of the FT's estimates of fire parameters. The FT algorithm will benefit from incorporating higher spatial resolution data and sub-daily fire information, as well as from evaluating the performance of the methodology in different locations and/or broader scales.

Evolving biophysical and socio-economical aspects influence the relationships between fire, vegetation, climate and human activities, which make fire regime classifications dynamic (de Faria et al., 2017; Staal et al., 2020). Thus, it is imperative to capture land-cover heterogeneity and fire regime variability to adapt the models to a rapidly changing scenario. In this regard, our study focusing on fire regimes in the BLA poses an advantage compared to global pyrome classifications since fire drivers vary depending on the scale of the measurements and the study



area. Keeping track of the spatial and temporal heterogeneity of fire drivers is especially relevant in a global conservation priority hotspot like the Amazon, which is witnessing increased anthropogenic pressures. In our study, the application of the individual fires approach in the FT algorithm allows not only to estimate single fires size, duration and rate of spread, as the GFA dataset does, but also the aggregated intensity of each event for the first time in the area. Fire models show a deviation in fire activity from eco-climatic fire regimes towards anthropogenic fire regimes (Le Page et al., 2010; Chen et al., 2016; Lasslop and Kloster, 2017), in which land-cover changes play a significant role. Nowadays, human representation in fire-enabled DGVMs has been identified as a research priority (Marchal et al., 2017; Forkel et al., 2019; McLauchlan et al., 2020) in order to simulate current fire patterns and emissions, and capture their impacts. The fire regimes we have identified in this study for tropical land-cover types can be used to optimise the parametrization of human ignitions and, thus, make progress in projecting the impacts of future land-cover changes on associated fire regimes. Besides, a better fuel characterization in the models means that adapted firefighting strategies can be planned, and evaluations of the current fire regimes simulated by process-based fire models can be performed.

## 5 Conclusions

To capture the regional heterogeneity in burning characteristics is key to assess the specific impacts and further implications of different fire regimes. To this purpose, we employ the novel FT algorithm that draws upon remotely sensed fire and land-cover data and applies network theory to identify individual fires in the BLA over the period 2002-2020. The FT algorithm estimates fire size, duration, rate of spread, and intensity - provided for the first time in the Amazon - and recognises six different land cover-specific fire regimes described qualitatively as follows:

- Savanna: large, long, intense, fast-spreading fires
- Evergreen forests: large, long, intense, moderate spreading
- Grasslands: moderate size, duration, and spread, fast spreading
- Woody savannas: moderate size, duration, intensity and spread
- Croplands: small, short, moderate intensity, slow spreading

- Deciduous forests: small, short, low intensity, slow spreading

Our results align with previous studies that show how humans influence fire regimes by changing fuel type, structure and continuity as well as by controlling ignition sources, and contribute new data to the challenge of improving our understanding of the specific combination of fire attributes that define current human-dominated fire regimes. The information delivered here can help to better parametrise different fire regimes in DGVMs for more precise projections of future fire regimes and their effects.

## Acknowledgments

Open Access funding enabled and organized by Project DEAL. Authors want to thank the Potsdam Institute for Climate Impact Research for its high-performance computing facility. AC-C acknowledges the partial funding from the BMBF- and Belmont Forum-funded project “CLIMAX: Climate services through knowledge co-production: A Euro-South American initiative for strengthening societal adaptation response to extreme events” (FKZ 01LP1610A), and the FirEUrisk Project (H2020-LC-CLA-2018-2019-2020). GP-O was funded by a Research Fellowship of La Caixa Foundation. DT was partly supported by the State of Brandenburg through the Ministry of Science and Education (grant to Bookhagen B).

## Supplementary material

### Text S.III-1 Fire variables in the FireTracks (FT) dataset

The FT algorithm (Traxl, 2021) computes four key variables of individual fires: size (km<sup>2</sup>), duration (d), intensity (MW) and rate of spread (km<sup>2</sup>/d). Fire size reveals traits of the fuel type, load and flammability. It is commonly used to calculate biosphere-atmosphere emissions and fluxes (Strauss et al., 1989; Malamud et al., 1998). Fire intensity is defined as the rate of energy released per pixel and serves as a measure of the amount of biomass combusted (Wooster et al., 2005; Ichoku et al., 2008, Kumar et al., 2011). Therefore, it is directly related to fire emissions of gases and aerosols, and to the magnitude of the damage to the vegetation (Kaiser et al., 2012; Ichoku and Ellison, 2014). Intensity fluctuates with local variations in the amount and condition of the fuel, and wind characteristics (Roy and Kumar, 2017). Fire size and intensity are to some extent related because more intense fires usually result in larger fires (Fig. S.III-4) (Laurent et al., 2019). Fire rate of spread, the daily amount of area burned by fire, is estimated as the ratio between fire size and duration. It is mainly driven by wind, moisture, and slope (Spessa et al., 2013).

**Text S.III-2** Land-cover classes description in the FT dataset

The FT algorithm employs the MODIS MCD12Q1 Land Cover Type collection 6 product, which maps global land cover at 500-m spatial resolution every year (Friedl and Sulla-Menashe, 2019). The product is created using supervised classification of reflectance data from the MODIS sensors on-board the Terra and Aqua satellites. In this study, we use the following land-cover types from the classification scheme of the University of Maryland (UMD):

- *Croplands*: at least 60% of area is cultivated cropland
- *Cropland/Natural Vegetation Mosaics*: mosaics of small-scale cultivation 40-60% with natural tree, shrub, or herbaceous vegetation
- *Deciduous Broadleaf Forests*: dominated by deciduous broadleaf trees (canopy > 2 m). Tree cover > 60%
- *Evergreen Broadleaf Forests*: dominated by evergreen broadleaf and palmate trees (canopy > 2 m). Tree cover > 60%
- *Grasslands*: dominated by herbaceous annuals (< 2 m)
- *Mixed Forests*: dominated by neither deciduous nor evergreen (40-60% of each) tree type (canopy > 2 m). Tree cover > 60%
- *Savannas*: tree cover 10-30% (canopy > 2 m)
- *Woody Savannas*: tree cover 30-60% (canopy > 2 m)

We create the following aggregated land-cover classes from the list above to feed the FT algorithm and produce the individual fires dataset:

- Croplands: *Croplands* and *Cropland/Natural Vegetation Mosaics*
- Deciduous forests: *Deciduous Broadleaf Forests*
- Evergreen forests: *Evergreen Broadleaf Forests* and *Mixed Forests*
- Grasslands: *Grasslands*
- Savannas: *Savannas*
- Woody savannas: *Woody Savannas*

These aggregated land-cover classes correspond to the following categories of the Phytogeographical classification of the Brazilian vegetation (IBGE, 2012) and the Land-use classification scheme for anthropic areas (IBGE, 2013) for croplands and grasslands:

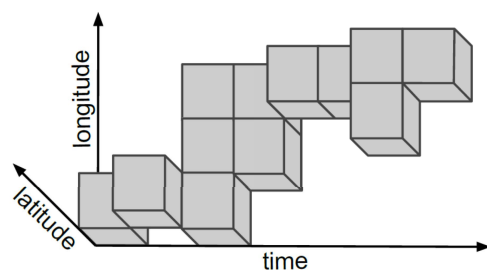
- Croplands: *culturas temporarias* and *permanentes, cultivo agroflorestal*
- Deciduous forests: *floresta estacional semidecidual*

- Evergreen forests: *floresta ombrófila densa* and *aberta*
- Grasslands: *pastagens*
- Savannas: *cerrado* (tree cover 10-30%)
- Woody savannas: *cerrado* (tree cover 30-60%); similar to the class *cerradão* described in Ribeiro and Walter (2008).

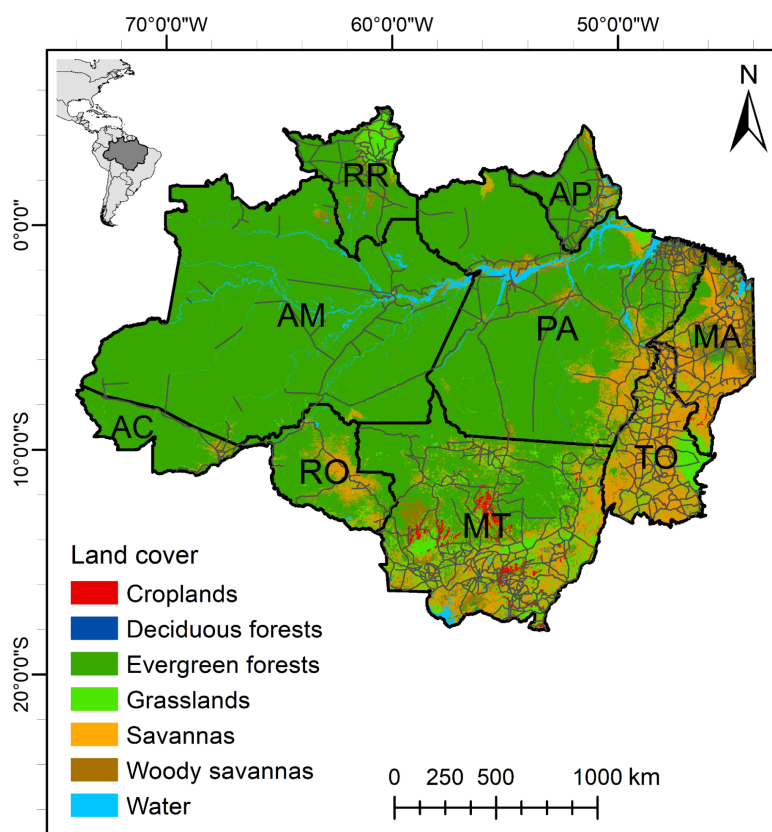
See IBGE (2012; 2013) for an exhaustive description, floristic composition and detailed pictures of the different land-cover classes.

Both the FT and GFA datasets employ the UMD land-cover scheme of the MODIS MCD12Q1 product and therefore, share the same land-cover classes. However, for the comparison of the fire variables in the different land covers estimated by the FT vs. Global Fire Atlas (GFA, Andela et al., 2019b), it is necessary to further aggregate our land-cover types into four final classes to match those given in the GFA dataset:

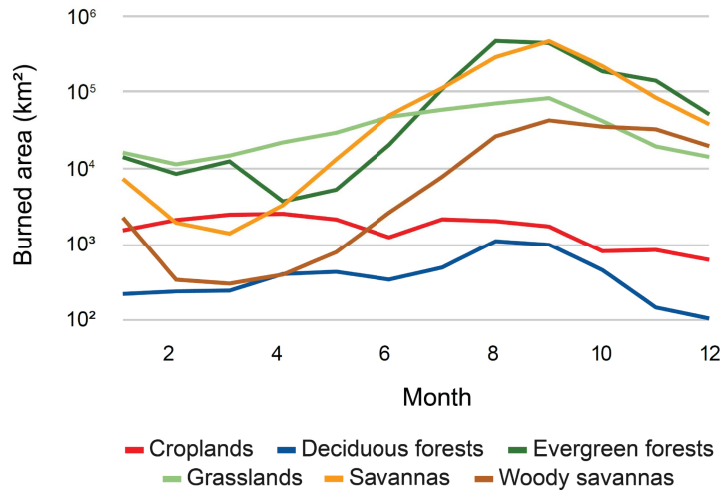
- Croplands
- Forests: Evergreen forests and deciduous forests
- Grasslands
- Savannas: Savannas and woody savannas



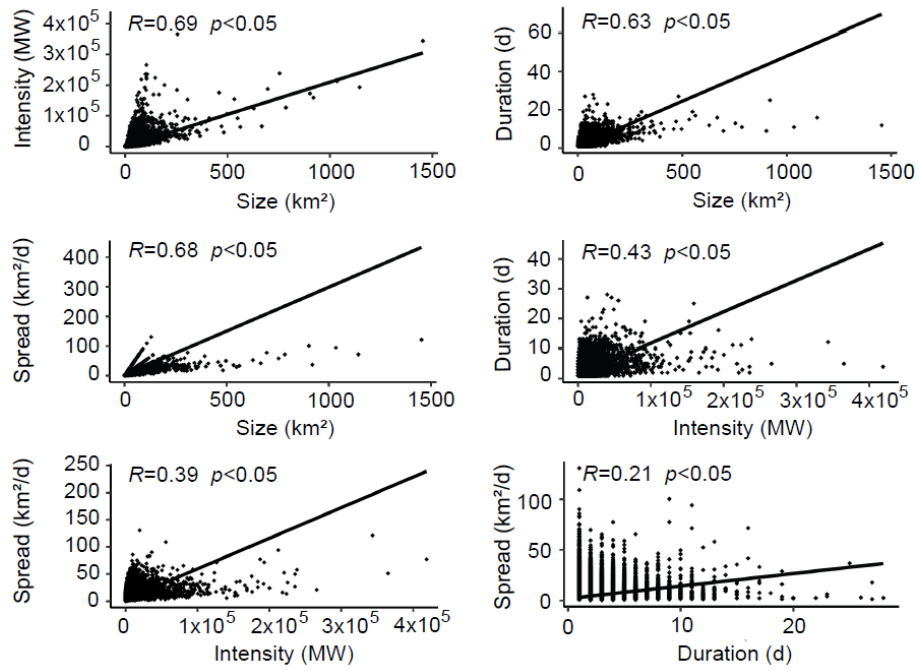
**Figure S.III-1** Sketch of an individual fire in the FireTracks dataset propagating in space and time. Each cube depicts a MODIS 1-km size active fire (MOD/MYD14A1) within the individual fire. A temporal axis is added to the MODIS latitude and longitude coordinates and spatio-temporal connected active fires are identified as the components of the individual fire



**Figure S.III-2** Land-cover spatial distribution in the Brazilian Legal Amazon in 2001 (Friedl and Sulla-Menashe, 2019), at the beginning of the analysed period (2002-2020). The inserted map shows the location of the BLA (in dark grey) within South America. The study area comprises the states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO), and part of Maranhão (MA). Black lines are political boundaries. Grey lines indicate the location of the main national roads (IBGE, 2014). The few small deciduous forest spots are not visible at the scale of the map



**Figure S.III-3** Monthly burned area distribution in the different land-cover types in the FireTracks dataset ( $n = 857,942$ ) in the Brazilian Legal Amazon over the period 2002-2020. Y-axis is in logarithmic scale



**Figure S.III-4** Scatter plots of the fire variables in the FireTracks dataset ( $n = 857,942$ ) plotted against each other. The Pearson correlation coefficient ( $R$ ),  $p$ -value and the ordinary least squares regression line are shown in each panel

**Table S.III-1** Distribution of the fire variables in the FireTracks (FT) and Global Fire Atlas (GFA, in italics) datasets in the Brazilian Legal Amazon (2003-2016)

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Size (km <sup>2</sup> )	0.86	0.86	2.58	4.16	4.29	12.88	1453.67
	<i>0.21</i>	<i>0.21</i>	<i>0.86</i>	<i>3.96</i>	<i>2.36</i>	<i>13.51</i>	<i>2915.63</i>
Duration (d)	1	1	1	1.14	1	2	27
	<i>1</i>	<i>1</i>	<i>3</i>	<i>5.33</i>	<i>8</i>	<i>17</i>	<i>80</i>
Spread (km <sup>2</sup> /d)	0.43	1.72	2.58	4.11	5.15	9.45	130.5
	<i>0.03</i>	<i>0.18</i>	<i>0.36</i>	<i>0.65</i>	<i>0.64</i>	<i>2.06</i>	<i>124.98</i>

Size, duration:  $n_{FT} = 652,892$ ,  $n_{GFA} = 443,863$ ; rate of spread:  $n_{FT} = 487,347$ ,  $n_{GFA} = 315,648$

**Table S.III-2** Distribution of the fire variables in the FireTracks dataset in the Brazilian Legal Amazon (2002-2020)

	Min.	1st Qu.	Median	Mean	3rd Qu.	95th	Max.
Size (km <sup>2</sup> )	0.86	0.86	2.58	4.15	4.29	12.88	1453.67
Duration (d)	1	1	1	1.14	1	2	27
Intensity (MW)	1.7	18.6	49.6	357.5	169.6	1226.9	418,976.1
Rate of spread (km <sup>2</sup> /d)	0.43	1.72	2.58	4.1	5.15	10.59	130.5

Size, duration, intensity:  $n = 857,942$ ; rate of spread:  $n = 639,579$



## Chapter IV

# Spatio-temporal patterns of extreme fires in Amazonian forests

Cano-Crespo A, Traxl D, Thonicke K (2021)

An edited version of this chapter has been published in the European Physical Journal Special Topics 230, 3033-3044

## **Abstract**

Fires are a fundamental part of the Earth System. In the last decades, they have been altering ecosystem structure, biogeochemical cycles and atmospheric composition with unprecedented rapidity. In this study, we implement a complex networks-based methodology to track individual fires over space and time. We focus on extreme fires - the 5% most intense fires - in the tropical forests of the Brazilian Legal Amazon over the period 2002-2019. We analyse the interannual variability in the number and spatial patterns of extreme forest fires in years with diverse climatic conditions and anthropogenic pressure to examine potential synergies between climate and anthropogenic drivers. We observe that major droughts, that increase forest flammability, co-occur with high extreme fire years but also that it is fundamental to consider anthropogenic activities to understand the distribution of extreme fires. Deforestation fires, fires escaping from managed lands, and other types of forest degradation and fragmentation provide the ignition sources for fires to ignite in the forests. We find that all extreme forest fires identified are located within a 0.5-km distance from forest edges, and up to 56% of them are within a 1-km distance from roads (which increases to 73% within 5 km), showing a strong correlation that defines spatial patterns of extreme fires.

## **1 Introduction**

Fire is an Earth system process that has been shaping vegetation dynamics and influencing atmospheric composition for millions of years. Humans have been using fire to manage the landscape for millennia (Marlon et al., 2008; Bowman et al., 2011; Lewis et al., 2015). Centuries of experience in managing fuel to lower fire risk and maintain a diverse landscape is captured in traditional and often indigenous knowledge in many tropical semi-arid regions, such as African savannas, Australia or the Brazilian cerrado (Mistry et al., 2005; Pivello, 2011). However, over the past decades fires have often been used as a cheap tool in deforesting tropical forests, which are not adapted to fires and undergo significant alterations in composition, structure and functions (Cochrane and Schulze, 1999; Brando et al., 2014). In the Brazilian Legal Amazon (BLA), about 4600 km<sup>2</sup> of forest were lost to deforestation in low (2012) and up to 27800 km<sup>2</sup> in high (2004) deforestation years (INPE, 2021a).

The establishment and enforcement of the Action Plan to Prevent and Control Deforestation in the Brazilian Legal Amazon (PPCDAm) in 2004, together with the Soy Moratorium in 2006, and the Zero-Deforestation Cattle Agreements in 2009 allowed to progressively reduce deforestation rates from 2005 onwards (Nepstad et al., 2014; Gibbs et al., 2015). While the use of fire in deforestation was an accepted paradigm for a long time, Aragão et al. (2018) suggested a decoupling between deforestation and fire because the decrease in fire activity was not as strong as the decline in deforestation during the period 2003-2015. However, Libonati et al. (2021) revisited the decoupling hypothesis recently and found a much weaker decoupling for the same period, which consequently reinforces the role of deforestation as a major driver of fire in Amazonia. Management fires that escaped from agricultural lands and cattle pastures in previously deforested areas into the surrounding forests became a large driver of forest burning (Silva Junior et al., 2018). Despite reduced deforestation, fire frequency increased in drought years which is usually linked to anomalously warm phases of the tropical eastern Pacific (related to the El Niño Southern Oscillation, ENSO) and the northern Atlantic oceans (related to the Atlantic Multidecadal Oscillation, AMO).

Anomalously warm Sea Surface Temperature (SST) in the tropical North Atlantic weakens northeast trade wind moisture transport during the summer resulting in reduced rainfall during the dry season especially in western and southwestern Amazon (Zeng et al., 2008; Lewis et al., 2011). Warm SST anomalies in the equatorial Pacific suppress convection and subsequent rainfall over the northern, central and eastern Amazon (Panisset et al., 2018; Jimenez et al., 2018; Silva Junior et al., 2019). A combination of eastern Pacific and tropical north Atlantic warming may cause more severe, prolonged and/or widespread droughts (Yoon and Zeng, 2010; Marengo et al., 2011; Coelho et al., 2012; Zou et al., 2016). In addition to extreme droughts, ongoing climate change has already influenced rainfall seasonality in the Amazon basin, by delaying the onset of the rainy season at the end of the calendar year which is projected to continue in the future (Marengo et al., 2018). This is not only putting the functioning of the tropical rainforest at risk but also the livelihoods of local communities living from the goods and services the Amazon rainforest provides to them (Nobre et al., 2016).

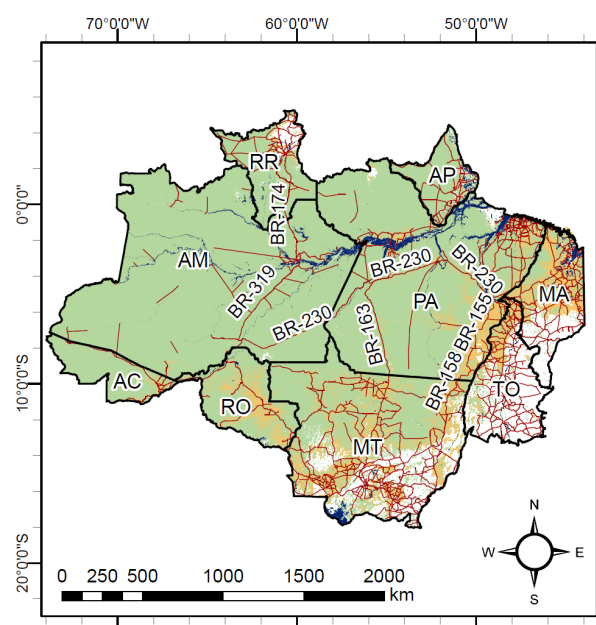
In the vast Brazilian Amazonia, ground-based information on fire occurrence and impact on vegetation is scarce or anecdotal. High-resolution data are required to determine fire regimes and their respective changes caused by climate and human LUC (Silvestrini et al., 2011; Gutiérrez-Vélez et al., 2014; Roy and Kumar, 2017). Remotely sensed data on fire occurrence (active fires) (Giglio et al., 2016) and extension (burned areas) (Giglio et al., 2018) enable us to fill this data gap and explore large and diverse areas such as the Brazilian Legal Amazon of more than 5 million km<sup>2</sup> in size.

While complex network approaches have been applied to examine extreme rainfall events (Boers et al., 2014), long-term rainfall variability (Ciemer et al., 2019), continental moisture transport (Zemp et al., 2014) and climatic factors influencing global mean temperature (Goswami et al., 2013), they have not been used so far to explore fire extremes. We apply the complex networks-based methodology developed in Traxl et al. (2016b) to fire data for the first time. We implement this novel methodology to identify individual fires and track their evolution over space and time. The advantages of such an individual-fires approach have been highlighted in a recent study by Andela et al. (2019a). Thus, it is possible to calculate the integrated fire intensity for individual fires, and use it for the definition of extreme events. In this study, we define extreme fires as the 5% most intense fires. This subset of extreme fires is responsible for almost 30% of the total burned area in the BLA over the study period 2002-2019. We compare spatial occurrence and interannual variability of extreme fires in evergreen forests of the BLA and interpret both spatial and temporal patterns in relation to large-scale climate events, and to anthropogenic drivers such as deforestation and road development. We address the following objectives: (1) apply a novel network-based methodological approach that enables us to identify individual fires for the evaluation of spatio-temporal dynamics of extreme fires in Amazonian evergreen forests; (2) Inspect spatio-temporal differences in the distribution of extreme forest fires in years with diverse climatic conditions and degrees of anthropogenic pressure; (3) Identify potential impacts of climatic drivers such as the ENSO- and AMO-associated severe droughts, as well as anthropogenic drivers such as deforestation and distance from roads and forest edges on the spatio-temporal variability of extreme fires.

## 2 Methodology

### 2.1 Area of interest

We define our study area following the boundaries of the Brazilian Legal Amazon (BLA), a political concept conceived to plan and promote regional development. It encompasses the states of Acre (AC), Amapá (AP), Amazonas (AM), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR), Tocantins (TO) and part of Maranhão (MA) (ca. 5 million km<sup>2</sup>).



**Figure IV-1** Extension of tropical evergreen forests in 2018 (Friedl and Sulla-Menashe, 2019) (green shaded area) and cumulative deforested area over the period 1988-2018 (INPE, 2021a) (orange shaded area) in the different states of the Brazilian Legal Amazon: Acre (AC), Amapá (AP), Amazonas (AM), Maranhão (MA), Mato Grosso (MT), Pará (PA), Rondônia (RO), Roraima (RR) and Tocantins (TO). Main rivers are depicted in blue. Dark red solid lines indicate the geographical location of main roads (IBGE, 2014). Primary roads in the tropical forest are labelled. The Trans-Amazonian highway (BR-230), the most extensive project ever planned in the Amazon tropical forest, runs along 4000 km from the state of Paraíba in the northeast region of Brazil to the state of AM. The BR-163 links Cuiabá, in central Brazil, and Santarém (PA), on the southern margin of the Amazon river, connecting crop production centres in MT with the international port of

Santarém. The BR-158 and BR-155 were planned to connect agricultural poles in northeastern MT and the port of Marabá (PA). The BR-319 runs through a pristine area of the Amazon tropical forest from Manaus (AM) to Porto Velho (RO) as an alternative to the waterway to transport products from the Manaus Free Trade Zone to São Paulo. The BR-174 connects Manaus (AM) with the state of RR and continues to Venezuela, being the only road connection of the state of RR with the rest of the country

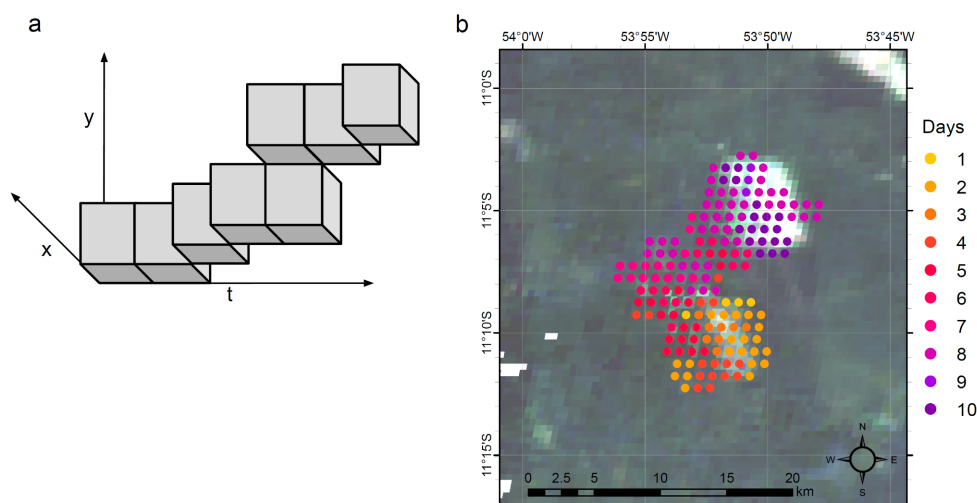
Approximately, 66% of this territory was covered by tropical evergreen forests in 2018 (Friedl and Sulla-Menashe, 2019) (Fig. IV-1), on which we focus in the present study. Apart from the Amazon biome, the BLA also includes part of the Cerrado biome, along southern MT, TO and MA, and part of the Pantanal biome in southwestern MT (IBGE, 2019).

## 2.2 Data

We retrieve the Thermal Anomalies and Fire MOD14A1 and MYD14A1 C6 datasets over the period from 2002 to 2019 to feed our spatio-temporal fire clusters algorithm. These products, which register daily hot pixels in a 1-km sinusoidal grid, are provided by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensors on board the satellites Terra and Aqua (Giglio and Justice, 2015). Furthermore, we overlay the fire data with the annual 500-m IGBP classification scheme of the MODIS MCD12Q1 Land Cover Type C6 product in the previous year to select only those fires that occurred in evergreen forests (Friedl and Sulla-Menashe, 2019). Each 1-km resolution active fire has four 500-m resolution pixels with land-cover information. To assign a land cover to the fire clusters, we aggregate the land-cover information of all the constituent events within and select the class that covers at least 80% of the cluster area. If none of the landcover classes within the cluster reach that threshold, we discard the fire. Thus, we make sure that the fires we work with are really located in a particular land-cover type. Deforestation data is supplied by the PRODES project, which monitors clear cut deforestation in the BLA since 1988 (INPE, 2021a), and the road network is provided by the Brazilian Institute of Geography and Statistics (IBGE, 2005; 2014).

## 2.3 Data analysis

To aggregate fire data into spatio-temporal clusters that we can track over space and time, we employ network theory. In network theory, a complex system is represented as a graph. The individual parts of the system are represented by the graph's nodes, and their pairwise relations by edges. Here, we represent the MODIS fire and land-cover remote-sensing data as a graph. Pixels within the study region affected by fire constitute the nodes of the graph, while edges between them are created upon spatio-temporal proximity (Fig. IV-2a). We consider a pair of fire events as neighbours if they are in the same three-dimensional (latitude, longitude, time) Moore neighbourhood, and no spatial or temporal gaps are allowed. The structure emerging from the constructed edges between neighbouring fire events allows us to identify spatio-temporal fire clusters as the connected components of the graph (Fig. IV-2b). Details of the methodology used to determine the clusters computationally can be found in Traxl et al. (2016b).



**Figure IV-2** **a** Sketch of a spatio-temporal fire cluster propagating in space ( $x,y$ ) and time ( $t$ ). A temporal axis is added to the MODIS sinusoidal grid (longitude and latitude). MOD14A1 and MYD14A1 active fires constitute the nodes of the network, and edges indicate whether fires are neighbours on the spacetime grid. Connected nodes in the system generate the individual fire clusters. **b** High-resolution illustration showing the progression over space and time of an extreme fire registered in northeastern Mato Grosso in 2004. It lasted 10 days, starting on the 04.09.2004. Each dot represents an active fire within the extreme fire cluster, and the different colours indicate each of the time steps of the extreme fire cluster development. Background is the MODIS Nadir BRDF-Adjusted Reflectance (NBAR) 500-m resolution daily product (MCD43A4) (Schaaf and Wang, 2021) on the day when the fire started

Once the individual fires - i.e., spatio-temporal fire clusters - are identified, the integrated fire variables of their constituent fire events can be computed. Unlike in other studies where burned areas or single-pixel hotspots are employed, the individual-fires approach allows to determine which of them are extreme fires based on their integrated intensity, i.e. the Fire Radiative Power (FRP). We chose to analyse fire intensity (i.e. the radiant energy released by fires), because it is a crucial variable to estimate socio-ecological impacts of fires as well as burned biomass and fire-induced emissions (Crutzen and Andreae, 1990; Wooster et al., 2005). We select only extreme forest fires, meaning those fires whose intensity (FRP) was greater than or equal to the 95th percentile of the variables' distribution, i.e. the most intense 5% of the sample. Extreme fires largely contribute to the total forest burned, since 70% of the extreme fires are also within the 5% largest fires (by area) identified. In the context of the entire study period, extreme fires accounted for almost 70% of the total integrated intensity, and almost 30% of the total integrated burned area in the BLA forests (data not shown). Henceforth, we will refer to the extreme individual fires in Amazonian tropical forests simply as extreme fires.

## 3 Results and Discussion

### 3.1 Temporal variability

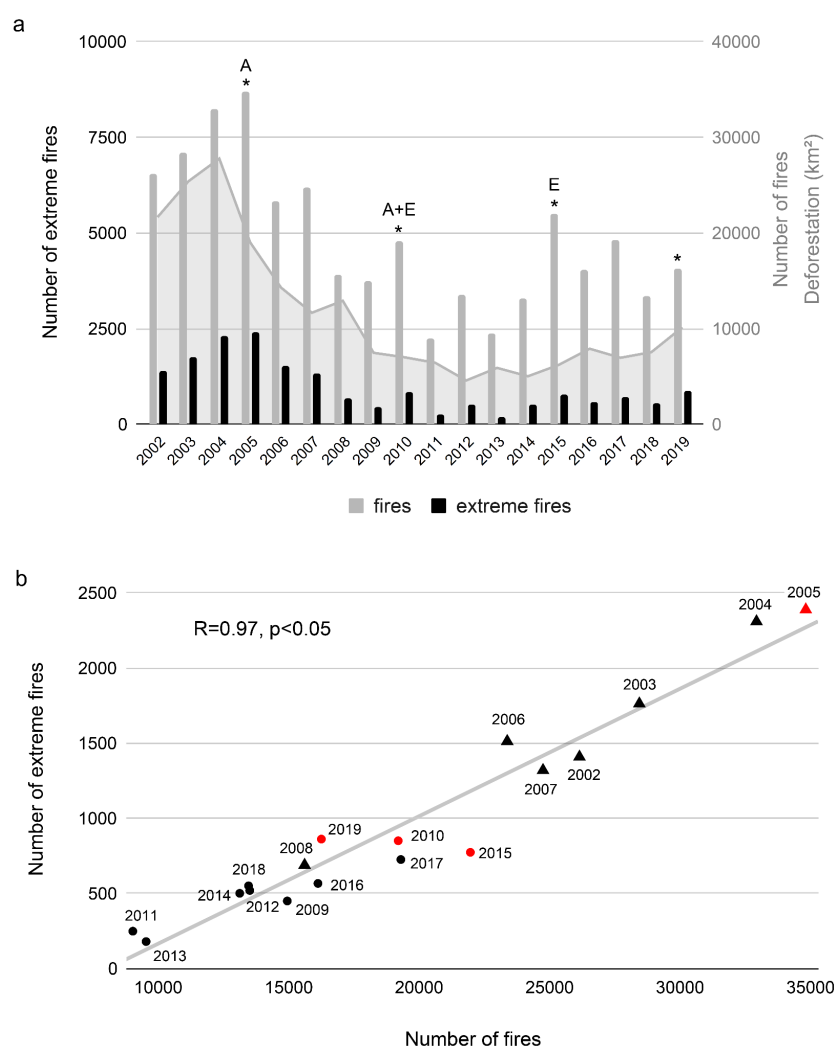
We find a total of 351,991 fire clusters in tropical evergreen forests of the BLA over the period 2002-2019, which account for 43% of the total number of fire clusters registered in the 18-year period in the region. Of those, a total of 17,606 fire clusters were categorised as extreme events - the most intense 5% - and selected from the sample. We observe that the interannual variability of extreme forest fires shows a strong, positive relationship with drought and/or high deforestation years (Fig. IV-3a). When plotting the annual number of extreme fires against the total number of fires, we find a strong linear correlation with a Pearson correlation coefficient of 0.97. The highest ratios are observed at the beginning of the study period (2003-2006) when deforestation rates were the highest (Fig. IV-3b).

The most severe droughts registered in Amazonia in the twenty-first century were linked to ENSO and/or AMO events. As several studies have reported, those events are associated with increased mean temperature, decreased levels of rainfall, and an extended dry season (Fu et al., 2013; Marengo and Espinoza, 2016; Panisset et al., 2018). The year 2005 witnessed an extensive AMO-associated drought identified as a 1-in-100-year event in the BLA (Marengo et al., 2008; Lewis et al., 2011). The 2010 drought started during an El Niño event and then became more intense with the anomalous warming of the tropical north Atlantic (Lewis et al., 2011; Marengo et al., 2011). The combination of both phenomena caused the 2010 drought to be more severe and remain for longer than the 2005 drought (Jiménez-Muñoz et al., 2016). Lewis et al. (2011) found that ca. 60% more area was affected by the drought in 2010 compared to the year 2005. At the end of the year 2015 and beginning of 2016, one of the greatest El Niño events of the last decades - combined with the regional warming trend - struck the region with unprecedented warming and the most extensive area under extreme drought severity (Cunha et al., 2019; Silva Junior et al., 2019).

Of the total deforestation in the BLA over the study period, 45% occurred in the first four years (2002-2005) (INPE, 2021a), peaking in 2004 (Fig. IV-3a). At that time, as Aragão et al. (2008) stated, land conversion through deforestation was one of the main drivers of fire dynamics in the region. Through successful public policy



(PPCDAm) and later interventions in beef and soy supply chains (Arima et al., 2014; Tasker and Arima, 2016), a declining deforestation trend was observed from 2005 onward (Fig. IV-3a). However, as already discovered by Aragão and Shimabukuro (2010), forest fire numbers did not show the same decrease as deforestation rates at that time because most of the burned forests were driven by escaping fires from managed land (Silva Junior et al., 2018). The increase in fire numbers observed in the most recent years (Fig. IV-3a) has been linked to the current increased deforestation activities (Barlow et al., 2020).



**Figure IV-3 a** Annual amount of fires (grey bars, right y-axis) and extreme fires (black bars, left y-axis) in tropical forests of the Brazilian Legal Amazon over the period 2002-2019. The grey line (right y-axis) displays the annual deforested area. Labels A and E indicate the anomalous warming of the northern Atlantic (AMO) and tropical eastern Pacific (ENSO) oceans, respectively, which are related with reduced rainfall. Stars denote the selected years for the analysis. **b** Relationship between annual extreme fires and total fires. Triangles denote high deforestation years (above average for the period 2002-2019). Symbols of years selected for the analysis are shown in red

We find that extreme fire activity in Amazonian tropical forests upsurged during the three most severe droughts of the last 100 years in 2005, 2010 and 2015 (Fig. IV-3a), with a total of 2388, 850 and 773 extreme fires, respectively. The largest density of extreme fires over the evergreen forests of the BLA was observed in 2005 ( $7.2 \times 10^{-4}$  extreme fires/km<sup>2</sup> tropical forest) coinciding with high deforestation rates. High density values were also detected in the drought years of 2010 ( $2.5 \times 10^{-4}$  extreme fires/km<sup>2</sup>) and 2015 ( $2.3 \times 10^{-4}$  extreme fires/km<sup>2</sup>) with lower deforestation rates. The increase in extreme fires found in 2012 (519 events, Fig. IV-3a) may be related to the progressive grass invasion of burned forests described by Veldman and Putz (2011). Silvério et al. (2013) found that grasses advanced much faster into the burned forests between 2008 and 2011 - after the 2007 fires, than they did in the years 2004-2006. As a result of the accumulation of grassy fine fuel loads on the forest ground, forest fires became up to four times more intense. Thus, rapid colonisation by grasses contributed to create the scenario for more intense forest fires in 2012. We registered another increase in extreme fire activity in 2017 (725 events, Fig. IV-3a) that we connect to the extreme heat and widespread drought severity in the years 2015-2016. Jiménez-Muñoz et al. (2016) found that up to 13% of Amazonian tropical forests endured extreme drought at the beginning of 2016, which set the conditions for more extreme forest fires in 2017. On the other hand, the year 2013 was classified as exceptionally wet based on the positive rainfall anomalies and a short dry season (Aragão et al., 2018). These conditions did not promote high intensity forest fires and therefore, we observed the lowest number of extreme fires (179 events, Fig. IV-3a) over the study period in that year.

In the year 2019, in the absence of particular drought conditions, we find an increase of 57% in extreme fires compared to the previous year, and the highest number since 2007 (Fig. IV-3a). The density of extreme fires over the BLA in 2019 ( $2.6 \times 10^{-4}$  extreme fires/km<sup>2</sup> tropical forest) was even greater than in years when severe droughts struck the region, e.g. in 2010 and 2015 (Fig. IV-3a). In Amazonia, Barlow et al. (2020) observed three times as many active fires in August 2019 - typically the peak of the fire season (alongside September) - than in the same month in 2018. Also, Lizundia-Loiola et al. (2020) found a larger amount of burned area in Brazil in 2019 than in the previous year. Both studies align with our findings of increased extreme fire activity in the tropical forests of the BLA in 2019 compared to the

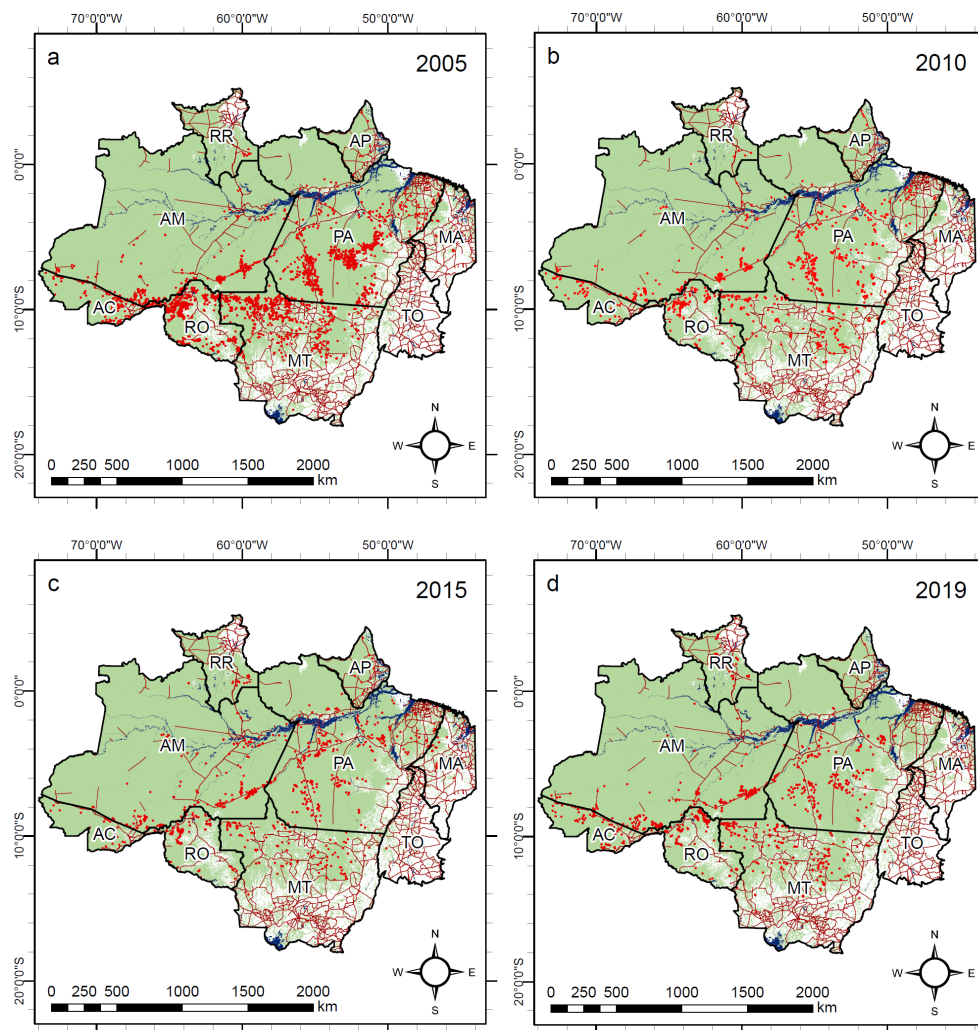
previous year. When we consider the most recent years, i.e. the time interval from 2007 to 2019, we find an above-average number of extreme fires in 2019. However, if set into the context of the entire study period (2002-2019), we observe that 2019 is below average. When taking this 18-year period into account, the highest extreme fire years are concentrated at the beginning of the time-series (Fig. IV-3a), or at the upper end when plotting numbers of extreme fires against numbers of fires (Fig. IV-3b). Lizundia-Loiola et al. (2020) also reported the 2019 annual area burned in Brazil being close to the long-term average. The increase in extreme fire activity which we also found in 2019 (Fig. IV-3a) has been associated with increasing deforestation rates by several studies (Fonseca et al., 2019; Montibeller et al., 2020; Silveira et al., 2020). In agreement with that, we find 34% more deforested area in 2019 than in the previous year, and the highest deforestation rate since 2009 (Fig. IV-3a). Clear-cut deforestation for agriculture and rangelands raises emissions of aerosols and greenhouse gases from fires used in the process (Morgan et al., 2019). In 2019, thick, dark smoke from the Amazon deforestation fires reached distant big cities, including São Paulo (Pereira et al., 2021), which received a lot of political attention and media coverage. Public awareness of the critical situation of the Amazon forests and the negative impact of these fires on public health increased during this episode (HRW, 2020).

### **3.2 Spatial variability**

Our study reveals differences in the spatial distribution of extreme forest fires as well as certain patterns that remain stable over the study period. Droughts co-occur with a high number of extreme fires in the years 2005, 2010 and 2015 (Fig. IV-3a), although there is some variability in the spatial distribution. We find a large number of extreme fires concentrated in the states of Acre, Rondônia, northern half of Mato Grosso and Pará in 2005 (Fig. IV-4a). This is consistent with previous studies that locate the epicentre of the AMO-driven drought of 2005 in western Amazonia (Aragão et al., 2007; Chen et al., 2011). In 2010, both the El Niño and warming of the tropical north Atlantic occurred simultaneously and areas in the southwestern Amazonia and the state of MT were especially affected, as reported by previous research (Lewis et al., 2011; Marengo and Espinoza, 2016), and as shown in Fig. IV-4b. In 2015, extreme fires concentrated in northeastern Amazonia (Fig. IV-4c) as a result of the impact of one of the strongest ENSO events on record (Chen et al.,

2017; Fonseca et al., 2017). By estimating the relative percentage difference between the extreme fires distribution per states in 2015 and 2005, the spatial shift becomes apparent. In 2015, the number of extreme fires increased only in the states of Roraima and Maranhão (157% and 47% of increase, respectively) compared to values in 2005. The most significant decrease in the number of extreme forest fires in 2015 was observed in Mato Grosso (83%), Rondônia (81%) and Acre (78%). This means, more extreme fires occurred in the southwestern states (MT, RO and AC) in 2005, but concentrated in the northern and eastern states (RR, MA) in 2015.

The fact that the drought in 2015 was more intense and extensive but registered lower fire activity than during the 2005 drought (Fig. IV-4a vs. Fig. IV-4c) points to deforestation as the dominant driver of extreme fires. It is known that forest fragmentation and edge effects from deforestation expose forests to warm conditions allowing fuel loads to dry out more rapidly and therefore, sustain higher-intensity fires (Uhl and Kauffman, 1990; Barlow and Peres, 2008). Thus, the high deforestation rate registered in 2005 (Fig. IV-3a) is linked to the high number of extreme fires in that year. We discover that every single extreme fire we identified in the tropical forests over the entire study period is within 0.5-km reaching distance from forest edges, i.e. deforested areas, activities related to mining and logging, as well as clearings for small ranching and farming, both legal and illegal. The states of Amazonas and Pará accounted for 73% of the evergreen forests in the BLA in 2018. However, while PA concentrated 32% of the total deforestation in the BLA over the period 2002-2019, AM accumulated only 8% of the total deforestation (INPE, 2021a). Tropical forests in PA have been more heavily impacted than in AM, mainly due to the higher number of roads developed in PA (Fig. IV-1, Fig. IV-4).

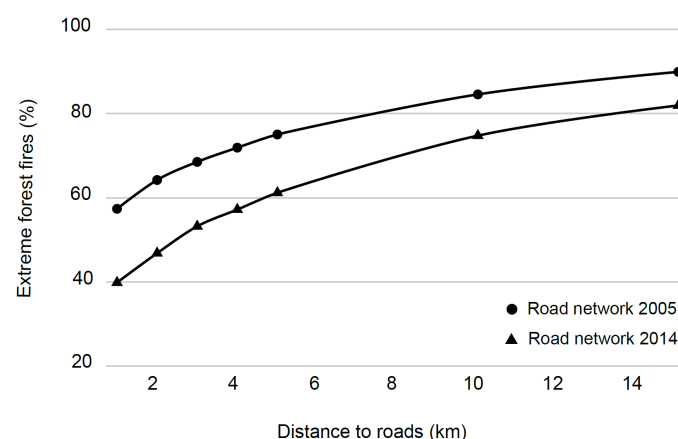


**Figure IV-4** Spatial distribution of extreme forest fires in the Brazilian Legal Amazon in **a** 2005, **b** 2010, **c** 2015, and **d** 2019. Fire clusters are represented by red points. Dark red solid lines indicate the geographical location of main roads (IBGE, 2014). The extension of the tropical evergreen forest (Friedl and Sulla-Menashe, 2019) is demarcated in green. See Figure IV-1 for names and details of the roads

There is a consensus that roads are directly and indirectly related to deforestation (Nepstad et al., 2001; Alves, 2002; Soares-Filho et al., 2004). The transportation network increases forest accessibility and rapid expansion of the agricultural frontier into the forests, which perpetuates forest degradation (Fearnside and de Alencastro Graça, 2006; Fearnside, 2007; Armenteras et al., 2017). The typical pattern of forest colonisation leads to the opening of secondary paths branching from main roads, which allow new settlers to penetrate further into the tropical forests. We observe a clear arrangement of extreme fires along roads, for instance following the Trans-Amazonian highway (BR-230), the largest infrastructure project through the tropical forest in the BLA (Fig. IV-1, Fig. IV-4). Another example is the characteristic

fire pattern in PA along a polygon formed by the highways BR-163, BR-230, BR-155 and BR-158, which connect agricultural and timber production centres with distribution ports (Fig. IV-1, Fig. IV-4).

We explore the spatial distribution of extreme fires with respect to the road network in 2005 (IBGE, 2005) and 2014 (IBGE, 2014) and find a strong correlation between them. We notice that 57% and 40% of the total number of extreme fires are within 1-km distance from roads in 2005 and 2014, respectively (Fig. IV-5). If the distance is expanded to a radius of 5 km from roads, we find 75% in 2005 and 61% in 2014 of the extreme fires within that area. We deduce that the higher number of extreme fires close to roads in 2005 compared to 2014 is related to the high deforestation activity reported in 2005 (Fig. IV-3a) and the need of a very large number of paths in the tropical forests to reach the deforestation sites. By the year 2014, following a significant drop in deforestation rates (Fig. IV-3a), road opening activities had decreased very much, and also an important number of the paths constructed in 2005 had been abandoned. Thus, the lower number of roads in use in 2014 led to a reduced number of extreme fires linked to roads. It is very important to consider that new unofficial or illegal unpaved roads are constantly being opened in the tropical forests (Barber et al., 2014), which makes it difficult to keep road maps in the region up to date. This suggests that even higher numbers of extreme fires may be connected to roads in Amazonian forests than quantified in our analysis.



**Figure IV-5** Cumulative number of extreme fires in the Brazilian Legal Amazon (in percentage) within various distances from the road network in 2005 (points) (IBGE, 2005) and 2014 (triangles) (IBGE, 2014). Input data is subject to uncertainty due to the lack of resources to register unofficial or illegal unpaved roads. Even higher numbers of extreme fires may be connected to roads in Amazonian forests than quantified here

The dominance of anthropogenic drivers on the spatial distribution of extreme forest fires is also observed in 2019, when significant fire activity was registered despite average climatic conditions. In that year, the highest deforestation rate in the BLA since 2009 helps to explain the high fire activity (Fig. IV-3a). The spatio-temporal link between deforestation and fire that was observed in the early 2000s has been reported again in the last years (Fonseca et al., 2019). We detected some unusual fire activity in the states of Roraima and the southern and central regions of Amazonas in 2019 (Fig. IV-4d), compared to the spatial patterns of extreme fires in the other years analysed. Thus, extreme fire distribution in RR and AM is likely to be related to ignition sources provided by increasing deforestation activities for agricultural expansion, the main driver of fire activity in the region in 2019 (Lizundia-Loiola et al., 2020). Agriculture frontier expansion increases the risk of escaping fires from managed agro-pastoral lands (Arvor, 2012; Cammelli and Angelsen, 2019). The current Brazilian government, strongly supported by the powerful agribusiness sector, operates to open the vast and ecologically sensitive Amazon rainforests to greater commercial exploitation (Rochedo et al., 2018; Senc  b   et al., 2020), which poses an additional threat to tropical forest conservation.

While global climate change has the potential to increase drought conditions, anthropogenic drivers of forest degradation (deforestation, roads, logging, mining, farming, etc.) provide the ignition sources that determine fire distribution in the sensitive tropical forests of the BLA (Fonseca et al., 2017; Brando et al., 2020). Furthermore, anthropogenic fire behaviour adapts to the eco-climatic conditions (Le Page et al., 2010; Staal et al., 2020). Even localised drought conditions may encourage anomalous increased anthropogenic fire activity through deforestation and land management (Morton et al., 2008). In line with this, we observe spatio-temporal correspondence between high extreme fire years and drought years and/or high deforestation years. According to our findings, all the extreme fires are a direct consequence of forest clearing, and therefore, they are always associated with forest edges. Among the activities responsible for creating forest edges, we find that roads are a prominent factor in defining the spatial distribution of extreme fires. Comparing the spatial patterns of extreme fires in years with different regional climatic conditions and degrees of human influence helps us to identify the most

affected areas in each case (Fig. IV-4). The individual-fires approach also allows us to flag locations that burn for the first time, e.g. are part of the pristine tropical evergreen forests or previously protected areas, and to disentangle the diverse and interrelated fire driving forces. Focus should be put on identifying the agents who cause fires, and applying specific measures to halt the fire-driven transformation of tropical Amazonian forests and, therefore, reduce its associated carbon emissions.

## **4 Conclusions**

In this study, we use a novel network-based representation of fire events in order to track and investigate local formations of spatio-temporal fire clusters of high intensity in evergreen forests of the BLA. Our findings are in line with previous studies underscoring that both climatic and anthropogenic factors determine the spatio-temporal distribution of extreme fires in the region. We observe that climatic extreme events define the interannual fluctuation of extreme fires but they also affect their spatial distribution. The epicentre/s of droughts induced by ENSO- and AMO-events or a combination of both, are usually spatially distinct in Amazonian tropical forests. The interannual variability and spatial distribution of deforestation also helps to explain extreme fire patterns in Amazonian tropical forests. The link between fire activity and deforestation was strong until the year 2005, after which policies implemented to prevent deforestation led to some spatio-temporal decoupling between both processes. However, in recent years, and especially in 2019, data suggest that the connection between fire activity and deforestation is getting stronger again. Spatially, all identified extreme fires were located within 0.5-km distance from forest edges, which are constantly growing as a consequence of forest-clearing for a wide range of purposes. Extreme fires are closely distributed along the roads that run through the Amazon tropical forests. Apart from augmenting forest flammability at the drier forest edges, roads allow further colonisation of the Amazon pristine forest bringing ignition sources into the forests through activities such as logging, grazing and farming. We find up to 57% of extreme fires within 1-km distance from roads and up to 75% if the distance is extended to 5 km. Our results highlight the relevance of properly assessing the synergistic effects of continued deforestation, ongoing climate change and fire to control the advancement of forest



degradation. This knowledge should feed into the strategies and policy mechanisms aimed to protect the undisturbed Amazonian forests.

## **Acknowledgments**

AC-C acknowledges the financial support from the IRTG 1740/TRP (2011/50151-0) funded by the DFG/FAPESP, and the BMBF- and Belmont Forum-funded project “CLIMAX: Climate services through knowledge co-production: A Euro-South American initiative for strengthening societal adaptation response to extreme events” (FKZ 01LP1610A). DT was also supported by the IRTG 1740/TRP and the State of Brandenburg (Germany) through the Ministry of Science and Education (grant to Bookhagen B). Authors want to thank the Potsdam Institute for Climate Impact Research for its high-performance computing facility.

# Chapter V

## Synthesis

## 1 Summary

This dissertation aimed to investigate the spatio-temporal fire dynamics in the BLA over the last two decades, especially in the tropical evergreen forests, and understand the processes that control current fire occurrence and distribution. Despite its critical importance for the Earth system, biodiversity and people, the combination of both climatic and anthropogenic factors have caused an increase in fire activity and carbon emissions over the last decades. Extreme droughts in the region have become more frequent and dry seasons have intensified, which translate into higher loads of dry fuel. Advancing deforestation, forest fragmentation and degradation, and land management activities provide the ignition sources for the fires to start. I particularly focused on the analysis of tropical forest edge burnings as a consequence of fires escaping from cattle pastures, agricultural lands and other means of forest fragmentation such as roads. I also concentrated on identifying the characteristics of the fires taking place in the different land-cover types as a way of improving the representation of various fire regimes in the DGVMs. Thus, [Chapters II, III and IV](#) contributed to disentangle the diverse fire driving forces in the BLA and to determine the dominant fire features in the different land-cover types. In the following, I summarise the findings of [Chapters II, III and IV](#) that address the three main research questions introduced in [Chapter I-3](#).

### 1.1 What are the anthropogenic drivers of tropical forest fires in the Amazon?

In [Chapter II](#) the spatial distribution of the burned area is analysed in three states of the BLA - Pará (PA), Mato Grosso (MT) and Rondônia (RO) - that concentrated most of the BLA's deforestation and shared large-scale anthropogenic pressure. Remotely sensed burned area maps were evaluated in 2008, a regular year, and 2010, an extreme drought year as a result of the combination of an ENSO event and a subsequent AMO event. Excluding savanna-type vegetation, most of the burned area was located in pastures in the three states in 2008, followed by tropical forests, except in MT where a large proportion of the burned area was found in agriculture. The amount of burned area increased significantly in 2010, especially in southeast PA and northeast MT. The larger increase in burned area was observed in forests in MT, and in pastures in PA and RO. The increase of burned area detected in deforested areas in 2010 was small in comparison to the changes in other

land-cover classes, and neither deforestation (2001-2010) nor forest degradation (2007-2011) had a significant relationship with the annual amount of burned area.

Despite the low correlation, a high proportion of burned area occurred in forests - between 15%-25% of the total in 2008, depending on the state -, which led me to analyse the fire distribution in old (2001-2006) vs. new (2007-2010) deforested areas. By doing that, it was possible to recognise burned areas from management fires in cattle pastures and agricultural lands established in previously deforested areas (old deforestation) vs. burned areas linked to the deforestation process itself (new deforestation). On average, 74% of the burned area in 2010 occurred in old deforestation, which together with the fact that most of the burned area was located in pastures in 2008 (30%-34% of the total, depending on the state), pointed to fires in managed lands as a pivotal driver of burning forests. A 3-step algorithm was specifically designed to identify those burned areas in forests caused by escaping fires from managed lands. In 2010, between 68% and 87% of the forest burned areas were adjacent to pasture burned areas. Conservatively, I estimated that between 32% and 52% of burned forest edges originated from escaping fires from pastures. A lower amount of burned forest edges are a consequence of fires that escape from agricultural lands (5%-22%, depending on the state). These results provided the first estimate of the contribution of managed lands to forest edge burning by escaping fires in the region.

## **1.2 How do fire regimes differ between the land-cover types in the Amazon?**

In [Chapter III](#) I expanded [Chapter II](#)'s study area to cover the entire BLA and extended the study period to the 19-year period from 2002 to 2020. I employed the recently developed FireTracks Scientific Dataset (FT), that contains individual fires, i.e. single fires delimited within burned areas. The FT network clustering algorithm processes remotely sensed data on fire occurrence and land cover, identifies individual fires, and tracks them over space and time. The individual fires approach allows to compute the variables - size, duration, intensity and rate of spread - of each individual fire for the study of changing fire regimes. The analysis of the fire variables revealed that the frequency distribution of fire size is best described by a truncated power law, where the lower values showed the highest frequencies, and few fires substantially larger result in mean values larger than the median values. The fire

duration frequency distribution followed a power law with few dominant low values (91% of the sample lasted one day). Fire intensity and spread showed a positively skewed log-normal frequency distribution that peaks at 10 MW and 1.72 km<sup>2</sup>/d, respectively. By estimating the integrated variables - size, duration, intensity and rate of spread - of individual fires in the different land-cover types, I identified six land-cover specific fire regimes.

The results described fires in savannas as large, long, intense and with high rates of spread. In evergreen forests, fires tended to be large, long and intense, too, but they usually had much lower rates of spread than savanna and grasslands fires. Compared to fires in savannas, fires in woody savannas were smaller, shorter, less intense and with slower rates of spread. Although grassland fires were smaller, shorter and less intense than savanna and evergreen forest fires, they may reach rates of spread close to those in savannas. Fires in croplands and deciduous forests were likely to be smaller, shorter, less intense and slower spreading fires than those in the rest of the land-cover types. Size, duration and spread were of the same order of magnitude in cropland and deciduous forest fires, but although the former usually endured higher intensities if large amounts of drying harvest residuals are in the fields. The findings constituted a comprehensive dataset of individual fires and their characteristics in the BLA, including intensity for the first time, in the different land cover-dependent fire regimes.

Due to the novelty of the FT dataset, [Chapter III](#) includes an exhaustive comparison of the FireTracks' fire size, duration and rate of spread estimates with those reported by the Global Fire Atlas dataset, the most extensive study on individual fires so far.

### **1.3 How do changing climatic conditions and other anthropogenic drivers impact the spatio-temporal distribution of high-intense fires in the Amazon tropical forests?**

The study in [Chapter IV](#) was developed in the same study area (BLA), during the same study period (2002-2019), and using the same database as in [Chapter III](#). However, in [Chapter IV](#), individual fires occurring in tropical evergreen forests became the focus of the analysis. The integrated fire intensity was used to identify extreme events, i.e. the 5% most intense fires. Apart from determining the amount of

biomass combusted and related emissions, fire intensity controls fire severity. It has been observed that even small shifts in fire intensities can increase tree mortality in Amazonian forests (Brando et al., 2014). I observed that the extreme fires accounted for almost 30% of the total burned area in the BLA forests during the study period. Interannual temporal and spatial fire distributions were examined and I discussed the climatic and anthropogenic drivers leading to such patterns. The results aligned with previous research revealing that the interannual variability of forest fires showed a strong, positive relationship with drought and/or high deforestation years.

During the three most severe droughts of the last 100 years in 2005, 2010 and 2015 (see Chapter I-2), extreme fire activity in Amazonian tropical forests upsurged. However, there were years when fire activity increased in the absence of particular drought conditions, as it was the case of the year 2019, when there was an increase of 57% in extreme fires compared to the previous year, and the highest number since 2007. The density of extreme forest fires over the BLA in 2019 was even greater than in years when severe droughts struck the region, e.g. in 2010 and 2015, and coincided with increased deforestation rates since 2017. Spatially, the study showed some interannual variability in the distribution of extreme forest fires as well as certain patterns that remain stable over the study period. The epicentre/s of droughts induced by ENSO- and/or AMO-events were usually spatially distinct in Amazonian tropical forests. At the same time, all the extreme fires concentrated within 0.5-km reaching distance from forest edges, and up to 57% of them were within 1-km distance from roads. While global climate change has the potential to increase drought conditions, anthropogenic drivers of forest fragmentation - deforestation, roads, logging, mining, farming, etc. - provide the ignition sources that determine fire distribution in the sensitive tropical forests in the BLA.

## **2 Main conclusions and implications**

Given the diversity of ways in which fire interacts with evolutionary processes, three emergent themes have been identified as research priorities in the review by McLauchlan et al. (2020). In order to gain understanding of the causes and consequences of future fires, it is needed: (1) to study fire across temporal scales, (2) to determine the drivers behind the ecological feedbacks involving fire, and (3) to

better characterise fire and its effects in models for the purpose of properly projecting fire behaviour and impacts in the future. In this dissertation I provide new insights into fire activity especially contributing to themes (2) and (3). Along [Chapters II, III and IV](#), I cover and discuss a variety of climatic and anthropogenic drivers that control fire occurrence and distribution in the BLA (2). Based on this knowledge, fire driving forces in the Brazilian Amazon, and particularly anthropogenic forces, can be better represented into fire models, which will improve the quality of the projections ([Chapter III](#)). In the following, the conclusions and implications of the research are structured along the three main research questions introduced in Chapter I-3.

## **2.1 What are the anthropogenic drivers of tropical forest fires in the Amazon?**

My research results described in [Chapter II](#) provide important insights into the association between fires and anthropogenic LUC. The large amount of burned area I found in evergreen forests (between 18%-25.6% of the total registered in 2008) cannot be fully explained by fires used in deforestation processes per se because no significant relationship was found between annual burned area and new deforested area over the period 2001-2010 (Figure II-6). I estimated that 74% of the burned area in 2010 is associated with regular burnings in previously deforested areas that were converted into pastures and agricultural lands. This suggests a disconnection between deforestation and fire from the year 2004 onwards (later corroborated by Aragao et al., 2018; Morgan et al., 2019, among others), when the Action Plan to Prevent and Control Deforestation in the Brazilian Legal Amazon (PPCDAm) was implemented, together with the Soy Moratorium (2006), and the Zero-Deforestation Cattle Agreements (2009). Nevertheless, the connection between deforestation and fire evolves over time as fire regimes and our relationships with fire continue to change. Despite the decoupling I observed from 2001-2010, increases in fire activity in recent years, e.g. in 2019 (Figure IV-3a), were very much associated with increasing deforestation rates in the region since 2017 (Silveira et al., 2020). In addition to this, recent corrections of fire datasets have warranted a reassessment of the relationship between deforestation and fire revealing a weaker decoupling than the initially proposed for the period 2003-2015 (Libonati et al., 2021).

Degradation also showed a reduced influence on forest fires according to my results, but given the limitations of the satellite sensors in registering small burnings, burned

areas below the canopy, or burned areas that are quickly covered by vegetation (Matricardi et al., 2010), the amount of forest degradation driven by fire may be larger, and thus, my results presented a lower bound estimate. Sub-yearly temporal resolution maps would advance the assessment of transient degraded areas through satellite imagery. The research in [Chapter II](#) revealed that annual amounts of degraded area were larger than annual deforestation rates between the years 2007 and 2011, when both data series overlapped (Figure II-7). Therefore, targeting forest degradation in addition to deforestation is crucial since cleared and degraded forests are both a source of GHG emissions. In line with this finding, Matricardi et al. (2020) have later confirmed that the extent and rate of degradation was equal to or greater than deforestation over a 22-year period up to 2014 in the Brazilian Amazon. As a consequence, carbon loss from forests' degradation exceeded that from deforestation from 2010 to 2019 in the region (Qin et al., 2021). The implications for the carbon cycle and thus, for the global climate, demand policies based on reducing emissions from both deforestation and forest degradation to preserve forest carbon stocks (REDD+) and mitigate climate change.

The results in [Chapter II](#) support the assumption that fire incidence responds strongly to anthropogenic activities. I show that most of the forest burned area was associated with the use of fire in managed lands, especially in pastures, in previously deforested areas (Figure II-8). The findings provide the first estimate of the contribution of cattle pastures and agricultural lands to forest edge burning by escaping fires in the region. Given the significant amount of fires that penetrate into the forests from the outside, there is a demand for considering escaping fires in REDD+ policies and prevention plans.

A good understanding of the dynamics of fires occurring in pastures and agriculture is needed to develop initiatives to minimise edge-driven fire processes before the fire season starts, and for policy development targeting reduced carbon emissions from forests. Additional studies are required to quantify the effect of burned area changes in the respective land covers in terms of total fire-related emissions, since small fires burning in high biomass forests can release as much carbon as large-scale fires burning in low-biomass land-use types. On top of that, a transition plan towards a fire-free land management should be designed and implemented to abate one of the



major sources of carbon emissions in Amazonia (Gatti et al., 2021). Policies should focus on assisting smallholders, indigenous people and traditional communities in adopting fire-free alternative techniques, by incentives for land users who complies, and penalties for the illegal use of fire.

## **2.2 How do fire regimes differ between the land-cover types in the Amazon?**

While in [Chapters II](#) and [IV](#) I explore the reasons behind the spatio-temporal distribution of fire activity, [Chapter III](#) specifically concentrates on characterising the fire behaviour in different land-cover types in the BLA. Fire regimes are controlled by the amount, attributes and condition of the fuel, and the available ignition sources. In turn, these factors are influenced by local weather and climate, vegetation composition and structure, and human activities (Le Page et al., 2010; Pausas and Keeley, 2014). The interactions among all these elements resulted in the high temporal (see sections II-3.1 and IV-3.1) and spatial variability (see sections II-3.1, III-3.1 and IV-3.2) in fire activity and fire types.

The novel FireTracks algorithm used in [Chapters III](#) and [IV](#) offers the possibility of working with individual fires, instead of providing larger burned areas or single active fires. Each individual fire stores information about its location, which allowed me to classify them by the land-cover type where they occur.

In [Chapter III](#) I estimated fire size, duration, intensity and rate of spread, and derive particular sets of interrelated fire characteristics for each land-cover type (Table III-1). Although the probability density distribution of the fire variables follow a similar pattern regardless of the land cover, probabilities largely differ between them and serve as means of recognising different types of fire regimes (Figure III-5). The detailed information on fire features in each land-cover type can be incorporated into fire models in order to capture the anthropogenic signal. To include other factors besides climate in fire models is currently a key challenge in fire ecology (Andela et al., 2017). Model projections on future fire activity and impacts on ecosystems, climate, and society will greatly benefit from high resolution land-cover data combined with a better parametrisation of different fire regimes. Fire science leading to improve our understanding of human-dominated fires is essential to support

long-term policies with the goal of preventing forest fires, regulating savanna fires, implementing adaptation and mitigation measures, etc.

### **2.3 How do changing climatic conditions and other anthropogenic drivers impact the spatio-temporal distribution of high-intense fires in the Amazon tropical forests?**

While results in [Chapter II](#) revealed the large amount of burned area occurring in evergreen forests in the BLA (Figure II-3b, Table II-1), in [Chapter III](#) I found that tropical forest fires have escalated from being naturally rare to showing characteristics more typical of savanna fires (Figure III-5, Table III-1). [Chapter IV](#) is for those reasons solely focused on disentangling the combination of human and climate influence that control extreme, i.e. high-intensity, forest fires distribution. Projections for the 21st century in the region suggest increases in fire activity and intensity with severe effects on tropical forest stability (Brando et al., 2014; 2020; de Faria, 2017; Silvério et al., 2019). Most tree species are poorly adapted to survive even low-intensity fires and small increases in fire intensity can cause cambial damage and thus mortality. However, advances in the understanding of the elements governing high-intensity fire activity are still needed in order to achieve precise estimates of post-fire tree mortality, forest fires emissions, and future changes in the tropical forest carbon pool.

Findings in [Chapter IV](#) provide explicit evidence of a complex interplay among human activities and climatic factors that explain the interannual variability of extreme fire activity. Forests are exposed to warmer conditions and fuels dry out more rapidly as a consequence of the combined effect of climate change and edge effects from forest fragmentation. More flammable evergreen forests are able to sustain higher-intensity fires, which cause large alterations in forest carbon stocks, and consequently in the carbon emissions from fires. In line with this, my results showed the largest increases in extreme fire activity in Amazonian tropical forests during the three most severe droughts of the last 100 years (2005, 2010 and 2015) and/or high deforestation years (mainly in the early years of the twenty-first century) (Figure IV-3a). I also found that spatial heterogeneity is partly attributed to the type of drought, i.e. AMO-driven droughts tend to concentrate in western Amazonia,

whereas northeastern Amazonia is usually more affected during ENSO-driven droughts.

On the other hand, I observed certain stable spatial patterns over the study period associated with the road network and the agricultural frontier that fragment tropical forests (Figure IV-4). Since the early 2000s, infrastructural investments as part of governmental plans to accelerate economic growth in the region promoted roads along the pristine tropical forest for the first time (Avança Brazil and Programa de Aceleração do Crescimento, launched in 2000 and 2007, respectively). The road network has since expanded to encourage agroindustrial production and facilitate access to national markets. Roads, legal and illegal, by themselves fragment tropical forests and yet at the same time indirectly increase forest accessibility, therefore perpetuating forest degradation along the agricultural frontier. Conservation should be a major concern in any future infrastructure plan placing the focus on the cause of the problem. Fire prevention policies must be prioritised in the various activities taking place along the already built roads, e.g. promoting sustainable agricultural and fire-free techniques in managed lands, monitoring and restricting deforestation and forest degradation activities, etc.

The conclusions of this dissertation highlight the relevance of considering and properly assessing the diverse ways in which humans alter fire regimes beyond climate warming, especially in the evergreen forests of the Brazilian Amazon. To capture the high heterogeneity in the distribution of fire activity in the region, it is crucial to reduce uncertainty in fire regime projections and thus, in future fire impacts and emission estimates.

### **3 Outlook**

The research I described in this dissertation advances the understanding of the diverse climatic and anthropogenic drivers, and the interactions between them, governing fire activity and distribution in the Brazilian Amazon. This work also brings to light the high spatial and temporal variability in fire regimes, and discloses the particularities of fire behaviour in the different land-cover types by estimating and analysing fire size, duration, intensity and rate of spread. Especially, I provide important insights into the reasons behind fire location and behaviour in the sensitive

tropical evergreen forests. The results show that as a consequence of a wide variety of anthropogenic ignition sources - from deforestation, degradation, logging, fire-managed lands, road construction, etc. -, fires in tropical forests have become more frequent, widespread, and may exhibit characteristics similar to savanna fires. As the complex human-fire-climate interactions evolve over time, fire regimes continue to change. In this context, the outcome of this dissertation provides essential explicit information on the fire features in diverse land-cover types that can be used to improve the parameterisation of different fire regimes in DGVMs. Thus, better estimates of current and future fire emissions and impacts will follow.

The core of the research I present in this dissertation is based on the analysis of remotely sensed data from multispectral space-borne sensor systems. Any further refinement in the detection and classification algorithms will have a direct impact on the analyses carried out with those datasets. Currently, high spatial resolution fire and land-cover datasets exist for the region (e.g. 30-m resolution TerraClass, MapBiomas v6, PRODES, DEGRAD, BDQueimadas datasets, among others), which allow to perform spatial analyses in great detail in the absence of ground data. However, they are usually produced at best once per year, or fortnightly (in the case of the BDQueimadas).

On the other hand, daily resolution data are regularly released at moderate spatial resolution (500-m resolution MCD64A1 v6 burned areas and MCD12Q1 v6 land cover, and 1-km resolution MCD14ML v6.1 and MOD/MYD14A1 v6 active fires products, to name a few). To select the most appropriate datasets implies a compromise between spatial and temporal resolution, apart from other aspects such as the length of the time series or the area coverage. Definitely, subdaily fire resolution will provide in the future a more precise classification of the amount of burned forests related to escaping fires from managed pasture and agricultural lands ([Chapter II](#)). Finer temporal resolution will also improve the identification and delimitation of individual fires by the FireTracks algorithm ([Chapters III and IV](#)), and therefore, the representation of fire behaviour in fire models. Furthermore, additional subclassification and/or introduction of new anthropogenic-related land uses in land-cover classification schemes will also bring more accurate estimates of human-associated fire activity and emissions (e.g. different types of crops within the

agriculture class, various states of degradation within the evergreen forests class, etc.). All in all, MODIS sensors offer a long term data record (usually from the early 2000s) with global image collection, which is of interest if local and regional assessments are intended to be replicated globally, for studies conducted to evaluate changes in the reflectance or temperature of the surface over time.

Future directions include the application of the algorithm that identifies the share of burned forests related to escaping fires from managed lands ([Chapter II](#)) to other states, Amazonian regions or countries. Such an analysis would allow us to examine the impacts of diverse degrees of human pressure on ecosystems at different locations. A similar procedure can be carried out with the FireTracks dataset ([Chapters III and IV](#)) comparing the individual fires activity and patterns at different locations with distinct natural and socioeconomic dynamics. As individual fires in the FireTracks dataset contain information on their integrated fire variables, another future research line could explore the trends of those fire characteristics over time at a particular land-cover type or location as a way of improving our capacity to anticipate future shifts in fire regimes.

The largest uncertainties in global fire modelling are associated with the representation of anthropogenic ignitions and suppression, and land-use effects on vegetation and fire (Teckentrup et al., 2019). Although there have been attempts to include, e.g., the effects of cropland and pasture management on fires (Rabin et al., 2018), the complex feedbacks between humans and fire make the representation of anthropogenic-driven fire regimes in fire-enabled DGVMs complicated (Andela et al., 2017; Forkel et al., 2019; Hantson et al., 2020). On top of that, the large heterogeneity in the distribution of anthropogenic drivers that emerges throughout this dissertation, complicates even more large-scale fire modelling. The detailed characterization of fire types in the different land-cover types I present in [Chapter III](#) offers a strategy for improving projections of fire characteristics and impacts on ecosystems and human societies in the context of climate change.

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## **Declaration of independent work**

(Eidesstattliche Erklärung)

I declare that I have completed the thesis independently using only the aids and tools specified. I have not applied for a doctor's degree in the doctoral subject elsewhere and do not hold a corresponding doctor's degree. I have taken due note of the Faculty of Mathematics and Natural Sciences PhD Regulations, published in the Official Gazette of Humboldt-Universität zu Berlin no. 42/2018 on 11/07/2018.