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Three Decades of Anthropogenic Fire Activity in a Neotropical Agricultural Frontier

A dissertation submitted in partial satisfaction of the
requirements for the degree Doctor of Philosophy
in Geography

by

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September 2019

The dissertation of Gabriel Antunes Daldegan is approved.

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September 2019

Three Decades of Anthropogenic Fire Activity in a Neotropical Agricultural Frontier

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by

Gabriel Antunes Daldegan

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ABSTRACT

Three Decades of Anthropogenic Fire Activity in a Neotropical Agricultural Frontier

By Gabriel Antunes Daldegan

In this dissertation, I evaluated the spatiotemporal dynamics of anthropogenic fire activity in a neotropical rainforest-savanna agricultural frontier. Given its fast and affordable nature, fire is used around the globe as a cost-effective way to clear and manage lands. This scenario is especially common in tropical regions experiencing high deforestation rates. The Amazon-Cerrado transition zone has been subject to the highest deforestation rates in Brazil over the last four decades. In this ecotone, fire is mainly used to clear natural vegetation lands and to manage encroachment of shrubs and trees in pasturelands; often, these fires spread accidentally. Nonetheless, the dynamics of the human-fire interaction are still not fully understood.

To assess this relationship at a fine-scale, I developed a semi-automatic burned area mapping algorithm in Google Earth Engine that applies spectral mixture analysis to time-series of Landsat imagery: Burned Area Spectral Mixture Analysis (BASMA). Using BASMA, I generated annual burned area maps for a 32-year time-series (1985 to 2017), testing whether spectral mixture analysis is a robust means for mapping fire scars that is stable over time and space. Results showed that BASMA successfully identified char fractions and delineated burned area in Landsat imagery for a 36 million hectares study region. Accuracy assessment performed against independent burned area products returned high Dice coefficients (0.86 on

average) demonstrating that BASMA is an effective algorithm to map fire scars for a large extent over long time-series analysis.

The pyric transition, as proposed by Pyne (2001), suggests that human-driven fire activity increases at early stages of human occupation in a given region, and then decreases as the area is further industrialized. In my third chapter, I developed a conceptual model that combines the BASMA-derived burned area maps with a land use and land cover (LULC) database produced by the MapBiomas Project to evaluate the validity of the pyric transition hypothesis. Merging these two fine-scale datasets spanning a long time-series allowed me to quantitatively characterize spatiotemporal changes in fire activity occurring in parallel to human occupation dynamics. Two pyric phase transitions were observed: from 'wildland anthropogenic fire' to 'agricultural anthropogenic fire', and then to 'fire suppression and wildfires' phase.

In my final chapter, I evaluated spatiotemporal patterns of traditional burnings in remnants areas of the Cerrado biome within four indigenous lands, assessing whether fire frequency can be modeled by statistical models. Three probability distribution models were tested: continuous and discrete two-parameter Weibull and the discrete lognormal. Results agreed with previous studies, finding a mean fire interval of 3 years, similar to metrics estimated in other protected areas of the Cerrado. However, the parameters estimated for the probability distribution models showed that the study area does not have a homogeneous fire regime, indicating that further studies must be conducted to better quantify the fire return interval in these fire-prone ecosystems. Thus, we suggest that subdividing the fire frequency

modelling by each of the indigenous lands could potentially return better results.

Ultimately, this dissertation clearly demonstrates the advantages of having fine-scale burned area products covering long time-series over large extents.

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Chapter 1: Introduction

1.1 Motivation

Accurately mapping burned area and characterizing human-fire dynamics are critical for estimating carbon emissions (Aragão and Shimabukuro, 2010; Chuvieco et al., 2018, 2016; Mouillot et al., 2014; Noojipady et al., 2017; Padilla et al., 2015; Urbanski et al., 2018) and to improve understanding of vegetation and climate relationship (Aragão et al., 2008; Balch et al., 2008; Bowman et al., 2011; Brando et al., 2014; Santos et al., 2003; Veenendaal et al., 2018). Further, it also helps to evaluate the impacts of fire as a land management tool (Driscoll et al., 2010; Fidelis and Pivello, 2011; Pivello, 2011; Ramos-Neto and Pivello, 2000; Thonicke et al., 2001) and for assessing trends and spatiotemporal patterns in fire occurrence (Andela et al., 2017; Andela and van der Werf, 2014; Boschetti et al., 2015; Daldegan et al., 2014; Hawbaker et al., 2017; Moreira de Araújo et al., 2012). Given its fast and affordable nature, fire has been traditionally used around the globe as a cost-effective way to clear and manage lands (Pyne, 1997; Cochrane, 2009; Pivello, 2011; Schmidt et al., 2011; Scott et al., 2014). This scenario is especially common in tropical regions experiencing high deforestation rates (Cochrane, 2009). Targeting the international agricultural market for commodity crops, Brazil led the worldwide ranking for deforestation of primary forests in 2018 (Global Forest Watch: <https://www.globalforestwatch.org>, last accessed August 5th, 2019).

The two most extensive biomes in South America, the Amazon forest and the Brazilian savanna (Cerrado biome) are well-known for their biodiversity richness

and importance worldwide. However, these vegetation domains are experiencing high deforestation rates and large extents of their natural vegetation are already cleared due to intensive human development occurring at a fast pace and in unsustainable way (Nobre et al., 2016). A substantial amount of these areas has been converted to farming activities, of which mostly are agriculture targeting commodity crops and pasture, among other economic activities (Barreto et al., 2006; Davidson et al., 2012).

The anthropogenic use of fire is of particular interest in these environments, serving as a cost-effective tool to open extensive areas in near-pristine condition landscapes and/or maintenance of already opened lands (Cochrane, 2003; Pivello, 2011; Souza, Jr. et al., 2013). Even so, the dynamics of the human-fire interaction are still not fully understood (Bowman et al., 2011) and to best comprehend the use of fire and its relationship to land-use and land cover change, it is necessary to analyze changes in fire activity concurring in space and time with fast increase in human occupation dynamics. In this regard, the pyric transition concept proposed by Pyne (2001) predicts that the use of fire increases at the early stages of human occupation and decreases when the land is further colonized, although, several studies claim that this concept has yet to be quantitatively evaluated.

As a savanna, the Cerrado has evolved to be adapted to fire (Coutinho, 1977; Coutinho, 1990) and is considered a fire-dependent biome (Myers, 2006; Pivello, 2011). Some studies claim that the Cerrado has been exposed to fire for the last 25 million years, forging the diversification of many C4 grass species, for example (Miranda et al., 2010). Yet, Myers (2006) asserts that many tropical fire-dependent

(pyrophilic) ecosystems may be experiencing too frequent burnings and that there is an overall lack of knowledge regarding the nature and the ecological appropriateness of present fire regimes in many of those environments. Thus, it is critical to objectively describe the spatiotemporal dynamics of burnings in a pyrophilic ecosystem to better evaluate how vegetation is responding to contemporary fire activity.

In contrast to the savanna environment, the Amazon moist broadleaf forest is recognized as a fire-sensitive vegetation (Pivello, 2011). Nonetheless, studies have shown that forest patches that have already been disturbed become more prone to experience recurrent burns (Cochrane et al., 1999; Laurance et al., 2007). Further, forest patches that are adjacent to open/converted areas have their edges exposed to more insolation and turbulence, which helps dry out their understory vegetation and litter, making those areas even more susceptible to fire. In cases where grass species are established in the understory, these can be a renewable source of fuel for recurrent burns (Cochrane and Schulze, 1999; Aragão et al., 2008).

The Amazon-Cerrado transition zone, a region known as “Arc of Deforestation,” is subject to the highest deforestation rates in Brazil over the last four decades (Valeriano et al., 2004). In this ecotone, fire is mainly used to convert natural vegetation to agricultural activities (slash and burn) and to manage pasture for livestock (Cochrane, 2009). Often, these fires spread accidentally, getting out of control. In the Cerrado biome, fire is often used to stimulate the regrowth of natural grasses used as pasture, and also to open new lands for agriculture (Pivello, 2011). Conversely, the Amazon forest has not historically been subject to recurrent

burnings, and its cycle of deforestation started in the middle of the last century with the federal government promoting occupation of the region (Becker, 1974). More recently, deforestation has been stimulated by increases in commodities prices, like soybean and corn, croplands that have traditionally occupied vast areas of the Cerrado biome and are gradually advancing on the rainforest. In the Amazon forest, fire is frequently used to further open lands that were previously selectively logged and later converted to cattle ranching and agriculture crops. This dynamic has been evident over the last four decades, especially in Mato Grosso state (Cochrane, 2009; Macedo et al., 2012).

Alongside, there are numerous indigenous lands and protected areas in Mato Grosso state where land use and land cover have not changed much in the recent period. These large extents of natural vegetation remnants offer the opportunity to assess the traditional spatiotemporal dynamics of burnings and to model fire-return intervals. Located in a region entirely covered with savanna ecosystems, the Paresi plateau hosts several indigenous lands where the Hailiti-Paresi people have been traditionally using fire over centuries for many purposes, such as to manage biomass in a way to avoid severe burnings, for hunting activities, among others. Beginning in 2017, the Brazilian National Center for Prevention and Fighting Forest Fires (PrevFogo: <https://www.ibama.gov.br/prevfogo>, last accessed in August 5th, 2019) started to implement an Integrated Fire Management plan that seeks to restore and maintain the traditional use of fire that was historically applied by the Haliti-Paresi people. Accounting for the lack of knowledge of current fire regime in this area, quantitatively characterizing the current spatiotemporal burning patterns in

this region will certainly help to monitor how the Integrated Fire Management plan is changing fire activity and vegetation on the Paresi plateau.

1.2 Background (Climate, Fire and Remote Sensing)

The occurrence of fire has a direct relationship to the climate of a region (Scott et al., 2014), and the synergistic interaction of rainfall anomalies and anthropogenic disturbances, such as deforestation and forest degradation, significantly impact the number of fire events in the Amazon and the Cerrado landscapes (Davidson et al., 2012). The macroclimate of South America is strongly influenced by the South America Monsoon System (SAMS), which is primarily driven by the heat difference between the continent and the Atlantic Ocean. The continent has a substantial landmass within tropical latitudes and is delimited by the South Atlantic to the east. These characteristics, combined with the Andes mountain range to the west create and maintain SAMS (Carvalho and Cavalcanti, 2016). SAMS is characterized by the presence of an upper-level anticyclone over Bolivia, commonly referred to as the Bolivia High, and the enhancement of the lower-level cyclone over the Chaco, region located in northwest Argentina and Paraguay (Liebman and Mechoso, 2010). Furthermore, Carvalho and Cavalcanti (2016) assert that the South Atlantic Convergence Zone (SACZ) is the unique and most significant features of SAMS. Under the direct influence of SAMS, the climate of the Amazon-Cerrado transition zone is characterized by two well-marked seasons: the wet season concentrating the vast majority of precipitation (from October to April), and a pronounced dry-season lasting from May to September (Grimm, 2011).

Aragão et al. (2008) and van der Werf et al. (2009) reported that fire in the Amazon-Cerrado transition zone is mainly anthropogenic, meaning that most fire events are concentrated in the dry season, normally from May to October (Grimm, 2011). Lightning strikes are the cause of natural fires (Ramos-Neto & Pivello, 2000), though this type of ignitions are rare when compared to human induced burning in the region. Grimm (2011) summarizes the annual cycles of precipitation over the South America and her results were used as a proxy to assess the time and geography under the influence of the dry season.

Remote sensing has been extensively used by a large number of researchers studying fire occurrence at a global scale, as well as in both biomes mentioned above. Digital image processing aiming to map burned area has been applied to a diversity of remotely sensed datasets from sensors of various spatial, temporal, and spectral resolutions (Bastarrika et al., 2014, 2011; Brewer et al., 2005; Chuvieco et al., 2016; Lentile et al., 2006; Merino-de-Miguel et al., 2010; Quintano et al., 2013, 2006; Roy et al., 2005; Roy and Landmann, 2005). More specifically, several studies have used Landsat data to map fire scars in the Amazon forest and in the Cerrado (Alencar et al., 2006, 2004; Daldegan et al., 2019, 2014; França et al., 2007; Pereira, 2003; Pereira Júnior et al., 2014). An advantage of using Landsat data is the potential to map fire scars at a finer spatial resolution when compared to products derived from sensors featuring better temporal resolution but coarser spatial resolution, such as the Moderate Resolution Imaging Spectrometer (MODIS: Giglio et al., 2018, 2016; Roy et al., 2008, 2005) and Geostationary Operational Environmental Satellite (GOES: Schmidt and Prins, 2003). Despite having high

temporal resolutions, these sensors have the disadvantage of not being able to detect relatively small burned areas (Alonso-Canas & Chuvieco, 2015). Landsat imagery, in contrast, has been shown to allow improvements in the delineation of smaller fragments of fire scars (Pereira et al., 1997).

The Landsat family of sensors is recognized for its consistency on imaging the globe (Hansen and Loveland, 2012). These sensors have been collecting images from Brazil for more than 40 years, and their imagery is one of the most used remote sensing data applied to research in the country. Several studies have demonstrated the advantages of Landsat imagery, not only for mapping fire activity (Alencar et al., 2004; Daldegan et al., 2019, 2014; Pereira Júnior et al., 2014), but also for several other applications, such as monitoring deforestation and land degradation (Matricardi et al., 2010; Souza Jr., et al., 2013, 2005; Valeriano et al., 2004).

In 2008, the policy that regulates the distribution of Landsat imagery changed and this data archive was made available to the public at no costs. This fact was unprecedented and has had a significant impact in the remote sensing community, boosting the number of studies that use Landsat data (Wulder et al., 2016). Moreover, with the increasing availability of imagery, there has been a consequent increase in the demand for high-performance processing capabilities in order to enable the mining of the rapidly growing data archive (Hansen and Loveland, 2012). The advent of the Google Earth Engine (GEE) API has been considered a valuable advance in facilitating remote sensing data mining (Gorelick et al., 2017). In the

GEE platform it is possible to access all Landsat legacy data stored at Google's servers and to apply a growing number of remote sensing techniques and methods. Beginning with Landsat 5 Thematic Mapper (TM) and its successors Landsat 7 Enhanced Thematic Mapper (ETM+) and Landsat 8 Operational Land Imager (OLI), the Landsat family of sensors is the most appropriate data source for time-series analysis of fire in the Amazon-Cerrado ecotone, given its time of operation and spectral, temporal and spatial resolutions. These sensors have similar specifications, including three visible (486, 571, 661 nm), one Near-infrared (837 nm), two Short-wave infrared (SWIR, 1677 and 2215 nm) bands, a spatial resolution of 30 meters, and revisit time of 16 days.

Various technical approaches have been applied to multispectral imagery to identify and map fire-affected areas around the globe. Pereira et al. (1997) reviewed several digital image processing methodologies applied to map fire scars. After discussing the details of each of most common techniques, the authors concluded that Spectral Mixture Analysis (SMA) is one of the most reliable methods, being more efficient than burned area index based approaches, such as Normalized Burn Ratio (NBR: López & Caselles, 1991; Key & Benson, 2005), given its skills to model inter-pixel spectra responses. Cochrane (1998) showed the potential of SMA to map fire scars in tropical landscapes. Further, Veraverbeke et al. (2012) asserts that SMA is effective in addressing sub-pixel fractions of fire scars. SMA out performs other methodologies mainly due to its ability to minimize the amount of confusion between fire-affected areas and well-known sources of confusion, such as urban area, water bodies and wetlands (Quintano et al., 2006). Nonetheless, it is more

effective to mask these major confusion sources out of the analysis (Pereira et al., 1997).

1.3 Research Objectives and Overarching Questions

This research aims to evaluate the spatiotemporal dynamics of anthropogenic fire activity in a neotropical rainforest-savanna agricultural frontier.

These are the overarching questions that guided this study:

Question 1 – Can fire scars be mapped semi-automatically at high accuracy over an extended time series and large geographic extent using spectral mixture analysis and cloud-based analysis tools?

Question 2 – How has the distinct phases of human occupation influenced the fire activity between 1985 and 2017? Did the spatiotemporal burning pattern follow a pyric transition as proposed by Pyne (2001)?

Question 3 – What are the current spatiotemporal dynamics and the fire return interval in remnants patches of natural vegetation which have been traditionally under indigenous people fire management?

To thoroughly answer these questions, it was necessary to generate a map of fire scars for each year of the time-series. Hence, in Chapter Two, I developed a Google Earth Engine semi-automatic burned area mapping algorithm that applies SMA in Landsat time-series: The Burned Area Spectral Mixture Analysis (BASMA). In it, I tested whether SMA is a robust means for mapping fire scars present in Landsat imagery for the Amazon-Cerrado transition zone that is stable over time and over space. In Chapter Three, I tested the hypothesis of fire activity following a pyric transition in the most productive agricultural region in Mato Grosso state. In

Chapter Four, I aimed to characterize the spatiotemporal patterns in remnants areas of the Cerrado biome under traditional burnings, assessing whether fire frequency can be modeled by statistical models.

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Chapter 2: Spectral Mixture Analysis in Google Earth Engine to Model and Delineate Fire Scars Over a Large Extent and a Long Time-Series in a Rainforest-Savanna Transition Zone

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2.0 Abstract

Fire is used worldwide to clear natural vegetation areas for economic activities and to manage the regeneration of already opened sites. In Brazil, fire has been traditionally used to convert natural vegetation areas to agricultural lands (slash and burn) and to manage pastures for livestock. We developed the Burned Area Spectral Mixture Analysis (BASMA) algorithm in Google Earth Engine, which is designed to process Landsat data to produce a multi-temporal fire scar database representing annual burned area for an extent of 362,000 km² in the transition zone between the Amazon forest and the Cerrado biome. This region is considered a conservation hotspot, given its high deforestation rates over the last four decades. We digitally processed a 32-year time-series (1985 to 2017) of Landsat 5 Thematic Mapper, Landsat 7 Enhanced Thematic Mapper+, and Landsat 8 Operational Land Imager data to map fire scars based on sub-pixel char fraction, aiming to generate a consistent burned area product at a finer scale and covering a longer period than those currently available for the region. Manually interpreted reference burned area polygons for each annual mosaic was used to guide the definition of the best fire scar endmember and its fraction threshold. To assess our BASMA-delineated fire scar, they were compared to independent datasets of manually delineated burned area produced by visual analysis of finer spatial resolution imagery, returning an average Dice Coefficient value of 0.86. Accuracy was also measured against the 30-meter Burned Area product available at the 'Queimadas' data portal. A total of 11,106,258 ha was mapped as having been affected by fire during the annual dry season over the 32 years, which represents 30.7% of the study region. Results

showed a decreasing trend in the annual amount of burned area over the time-series. It reflects a similar pattern shown in the deforestation rate for the Legal Amazon, measured by the Brazilian National Institute of Space Research - INPE. Moreover, the Cerrado biome subset of the study region consistently showed higher burned area when compared to the Amazon forest subset. Our findings provide robust evidence that our approach is a consistent method to identify and delineate fire scars for large areas over a long time-series in a very efficient fashion, given the digital processing power of Google Earth Engine, which reduces the time necessary to analyze such big amount of data.

Keywords: Landsat, Spectral Mixture Analysis, Endmember, Burned Area, Time-series, Amazon Forest, Cerrado Biome, Google Earth Engine

2.1 Introduction

Accurately mapping burned area is essential for quantifying carbon budgets (Aragão and Shimabukuro, 2010; Chuvieco et al., 2018, 2016; Mouillot et al., 2014; Noojipady et al., 2017; Padilla et al., 2015; Urbanski et al., 2018) and for analyzing the relationship between vegetation and climate (Aragão et al., 2008; Balch et al., 2008; Bowman et al., 2011; Brando et al., 2014; Santos et al., 2003; Veenendaal et al., 2018). It is also needed for assessing the impacts of fire as a land management tool (Driscoll et al., 2010; Fidelis and Pivello, 2011; Pivello, 2011; Ramos-Neto and Pivello, 2000; Thonicke et al., 2001) and for quantifying trends and patterns in fire occurrence (Andela et al., 2017; Andela and van der Werf, 2014; Boschetti et al., 2015; Daldegan et al., 2014; Hawbaker et al., 2017; Moreira de Araújo et al., 2012), among other relevant applications.

Remote sensing has been extensively used by many researchers studying fire occurrence at global, regional, and local scale. Digital image processing aiming to map fire activity has been applied to a variety of imagery from sensors of various spatial, temporal, and spectral resolutions (Alonso-Canas and Chuvieco, 2015; Bastarrika et al., 2014, 2011; Boschetti et al., 2015; Chuvieco et al., 2018, 2016; Daldegan et al., 2014; Giglio et al., 2018, 2016; Lentile et al., 2006; Libonati et al., 2015; Melchiori et al., 2014; Merino-de-Miguel et al., 2010; Oliva and Schroeder, 2015; Pereira et al., 2017; Quintano et al., 2013, 2006; Ramo et al., 2018; Roy et al., 2008; Stroppiana et al., 2002; Urbanski et al., 2018; Veraverbeke et al., 2018, 2012). Burned area products covering large extents and long periods are typically extracted from imagery of sensors featuring short revisiting time, such as the

Geostationary Operational Environmental Satellite (GOES: Schmidt and Prins, 2003), the Moderate Resolution Imaging Spectrometer (MODIS: Giglio et al., 2018, 2016; Roy et al., 2008, 2005), the Satellite Pour l'Observation de la Terre Vegetation (SPOT Vegetation: Tansey et al., 2008, 2004) and the Medium Resolution Imaging Spectrometer (MERIS: Chuvieco et al., 2016). In spite of having high temporal resolutions, these sensors have the disadvantage of not being able to resolve relatively small burned areas due to their coarse spatial resolution (Alonso-Canas and Chuvieco, 2015; Boschetti et al., 2015; Chuvieco et al., 2016; Hawbaker et al., 2017; Morton et al., 2013). Consequently, small burned area contributions to carbon emissions are still not fully understood (Randerson et al., 2012).

Mapping burned area at a finer spatial resolution is one of the demands from end-users of burned area products (Mouillot et al., 2014), and could facilitate spatial analysis to assess how fire varies among land covers and vegetation types, helping to improve fire emission modeling (Hawbaker et al., 2017). Landsat imagery has been shown to improve the delineation of smaller fragments of fire scars (Bastarrika et al., 2014, 2011; Boschetti et al., 2015; Daldegan et al., 2014; Hawbaker et al., 2017; Liu et al., 2018, Quintano et al., 2017, 2013, 2006). The Landsat program comprises the longest continuous Earth Observation mission, which has been imaging the surface of the Earth for more than 40 years (Wulder et al., 2016). Moreover, it features a consistent spatial and temporal imagery collection, given that starting with Landsat 4 Thematic Mapper (TM), sensors have identical spatial and spectral resolutions. Recently, digital processing of Landsat data over large extents and long time-series has become considerably more cost-effective, given

the powerful computational processing of Google Earth Engine (GEE). GEE is a remote sensing platform based in the cloud that is designed to perform planetary-scale analysis of geospatial data. Its catalog stores a massive amount of publicly available geospatial datasets, which is accessed and manipulated through an application programming interface (API: Gorelick et al., 2017).

Methodological approaches aiming to map burned area using Landsat imagery usually rely on multi-temporal (pre-fire and post-fire) reflectance change detection, often using complicated rules for combining results from distinct classifiers (Hawbaker et al., 2017). Goodwin and Collett (2014) developed an automated burned area mapping algorithm that combines temporal, spectral, and contextual metrics. Their approach processes one Landsat Path/Row at a time and requires three key processing stages: detection of time-series outliers; region-growing of change regions; and attribution of change regions. Bastarrika et al. (2011, 2014) designed a two-phase algorithm that first aims to minimize commission errors, and secondly aims to reduce omission errors. The approach is based on the calculation of a series of burned area spectral indices, each one requiring the selection of a threshold value, to identify seed burned pixels and subsequently the application of a region-growing algorithm for shaping the burned area. Boschetti et al. (2015) introduced a multistage burned area mapping method that uses an initial per-pixel change detection centered on the spectral-rule based pre-classification of Landsat time-series to identify burned area candidates and on the comparison of these candidates with concurrent MODIS active fire signal. The Landsat Burned Area Essential Climate Variable algorithm (BAECV: Hawbaker et al., 2017) requires pre-

fire reference conditions to apply gradient boosted regression models to estimate the probability that a pixel was burned. BAECV uses all bands from Landsat 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper (ETM+) sensors plus seven other derived predictors that are ingested to the regression model.

Among the approaches used to map burned area, Spectral Mixture Analysis (SMA) is not commonly used relative to other methods (Cochrane, 1998; Eckmann et al., 2008; Fernandez-Manso et al., 2016; Quintano et al., 2017, 2013, 2006; Shimabukuro et al., 2009; Souza et al., 2005). SMA is based on the assumption that the reflectance spectrum recorded by a pixel is a linear mixture of the spectra of many objects, commonly referred as spectral endmembers, present in the scene (Adams et al., 1993, Roberts et al., 1993; Settle and Drake, 1993). Each pixel of a Landsat image covers an area of 900 m², which is sufficiently large enough to combine distinct land surfaces into one pixel - i.e., green vegetation (GV), Non-Photosynthetic Vegetation (NPV), soil, and shade. Accounting for this characteristic, SMA has the capability of retrieving sub-pixel fractions and thus potentially permitting more accurate results when compared to ordinary classification methods (Pereira et al., 1997). In their review paper, Pereira et al. (1997) asserted that SMA is advantageous over vegetation index-based methods, concluding that SMA produces interesting results for burned area detection. Likewise, Smith et al. (2007) compared different methods applied to Landsat 7 ETM+ data aiming to identify and map fire-affected area, concluding that SMA was the best approach. More recently, Quintano et al. (2017, 2013) used SMA to assess burn severity in Mediterranean countries, reaching promising results.

Given the potential of SMA to accurately delineate burned areas, there is a need to further assess its efficiency and stability over time and space. This study aims to develop a GEE semi-automatic burned area mapping algorithm that applies SMA in Landsat time-series: The Burned Area Spectral Mixture Analysis (BASMA). The algorithm takes advantage of the Landsat imagery collections stored in the cloud and of the high processing power of the GEE platform. Therefore, there is no need to download imagery or to process each scene individually. The algorithm is based on the permanence of post-fire reflectance changes. Furthermore, it does not require a multi-temporal (pre and post-fire) change detection, which is a significant advantage for large study sites in tropical regions, given that it can be challenging to create two or more annual mosaics covering the entire area of interest due to cloud coverage. The specific objective of BASMA is to accurately map burned area over large extents and for long time-series of Landsat imagery, generating results in an efficient processing time. Our assumption is that mapping historical spatiotemporal patterns of fire events at a finer scale and over long time-series has great potential to bring better understandings of fire-driven disturbances and to better characterize fire regimes, allowing us to further explore relationships of burning patterns to several climatic, economic, and social variables. Moreover, it could increase the accuracy of future fire models, as suggested by Andela et al. (2017), and improve the estimates of aerosol emission due to biomass burning, thus also improving climate models predictions (Mouillot et al., 2014; Roberts et al., 2005).

2.2 Materials and Methods

2.2.1 Study Region

Fire is one of the most important factors that has shaped tropical savannas (Bond et al., 2004) including the Cerrado biome (Medeiros and Miranda, 2005), which is considered the most biodiverse savanna in the world (Klink and Machado, 2005; Myers et al., 2000). Conversely, fire has not played a major role during the evolution of the Amazon rainforest, due to its strong capacity to resist burning (Laurance and Williamson, 2001; Pivello, 2011). However, as the deforestation vector moves towards the Amazon forest, it modifies the natural moist microclimate on the edges of the forest patches, allowing fire to occur more frequently within the rainforest environment (Balch et al., 2008; Cochrane, 2003). Every year these biomes are subject to many natural or human-induced fire events, which are responsible for enormous burned extents and greenhouse gas emissions, causing loss of biomass, biodiversity, and soil nutrients, among other fire-related environmental consequences (Alencar et al., 2004; Balch et al., 2015, 2011; Cochrane, 2009; Laurance and Williamson, 2001; Morton et al., 2011; Pereira et al., 2017; Pereira Júnior et al., 2014; Shimabukuro et al., 2009).

The region chosen for this study is a subset of the transition zone between the Amazon forest and the Cerrado biome known as the arc of deforestation, due to its elevated deforestation rates over the last few decades. This region is considered as one of the most active agricultural frontiers in the world, (Laurance and Williamson, 2001; Morton et al., 2006; Souza, Jr et al., 2013). More specifically, the study region is located in the State of Mato Grosso - Brazil and extends to approximately

360,000 km², requiring 21 Landsat scenes to cover its area completely (**Figure 2.1**).

The coordinates of the upper-left corner and lower-right corner of the rectangle defining the study region are (Lat., Long.): -10.0, -60.0; -15.0, -54.0, respectively.

The defined scale for the products derived from the Landsat imagery is 1:100,000, and the Coordinate Reference System is the South America Albers Equal Area Conic, Datum South American Datum 1969, units in meters (EPSG: 102033).

Based on the Brazilian official biome delimitation, the study region extent is split into two biomes: 58% in the Amazon forest and 42% in the Cerrado savanna.

Hence, it is composed of a heterogeneous mosaic of vegetation types: tropical rainforests, swamps, woodlands, savanna and grasslands ecosystems. The

topography of the study region is dominated by low lands, predominantly featuring elevation not rising more than 300 meters above sea level. In its southernmost part, the elevation reaches highest values at the Chapada dos Guimarães plateaus, with values about 800 meters above sea level. The region is under the influence of the South America Monsoons System (SAMS: Carvalho and Cavalcanti, 2016), with two well-defined seasons: a wet one from October/November to March/April, and a dry one from April/May to September/October (Grimm, 2011).

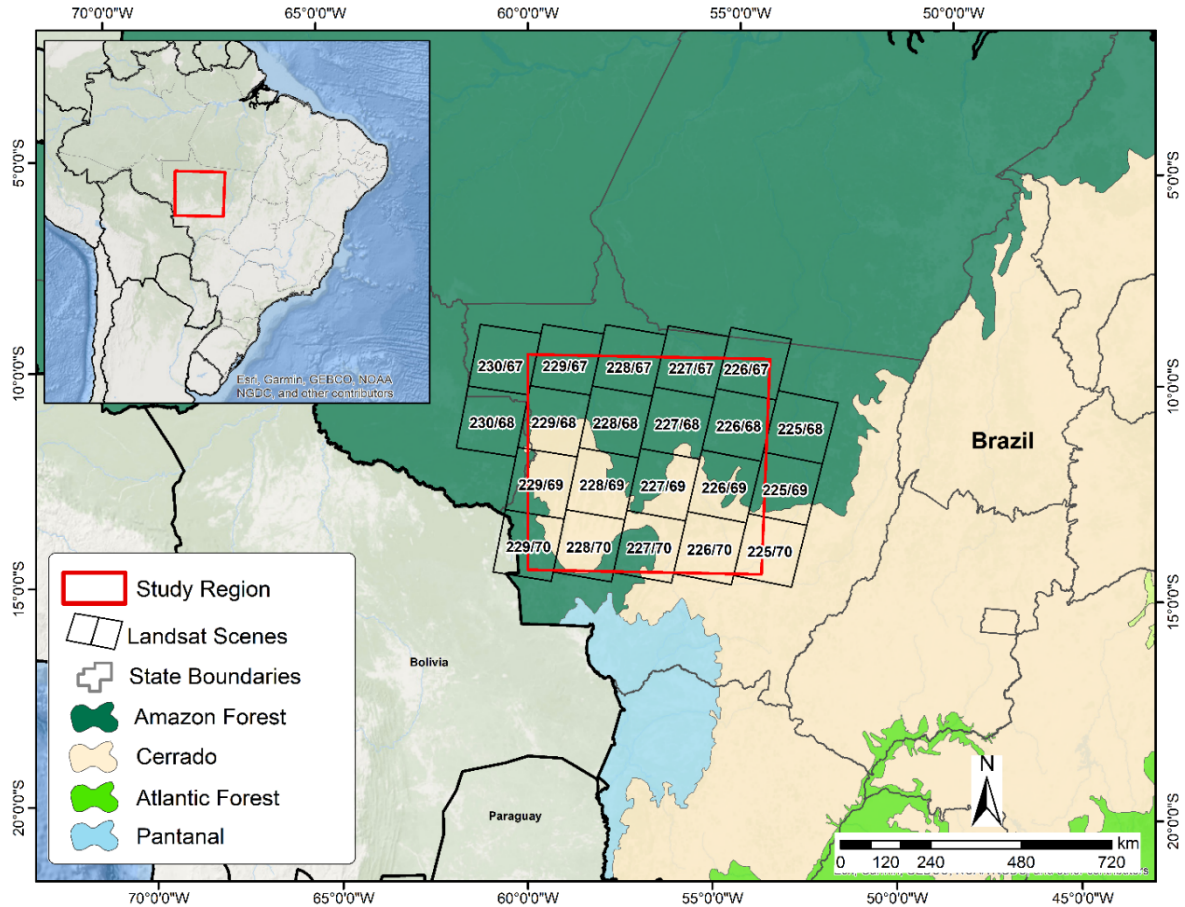


Figure 2.1. The study region is located within the Mato Grosso state, Brazil, and is split between the Amazon rainforest and the Cerrado savanna. The grid represents the individual Landsat scenes required to cover the study region completely, and the numbers are their respective path and row.

Typically, temperatures are high throughout most of the year, frequently exceeding 40°C during Spring. The mean temperatures during the warm months, September and October, vary from 32°C to 36°C, with the majority of the region having less than a full month with temperatures below 20°C during the winter. Rainfall varies considerably with latitude in this region. In its northern part, the mean precipitation is around 2,750 mm/yr., gradually decreasing towards the south, reaching values of 2,000 mm/yr. Over 70% of the annual precipitation occurs from November to March, with January-February-March having the highest values. From June through September precipitation is generally below 100mm/mo. and relative

humidity is extremely low, which characterizes the dry season in this area (Nimer, 1989; Grimm 2011). The combination of these climatic factors increases the fire risk in the region dramatically.

Aragão et al. (2008) observed a peak of hot pixels coinciding with the driest months, demonstrating that human-induced forces, such as land-use change, is critical to determine seasonality and annual patterns of burning activity. Lightning strikes are the cause of natural fires (Ramos-Neto and Pivello, 2000), and this type of ignition source is rare when compared to human-induced burning. Grimm (2011) summarized the annual cycles of precipitation over South America and her results were used as a proxy to portray time and space under the influence of the dry season.

2.2.2 BASMA Workflow

The general procedures to run the BASMA algorithm are summarized in a workflow shown in **Figure 2.2**. Individual methodological steps are presented and discussed in detail in the following subsections.

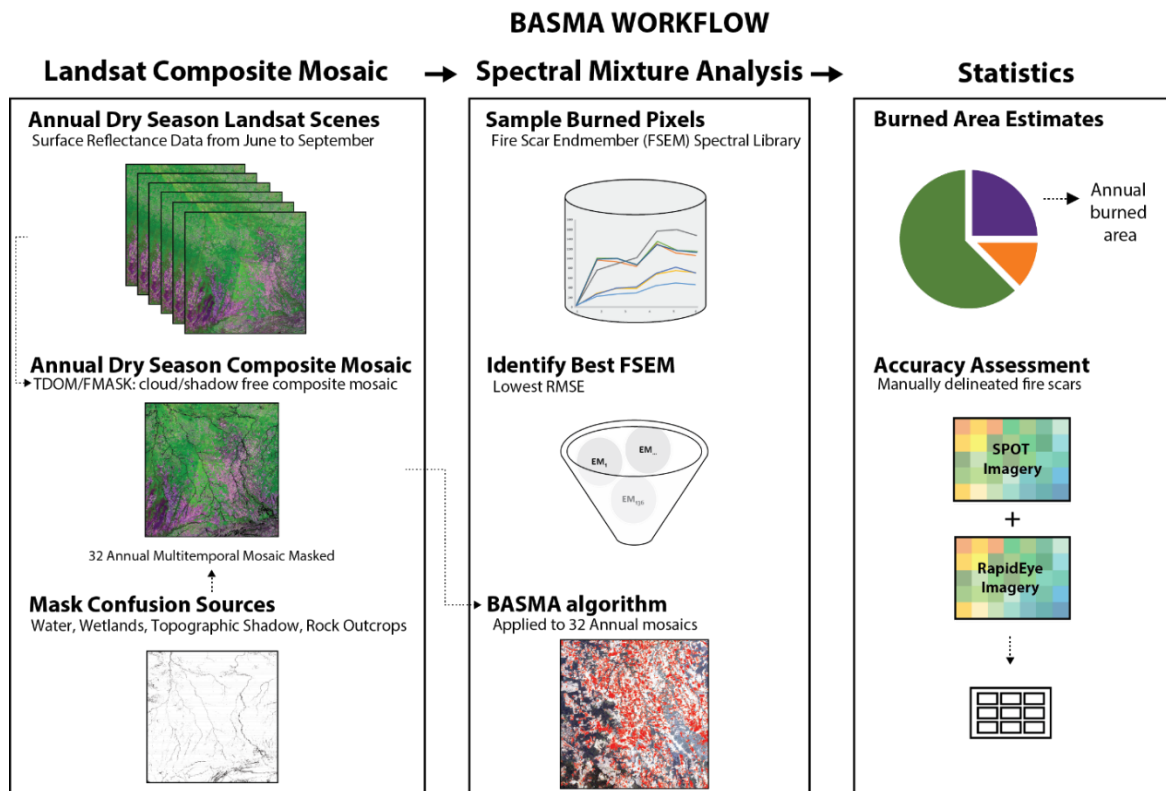


Figure 2.2. Burned Area Spectral Mixture Analysis (BASMA) workflow, showing the general procedures used to run the algorithm and to validate the results. Annual composite mosaics were built using multiple scenes from the dry season (June to September) and had the confusion sources masked. Fire scar endmembers (FSEM) were sampled from Landsat 5 TM and Landsat 7 ETM+ scenes covering a controlled vegetation burning area. The FSEM that best modeled burned area was identified by iteratively testing each endmember in the spectral library. Accuracy assessment was calculated based on the agreement and disagreement between the BASMA product and independent burned areas manually delineated from SPOT and RapidEye imagery.

2.2.3 Landsat composite mosaics

The Landsat data used in this project were converted to surface reflectance by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) algorithm (Schmidt et al., 2013). Imagery was accessed and digitally processed through the GEE Code Editor (<https://earthengine.google.com/>, last accessed January 8th, 2019). GEE is a powerful cloud platform that stores most Landsat collection and imagery from other freely available sensors, as well - e.g., the Advanced Very High-Resolution Radiometer (AVHRR), the Advanced Spaceborne

Thermal Emission and Reflection Radiometer (ASTER), MODIS, and the Sentinel family of sensors. Also, GEE provides an application programming interface (API) featuring several image visualization and processing algorithms, including functions to perform SMA (Gorelick et al., 2017; Housman et al., 2018).

The analyzed time-series covers the period between 1985 and 2017. Based on the availability of images, we built annual multi-temporal composite mosaics for the dry season using Landsat 5 TM for most years of the time-series (1985 to 2011). Within these years, Landsat 7 ETM+ was used for 2001 and 2002, which lacked Landsat 5 TM coverage for the study region. For the years from 2013 to 2017, we used Landsat 8 OLI imagery to build the annual composite mosaics. Despite the small difference among sensors, we performed a spectral transformation process by applying the ordinary least squares regression coefficients provided by Roy et al. (2016), in order to broadly normalize the reflectance measured by the six comparable Landsat OLI and Landsat ETM+ reflective bands. The year 2012 is the only one missing from our time-series since there is no high-quality imagery available from the Landsat series of sensors.

Annual dry season Landsat mosaics covering the entire study region were created using the approach described in Housman et al. (2018). The authors built an algorithm in GEE that takes advantage of the massive Landsat image collection available to increase the likelihood of producing a composite mosaic that is free of clouds and cloud shadows. We used the medoid method to build our annual mosaics, which retains single date observation across all bands for a given pixel. Building multi-temporal image compositing mosaics was critical to consistently have

full coverage of the study region for each year (Pereira, 2003), given that the study region has abundant presence of cloud cover due to the South Atlantic Convergence Zone (Carvalho et al., 2004). Thus, the annual multi-temporal composite mosaics were built using multiple scenes (**Figure 2.2**), meaning that pixels from early dry season could be side by side with pixels from late dry season. No criteria to favor pixels from later dates within the dry season was implemented when building the annual mosaic. Thus, the composite mosaics do not provide a complete record of the annual burned area within the study region as some burned pixel are likely to be excluded when generating the mosaics. Each mosaic contains pixels from at least 11 and up to 15 different imaging dates spanning from June through September. We selected this intra-annual period to ensure that all 32 composite mosaics represent the core dry season across the time-series (Grimm, 2011, 2004, 2003). Using a shorter intra-annual period resulted in a deficiency in pixel coverage for all the years analyzed.

2.2.4 Water bodies, Wetlands, Topographic Shade, and Rock Outcrops: well-known sources of confusions with fire scars

We created a surface water layer by combining the Joint Research Consortium (JRC) Yearly Water Classification History v1.0, a high-resolution layer representing global surface water (Pekel et al., 2016), to a water layer created using the Normalized Difference Water Index – NDWI (McFeeters, 1996). This surface water layer was applied to each annual mosaic, masking out major surface water bodies present in the study area. A 30 m buffer equivalent to a Landsat pixel size was created around the surface water layer in order to mask out pixels immediately

adjacent to water bodies. Additionally, fire scar false positives triggered by topographic shadows were eliminated by deriving a hillshade masking layer from the SRTM 30 m DEM (Farr et al.; 2007) for the region and setting a threshold to select topographic shaded areas.

To the best of our knowledge, there is no independent dataset delineating wetlands and rock outcrops for the study region. While testing the BASMA algorithm, a meticulous visual revision of the fire scar fractions was performed over the entire extent of the study region aiming to identify confusion with these particular surfaces. Areas interpreted as wetlands and rock outcrops were selected and assembled into a final layer, which was carefully compared to high spatial resolution imagery present in Google Earth Pro to confirm their precise delineation. In a final step, this layer was merged to the surface water and shade masks, producing a final mask composed of water bodies, shade, rock outcrops, and wetlands (**Figure 2.2**).

It is important to stress that the process of identifying sources of confusion with burned area was performed during the BASMA testing phase, and that the final mask was consolidated before running the algorithm to produce the results reported in this study. Therefore, the final BA product reported in this study did not go through visual inspection to eliminate potential confusion.

2.2.5 Visual Delineation of Reference Burned Area

Each annual dry season (June to September) composite mosaic was visually interpreted aiming to manually delineate conspicuous burned area polygons. A set of 11 polygons representing fire-affected areas was delineated for each year of the

time-series using an R: SWIR1(band 5), G: NIR (band 4), B: red (band 3) composite. Band composites using near-infrared and shortwave infrared channels readily allow for the clear identification of pixels representing burned areas (Roy et al., 2005; Pereira et al., 1997). Polygons were then uploaded to GEE as vector files (shapefiles) and overlaid on their respective annual mosaic to align with reference burned areas. They were used as a reference for delineating fire-affected shape and area, guiding the selection of the fire scar endmember (FSEM) that best modeled burned area and its fraction threshold when applying BASMA to map fire scars automatically.

2.2.6 Spectral Mixture Analysis (SMA)

Spectral Mixture Analysis (SMA) is a physically based model in which a mixed spectrum recorded in a pixel is modeled as a combination of two or more pure spectra (Adams, et al., 1993; Dennison and Roberts, 2003; Roberts et al., 1998; Roberts et al., 1993, Shimabukuro & Smith, 1991) By applying SMA, the reflectance of a given pixel ($p'\lambda$) can be modeled as the sum of the reflectance of each spectral endmember that composes this pixel, multiplied by its fractional cover, following the equation:

$$p'\lambda = \sum_{k=0}^n f_i * p_{i\lambda} + \varepsilon\lambda, \quad \text{with} \quad \sum_{k=0}^n f_i = 1.0 \quad \text{and} \quad f_i \geq 0, \quad (2.1)$$

where $p_{i\lambda}$ is the reflectance of a given endmember i for a specific band (λ); f_i is the fractional cover of this endmember i ; n is the number of endmembers; and $\varepsilon\lambda$ is the residual error. It is preferable to coerce the endmembers fractions to sum to 1 and to have positive values to guarantee that results are physically meaningful

(Adams et al., 1993; Shimabukuro & Smith, 1991; Somers et al., 2011). Thus, we constrained the equation to sum to 1 and to have nonnegative fractions. SMA model is assessed by the model residual error ($\epsilon\lambda$), reported as the root mean squared error (RMSE):

$$\text{RMSE} = \sqrt{\frac{\sum_{\lambda=0}^M (\epsilon\lambda)^2}{M}}, \quad (2.2)$$

Where M is the number of bands. SMA accounts for the fact that GV, NPV, and char endmembers are universal in most fire-affected natural landscapes.

Consequently, there is no need for extra training data after the best endmembers have been identified (Smith et al., 2007). Therefore, it requires less a priori information about the study site compared to more traditional classification methods. Moreover, the estimation of endmember fractions at the sub-pixel level provides detailed information about different successional stages related to fire scars (e.g., recently burned areas, vegetation regrowth, non-burned), which are critical for monitoring carbon accumulation, for example.

A spectral library containing 136 FSEM from 16 different years within the time-series was built using VIPER Tools'

(<https://sites.google.com/site/ucsbvipperlabor/viper-tools>, last accessed January 8th,

2019) EMC (**E**AR – Endmember Average Root Mean Square Error (Dennison and Roberts, 2003); **M**ASA – Minimum Average Spectral Angle (Dennison et al., 2004);

CoB – Count based Endmember (Roberts et al., 2003)) endmember selection

methodology. EMC is commonly used as a library pruning tool (Franke et al., 2009;

Tane et al, 2018), in which each iteration of identifying optimal endmembers (EAR,

MASA, and COB) tends to select a slightly different set of endmembers based on subtle discrepancies in spectra. Thus, EMC allows us to capture the endmember variability of a specific class. These FSEM are Landsat 5 TM and Landsat 7 ETM+ image endmembers extracted from fire-affected pixels sampled from scenes covering a controlled vegetation burning area, which is part of the International Long Term Ecological Research Network (ILTER) Fire Project at the IBGE Ecological Reserve in the surroundings of Brasília, Brazil (Miranda et al., 2010). No Landsat 8 OLI based image endmember was evaluated, given that its spectral bands are slightly different from Landsat 5 TM and Landsat 7 ETM+ bands, yet they have high similarities (Li et al., 2013). BASMA was applied to the 32 mosaics individually (**Figure 2.2**), using all six reflective bands and allowing only the FSEM to vary. GV, NPV, and Soil endmembers values were kindly shared by the MapBIOMAS project (<http://mapbiomas.org/>, last accessed January 8th, 2019). These endmembers were fixed for all the 32 annual models, given that these are not the focus of this research. The FSEM that best modeled burned area was identified by iteratively testing each one in the spectral library. This step was executed by running BASMA models several times for a given year. Each time a unique FSEM was assessed in terms of their RMSE values and the extent of modeled char fraction against the abovementioned set of 11 reference burned area polygons. Given the fact that shadow is an acknowledged error source for burned area (Pereira et al., 1997), it was necessary to establish a threshold for the char fraction that would reduce its confusion with the inherent shade fraction. A char fraction greater than or equal to

98% was defined, aiming to return only those pixels composed by high char fraction and consequently enhancing confidence regarding modeled fire scar extent.

2.2.7 Fire Scars Validation

Independent validation of the BASMA derived burned area was performed in several subsets of the study region. For this, we used a high spatial resolution (2.5 m) mosaic of Satellite Pour l'Observation de la Terre (SPOT) imagery from August 2007, kindly shared by The Nature Conservancy Brazil, and 17 RapidEye (spatial resolution of 5 m) scenes spanning the years of 2011, 2013, 2014, and 2015 (**Figure 2.3**), and collected between June and September (**Table 2.1**). There are no clouds in the SPOT mosaic and a maximum of 10% of cloud cover was set when selecting the RapidEye scenes. Parts of the RapidEye images that showed cloud cover were disregarded when validating BASMA results. Visual analysis was applied to manually delineate fire scars, resulting in a set of 92 polygons representing burned area that could be used as a reference. A false-color band composite was used for visual interpretation of the SPOT imagery: R: SWIR (band 4), G: NIR (band 3), B: red (band 2); and the RapidEye imagery: R: red-edge (band 4), G: NIR (band 5), B: red (band 3). In total, 9,572 ha of manually delineated burned area were used as reference to validate the BASMA results (**Table 2.1**). RapidEye imagery was provided by INPE, and the scenes used were based on data availability. Unburned reference data were assumed as the complement of the visually interpreted polygons representing reference burned area, excluding those parts of the imagery with presence of cloud and/or cloud shadows.

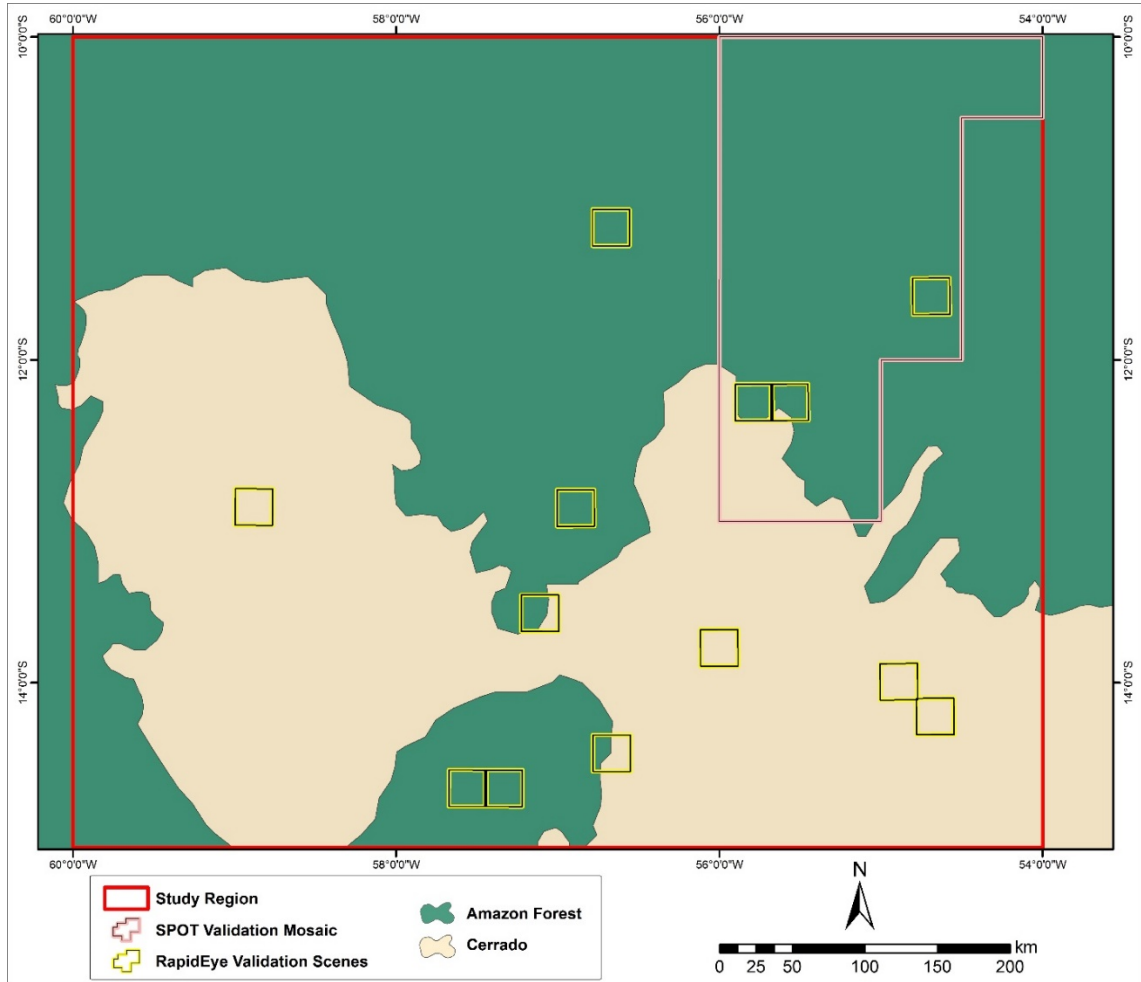


Figure 2.3. Spatial distribution of the SPOT and RapidEye independent validation subsets over the study region.

Accuracy estimates were calculated based on the agreement and disagreement between the BASMA product and references. Given that BASMA produces the burned area present in the imagery, which is usually a small fraction of the unburned area, the Dice Coefficient (DC) is a more adequate accuracy measurement (Chuvieco et al., 2018; Padilla et al., 2017, 2015). DC is defined as the probability that a classifier identifies a pixel as burned given that reference validation dataset also identifies it as burned (Fleiss, 1981). DC was calculated as follows:

$$DC = \frac{2 * Agreement}{2 * Agreement + False Positives + False Negatives} \quad (2.3)$$

Where *Agreement* represents the burned area that was mapped by BASMA and the reference validation dataset, *False Positives* represents the burned area that was over mapped by BASMA, and *False Negatives* represents the burned area that was under-mapped by BASMA.

2.2.8 Inter-comparison to other Landsat burned area products

In addition to the independent validation of the BASMA derived fire scars against visually interpreted burned area derived from finer spatial resolution imagery, we further assessed the quality of our product by inter-comparing it to supplementary burned area products derived from Landsat imagery. Comparison of BA products derived from the same imagery using different methods are reported to provide additional assessment of the algorithm results. We compared the BASMA results against burned area polygons extracted from subsets of four randomly selected mosaics out of the 32 annual mosaics in which we tested the algorithm. In order to create a database of manually delineated burned area, we visually interpreted these subsets of the Landsat mosaics using the R: SWIR1 (band 5), G: NIR (band 4), B: red (band 3) false-color band composite. These burned areas polygons were delineated over the Amazon and the Cerrado portions of the study region and are independent from those used as a reference when testing BASMA parameters.

Finally, we performed an inter-comparison between results from BASMA and the burned area layers consolidated by the Queimadas program managed by the Brazilian National Institute for Space Research – INPE (<http://prodwww->

queimadas.dgi.inpe.br/aq30m/#, last accessed January 8th, 2019). This portal hosts burned area polygon vectors derived from Landsat based on the calculation of Normalized Difference Vegetation Index (NDVI) and Normalized Burn Ratio Long SWIR Variation indexes, a methodology developed by Melchiori et al. (2014). Queimadas is the most comprehensive spatial database for fire events in South America. Nevertheless, the current limitations of this spatially-explicit database are that it only stores layers for 6 years (2011, 2013, 2014, 2015, 2016, and 2017) and only includes the Cerrado biome. Thus, it does not cover the entire study region nor the full time-series.

We implemented a site-specific comparison for several Landsat 5 TM and Landsat 8 OLI scenes, meaning that a judgement was performed polygon by polygon comparing burned area mapped by BASMA to burned area mapped by Queimadas. The selection of the validation scenes was based on Queimadas' burned area product availability. As the mosaics covering the entire study region are annual dry season composites (June through September), the INPE product does not represent the same period, given it is produced scene-by-scene. Therefore, we downloaded from the Queimadas database shapefiles representing burned areas and the respective Landsat scenes from which they were derived. Only those scenes that intersected the study region were selected. We performed a visual inventory of the downloaded imagery, aiming to avoid scenes featuring radiometric issues and to prioritize those scenes with less than 10% of cloud cover. We identified 11 Landsat scenes that met this criterion to further run the BASMA algorithm implemented in GEE to delineate burned area. Consecutively, we

performed a direct inter-comparison between the burned area modeled by BASMA and the burned areas generated by INPE. Inter-comparisons are reported as an agreement between BASMA results and the other burned area products.

2.3 Results

2.3.1 Spectral Mixture Analysis

Individual analysis of the 136 FSEM evaluating their corresponding RMSE values and burned area extent allowed us to identify a unique FSEM that consistently modeled fire-affected pixels over the 32 annual Landsat mosaics. This unique FSEM was extracted from the Landsat 5 TM path 221/row 71 from 20th of September 2003 scene (**Figure 2.4**). The application of BASMA produced a set of 32 layers representing fire scars present on each of the annual Landsat composite mosaics. These layers depict the spatiotemporal distribution of fire scars throughout the time-series.

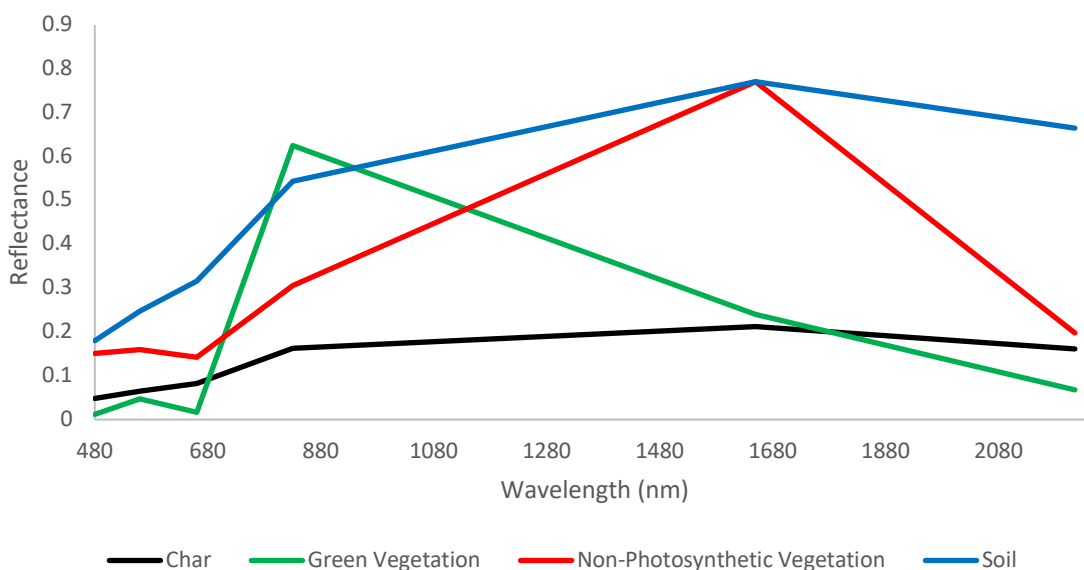


Figure 2.4. Endmembers spectra used as reference to run the Burned Area Spectral Mixture Analysis (BASMA) algorithm. Green vegetation (GV) is represented by the green line, non-

photosynthetic vegetation (NPV) is represented by the red line, Soil is represented by blue, and the char endmember is represented by the dark line.

2.3.2 Burned area extent

It is important to highlight that burned area results reported in this study refer to the dry season within each year of the time-series. From the total extent of the study site (36,196,320 ha), a total of 11,106,258 ha (30.7%) was mapped as having been burned at least once over 32 years (**Figure 2.5**). The burned area was highest in 1987, at 891,522 ha. The next largest burned area extents occurred in 1985 (773,514 ha), 1990 (758,202 ha), and 1986 (573,790 ha). In contrast, 2017, 2013, 2015 and 2016 had the lowest burned area, with 56,255 ha, 66,310 ha, 97,064 ha, and 104,041 ha respectively. The largest fire scar covers an area of 112,496 ha, located in the Paresi plateau. Regarding the mean size of fire scars mapped per year, 2014 had the highest value (17.69 ha), followed by 2001 (16.95 ha), 2015 (15.62 ha), and 2003 (15.23 ha). Conversely, the years displaying the lowest average burned area size were 1992 (4.93 ha), 1994 (8.32 ha), 1996 (8.50 ha), and 1995 (8.90 ha). The variance of the burned area was the highest in 1999, with a standard deviation equal to 743.55 ha, followed by 2001, with a standard deviation of 669.53 ha, 2007 (SD = 609.33 ha) and 2015 (SD = 593.94 ha). The lowest standard deviations were found for 1992 (60.55 ha), 1998 (171.06 ha), 2017 (176.11 ha), and 1988 (187.98 ha).

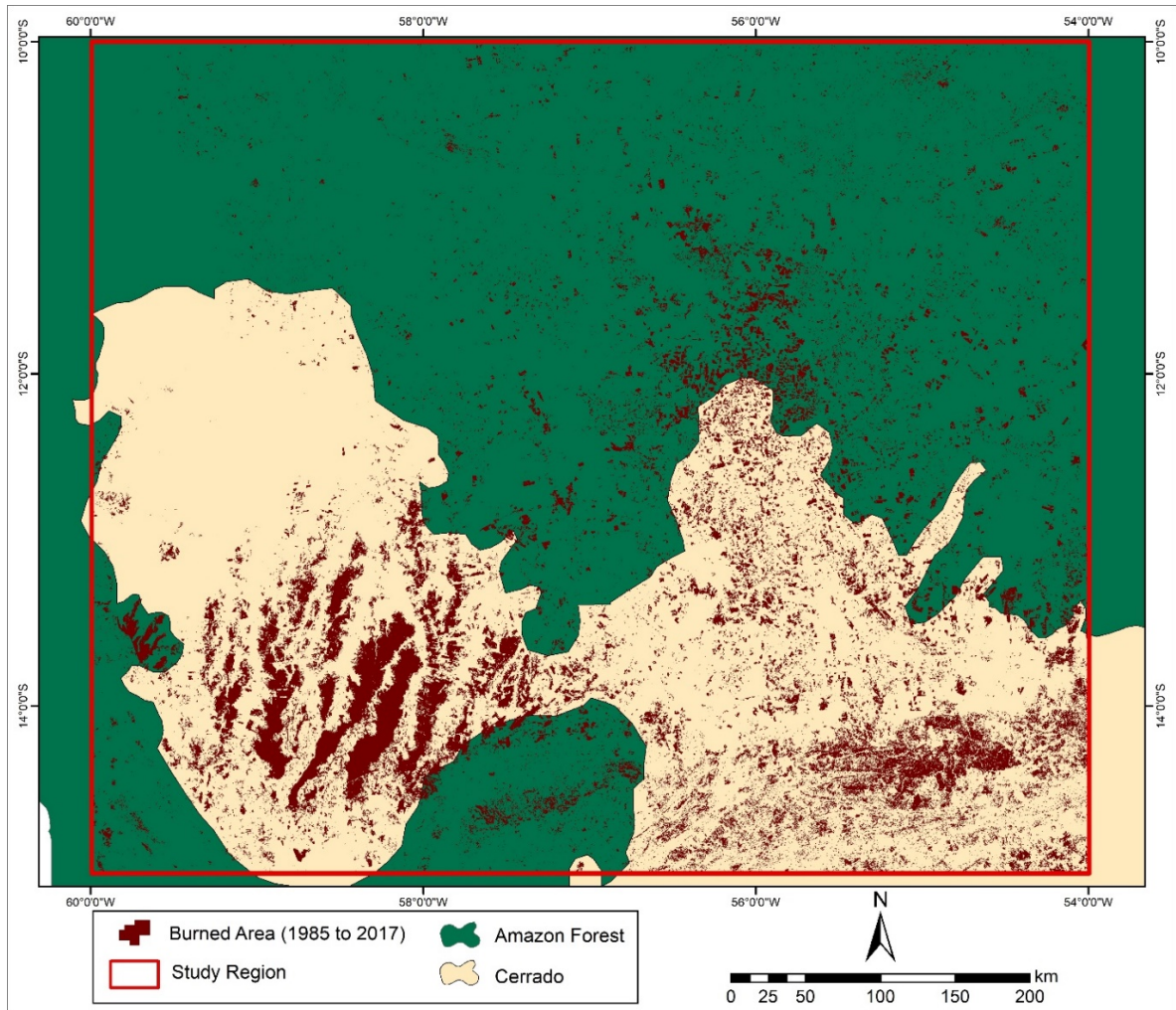


Figure 2.5. Burned area modeled by BASMA over the study region from 1985 to 2017.

2.3.3 Validation and inter-comparison to other Landsat burned area products

We validated the BASMA burned area product using independent reference layers produced by visual analysis of SPOT and RapidEye imagery for several years, returning an average Dice Coefficient equal to 0.86 (**Table 2.1**).

Table 2.1. Validation of burned area mapped by the BASMA algorithm against burned area mapped by visual analysis of the SPOT mosaic and the RapidEye imagery.

Day	Month	Year	Sensor	Reference burned area [ha]	BASMA burned area [ha]	Burned area under-mapped by BASMA [ha]	Burned area over-mapped by BASMA [ha]	Agreement between BASMA and reference [ha]	Dice Coefficient
15	August	2007	SPOT	3,253	2,980	457	185	2,795	0.90
19, 22	June	2011	RapidEye	1,922	1,943	282	303	1,640	0.85
2, 3, 22	August								
14	June	2013	RapidEye	1,073	1,107	129	163	944	0.87
3	August								
5	July	2014	RapidEye	1,109	1,269	107	267	1,002	0.84
11, 13	August								
5, 16, 17, 21	July	2015	RapidEye	2,215	2,569	219	573	1,996	0.83
3, 9, 16	August								

Further accuracy assessment was done by inter-comparison of the BASMA burned area to the Queimadas 30 m Burned Area product. **Table 2.2** displays values showing total burned area mapped by each methodology and the estimated agreement of the fire scars created with BASMA relative to the Queimadas dataset.

Table 2.2. Inter-comparison between burned area mapped by BASMA and the INPE/Queimadas burned area product.

Landsat Scene sensor_path_row_yyyymmdd	Queimadas Reference burned area [ha]	BASMA burned area [ha]	Burned area under-mapped by BASMA [ha]	Burned area over-mapped by BASMA [ha]	Agreement between BASMA and Queimadas [ha] (%)
L5TM_226_69_20110913	17,689	37,419	5,126	24,856	12,564 (71%)
L5TM_227_69_20110904	1,201	6,413	691	5,904	510 (42%)
L5TM_228_70_20110623	22,965	56,091	11,979	45,106	10,985 (48%)
L5TM_228_70_20110725	25,591	46,139	9,045	29,592	16,547 (65%)
L8OLI_226_69_20130716	1,597	3,177	426	2,005	1,171 (73%)
L8OLI_226_69_20140804	4,702	4,808	1,193	1,299	3,508 (75%)
L8OLI_226_69_20150807	771	1,066	323	618	448 (58%)
L8OLI_226_69_20150823	2,940	4,674	1,242	2,976	1,698 (58%)
L8OLI_226_70_20130716	6,614	9,743	1,597	4,725	5,017 (76%)
L8OLI_226_70_20140703	9,173	9,354	3,391	3,572	5,782 (63%)
L8OLI_228_70_20130730	36,302	90,201	11,577	65,476	24,725 (68%)
L8OLI_228_70_20140701	42,981	83,384	8,614	49,017	34,367 (80%)

Finally, we compared the BASMA fire scars to polygons manually delineated by visual analysis of the four randomly selected Landsat annual mosaics, taking advantage of the previously mentioned false color composite (R: SWIR1, G: NIR, B: red). Values summarized in **Table 2.3** report burned area mapped by each product and their agreement.

Table 2.3. Inter-comparison between burned areas mapped by BASMA and manually delineated polygons created by visual analysis of the Landsat annual mosaics.

Year	Visually interpreted burned area [ha]	BASMA burned area [ha]	Burned area under-mapped by BASMA [ha]	Burned area over mapped by BASMA [ha]	Agreement between BASMA and reference [ha] (%)
1995	29,547	27,735	10,891	9,079	18,655 (63%)
1997	57,899	50,085	19,969	12,156	37,929 (65%)
2001	107,051	78,202	32,507	3,658	74,543 (70%)
2010	9,740	7,522	2,882	664	6,858 (70%)

2.3.4 Burned Area per Biome

The Cerrado biome portion of the study region steadily showed more burned area than the Amazon forest portion between 1985 and 2017 (**Figure 2.6**), despite the study region having a greater area covered by the Amazon forest (58%) than Cerrado (42%). The Cerrado subset shows a higher variability in burned area and depicts a negative tendency, accounting for the vast majority of the burning at the early stages of human occupation of the study region, whereas the Amazon part shows considerably lower burned area for about 10 years (1985 to 1994). Beginning in 1995, the annual burned area started to increase within the Amazon portion of the study area. In 2002, the proportion of burned area in the Amazon forest surged from about 25% to 54% in relation to the burned area in the Cerrado, reaching its

peak in 2004 at 60%. After 2004, this proportion declined to rates similar to those seen during the first 10 years of the time-series.

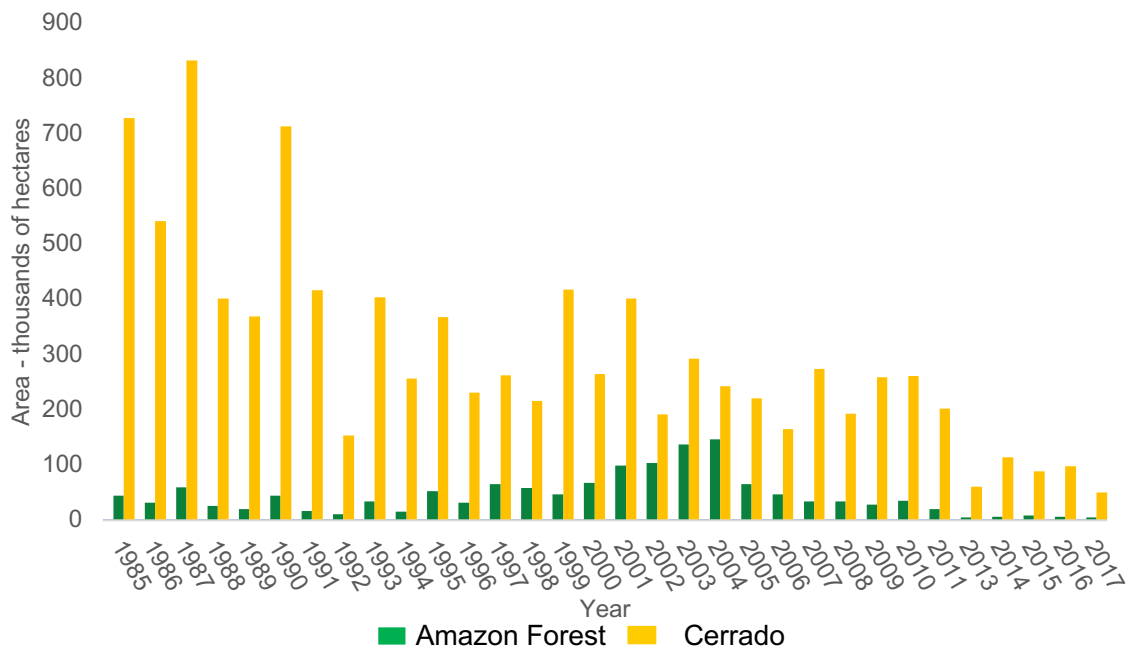


Figure 2.6. Temporal distribution of burned area per biome over the 32-year time-series.

2.3.5 Trends in Burned Area Over the Time-Series

A linear regression analysis revealed a decreasing trend in burned area over the period studied. The identified trend is statistically significant, returning a p-value < 0.01 (Degrees of Freedom = 27). This trend in the annual burned area is similar to the decreasing trend shown in the annual deforestation rate estimated by the Brazilian Legal Amazon Monitoring project - PRODES - from INPE (<http://www.obt.inpe.br/prodes/dashboard/prodes-rates.html#>, last accessed January 8th, 2019) estimated for the entire territory of Mato Grosso state (**Figure 2.7**), a link that has been observed in previous studies (Andela and van der Werf, 2014; Aragão et al., 2008) . The Pearson’s correlation test was performed between

these two variables over the time-series and found a significant linear correlation (Correlation Coefficient = 0.51, Degrees of Freedom = 27, p-value < 0.01). Note that the historical deforestation data started in 1988 when the PRODES project began. Thus, the correlation coefficient was estimated using data from 1988 to 2017.

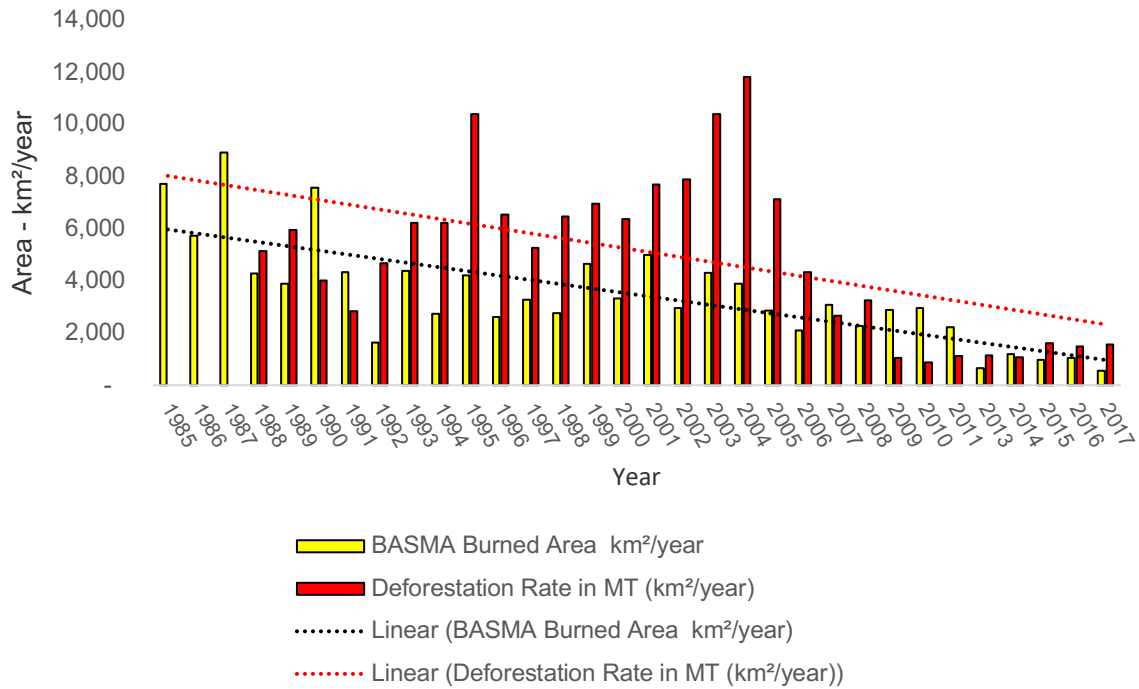


Figure 2.7. Decreasing trend in BASMA-derived burned area and in deforestation rate in the state of Mato Grosso measured by PRODES/INPE between 1988 and 2017.

2.4 Discussion

Given the multispectral properties of the Landsat sensors, it is often difficult to avoid confusion between fire scars and other dark surfaces such as wetlands, lakes, and shaded slopes. The application of BASMA over the 32 annual mosaics confirmed that water bodies, wetlands, and topographically-shaded areas were the major sources of classification confusion with fire scars, as shown in the literature (Bastarrika et al., 2011; Pereira et al., 1997; Pereira, 2003; Shimabukuro et al.,

2009). Fire scars are recognized by their lower reflectance in the visible (VIS), near (NIR) and short-wave infrared (SWIR) wavelengths of the electromagnetic spectrum. (Pereira, 2003; Veraverbeke et al., 2012). Additionally, fire scar spectral characteristics have intrinsic temporal and spatial variability, and despite the variety of methods applied to map burned areas in multispectral imagery, there are still complications to accurately discriminate char signals from well-known sources of confusion (Pereira et al., 1997). Hence, the assembly of a mask excluding lower albedo surfaces is a critical step in our methodology, minimizing well-known confusions and avoiding manual editing of the final results.

After identifying the FSEM that best modeled burned area and masking confusion sources for all annual mosaics, BASMA takes a few seconds to process a Landsat mosaic covering the entire study region, producing a burned area layer promptly. The short time it takes to process a large amount of data represents a substantial improvement in the implementation of SMA, given GEE's remarkable processing power. As stated by Somers et al. (2011), the key step for applying spectral mixture analysis is the ability to identify the best endmember that would model the variability of the target being mapped over space and time. Finding the endmember that consistently modeled fire scar fractions throughout the time-series and over the full extent of the study region was a challenging step, given that each endmember of the fire scar spectral library had to be assessed individually. Nonetheless, each round of individual endmember evaluation allowed us to discard those that did not appropriately modeled burned areas, and therefore the number of endmembers was considerably reduced after initial iterations.

Another advantageous feature of the tested methodology is the facility to adjust the char fraction threshold, allowing the analyst to define the level of confidence to be applied to the final product. The ease to modify the fraction threshold combined with the efficiency to digitally process a large amount of Landsat data permits a researcher to readily generate burned area products in seconds and ultimately compare their results. This means that one can be more or less critical when delineating burned area, helping to assess different circumstances. This characteristic would help, for instance, the calculation of CO₂ emissions under flexible or rigorous scenarios regarding fire-affected areas.

We validated the fire scars mapped by BASMA against independent burned area products extracted from finer spatial resolution imagery. Layers visually interpreted from SPOT (2.5 m) and RapidEye (5 m) imagery for several years were used to validate BASMA results, returning an average Dice coefficient of 0.86, leading to the conclusion that the methodology tested in this study is sufficient to identify and delineate fire scars. Additionally, we compared BASMA results to the 30 m Burned Area product generated by the Queimadas project from INPE, and to a set of four annual burned area layers produced by visual analysis over subsets of the same Landsat mosaics used to generate the SMA product. Agreement with these two independent products also derived from Landsat data returned average agreement of 64.7% with the Queimadas burned area and 67.2% with the manually interpreted burned area. The discrepancies shown in the agreement between BASMA and Queimadas products when comparing scene by scene are due to the

fact that there are substantial differences between these two products, as discussed further in this section.

Validation of a time-series product representing burned area has proven to be a challenging task (Roy and Boschetti, 2009), given the absence of continuous and consistent methods for validation and inter-comparison. Humber et al. (2018) conducted a study in which they compared four global burned area products (Fire_cci, Copernicus Burnt Area, MODIS MCD45A1, and MODIS MCD64A1) and found that these products lacked agreement on burn locations or timing, concluding that users of burned area products need to account for the inherent nature of omission and commission errors embedded in these products. Padilla et al. (2015, 2014) proposed a statistically rigorous validation method for validation of global burned area products, yet it relies on independent reference data derived from imagery featuring finer spatial resolution. Hence, comparison to burned area products derived from higher spatial resolution imagery is the typical validation process for coarser spatial resolution fire-affected products (Smith et al., 2007; Roy and Boschetti, 2009; Padilla et al., 2015, 2014).

Having a high accuracy is one of the major priorities for burned area end-users, as reported by Mouillot et al. (2014), who conducted a survey of users of remote sensing derived burned area products, and corroborated by Bastarrika et al. (2011). Comparing our results to other studies that delineate fire scars using Landsat imagery, we have comparable accuracies. Liu et al. (2018) estimated an overall accuracy of 79.2 % on their burned area product applying a harmonic model fit to a 16-year time-series in West African savannas, and Hawbaker et al. (2017) reported

an accuracy of 89% on their burned area product for the conterminous United States.

Fire scar extent generated with BASMA consistently estimated more fire-affected area when compared to the Queimadas product. We rationalize this by the fact that BASMA is a sub-pixel approach sensitive to burn heterogeneity and which delineates fire scars at a finer scale when compared to the approach used by Melchiori et al. (2014), and by the strong aptitude of the FSEM used to model the fire scar variability. Burning variability has a strong influence on the ability of a method to delineate fire scars (Cochrane, 1998). Fire disturbs vegetation in different ways due to local characteristics, such as topography, vegetation structures/types, and fuel availability and dryness. Variability in fire spread and intensity is strongly influenced by fuel condition and weather, leading to the formation of heterogeneous landscapes composed of different degrees of burned patches and unburned islands of biomass (Cochrane and Schulze, 1999; Lentile et al., 2006).

Moreover, sub-pixel analysis has the advantage of being able to model char fractions of relatively older fire scars that do not have sufficient signal to trigger classification algorithms based on spectral band ratios and/or visual analysis alone. An example is shown in **Figure 2.8**, which displays a false color composite, Queimadas 30m Burned Area and the BASMA-derived product. In this figure, a considerable agreement between the two fire products is evident. However, there are also important differences. For example, a comparison between the products shown in the first row, shows areas of pasture that were clearly not burned, yet are called burned in the Queimadas product (1), and other areas that were clearly

burned yet classified as unburned (2). Although the BASMA product is more accurate, it does show some areas that are clearly small-scale burns, yet those were not mapped as burned (3). Examples shown in the second and third rows clearly illustrate fire scars that were mapped by BASMA but missed by Queimadas product (4 & 5).

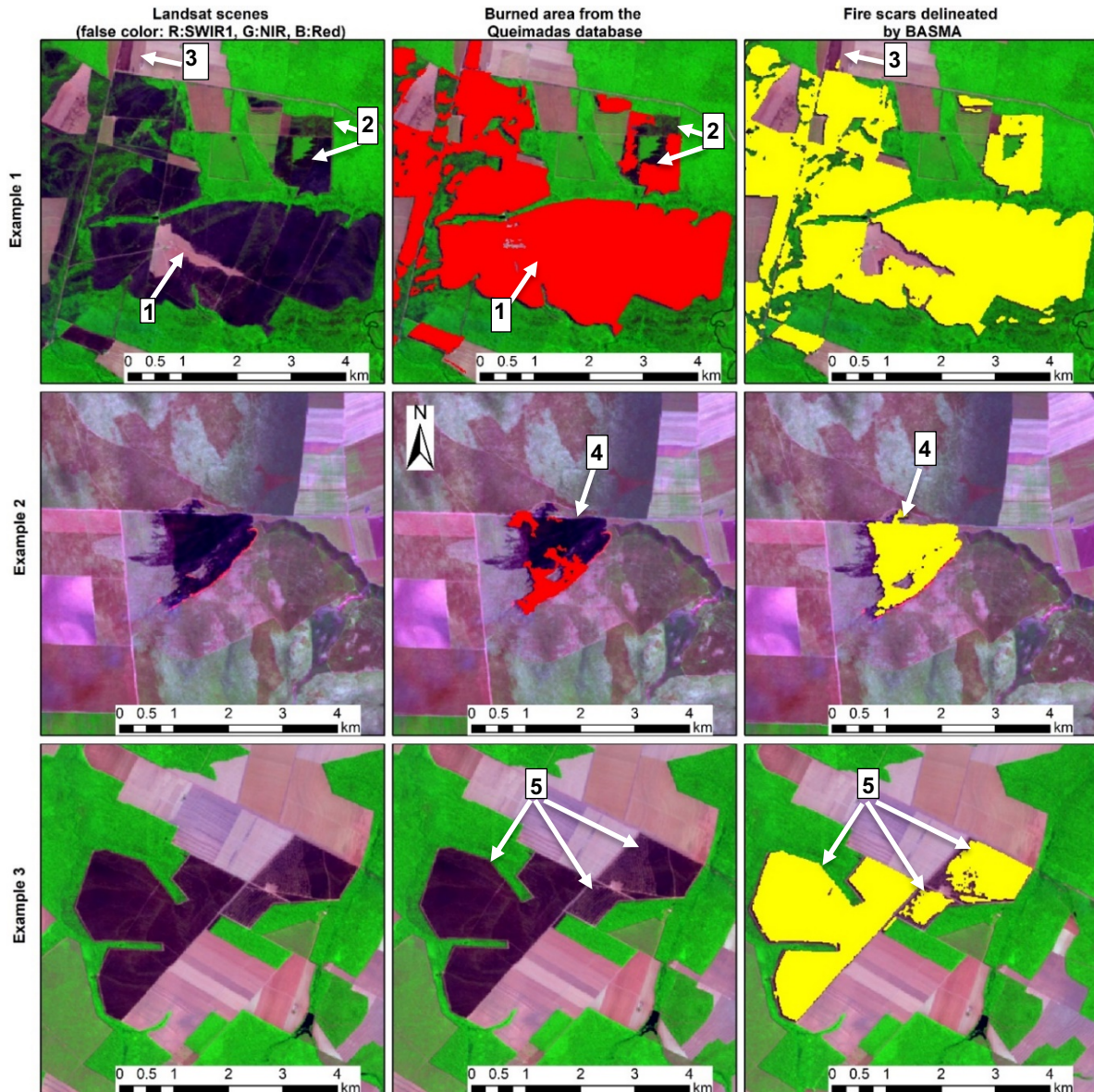


Figure 2.8. Comparison among fire scars shown in Landsat scenes (R: SWIR1, G: NIR, B: red), burned area from the Queimadas database and fire scars delineated by BASMA. Number 1 points to an area that was clearly not burned but was mapped as burned by Queimadas; numbers 2, 4 and 5

point to areas that were clearly burned but were not mapped by Queimadas; and number 3 points to a small-scale area that had burned but not consistently mapped by BASMA.

Zooming in on the southwestern quadrant of the study region, particularly in the grasslands of the Paresi plateau, it is possible to observe several fire scars in which dark purple pixels represent either recent burns compared to the date of passage of the Landsat sensor or burns that occurred in the late dry season when biomass is thoroughly dry, whereas lighter shades of purple represent relatively older fire scars and/or burns that occurred in early dry season when biomass is not thoroughly cured (**Figure 2.9**). Further inter-comparison between the BASMA-derived fire scars and the Queimadas product for this particular site demonstrates substantial agreement, yet some areas that clearly have burned are missed by the Queimadas product (6).

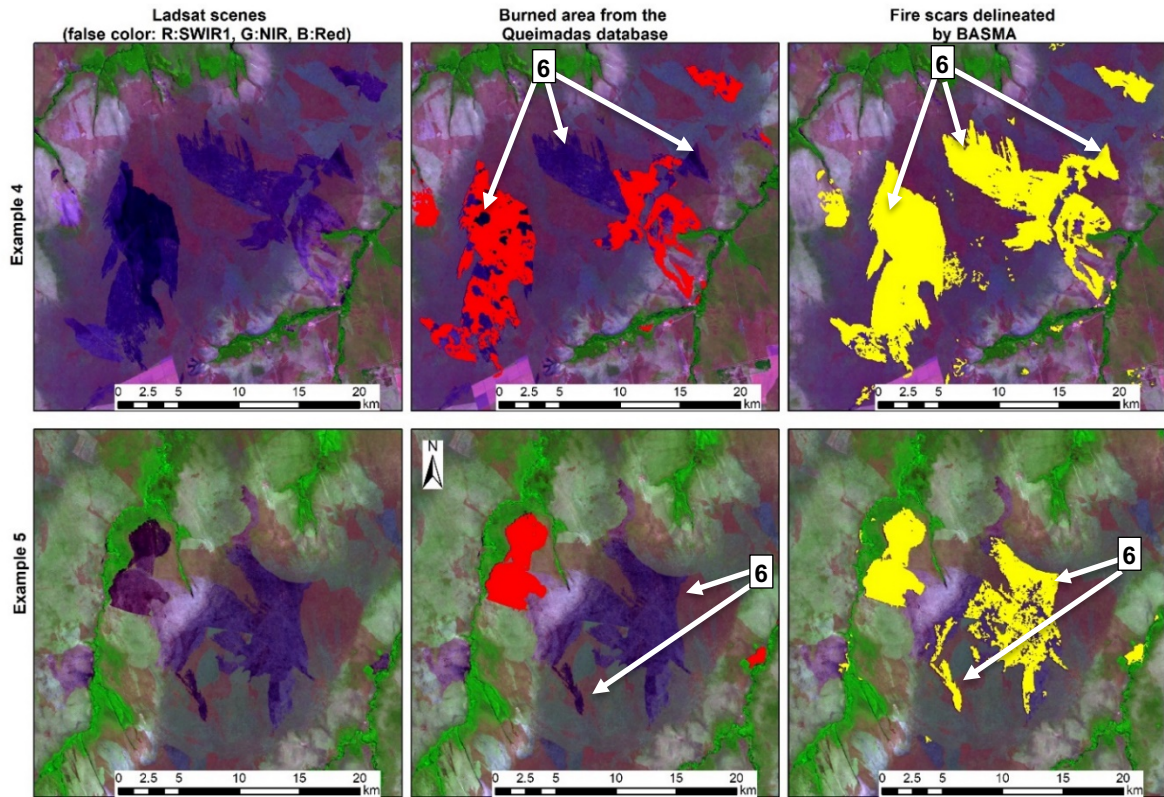


Figure 2.9. Comparison among fire scars shown in Landsat scenes (R: SWIR1, G: NIR, B: red), burned area from the Queimadas database and fire scars delineated by BASMA, for a subset of the Paresi plateau in the western part of the study region. Number 6 points to areas that had clearly burned but were missed by Queimadas burned area.

The Paresi plateau is the largest contiguous remnant of grasslands located in the state of Mato Grosso, displaying an extensive mosaic of indigenous people reserves with a fire regime grounded in the traditional knowledge regarding the use of fire by its historical dwellers (Falleiro, 2011; Falleiro et al., 2016). BASMA delineated large fire scars within these indigenous lands, some of them stretching to over 70 km in length. In contrast, the Queimadas product underestimates burned area within these grassland ecosystems, given that it misses significant fire scars as demonstrated in **Figure 2.9**. The aforementioned author, Rodrigo Falleiro, has extensive local experience and knowledge regarding the traditional use of fire by indigenous people living in these reserves. He endorsed the spatiotemporal

patterns of the SMA-delineated burned area during a personal communication in which he had the chance to visually inspect our burned area product for that specific area. Falleiro also stressed that the process of reestablishing the traditional fire management in this region is resulting in significant ecological benefits, given that it is covered by a pyrophilic ecosystem.

Overall, the burned area modeled by BASMA shows a decreasing trend over the 32-year time-series (**Figure 2.7**), a pattern that has been reported by Andela et al. (2017). This finding endorses the hypothesis of a pyric transition (Pyne, 2001), which suggests that fire activity is highest at the early stages of human occupation of a particular region and declines as the population settles. This tendency is explained by social characteristics, such as efforts to suppress burning due to the threats fire poses to society (health issues, property and economic losses), and by environmental characteristics, such as progressive discontinuity of fuel given the high level of fragmentation of the remnant vegetation. Inspecting the most frequently burned areas identified by the recurrence analysis we observed that a substantial extent of the study region displays a relatively high fire recurrence, considering that the vegetation covering the study area is an ecotone between rainforest and savanna. This suggests that those areas are exposed to higher risk of degradation, which often leads to the abandonment of these areas and consequently deforestation of new areas. A small extent corresponding to 0.02% of the total area was identified as having been burned 32 times over 32 years. Carefully analyzing these scattered pixels, we identified that all of them are within the grassland ecosystem of the Paresi plateau, an area under traditional fire

management that shows the largest fire extents and most recurrent burned areas. Therefore, although these may be artifacts in the products, it is not implausible that these results could be a product of an actual human-induced fire regime

2.4.1 BASMA Uncertainties and Limitations

Given the multi-temporal feature of the annual mosaics, the product reported in this study does not provide a complete record of the annual burned area within the study region as some burned pixels are likely to be excluded when generating each mosaic. Burned pixels could also have been either missed because they occurred late in the fire season and were outside of the multi-temporal composite window, or they occurred early enough and were masked by vegetation recovery. Thus, further exploration on how to build the annual mosaics is necessary, aiming to identify char pixels that better express fire-affected areas. In addition, given the extent of the study region and resolution of pixels, it is plausible that there are some non-burned dark pixels present in the annual mosaic composites (including small scale water dams) that were not excluded by the water-topographic shade-wetland mask. Thus, these could be likely included as burned area in the final result.

2.5 Conclusions

A generic and optimal context-independent method to detect and map fire scars is challenging to develop, given the spectral signal captured by spaceborne sensors (Pereira et al., 1997). Nevertheless, image endmembers have the advantage of having been measured at the same scale as the image data (Quintano et al., 2017). Our results demonstrate that BASMA successfully identified char fractions within Landsat pixels collected from 1985 to 2017 for an area of 36 million hectares,

allowing us to delineate burned areas. Imagery from Landsat 5 TM, Landsat 7 ETM+, and Landsat 8 OLI were digitally processed and burned area was consistently modeled by a single fire scar image endmember and a single fraction threshold. Accuracy assessment done against burned area products extracted from finer spatial resolution imagery for several years returned high Dice coefficients (varying from 0.83 to 0.90, with 0.86 of average). This is robust evidence that BASMA is an effective algorithm to map fire scars for a large extent over long time-series analysis using imagery acquired from sensors with similar spatial and spectral resolution. We suggest that our method should be tested in other landscapes and sensors. For that, the image endmembers must be selected from the image used as input to BASMA, assuring that it has the same scale as the imagery covering the study area and represents the same fire regime.

The lack of confidence for accurately mapping fire-affected areas in tropical landscapes is considered one of the major sources of error for calculations of pyrogenic emissions of carbon monoxide and carbon dioxide (Mouillot et al., 2014). Because of that, there is an urgent need for accurate burned area maps that would enhance the quality of emissions estimates (Smith et al., 2007). Mapping burned area using moderate to high spatial resolution time-series over large extents not only has the potential of improving emissions estimates but also allows us to better characterize spatiotemporal patterns of fire, given its finer scale results.

Furthermore, broadly analyzing the burned area database produced by BASMA raises the hypothesis that there is a positive correlation between commodities prices and the use of fire in this region, as suggested by Morton et al. (2006).

However, these are subjects that will be further explored in the next stage of our research.

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Chapter 3: Why burning so often? Three decades of anthropogenic fire activity in a Neotropical agricultural frontier.

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3.0 Abstract

In the Brazilian agricultural frontiers, anthropogenic fire is mainly used to convert natural vegetation to agriculture and grazing, to manage pastures and to eliminate crop residues. Featuring one of the most active agricultural frontiers in the globe, Mato Grosso state features a transition zone between the Amazon rainforest and the Cerrado savanna that has experienced intense fire activity over the last 4 decades. To understand the human use of fire and its relation to land use and land cover change (LULCC), it is necessary to analyze changes in fire activity that occur with an increase in human occupation. The pyric transition concept proposed by Pyne in 2001 predicts that the use of fire is high at the early stages of human occupation and decreases when the area is colonized, however, this concept still needs to be tested quantitatively. In this study, we combine two fine-scale (30-meter spatial resolution) remote sensing derived datasets spanning a long time-series (1985 to 2017) to test the pyric transition hypothesis at the tropical forest-savanna ecotone in southern Amazon forest. Our results showed clear shifts in burning activity, confirming the anthropogenic influence over the pyrogeography of our study area. Spatiotemporal patterns of burned area and LULCC demonstrated that fire activity increased in the study area as more land was opened for economic use during the intermediary period of the analyzed time-series, and that burning dramatically decreased towards the end of the analyzed period, mainly driven by public policies.

3.1 Introduction

One of the most active deforestation frontiers in the world in recent decades, the Arc of Deforestation in Mato Grosso state, Brazil, is marked by frequent and widespread anthropogenic fires (Daldegan et al., 2019; Macedo et al., 2012; Morton et al., 2006; van der Werf et al., 2009). Pyne (2001) asserts that human-driven fire activity in a given region tends to follow a pyric transition. This concept predicts that the use of fire increases at the early stages of human occupation and then decreases as the region is further developed and industrialized and fuels become increasingly fragmented. Furthermore, anthropogenic fire tends to decline due to the combination of fire suppression efforts, technology substitution, and increased law enforcement (Andela et al., 2017; Bowman et al., 2011; Mann et al., 2016; Pyne, 2009).

People have long used fire to manage lands for food and forage production (Cochrane, 2009; Pivello, 2011; Pyne, 1997; Schmidt et al., 2011). Bowman et al. (2011) and Roos et al. (2014) affirm that humans not only have direct influence over burning patterns via ignition sources and suppression efforts but also modify the type, load, structure and continuity of fuel; alter microclimates; and burn biomass in different seasons than non-anthropogenic fire regimes. Here we analyze a long-term (1985 to 2017) and fine-scale (30-meter spatial resolution) spatially-explicit database representing burned area and land-use and land-cover change (LULCC) for a subset of the active agricultural frontier in Mato Grosso state to characterize and quantify anthropogenic fire in relationship to land-use change. Accounting for the land-use trajectory over time, which reflects the different colonization stages of

the region over the last 30+ years, we propose that fire activity in the most productive agricultural part of Mato Grosso state has manifested a pyric transition, as predicted by Pyne (2001).

The study area lies in the transition zone from the Amazon rainforest to the Brazilian Cerrado, an area that has high biodiversity and is important for conservation (Marques et al., 2019). Featuring intensive human occupation over the last four decades, these biomes have been experiencing high deforestation rates and increasing fire frequency during the dry season (Aragão et al., 2008; Valeriano et al. 2004). A substantial extent of the natural vegetation has been converted mainly to agriculture and pasture uses, among other economic activities (Barreto et al., 2006; Davidson et al., 2012; Klink and Machado, 2005). The Brazilian National Institute for Space Research (INPE) estimates that 46.8% of the Cerrado's original extent has been converted to anthropogenic uses by 2018 (<http://terrabrasilis.dpi.inpe.br>, last accessed May 15th, 2019), while Nobre et al. (2016) reported that approximately 20% of the Amazon forest has been deforested.

The flora of the Cerrado biome is adapted to fire (Coutinho, 1977; Coutinho, 1990) and most of the Cerrado ecosystems are considered fire-dependent (pyrophilic: Myers, 2006; Pivello, 2011). In contrast, Amazonian rainforest ecosystems are generally considered fire-sensitive (pyrophobic: Myers, 2006; Pivello 2011). Once burned, these moist tropical forests are more likely to experience recurrent burns (Cochrane et al., 1999; Laurance et al., 2007). Also, forest patches that are adjacent to converted lands have their edges exposed to more insolation and turbulence, drying out their understory vegetation and litter,

making those areas more susceptible to fire (Cochrane, 2003). Grass species established in the understory can be a renewable source of fuel for recurrent burns (Aragão et al., 2008; Cochrane and Schulze, 1999).

Normally, the process of land occupation in the Brazilian agricultural frontier starts with selective logging of the most valuable timber species, followed by additional felling and burning to further clear the land (Cochrane, 2009). Morton et al. (2006) suggested that in Mato Grosso soybean expansion tends to occur on already-cleared lands. Likewise, Spera et al. (2014) affirmed that soybeans commonly expand over lands previously occupied by cattle pastures, and consequently additional lands are cleared for livestock. Thus, soybean expansion has an indirect impact on deforestation, given that it displaces cattle ranching towards the forest frontier. This process is often referred to as land-use intensification, where extensive land uses are replaced with intensive production (Macedo et al., 2012). In a global assessment of fire activities, Andela et al. (2017) assert that trends in regional fire use are directly related to trends in cropland expansion or deforestation.

Human activity is considered to be the primary ignition source in tropical forests, savannas, and agricultural systems (Andela et al., 2017). In the Brazilian agricultural frontier, fire is mainly used to convert natural vegetation to cropland and rangeland, to manage encroachment of shrubs and trees in pastures, and to eliminate crop residues (Cochrane, 2009; van der Werf et al., 2009). Fires may escape into native vegetation, slowly burning the forest understory or large extents of savanna remnants. Thus, anthropogenic fire can be classified into three kinds:

Land-clearing; pasture and cropland Maintenance; and Accidental fires (Morton et al., 2008; van der Werf et al., 2009). Land-clearing fires, also called slash-and-burn, are more intense than the latter two types; flaming combustion can last for many hours and smoldering combustion for many days (Cochrane, 2009, 2003).

Maintenance fires are used to manage shrub encroachment on pastures and croplands, preventing natural succession. Accidental fires vary in intensity and spread rate depending on the ecosystem. Fire escaping into mature forest tends to be understory, low-intensity surface fires that move slowly and consume litter and coarse woody debris. Accidental fires in previously disturbed forests can result in forest degradation, generally leading to canopy mortality and structure changes (Cochrane, 2009; Morton et al., 2011).

Andela et al. (2017) documented a decline in fire events and burned area globally between 1998 and 2015 but noted that the mechanisms regulating human use of fire in diverse ecosystems remain poorly understood. Likewise, Bowman et al. (2011) suggested that the pyric transition concept requires additional testing and that quantifying the transition from one pyric phase to another is critical for understanding the human-fire interaction dynamics and their consequences. For the southern Amazon frontier, Morton et al. (2008) asserted that the relationship between burning and deforestation remains poorly quantified. In this study, we combine two fine-scale remote sensing derived datasets spanning a long time-series to test the pyric hypothesis at the tropical forest-savanna ecotone in southern Amazonia. Following Bowman et al.'s (2011) model of pyric phases, we anticipate

observing two pyric transitions: from ‘wildland anthropogenic fire’ to ‘agricultural anthropogenic fire’, and then to ‘fire suppression and wildfires’ phase (**Figure 3.1**).

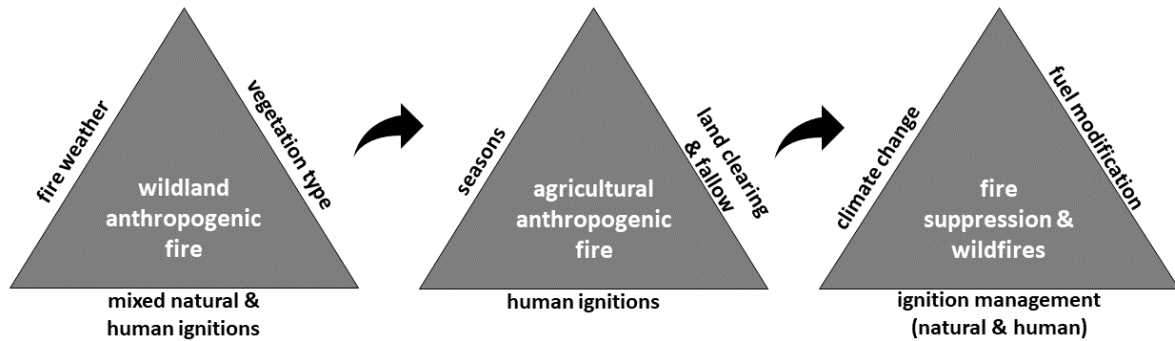


Figure 3.1. Conceptual scheme representing pyric phases transitions (adapted from Bowman et al., 2011).

3.2 Materials and Methods

3.2.1 Study Area

The study area spans 108,210 km², which encompasses the main agricultural region in Mato Grosso state (**Figure 3.2**), a region known for its high agricultural yields and for some of the municipalities included in the Brazilian Ministry of the Environment’s Deforestation Black List (MMA, 2013). It is split between the Amazon biome (69,019 km² - 64%) and the Cerrado biome (39,191 km² - 36%).

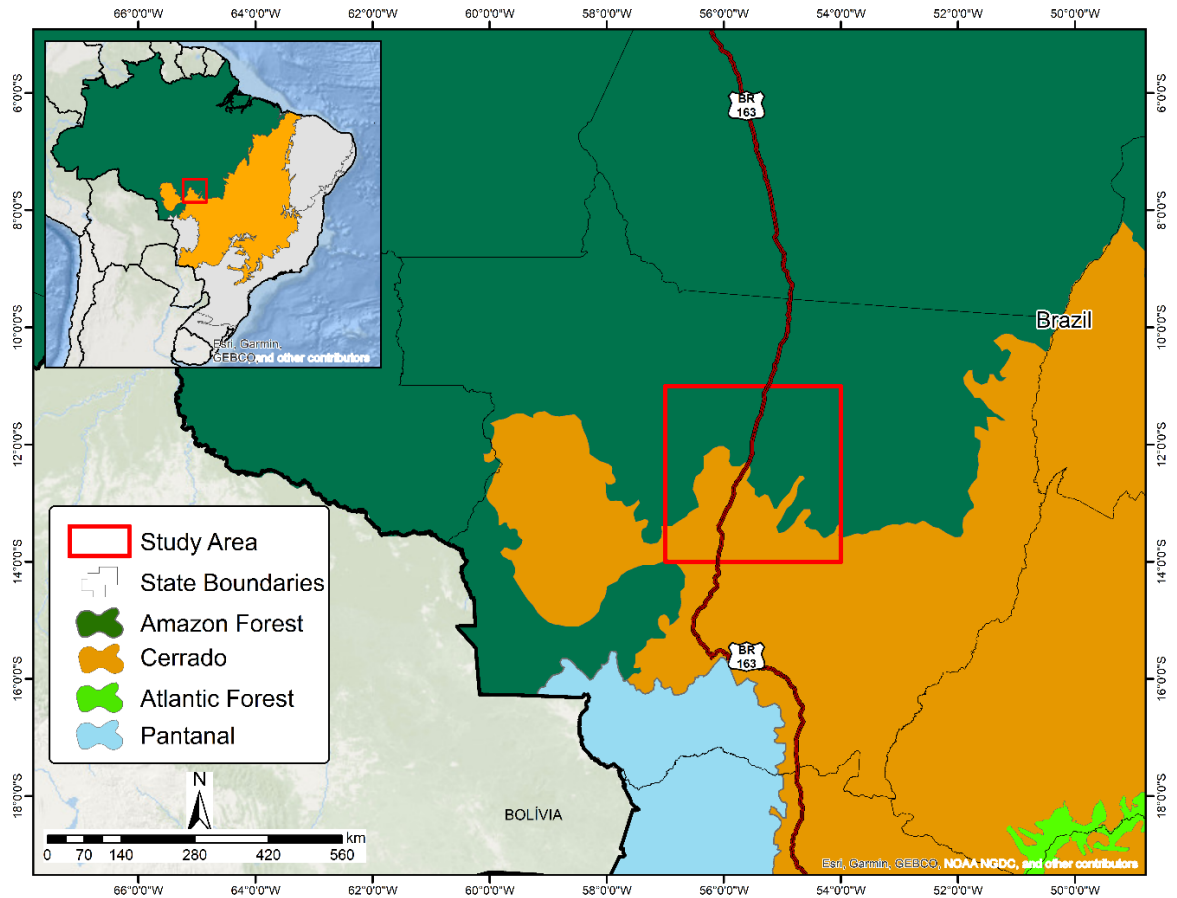


Figure 3.2. The study area covers the main agricultural lands in Mato Grosso state, Brazil, an area known for high deforestation rates over the last 4 decades and for high occurrence of anthropogenic fire. Study region corner coordinates are: -11.0° S, -57.0° W; -14.0° S, -54.0° W, respectively.

The Amazon-Cerrado transition zone is the world's largest tropical ecotone (Marques et al., 2019), characterized by well-marked seasons, nutrient-carbon hypercycling and the tendency to show faster mortality rates and stem recruitment compared to core areas of the Amazon forest (Marques et al., 2019). Most of the study area receives a relatively similar amount of rain (**Figure 3.3**, Funk et al., 2015), mainly distributed over a well-defined wet season (October to May: Grimm, 2011). Ackerly et al. (1989) and Marques et al. (2019) describe the transition zone from the Amazon forest to the Cerrado biome as a complex vegetational mosaic of varying width, exhibiting meanders and intrusions of savannas and forest. This

ecotone is composed of a mixture of vegetation types from both biomes: the rainforest increasingly limited to major river valleys at lower precipitation, and savannas spread over the relatively higher elevation plateaus. Ackerly et al. (1989) also highlight the influence of fire on maintaining the marked transition between these two biomes.

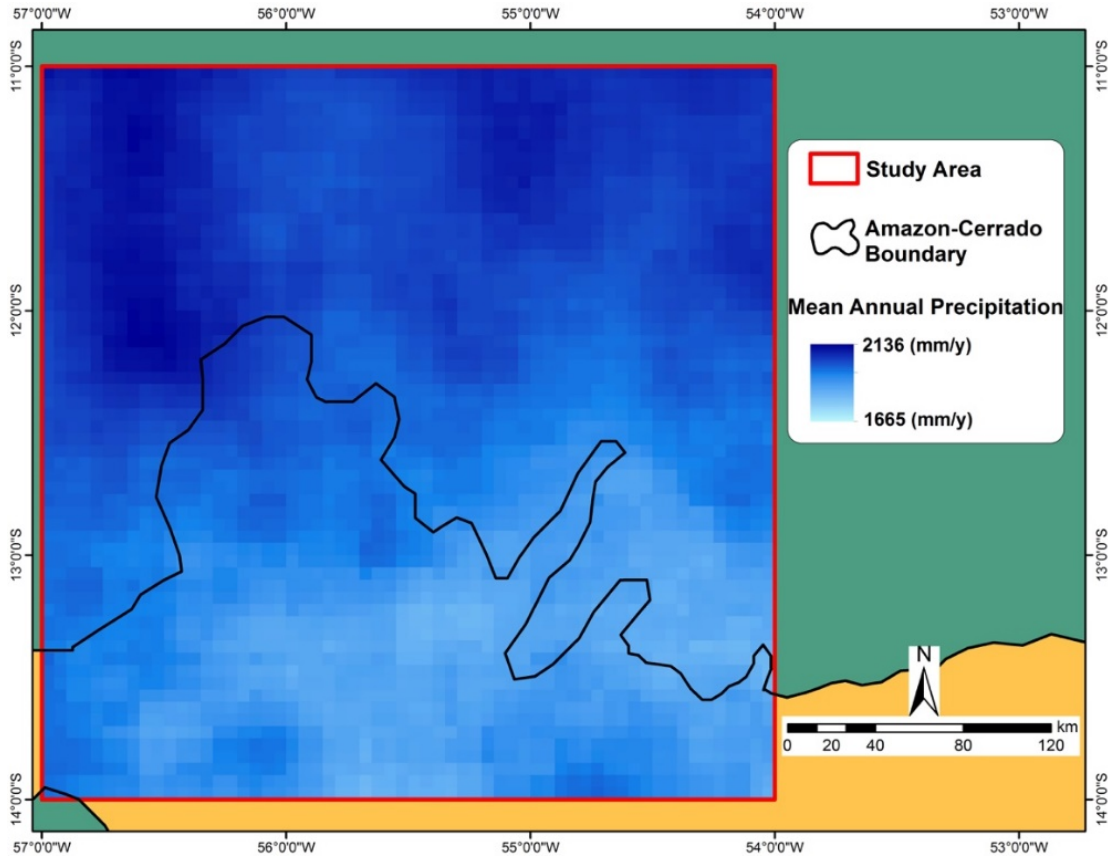


Figure 3.3. Mean annual precipitation for the study area estimated using the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) data for the period from 1985 to 2017.

Climate has a direct relationship to fire occurrence in a region, exerting a dominant control on burning activity by regulating vegetation productivity and fuel moisture (Andela et al., 2017; Scott et al. 2014). Vegetation grows during the wet season and in the dry season its biomass potentially becomes available fuel. The

climate in Mato Grosso state is characterized for having two well-defined seasons: a rainy season that lasts for about seven months (October to May) and a dry season that normally lasts for around 5 months (June to September: Grimm, 2011). The synergistic interaction of reduced rainfall and anthropogenic disturbances, such as deforestation and forest degradation, significantly impact the number of fire events in the Amazon-Cerrado transition zone (Davidson et al., 2012).

Human occupation of the study area strengthened during the mid-1970's with the opening of the Cuiabá-Santarém Highway (BR-163) – **Figure 3.2**, which crosses the region in the South-North direction (Fearnside, 2007; Margarit, 2013; Rosa et al., 2016). The Federal Government encouraged and supported colonization programs along the BR-163, mostly attracting people from southern Brazil to Mato Grosso state in search of land for agricultural production (Margarit, 2013; Rosa et al., 2016); several settlements founded during the 1970's became towns in late 1980's and early 1990's, such as Claudia, Lucas do Rio Verde, Santa Carmen, Sinop, and Vera. By 1985, 11.4% (12,325 km²) of the study area was converted to anthropogenic land uses (Project MapBiomass, 2019). Given the relative proximity to urban centers such as Cuiabá, colonization started in the Cerrado portion of the study area, moving north towards the Amazon, a process that is still occurring (Escada et al., 2009; Margarit, 2013; Pinheiro et al., 2016).

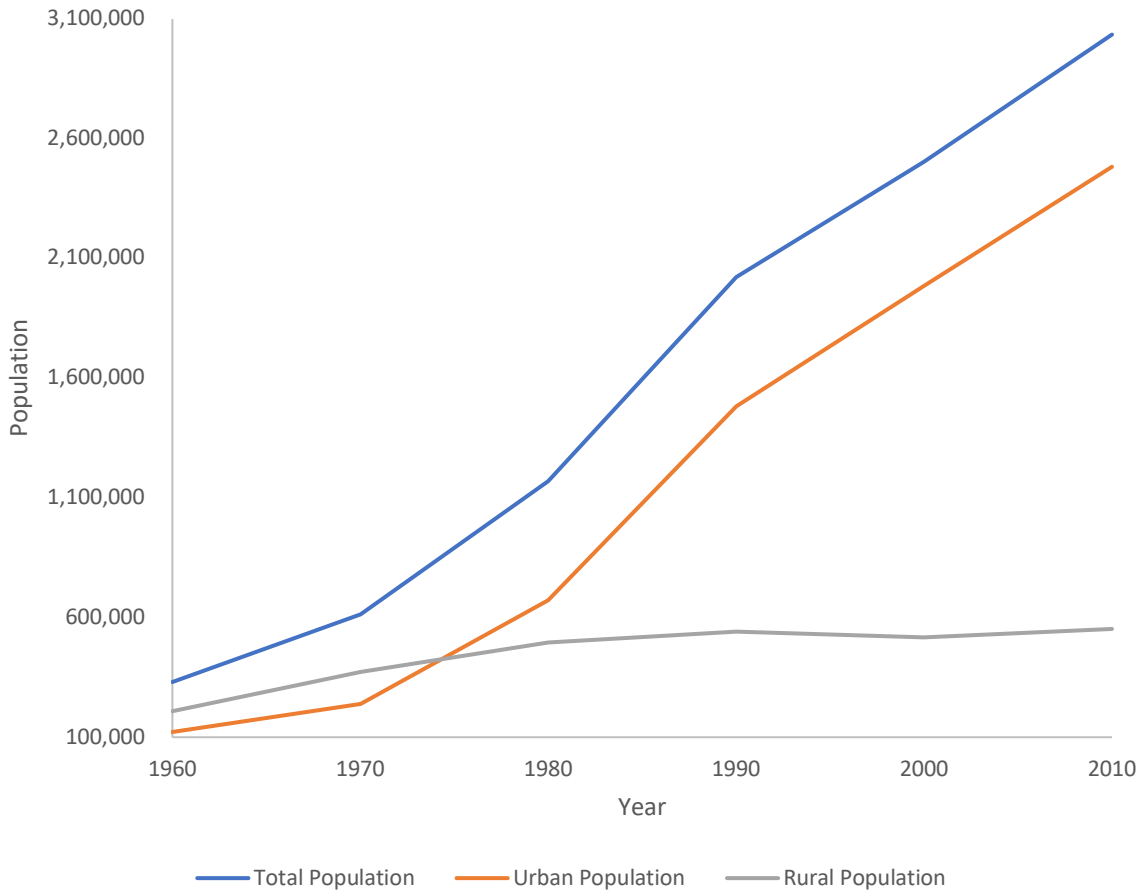


Figure 3.4. Total, urban and rural population growth in the Mato Grosso state from 1960 to 2010 (IBGE, 2011).

Population in Mato Grosso state increased considerably during the last 5 decades (IBGE, 2011). However, the observed population increase occurred mostly in urban areas, whereas population in rural areas has remained relatively stable since the 1980's (**Figure 3.4**). At the same time, land cover in the study area went through an intense change driven by land-use intensification, having a substantial fraction of its extent converted from natural vegetation to anthropogenic land-use (**Figure 3.5**, Project MapBiomass, 2019).

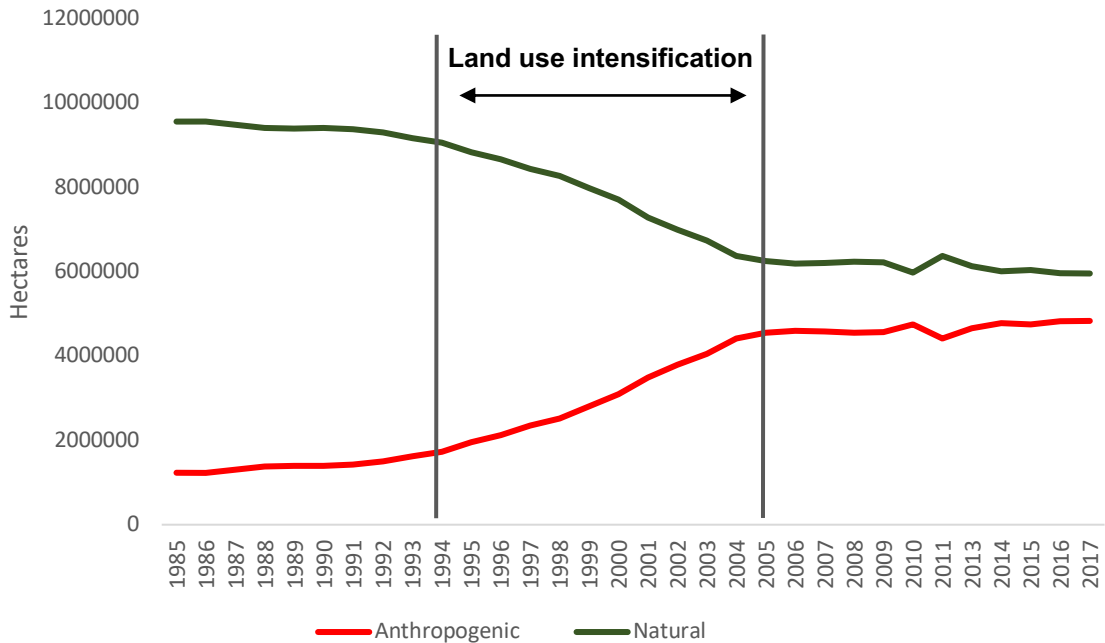


Figure 3.5. Trajectory of land use and land cover (LULCC) classes showing the increase of human occupation over the 32-year time-series in the study area (Project MapBiomias, 2019).

3.2.2 Burned Area and Land Use and Land Cover (LULCC) Datasets

Daldegan et al. (2019) developed the Burned Area Spectral Mixture Analysis (BASMA) algorithm implemented in the Google Earth Engine cloud-computing platform (Gorelick et al., 2017) to efficiently and accurately delineate fire-affected areas. A 32-year (1985 and 2017) time-series of Landsat imagery covering approximately 40% of Mato Grosso state was digitally processed using BASMA to map annual dry-season burned area. Accuracy assessment of the burned areas delineated by BASMA compared to an independent burned area reference dataset returned an average Dice coefficient of 0.86, indicating a high map accuracy.

In a separate effort, the MapBiomias project (<http://mapbiomas.org/pages/about/products>, last accessed in May 15th, 2019) generated LULCC annual layers derived from Landsat data for the entire Brazilian

territory, covering the same period (1985 and 2017). The MapBiomass methodology uses training samples acquired from temporally stable LULCC classes as input into a random forest classifier, which is followed by spatial and temporal filters to remove classification noises. LULCC layers produced by MapBiomass feature 14 different classes of land use, with accuracy assessment indicating an overall accuracy above 90% in the Amazon region and approximately 80% for the Cerrado region. For further detailed information on the methodology used to generate the LULCC layers, see the MapBiomass General Handbook (2018). In this analysis, we aggregated the original classes of the MapBiomass product into two classes: Native Vegetation and Anthropogenic Use (**Table 3.1**). The year of 2012 was excluded from the analysis, given that it lacks high-quality Landsat imagery.

Table 3.1. MapBiomass original LULCC classes regrouped into two main classes: Native Vegetation and Anthropogenic Use

MapBiomass Original Classes	Regrouped Classes
Forest Formation, Grassland Formation, Non-Forest Natural Formation, Other Non-Forest Natural Formation, Savanna Formation, Wetland	Native Vegetation
Agriculture, Annual and Perennial Crop, Farming, Forest Plantation, Mining, Mosaic of Agriculture and Pasture, Pasture, Semi-Perennial Crop	Anthropogenic Use

The annual layers representing burned area and LULCC were derived from the same Landsat imagery collection stored in Google Earth Engine, thus, these two datasets were produced using the same coordinate reference system. Further, we performed a visual inspection of the placement between the BA and LULCC datasets, detecting that their grids are perfectly aligned.

3.2.3 Fire classification

To classify anthropogenic fires into Accidental, Land-clearing and Maintenance, we needed to make some assumptions regarding the data used as input in this study. The burned area dataset produced using the BASMA algorithm (Daldegan et al., 2019) used multitemporal Landsat mosaics covering the June-September dry-season when the chance of lightning-induced ignition is minimal. Thus, we assume that all fire scars in this geospatial dataset are from anthropogenic fire.

The LULCC layers produced by the MapBiomias project is a unique fine-scale spatially-explicit dataset representing land use classes for the Amazon and the Cerrado biomes over 30+ years. By reorganizing the original 14 classes into only two land use categories (Native Vegetation and Anthropogenic Use), we assume that the MapBiomias product is correctly representing this binary classification within the study area. Also, it is critical to stress that the MapBiomias products does not distinguish primary from secondary or degraded forest, therefore these classes are not assessed in this study.

Morton et al. (2011) suggest that satellite observations spanning a three-year time-series could potentially be used to distinguish different disturbance activities occurring in the southern Amazonian region. Additionally, Morton et al. (2011, 2008, 2006) documented that the process of forest conversion in the study area is often completed in less than one year. Accounting for the dynamic trajectory of the land use over time, we developed a conceptual model that uses a three-year rule to classify the anthropogenic use of fire (**Table 3.2**). The LULCC class of a given burned area in the current year of the burning ($BA_{LandUse\ in\ t}$) is compared to its

LULCC class in the previous year of burning ($BA_{LandUse\ in\ t-1}$) and to its LULCC class in the following year of burning ($BA_{LandUse\ in\ t+1}$). Integrating burned area maps and LULCC maps allowed us to assign burned cells to one of the three fire types annually over the 32-year time-series. The development of such a conceptual model allows us to systematically investigate the two-way relationship between LULCC and fire activity at the landscape scale, observing changes in vegetation cover and the land use mosaic (Eva and Lambin, 2000).

Table 3.2. Three-year rule conceptual model used to classify the anthropogenic use of fire for a given burned area.

Land-Use and Land-Cover Change (LULCC) Trajectory			
LULCC Class of a Burned Area in the Previous Year of Burning ($t-1$)	LULCC Class of a Burned Area in the Year of Burning (t)	LULCC Class of a Burned Area in the Following Year of Burning ($t+1$)	Anthropogenic Use of Fire
Native Vegetation	Native Vegetation	Native Vegetation	→ Accidental
Native Vegetation	Native Vegetation	Anthropogenic Use	→ Land-clearing
Native Vegetation	Anthropogenic Use	Native Vegetation	→ Land-clearing
Native Vegetation	Anthropogenic Use	Anthropogenic Use	→ Land-clearing
Anthropogenic Use	Native Vegetation	Native Vegetation	→ Maintenance
Anthropogenic Use	Native Vegetation	Anthropogenic Use	→ Maintenance
Anthropogenic Use	Anthropogenic Use	Native Vegetation	→ Maintenance
Anthropogenic Use	Anthropogenic Use	Anthropogenic Use	→ Maintenance

Accidental fires escaping into mature forest normally tend to be slow-moving and low-intensity understory surface fires that consume litter and coarse woody debris (Cochrane, 2003), thus burned patches have the chance to fully recover; Land-clearing fires have a clear land use trajectory path; Maintenance fires are used in already opened lands to clear successional vegetation (van der Werf et al., 2009).

Geoprocessing analyses were performed using QGIS 3.8 software (QGIS, 2019). In a first step, corresponding annual burned area and LULCC layers were

intersected to allow the identification of the land use classes that burned in each year. Next, the layer representing burned area for a given year t was intersected with LULCC layers from years $t - 1$ and $t + 1$. Performing these three intersect geoprocessing tasks allowed us to characterize the land use trajectory of each individual polygon representing burned area over three years. Ultimately, descriptive statistics were estimated and summarized for each anthropogenic fire category.

3.3 Results

3.3.1 Burned area spatiotemporal distribution

Three distinct phases of the human use of fire are evident (**Figure 3.6**). During the early stages of the time series (1985-1992), maintenance fires were the dominant type of fire, given the fraction of the landscape that was already converted to anthropogenic land-uses prior to 1985. Land-clearing fires dominated between 1993 and 2004. Fire use decreased substantially towards the end of the period, especially after 2013.

Accidental fire consistently shows the lowest amount of burned area over the time-series, except for two years in the beginning of the period (1985 and 1987) and, most importantly, in 2010, when it burned more area than the other two kind of fires combined. Maintenance fire has a bimodal distribution, showing high values in 1985, 1987, 1988, and 1990, followed by three years of relatively modest figures (1991—1993), then by a large increase for a 10-year period (1995—2004). Land-clearing fires were most extensive from 1985 to 1987 and then from 1997 to 2004, reaching 80,000 ha in 2003. Probably, the most noticeable feature shown in **Figure**

3.6 is that all classes of fire sharply decreased after 2005, displaying low values consistently from 2013 to 2017.

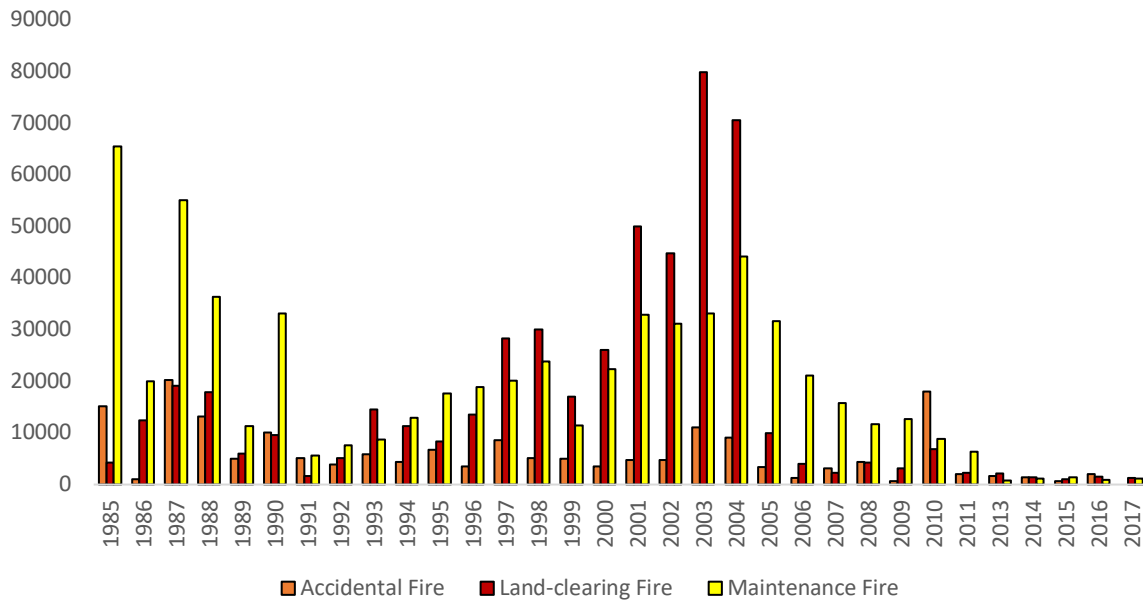


Figure 3.6. Total area burned by each of the three kinds of anthropogenic fire use from 1985 to 2017 for the study area. The year of 2012 was excluded from the analysis, given that it lacks high-quality Landsat imagery.

Accidental fire was concentrated in the Cerrado portion of the study area, spanning over its southernmost part. Additionally, two small clusters of Accidental fire can be observed, one in the center close to the northernmost portion of the Amazon-Cerrado boundary, and one in the north-west (**Figure 3.7**). Land-clearing and Maintenance fires are spread all over the study area, showing a broad south-north distribution (**Figures 3.8 and 3.9**). We could also observe that burned areas due to Land-clearing or Maintenance fires tend to have a regular shape, whereas areas affected by Accidental fire tend to show more irregular spatial patterns.

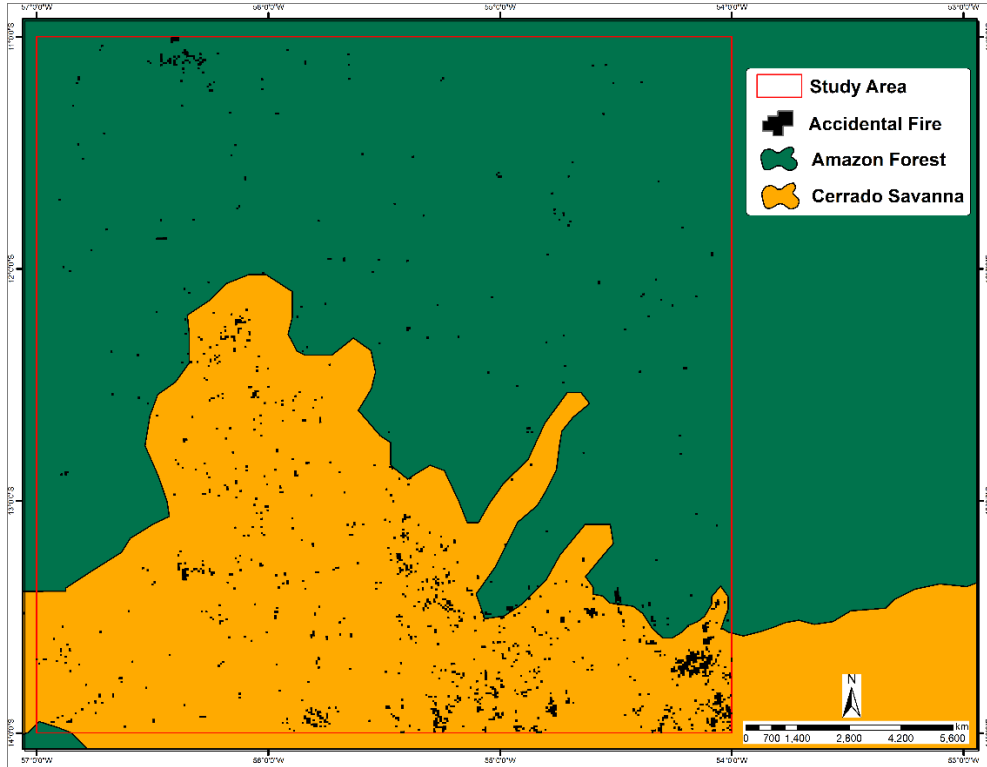


Figure 3.7. Spatial distribution of accidental fire mapped over the 32-year time-series, split into the Amazon and the Cerrado subsets of the study area.

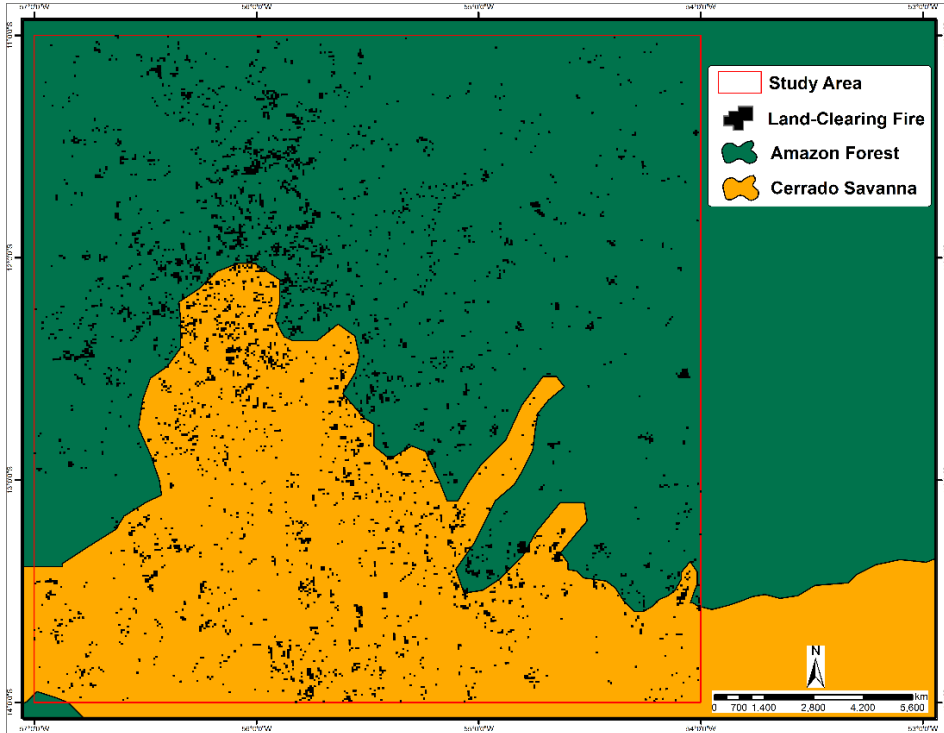


Figure 3.8. Spatial distribution of land-clearing fire mapped over the 32-year time-series, split into the Amazon and the Cerrado subsets of the study area.

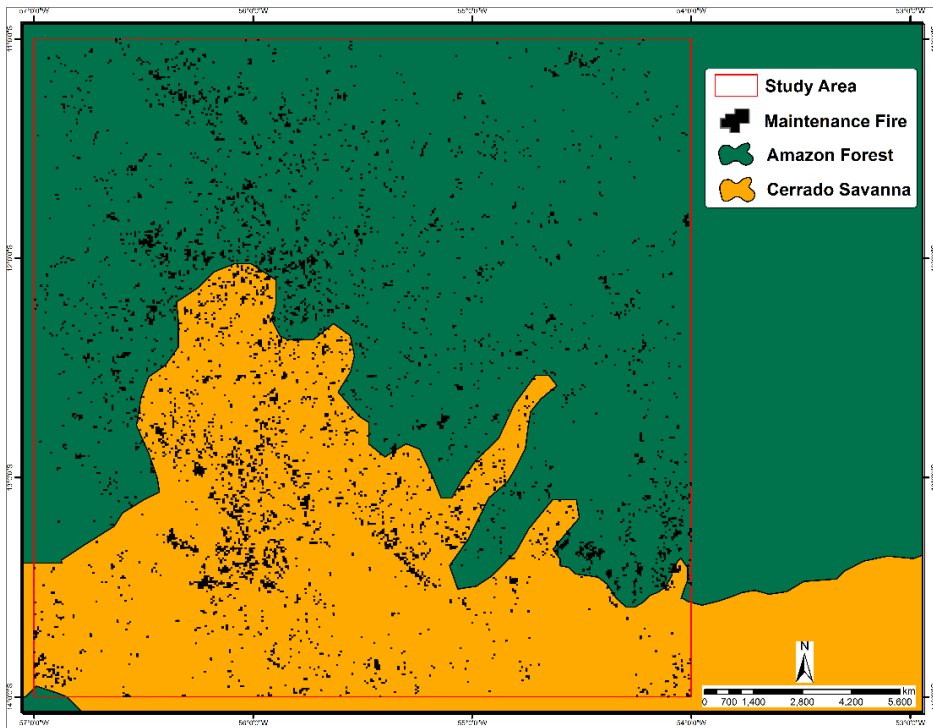


Figure 3.9. Spatial distribution of maintenance fire mapped over the 32-year time-series, split into the Amazon and the Cerrado subsets of the study area.

3.3.2 Burned area spatiotemporal distribution per biome

Table 3 presents the overall results of anthropogenic use of fire over the 32-year time-series per biome. Accidental fire consistently shows higher values in the Cerrado portion of the study area than its Amazon subset. Burned area due to Land-clearing fire has high values in the Cerrado subset of the study area from 1985 until 1995. Starting in 1996, this kind of fire burns larger areas in the Amazon subset for a period of 10 years, when this trend is markedly interrupted. Maintenance fire is clearly concentrated in the Cerrado portion of the study area during the first one-third of the time-series, similar to the Land-clearing fire distribution. Starting in 1996, this type of fire use steadily increases, showing consistent higher values in the Amazon share for the remaining period of the time-series (**Figure 3.10**).

Table 3.3. Anthropogenic use of fire over the 32-year time-series per biome: overall burned area in hectares, percent of the study area per biome subset burned and percent of the total study area extent burned.

Use of Fire	Biome	Burned Area [ha]	% of the Study Area per Biome Subset Burned	% of the Total Study Area Burned
Accidental	Amazon	25,424	0.37	0.23
	Cerrado	144,241	3.68	1.33
Land-clearing	Amazon	283,327	2.62	2.62
	Cerrado	221,944	5.66	2.05
Maintenance	Amazon	311,845	4.52	2.88
	Cerrado	247,089	6.30	2.28

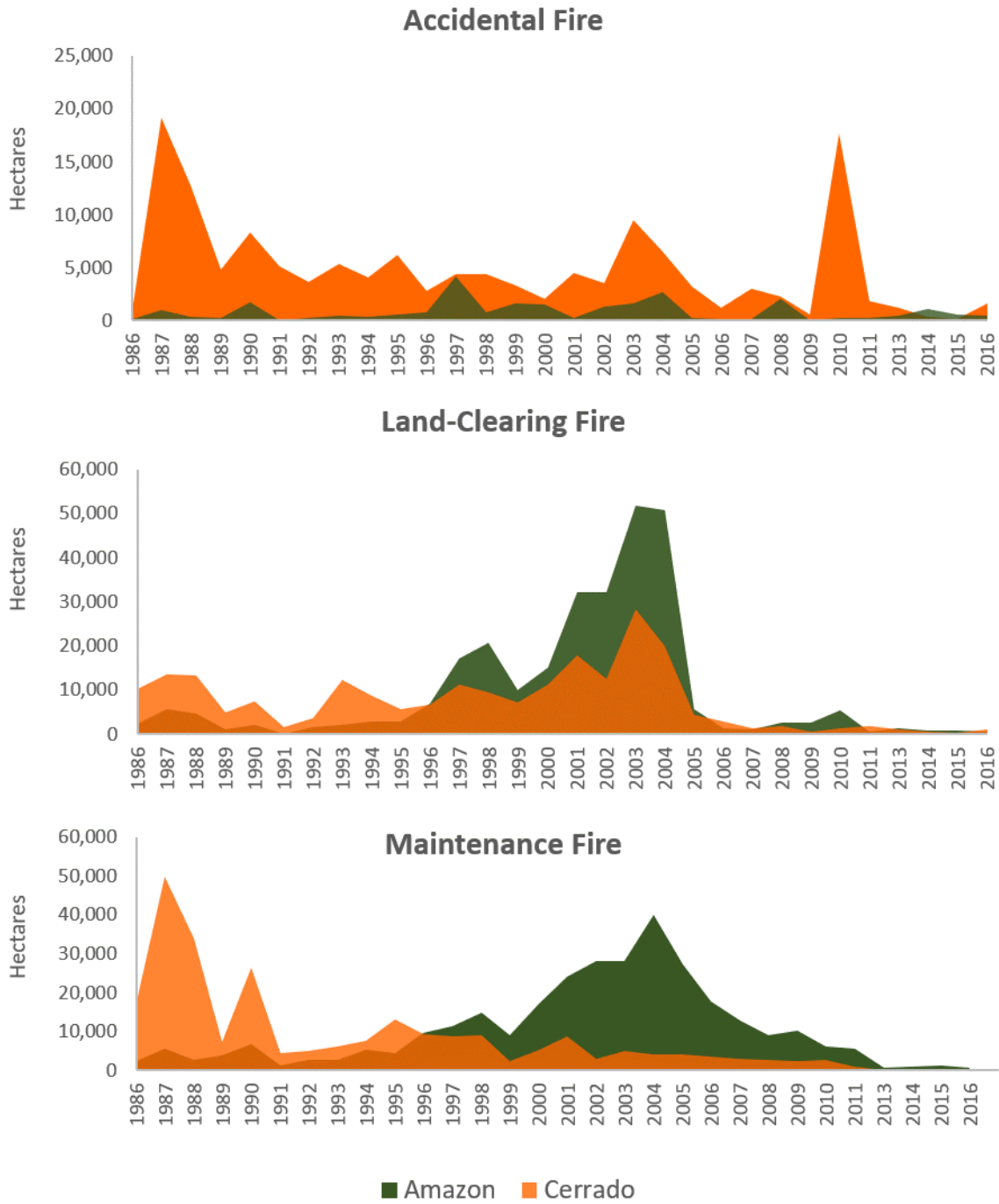


Figure 3.10. Temporal distribution of the three kinds of anthropogenic fire use split into the Amazon and the Cerrado subsets of the study area. Orange shaded area represents anthropogenic fire use in the Cerrado and Green shaded area represents anthropogenic fire use in the Amazon subset of the study area.

3.4 Discussion

Humans have modified fire regimes pervasively, including substantially increasing ignition sources, changing the fire season, and modifying fuel abundance and structure. To clearly identify anthropogenic influence over the pyrogeography of a given region it is necessary to demonstrate that changes in fire regime co-occur in space and time with changes in human occupation of that same region. Such changes in fire regime could be a result of colonization of new lands and increased fragmentation of the landscape, as well as economic, political, and technological advancements, as suggested by Bowman et al. (2011).

In the present study we analyzed burned area and LULCC spatially-explicit datasets derived from Landsat imagery to characterize fire activity during the annual dry season in a 108,210 km² extent spanning the Amazon-Cerrado transition zone. The anthropogenic use of fire in the selected subset of the Brazilian agricultural frontier shows clear spatiotemporal patterns over the time-series analyzed: Accidental fire is the only kind of fire that showed a downward trend over the entire period; Land-clearing fire peaked during the 2001—2004 period, an observation that is consistent with deforestation trends reported in previous studies (Diniz et al., 2015; Morton et al., 2008, 2006); Maintenance fire showed a bimodal distribution, peaking during the early human occupation of the study area (prior to 1991) and again during the period characterized by land use intensification due to increased commodities cultivation (1993 to 2004). Thus, our results clearly demonstrate the anthropogenic influence over the pyrogeography of our study area, recognizing marked shifts in burning activity in space and time in parallel to increasing human

occupation. Further, we quantitatively characterized two pyric phase transitions: from 'wildland anthropogenic fire' to 'agricultural anthropogenic fire', and then to 'fire suppression and wildfires' phase, as suggested by Bowman et al. (2011), confirming our pyric transition hypothesis.

We can identify Land-clearing burning with confidence given that it changes forest and savanna covered lands to other persistent land uses. Maintenance fire is also readily identifiable, given its occurrence in previously converted areas. Accidental fire is the least apparent type of anthropogenic fire, because it may be obscured by overstory vegetation or post-fire recovery. Relatively large-scale structural changes in the forest resulting from fire remain noticeable for long periods after burning, whereas canopy recovery removes the evidences of understory fire disturbance within one year (Asner et al., 2004.; Morton et al., 2011; Souza et al., 2005). This is further complicated given the subtle changes in surface reflectance related to understory burning, which could be obscured by surviving canopy trees and undergrowth vegetation (Morton et al., 2011), hindering clear remote sensing observations.

Generally, it is assumed that there is a direct relationship between human population and ignition density in a given region. However, this relationship is not necessarily linear. Population doubled from 1980 to 2010 in Mato Grosso state (IBGE, 2011) but the share of rural population remained relatively stable over this period, even slightly declining through the 1990s (**Figure 3.4**). Andela et al. (2017) observed that the spatiotemporal distribution of agricultural activity can influence burned area in a manner not predictable by population alone. Given that our study

area is dominated by agricultural lands with no large urban centers nearby, a more nuanced characterization of burns that recognizes different types of fire use helps to explain temporal changes in burned area over the 32-year time-series. Macedo et al. (2012) showed, for a similar subset of Mato Grosso state, that cropland substantially increased during the early 2000s, with the overall planted area of soybean doubling. At the same time, crop areas more than tripled during the same period within the Amazon southern frontier.

The bimodal pattern observed for Maintenance fires reflects the colonization history of the study area. Rudel et al. (2009) argue that before 1990 deforestation in the Amazon basin was due to smallholder colonists supported by government colonization programs that built roads and incentivized the occupation of inner lands, providing access to previously isolated areas. Careful observation of the early years of our results show the predominance of fire use to manage already opened lands, and relatively less occurrence of fires due to land-clearing activities. This pattern is even more obvious in the Cerrado part of the study area, where human occupation first occurred.

Starting in the early 1990s, private agricultural enterprise-driven deforestation arose to respond to increasing demand for agricultural commodities, such as soy beans and beef, mainly linked to international markets. This development drove human occupation to the northern part of the study area into lands covered with rainforest (Rudel et al., 2009). The spatial patterns of deforestation also changed as a result of the different occupation process. Extensive level areas suitable for mechanized agriculture were deforested following the enterprise-driven occupation.

As described by Spera et al. (2014), crop production commonly expands over lands previously occupied by cattle pastures, indirectly driving new deforestation by displacing cattle ranching towards the forest frontier. Thus, the second peak of Maintenance fire was a result of the land-use intensification of previously opened lands.

Assuming the use of fire to open new land as a proxy, our results suggest that this land use intensification started in mid-1990's and lasted until mid-2000's, a period when Land-clearing fire was predominant (**Figure 3.5**). Several studies (Macedo et al., 2012; Morton et al., 2006; Rudel et al., 2009) describe how the agricultural mechanization in this region around the early 2000's altered the nature of deforestation activities, observing that forest clearing for mechanized cropland was, on average, larger than clearing for livestock production. Specifically, use of fire peaked in the Amazon sub-area between 1997 and 2004, as more land was converted for agricultural activities, even without a substantial increase in rural population. Rudel et al. (2009) observed that slight increases in rural population density in the Brazilian Amazon are associated with high rates of deforestation. This surge in fire activity was driven by commodities prices, as previously reported by Morton et al. (2006) and Macedo et al. (2012).

Andela et al. (2017) suggest that the distribution of agricultural activities has a major role in explaining burned area over savannas and grasslands. At the same time, population density and agricultural activities are positively correlated with spatial patterns of burned area in humid tropical forests, as fire is used for cropland maintenance and for opening new lands, producing a sharp rise in fire use. With the

progressive human occupation in the landscape and more investment towards the agribusiness sector, fire activity will be reduced in both savannas and forests. This is most likely a result from improved land management using mechanized techniques and a social demand for increase in fire suppression.

The sharp decline in anthropogenic use of fire observed after 2005 mirrors the reduction in deforestation rates also observed for overall deforestation in the Legal Amazon as measured by the Program for Estimation of Amazon Deforestation (PRODES: Valeriano et al., 2004) and observed by other studies (Morton et al., 2013; Souza, Jr et al., 2013). The decreasing trend of fire activity starting in 2005 is believed to be linked to socio-political circumstances, such as international pressures regarding high rates of deforestation in the Amazon rainforest, as observed by Macedo et al. (2012). More specifically, the observed reduction in deforestation rates can be directly related to the improvement in the remote sensing surveillance systems designed to identify clear cutting within the forest (Morton et al., 2013). For instance, in 2004, the Brazilian federal government established the Federal Action Plan for Prevention and Control of Deforestation in the Amazon, with the objective to drastically reduce deforestation rates. Among the actions taken, INPE launched the Amazon Near Real-Time Deforestation Detection System – DETER, which relied on high temporal resolution (i.e. MODIS) imagery to detect occurrence of clear cutting and forest degradation (Diniz et al., 2015). Furthermore, the substantial reduction in anthropogenic use of fire observed for the last five years of the time-series (2013 – 2017) is most likely due to the Rural Environmental Registry (CAR) policy. CAR was established by the revised Forest Code approved

in May of 2012 and aims to enable the registration of all rural properties present in the Brazilian territory, improving transparency and environmental compliance by the agribusiness sector (Soares-Filho et al., 2014). **Table 3.4** below summarizes the previously reported major land use phases that occurred in the study area and respective references, and **Figure 3.11** shows the period of land use intensification and the public policies designed to monitor deforestation.

Table 3.4. Phases of human occupation of the study area previously reported and respective references

Phases of human occupation of the study area	References
Land use change prior to 1985	Fearnside (2006) Margarit (2013) Project MapBiomas (2019) Rosa et al. (2016)
Smallholder colonists vs. Enterprise-driven deforestation	Rudel et al. (2009)
Land use intensification	Macedo et al. (2012) Morton et al. (2006) Rudel et al. (2009) Spera et al. (2014)
Relationship between agricultural activities and burnings	Andela et al. (2017) Macedo et al. (2012) Morton et al. (2006) Morton et al. (2008) Morton et al. (2011) Morton et al. (2013)
Declining trend in burnings	Andela et al. (2017) Diniz et al. (2015) Morton et al. (2013) Souza, Jr. et al. (2013) Soares-Filho et al. (2014)

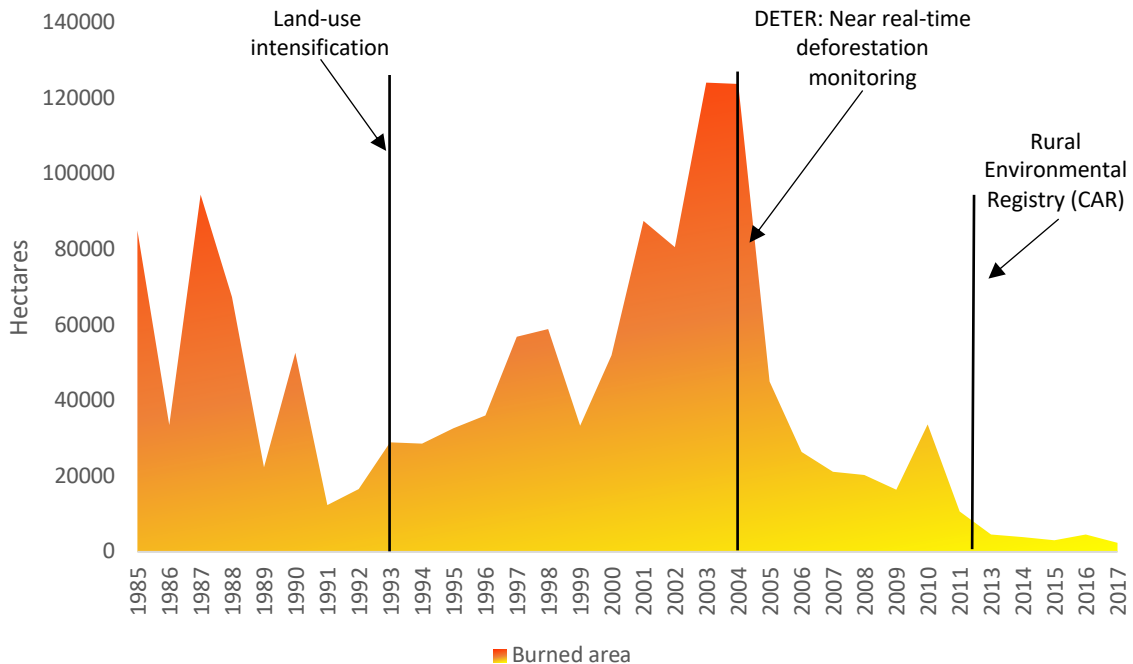


Figure 3.11. Overall burned area over the 32-year times-series and the eras of land use change: according to our results, land-use intensification started in 1993; in 2004 the Brazilian Institute for Space Research (INPE) launched the Near Real-Time Deforestation Monitoring (DETER) project; and in 2012 the revised Forest Code established the Rural Environmental Registry (CAR) program, which improved transparency and the environmental compliancy of the agribusiness sector.

3.5 Conclusions

Spatiotemporal dynamics of burned area and LULCC demonstrated that fire activity increased in the study area as more land was opened for economic use during the intermediary period of the analyzed time-series, and that burning was dramatically reduced towards the end of the period. Therefore, analyzing the anthropogenic use of fire in the study area we observed pyric transitions as expected: from ‘wildland anthropogenic fire’ to ‘agricultural anthropogenic fire’, and then to ‘fire suppression and wildfires’ phase (Bowman et al., 2011). At the very beginning of the analyzed time-series, human and natural ignitions co-occurred given the low fraction of the landscape modified by anthropogenic forces. Next, fire

activity increased dramatically, reflecting the high deforestation rates observed in the region, mostly driven by agribusiness interests. And finally, a shift in fire regime is noticed due to official deforestation monitoring programs and policies designed to incentive environmental compliancy of rural properties.

Such methodological approach should be tested in other active agricultural frontiers in the tropics. Currently, the MATOPIBA region located in the intersection of Maranhão, Tocantins, Piauí e Bahia, in central-northeastern Brazil, is foci of intensive land use and land cover change (Araújo et al., 2019; Graesser et al., 2015) offering the opportunity to further test the relationship between pyrogeography and anthropogenic activities.

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Chapter 4: Spatiotemporal Characterization of Burned Area Patterns in an Amazon-Cerrado transition zone.

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4.0 Abstract

Several studies have proposed that tropical rainforests and savannas exist as alternative stable systems controlled by fire. The Amazon-Cerrado transition zone in Mato Grosso state, Brazil, features a gradient of climate conditions and biomass productivity, leading researchers to assert that this region has all the necessary climatic conditions to support only rainforest, attributing the presence of the savanna to a high fire frequency. Many tropical fire-dependent ecosystems around the globe are thought to burn too frequently under current human-induced fire regimes. Although, there is an overall lack of knowledge regarding the nature and the ecological appropriateness of present fire frequency in many of those environments. To best comprehend how vegetation is responding to contemporary fire activity, it is important to characterize in detail the spatiotemporal patterns of burns in these pyrophilic ecosystems.

In this study we use a fine-scale dataset (30 m of spatial resolution) of burned areas over a long-term times-series (1985 to 2017) to characterize the spatiotemporal patterns of burns in four indigenous lands that span one of the last continuous remnant areas of Cerrado in Mato Grosso state. Based on this spatially-explicit dataset, we created a quantitative baseline describing the current vegetation burns practiced by the indigenous people living in the study area. This baseline would help to assess how the implementation of an Integrated Fire Management plan is changing the use of fire and the vegetation distribution in this region. Further, we tested three fire frequency statistical distributions to model the observed fire return interval: the continuous and discrete Weibull distribution, and the discrete

lognormal distribution. Parameters estimated using a maximum likelihood approach indicated that the study area does not have a homogeneous fire regime, demonstrating that further studies must be conducted to better quantify the fire return interval in this pyrophilic region. Thus, we suggest that subdividing the fire frequency modelling by each of the four indigenous lands could potentially return more plausible results.

4.1 Introduction

Fire is a natural process that has different levels of influence over many terrestrial ecosystems (Cochrane, 2003; Scott et al., 2014). In fire-sensitive ecosystems such as the Amazon forest, burning is a major agent of disturbance that is capable of extreme modification of landscapes (Fischer & Lindenmayer 2007; Lindenmayer et al., 2007). Fire-dependent ecosystems, such as tropical savannas, can be cleared of vegetation immediately after burning but return vigorously when not subject to recurrent disturbance (e.g., the Cerrado: Coutinho 1990). Myers (2006) suggested that many tropical fire-dependent (pyrophilic) ecosystems may be burning too frequently, and that there is an overall lack of knowledge regarding the nature and the ecological appropriateness of present fire frequency in many of those environments. To best understand how vegetation is responding to contemporary fire activity, it is important to characterize in detail spatiotemporal patterns of burnings in these pyrophilic ecosystems.

Fire interval distribution, which describes the time distribution of fire recurrence, helps to quantify burning activity patterns over time and space in a given area (Johnson & Gutssel, 1994; Johnson & Van Wagner, 1985; Oliveira et al., 2013). Fire frequency can be interpreted as a stochastic process, given the level of indeterminacy related to the timing of burnings (Benali et al., 2017; Bowman et al., 2009; Polakow and Dunne, 1999). Most studies aiming to characterize fire frequency tend to rely on measures of central tendency, whereas probability distribution models provide improvements to this type of analysis (Oliveira et al., 2013; Pereira Júnior et al., 2014). Johnson & Gutssel (1994) described the two-

parameter Weibull as the most common probability distributions used to model fire-return interval. Additionally, the authors assert that it is not rare to observe multimodal distribution when investigating empirical fire frequency, indicating variations of the average burning frequency over time and/or space. Analyzing fire activity in a tropical savanna, Oliveira et al. (2013) used the discrete lognormal as an alternative probability distribution to model fire frequency in northern Australia. They concluded that the discrete lognormal distribution is more suitable for landscapes experiencing very high fire frequency. Pereira Júnior et al. (2014) also successfully applied the discrete lognormal statistical distribution to model burning frequency in an area of Cerrado in Tocantins state, Brazil.

Bond et al. (2005) hypothesized that fire has played a major role on shaping tropical savannas and limiting rainforest coverage over the globe. Several studies have proposed that tropical rainforests and savannas exist as alternative stable systems controlled by fire; areas with low burning frequency tend to develop forest coverage, whereas areas frequently affected by fire are more likely to be covered by savannas (Murphy and Bowman, 2012; Scholes and Archer, 1997; Walker, 1987). The Amazon-Cerrado transition zone in Mato Grosso state, Brazil, features a gradient of climate conditions and biomass productivity: the north is dominated by fire-sensitive rainforest, whereas the south is dominated by fire-prone savanna (Pivello, 2011). According to Murphy and Bowman (2012), this region has all the necessary climatic conditions to support only rainforest and the authors attribute the presence of the savanna to a high fire frequency.

Fire is a common disturbance in the Brazilian Cerrado, particularly in grasslands ecosystems, which are composed of a thick layer of herbaceous species with scattered shrubs and small trees (Coutinho, 1990; Pivello, 2011; Ribeiro & Walter, 2008). Pivello (2011) asserts that prior to the current anthropogenic colonization the Cerrado had an average fire return interval between 10 and 20 years. Paleoecology research has shown that fire frequency in Cerrado vegetation has been high for thousands of years (Miranda et al., 2010), with charcoal particles indicating that burns were common during the period from 32,000 to 3,500 years before present (Salgado-Labouriau et al., 1994). Fire has played a major role in determining the Cerrado vegetation morphology among other environmental pressures, such as strong seasonality and nutrient scarcity in soils (Bond et al., 2005). Several other studies also indicate the direct influence of historical fire regimes in shaping the Cerrado spatial distribution, structure, composition and ecosystem process (Durigan & Ratter, 2016; Miranda et al., 2009; Salgado-Labouriau et al., 1997). Morphological and physiological adaptations to fire result in low plant mortality rates and lively flowering and sprouting just days or weeks after burning (Scott et al., 2014). Several of the Cerrado species display characteristics of fire adaptation (i.e., extensive subterranean organs), which are the result of adaptations to post-fire environmental conditions, such as the elimination of the necromass and consequent increase in availability of nutrients and light at the ground level (Miranda et al. 2010). Natural wildfires often occur in the Cerrado during the transition from wet-to-dry and dry-to-wet seasons, mainly caused by lightning, and are considered to be of low intensity and low severity (Ramos-Neto & Pivello 2000).

The subset of the Amazon-Cerrado transition zone in the western Mato Grosso state (**Figure 4.1**) situated in the Paresi plateau hosts several indigenous lands that are home for the Haliti-Paresi ethnic group. This plateau is mostly covered by grasslands (Project MapBiomass, 2019) and features a remarkable latitudinal savanna-rainforest transition zone (Marques et al., 2019). During the wet season (October to April: Grimm, 2011) there is a robust growth of biomass, which cures rapidly over the dry season (May to September: Grimm, 2011). Annual fire recurrence is common given the amount of precipitation that falls in the region, the high productivity of the grassland ecosystems, and the traditional use of fire by the indigenous people (Falleiro et al, 2016). Pyne (2014) asserts that “the advent of anthropogenic fire was a revolutionary event in Earth history,” given that fire had to no longer depend on natural ignition sources to occur. Pivello (2011) reported that human-driven fires have been influencing the Cerrado for at least 4,000 years, intensifying in recent periods due to the prevalence of late-dry season burnings.

The Haliti-Paresi people have traditionally used fire over the centuries for several reasons: to manage some of the Cerrado ecosystems by controlling the amount of biomass; for hunting activities; to open and prepare land for subsistence farming; to stimulate the fructification of species of interest; for communication purpose; to protect the communities (*aldeias*) by keeping the surroundings of the houses and communal areas clear of vegetation and free of venomous animals (Moura et al., 2019). These customary uses of fire are grounded in traditional knowledge and closely related to signals from nature: lunar phases, dry and wet seasons, plant phenology (Falleiro, 2011; Falleiro et al., 2016; Moura et al., 2019).

However, the traditional knowledge that guides burning activities is quickly fading, given that the younger Haliti-Paresi generations are not interested in learning and keeping the traditions of their culture (Moura et al., 2019). Over the last decades, burnings were not as closely tied to natural signals and fire was used during inappropriate seasons, resulting in very large burned areas that generally cannot be controlled or extinguished (Moura et al., 2019; Santana, 2017).

In the early 2010's, the Brazilian National Center for Prevention and Fighting Forest Fires (PrevFogo: <https://www.ibama.gov.br/prevfogo>, last accessed in July 22nd, 2019) created a project that aims to recover and catalog the traditional knowledge regarding the use of fire in several indigenous lands in Brazil (Moura et al., 2019). Falleiro (2011) and Falleiro et al. (2016) describe in detail how this process took place in several indigenous lands located in western Mato Grosso state. One of the most important actions of this project began in 2017 with the implementation of an Integrated Fire Management plan in some indigenous lands of the Paresi plateau. The concept of Integrated Fire Management (Myers, 2006) involves the integration of scientific and social knowledge with fire management technologies at multiple levels, aiming to address fire issues that account for environmental, ecological, cultural, socio-economic and political interactions. The Integrated Fire Management concept is composed of basic community perceptions regarding fire: Fire Management (fire prevention, fire suppression, & fire use); Fire Ecology (key ecological attributes of fire); and Fire Culture (socio-economic necessities & impacts). Therefore, fire management decisions in a given region should consider the ecological and socio-economic/cultural context (Myers, 2006).

The main focus of Integrated Fire Management plan implemented on the Paresi plateau is to avoid very large individual burned areas. PrevFogo is working with the Haliti-Paresi people to routinely burn several small patches of vegetation each year and it is expected that the execution of this plan would lead to a shift to denser vegetation ecosystems (from grasslands to savannas) in the medium to long term (Rodrigo Falleiro, personal communication).

Here we use a fine-scale dataset (30 m of spatial resolution) of burned areas over a long-term times-series (1985 to 2017) to analyze how frequently fire events occur in the Paresi plateau, one of the last continuous remnant areas of Cerrado in Mato Grosso state. The aim of the study is to characterize the spatiotemporal distribution of burned area patterns prior to establishment of the Integrated Fire Management plan. Our specific objective is to identify a fire frequency statistical model that best describes the observed burning recurrence. Characterizing the spatiotemporal patterns of burns and creating a quantitative baseline of the fire frequency prior to 2017 would help to evaluate how the Integrated Fire Management plan is changing the use of fire and the vegetation distribution in this region.

4.2 Material and Methods

4.2.1 Study Area

The study area (**Figure 4.1**) is composed of four indigenous lands that occupy an extent of approximately 1.2 million hectares on the Paresi plateau, located in the western part Mato Grosso state, Brazil -**Table 4.1**. Population density is low, ~ 2,200 indigenous people living in small family groups distributed over 68 communities (Moura et al., 2019).

The Paresi plateau is mostly covered by grasslands that spread over the extensive level flatlands; savannas and forests are concentrated along the valleys and rivers, respectively. There are also relatively localized croplands (**Figure 4.1**: Project MapBiomass, 2019). Also noticeable is a latitudinal vegetation gradient characterized by a complex Amazon-Cerrado transition zone that is composed of meanders and intrusions between dense forest and savanna vegetation types (Ackerly et al., 1989; Marques et. al., 2019). The climate of the region features a well-marked dry and wet season: precipitation is concentrated during the period from October to April, and the dry season lasts from May to September (Grimm, 2011), when fire risk increases over time due to dry biomass available to burn, warm temperatures, low relative humidity, and the constant source of ignition coming from anthropogenic activities

Table 4.1. Indigenous lands that encompass the study area.

Indigenous Lands	Area [ha]
Tirecatinga (1)	130,880
Utiariti (2)	409,673
Paresi (3)	562,560
Juininha (4)	70,460
Total Area	1,173,572

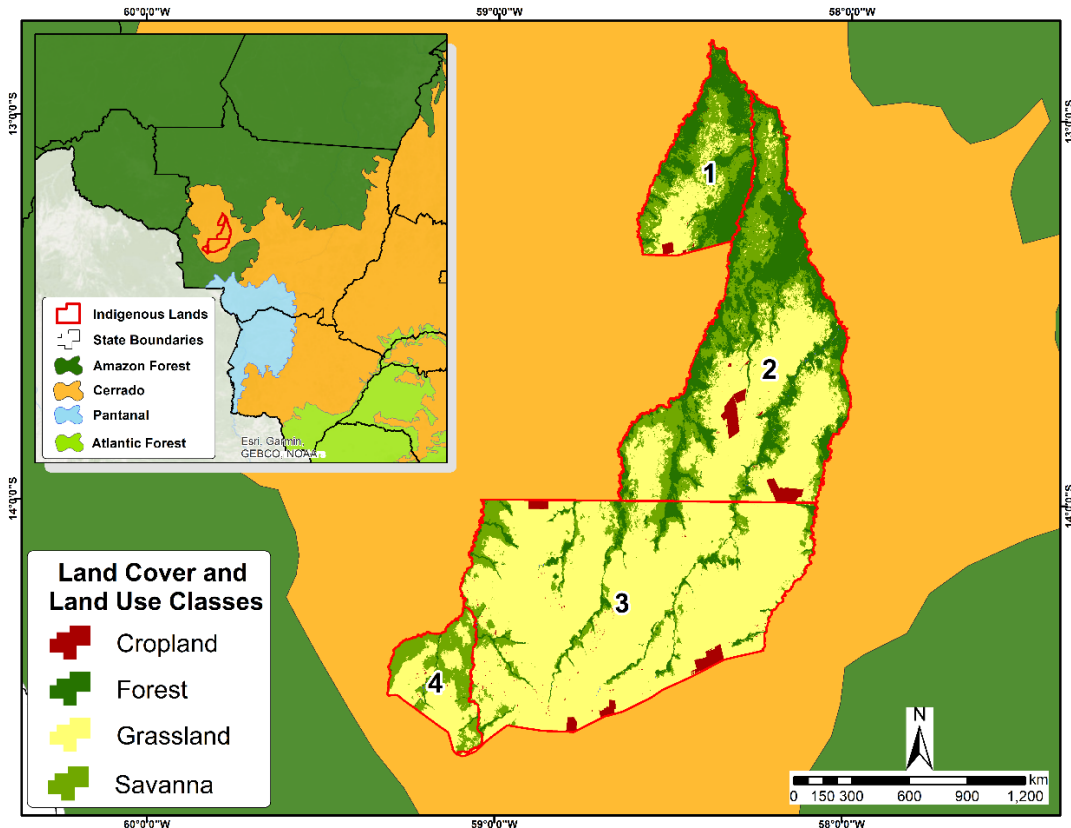


Figure 4.1. Study area showing the location of the four indigenous lands that occupy the Paresi plateau in west Mato Grosso state, Brazil (1- Tirecatinga, 2- Utiariti, 3- Paresi, 4- Juininha) and four major land cover/land use classes.

Vegetation burns are common within the indigenous lands located in the Paresi plateau (Falleiro et al., 2016), although extensive land cover change is rare (Morton et al., 2008; Nepstad et al., 2006).

4.2.2 Burned Area

The annual burned area (BA) dataset for the period 1985—2017 period was produced using the Burned Area Spectral Mixture Analysis algorithm (BASMA: Daldegan et al., 2019) applied to imagery from the Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM+), and Landsat 8 Operational Land Imager (OLI) sensors. The year 2012 is missing because there is no high-

quality imagery available from the Landsat sensors. BASMA is a semi-automatic algorithm designed to efficiently and accurately delineate burned area present in multispectral images. This fine-scale (30m-spatial resolution) spatially-explicit BA dataset covers the entire study area and is assumed to represent only anthropogenic fire events, given that the multitemporal composite mosaics used to run the BASMA algorithm cover the period from June to September, when the probability of lightning is minimal.

Descriptive statistics (Count of Annual Burned Patches, Annual Maximum Burned Patch Size, Annual Burned Patch Size, Annual Mean Burned Patch Size, Annual Burned Patch Size Standard Deviation) were estimated on an annual basis and are presented in **Table 4.2**. Fire recurrence analysis was performed in ArgGIS 10.6.1 (ESRI, 2019) by calculating the cell statistics derived from the 32 annual burned area layers. In this step, every annual burned area layer was stacked together with a perfect grid alignment: fire-affected pixel had value set to 1, and non-burned pixel to 0. By adding fire-affected pixels across the 32-year time-series, it was possible to estimate how frequently each pixel burned over the period.

4.2.3 Fire Rotation Period

The overall fire frequency was assessed with the fire rotation period (FRP), which is the length of time necessary to burn a region of the same extent as the study region (Heinselman, 1973). FRP is calculated by:

$$FRP = \frac{NS}{\sum A'} \quad (4.1)$$

where N is the number of years of the time-series; S is the area within the study area that is vulnerable to burn; A is the annual burned area; and Σ is the integration of A for the period N (Pereira Júnior et al., 2014).

4.2.4 Fire Frequency Modelling

Fire frequency modeling was performed with the objective of fitting a probability distribution curve of survival (that measures time-since-fire) and mortality (that measures fire interval: Johnson & Gutssel, 1994; Oliveira et al., 2013; Pereira Júnior et al., 2014). The survival and mortality distributions are tied together by the hazard of burning $\lambda(t)$, which is the individual age-specific mortality from burning, calculated as the fire interval divided by the time-since-fire distributions (Oliveira et al., 2013). We tested three statistical models to characterize fire frequency, previously demonstrated to work in other landscapes: the Weibull distribution, in its continuous and discrete versions; and the discrete lognormal (Oliveira et al., 2013; Pereira Júnior et al., 2014).

Following the requirements given by Johnson & Gutssel (1994), 100,000 random samples (points) were collected to extract fire interval data to estimate the probability distribution functions for the study area. No minimum distance constraint between points was set, allowing the 100,000 points to be completely randomized.

The continuous and discrete versions of the Weibull distribution have a shape parameter c and a scale parameter b . Likewise, the discrete lognormal distribution also has two parameters: μ is the mean and σ is the standard deviation of the of the random variable's natural logarithm. Thus, according to the Akaike Information Criterion (AIC), these models can be inter-compared in terms of their log-likelihood,

with the model best fitting the observed distribution returning the lowest AIC value. We used a maximum likelihood approach to estimate the model parameters (Johnson & Van Wagner, 1984), which included complete and single-censored fire intervals. Below we present the equations of the fundamental distributions applied in fire frequency analysis (Oliveira et al., 2013): the cumulative mortality distribution $F(t)$, which estimates the probability of a burning occurring before or at time t ; the fire interval distribution $f(t)$, which estimates the probability of a fire occurring in the period t to $t + \Delta t$; the time-since-fire, or survival distribution, $A(t)$, which estimates the probability of a given area going without fire for longer than t ; and the hazard of burning $\lambda(t)$, which estimates the probability of a given area to burn in an interval assuming that fire did not occur up to the beginning of the interval. For more details on the fundamental equations for fire frequency, see Johnson and Gutsell (1994) and Oliveira et al. (2013).

For the continuous Weibull model, these are the fundamental equations:

Cumulative mortality, $F(t)$:

$$F(t|c, b) = 1 - \exp \left[- \left(\frac{t}{b} \right)^c \right], \quad t > 0 \quad (4.2)$$

Fire interval, or mortality, $f(t)$:

$$f(t|c, b) = \frac{ct^{c-1}}{b^c} \exp \left[- \left(\frac{t}{b} \right)^c \right], \quad t > 0 \quad (4.3)$$

Time-since-fire, or survival, $A(t)$:

$$A(t|c, b) = \exp \left[- \left(\frac{t}{b} \right)^c \right], \quad t > 0 \quad (4.4)$$

Hazard of burning, $\lambda(t)$:

$$\lambda(t|c, b) = \frac{ct^{c-1}}{b^c}, \quad t > 0 \quad (4.5)$$

where c is the shape parameter and b is the scale parameter.

For the discrete version of the Weibull model, the fundamental distributions are estimated as follows:

Cumulative mortality, $F(t)$:

$$F(t|c, b) = \begin{cases} 1 - \exp\left[-\left(\frac{k}{b}\right)^c\right], & k \leq t \leq k + 1, \quad k = 1, 2, 3 \dots \\ 0, & t < 1 \end{cases} \quad (4.6)$$

Fire interval, or mortality, $f(t)$:

$$f(t|\mu, \sigma) = \begin{cases} \exp\left[-\left(\frac{t-1}{b}\right)^c\right] - \exp\left[-\left(\frac{t}{b}\right)^c\right], & t = 1, 2, 3 \dots \\ 0, & \text{otherwise} \end{cases} \quad (4.7)$$

Time-since-fire, or survival, $A(t)$:

$$A(t|c, b) = 1 - F(t|c, b), \quad t > 0 \quad (4.8)$$

Hazard of burning, $\lambda(t)$:

$$\lambda(t|c, b) = 1 - \frac{\exp\left[-\left(\frac{t}{b}\right)^c\right]}{\exp\left[-\left(\frac{t-1}{b}\right)^c\right]}, \quad t = 1, 2, 3 \dots \quad (4.9)$$

where c is the shape parameter and b is the scale parameter.

Under the discrete lognormal model, the fundamental fire frequency distribution functions can be described by the following equations. Parameter $\mu \in \mathbf{R}$ (real numbers) and $\sigma \in \mathbf{R}^+$ (positive real numbers, Oliveira et al. 2013):

Cumulative mortality $F(t)$:

$$F(t|\mu, \sigma) = \begin{cases} \phi\left(\frac{(\ln(k) - \mu)}{\sigma}\right), k \leq t < k + 1, & k = 1, 2 \dots \\ 0, & \text{otherwise} \end{cases} \quad (4.10)$$

Fire interval, or mortality, $f(t)$:

$$f(t|\mu, \sigma) = \begin{cases} \phi\left(\frac{\ln(t) - \mu}{\sigma}\right) - \phi\left(\frac{\ln(t-1) - \mu}{\sigma}\right), & t = 1, 2 \dots \\ 0, & \text{otherwise} \end{cases} \quad (4.11)$$

Time-since-fire, or survival, $A(t)$:

$$A(t|\mu, \sigma) = \begin{cases} 1 - \phi\left(\frac{\ln(k) - \mu}{\sigma}\right), k \leq t < k + 1, & k = 1, 2 \dots \\ 0, & \text{otherwise} \end{cases} \quad (4.12)$$

Hazard of burning, $\lambda(t)$:

$$\lambda(t|\mu, \sigma) = \begin{cases} 1 - \frac{\phi\left(\frac{\mu - \ln(t)}{\sigma}\right)}{\phi\left(\frac{\mu - \ln(t-1)}{\sigma}\right)}, & t = 1, 2 \dots \\ 0, & \text{otherwise} \end{cases} \quad (4.13)$$

where μ is the mean and σ is the standard deviation of the of the random variable's natural logarithm, ϕ is the distribution function of the standard normal distribution, t is the time span, and k is an integer number.

The modelling analysis incorporated both censored and uncensored fire interval data. Censored data refers to partial or incomplete information, i.e., when either the start or the end of the fire-free period is unknown. Uncensored data refers to complete fire intervals, i.e., when both the start and the end of the fire-free period are known. The majority of the mapped annual fire scars are assumed to be uncensored data, meaning that the fire event has occurred in a given year and not

in an unknown previous moment, but a significant subset of the study region is expected to have not burnt at all over the time series (double-censored observations), at the same time that some parts will have burned only once or become unburnable due to small-scale conversion to cultivated land (single-censored observations). Including both censored and uncensored observations is important to correctly estimate the parameters of the statistical models (Polakow & Dunne 1999).

4.3 Results

4.3.1 Burned Area Spatiotemporal Patterns

Over the 32 years studied, 29,731 polygons were delineated by BASMA, summing to a total burned area equal to 2,938,761 ha (**Table 4.2**), which corresponds to 2.5 times the extent of the study area. **Figure 4.2** summarizes the temporal distribution of burned area for the entire study area. The years with the highest value for burned area are 1990 (209,607 ha) and 2001 (201,182 ha), whereas 1992 (13,185 ha) and 2013 (22, 585 ha) show the lowest values.

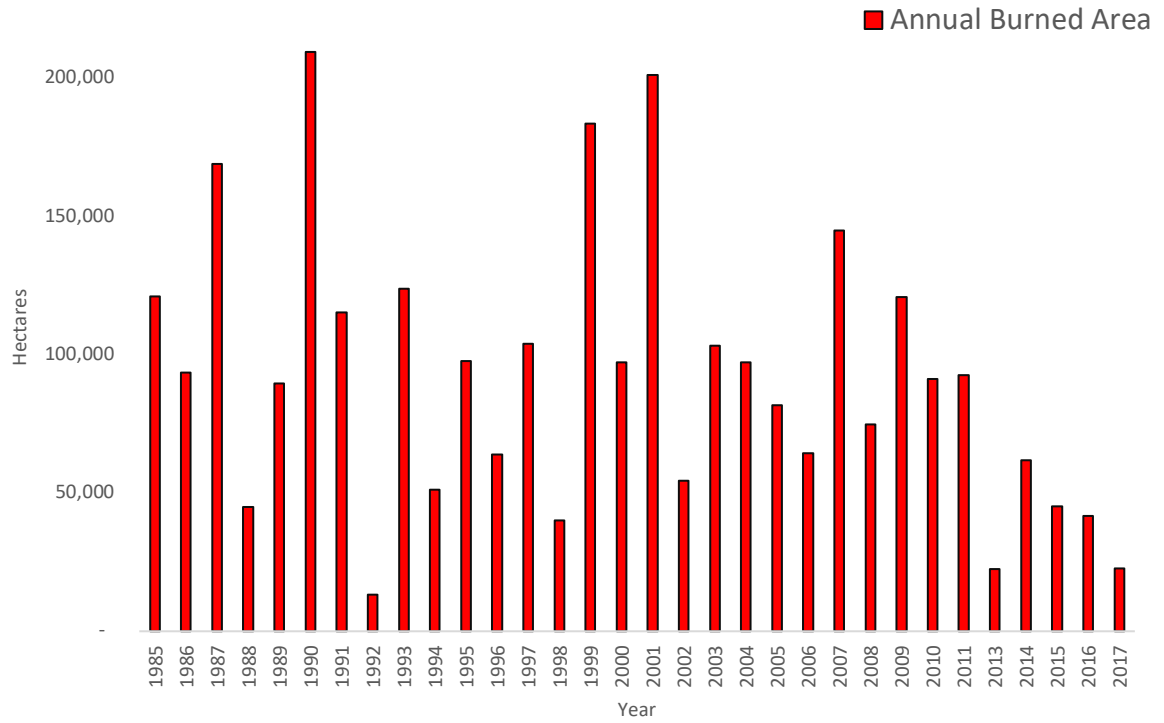


Figure 4.2. Annual burned area mapped within the four indigenous lands that comprise the study area for the period 1985-2017.

Table 4.2. Summary of descriptive statistics for annual burned area within the four indigenous lands that comprise the study area: Juninha, Paresi, Tirecatinga, and Utiariti.

Year	Count of Annual Burned Patches	Annual Maximum Burned Patch Size [ha]	Annual Burned Area [ha]	Annual Mean Burned Patch Size [ha]	Annual Burned Patch Size Standard Deviation [ha]
1985	1,020	26,469.23	121,221.71	118.84	1,110.36
1986	1,454	20,402.66	93,482.17	64.29	629.38
1987	1,199	75,075.38	168,956.47	140.91	2,274.12
1988	683	8,001.72	44,937.25	65.79	399.70
1989	1,324	39,157.73	89,554.38	67.64	1,106.44
1990	1,294	90,343.69	209,607.77	161.98	2,650.90
1991	905	18,707.70	115,363.96	127.47	984.69
1992	310	1,239.40	13,185.95	42.54	123.28
1993	1,191	38,546.00	123,889.04	104.02	1,337.18
1994	990	6,942.54	51,276.82	51.79	398.18
1995	1,028	17,634.58	97,695.00	95.03	814.44
1996	911	7,128.40	63,957.37	70.21	438.99
1997	1,123	13,140.48	104,004.71	92.61	721.64
1998	697	6,221.67	40,149.12	57.60	358.44
1999	1,241	50,590.87	183,512.83	147.87	1,721.41
2000	1,098	22,858.90	97,354.01	88.66	897.69
2001	1,048	41,546.54	201,182.21	191.97	2,156.71
2002	872	6,675.93	54,376.68	62.36	415.39
2003	1,031	15,706.79	103,341.71	100.23	810.09
2004	720	21,259.40	97,166.90	134.95	1,147.45
2005	1,077	12,206.84	81,715.99	75.87	606.49
2006	716	19,729.17	64,299.94	89.80	844.96
2007	1,010	31,513.81	145,035.69	143.60	1,490.41
2008	835	13,436.89	74,732.04	89.50	677.04
2009	1,233	25,349.70	120,869.53	98.03	956.92
2010	1,131	13,751.57	91,149.07	80.59	606.57
2011	827	29,146.57	92,560.18	111.92	1,106.91
2013	431	10,369.69	22,585.06	52.40	505.17
2014	758	12,093.72	61,807.05	81.54	575.10
2015	579	19,760.31	45,240.71	78.14	869.29
2016	754	6,523.36	41,817.89	55.46	320.88
2017	241	6,008.90	22,732.41	94.33	527.84
Total	29,731	-	2,938,761.60	-	-

Figures 4.3 and 4.4 present the spatial distribution of annual burned area over the time-series (1985--2017). It is noticeable that several years show very large burned patches, specially within the Paresi and the Utiariti indigenous lands,

corresponding to the overall annual burns. We can also observe that Juininha and Tiretatinga indigenous lands concentrated the least fire activity over the time-series.



Figure 4.3. Annual spatial distribution of burned area within the four indigenous lands that comprise the study area – 1985 to 2000.



Figure 4.4. Annual spatial distribution of burned area within the four indigenous lands that comprise the study area – 2001 to 2017

The cumulative fire recurrence analysis shows that 82.1% of the study area burned between 1 and 11 times over 32 year, approximately a burn event every three years – **Figure 4.5.** Fire recurrence analysis demonstrated that frequently burned areas are concentrated in the grassland ecosystems present in the Paresi

Plateau. Further, fire recurrence was higher in the eastern part of the study area, particularly in the Paresi indigenous lands, and lowest in Juininha – **Figure 4.6.**

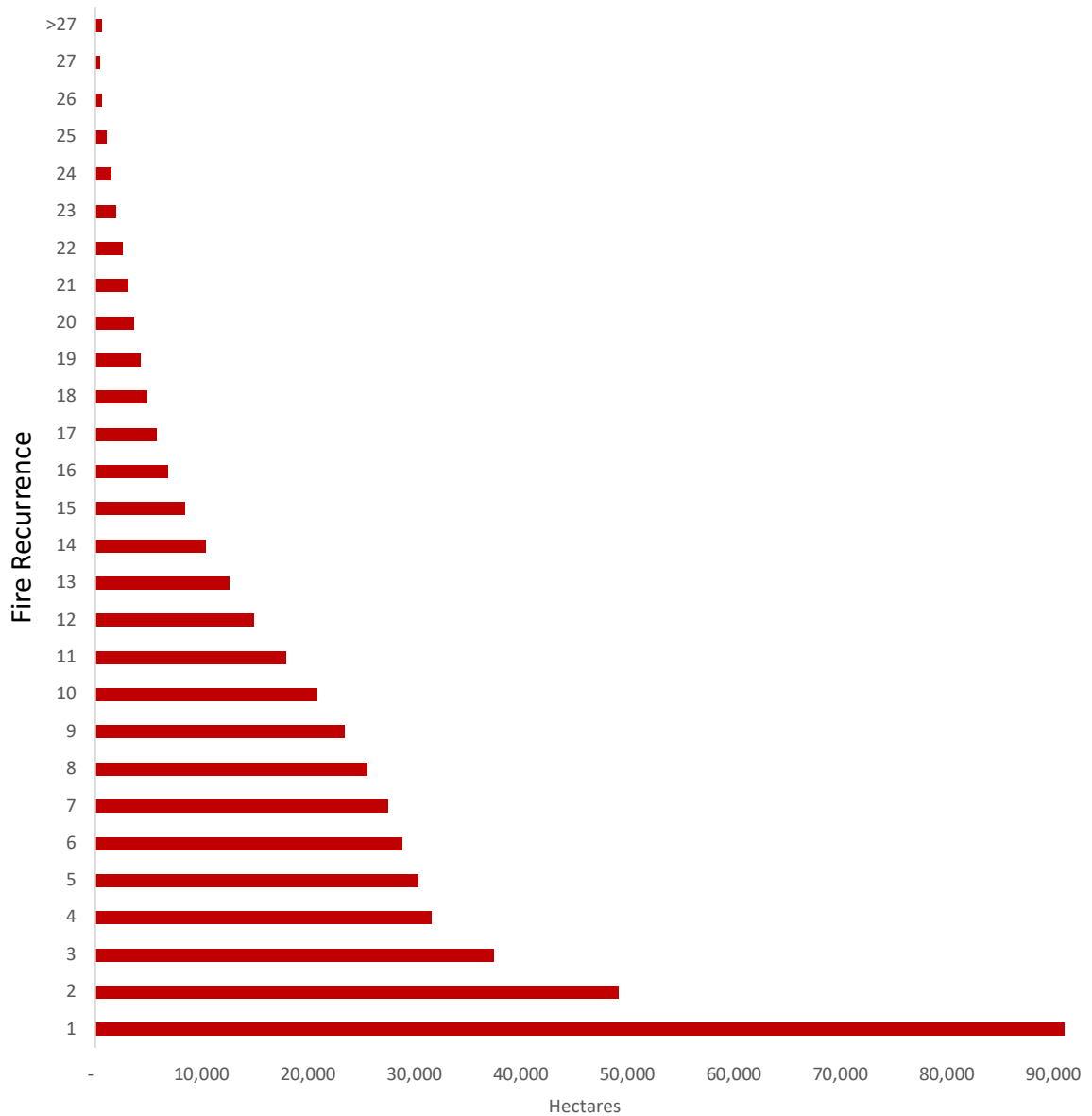


Figure 4.5. Fire recurrence analysis shows that the majority of the fire-affected area within the study area burned only once over the 32-year time-series.

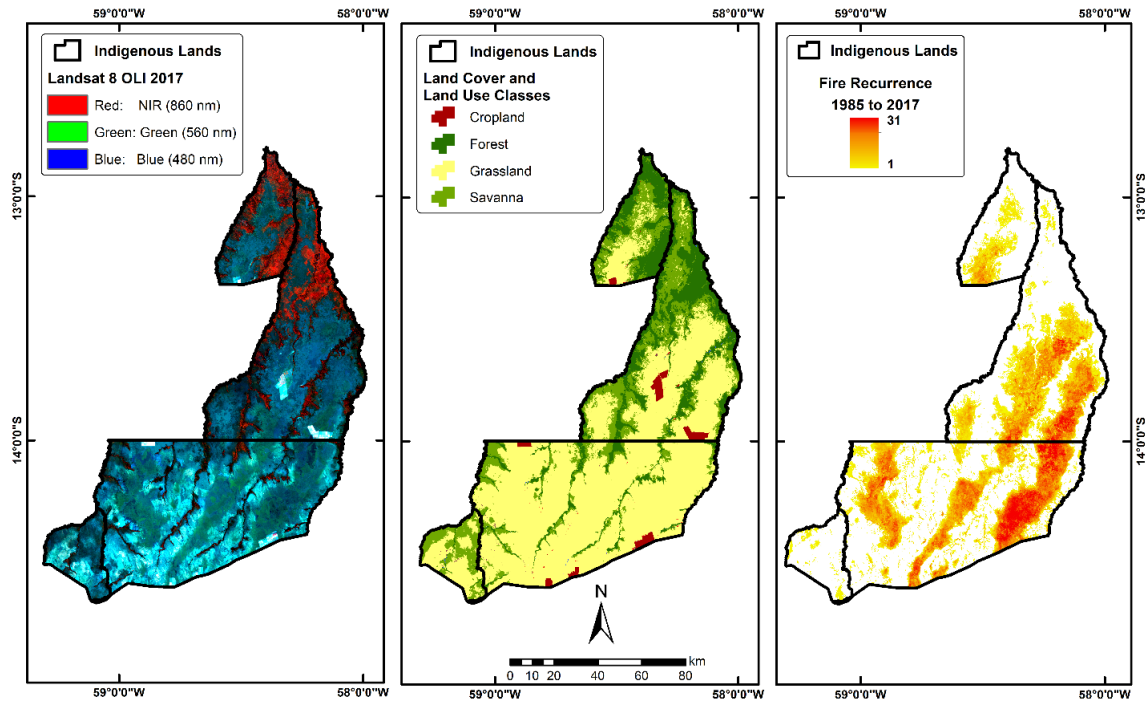


Figure 4.6. Fire recurrence analysis demonstrates that frequently burned areas are concentrated in the grassland ecosystems present in the study area. Panel A shows a false-color composite of Landsat 8 OLI multitemporal mosaic for 2017 – R: Red (band 4), G: NIR (band 5), B: Blue (band 2); Panel B shows land cover classes mapped by MapBiomias for 2017; Panel C shows the fire recurrence in a yellow-to-red color grade.

Subdividing fire recurrence analysis per vegetation classes mapped for the first year of the time-series (1985: Project Mapbiomas, 2019) demonstrated that grasslands had burned more frequently over the time-series - up to 31 times; followed by forest - some forest pixels show fire recurrence up to 24 times; and lastly savannas, with pixels burning up to 13 times (**Figure 4.7**). Croplands were excluded from this analysis, given that they are not included in the Integrated Fire Management plan. It is also obvious in **Figure 4.7** the large-scale difference of burned area for each vegetation class.

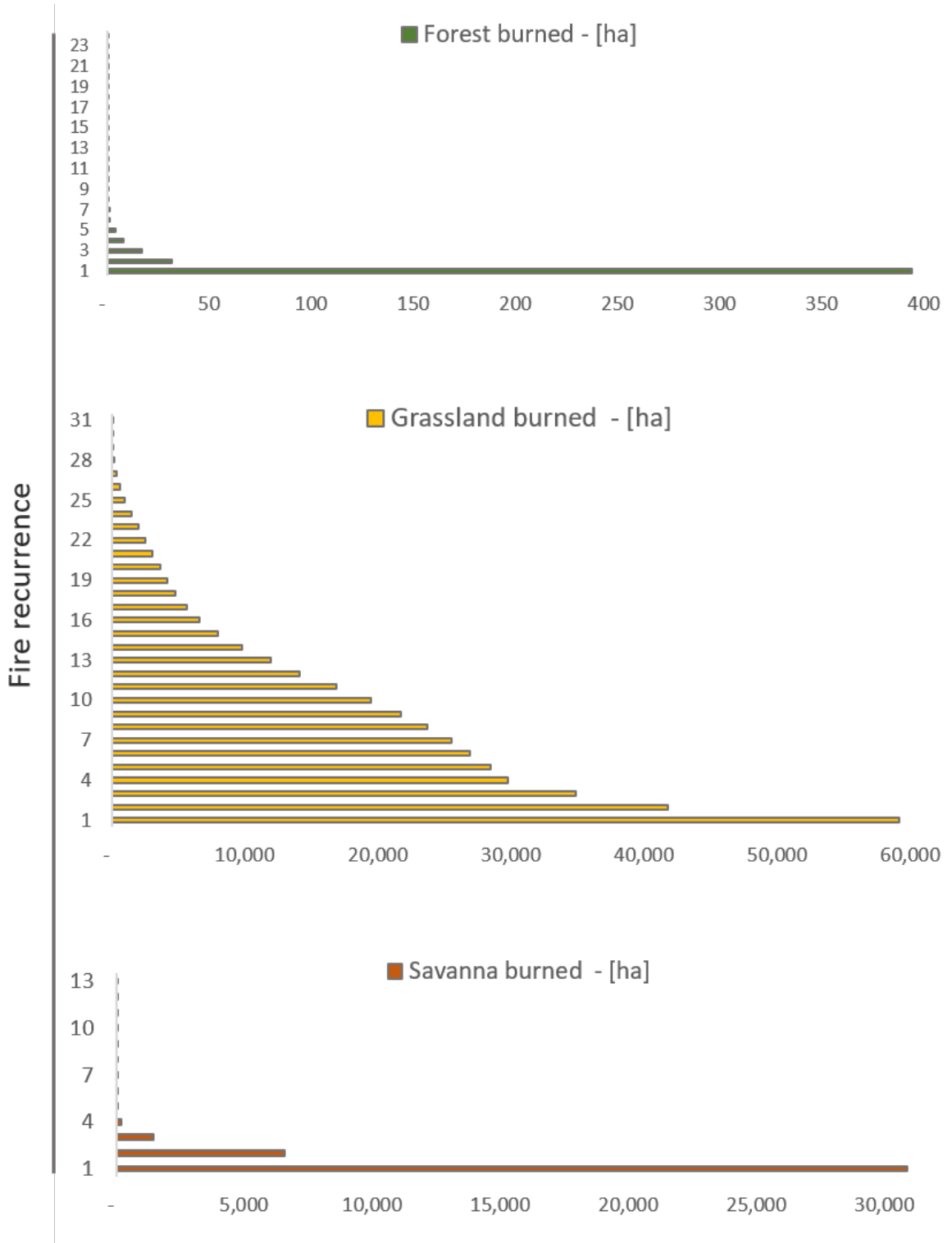


Figure 4.7. Fire recurrence analysis by vegetation type

4.3.2 Fire Rotation Period

The estimated FPR is equal to 12.78 years, meaning that on average it takes approximately 13 years to completely burn an area of the same extent as the study area. The annual percentage of area burned (APAB), the reciprocal of the FRP, is equal to 0.08, which means that 8% (~91,836 ha) of the study area extent burns annually.

4.3.3 Fire Frequency Modelling

Table 4.3 presents the distributions parameters for the three probability models tested and the values of the Akaike Information Criterion (AIC). The shape parameter c estimated for the probability distribution models returned a value < 1 , which is not considered realistic or feasible for fire regimes. It is a strong evidence that the study area does not have a homogeneous fire regime. Therefore, we did not continue the analysis of testing which probabilistic distribution would best fit the observed heterogeneous fire frequency.

Table 4.3. Parameters estimated using a maximum likelihood approach for the probability models tested. The continuous and discrete Weibull have c as the shape parameter and b as the scale parameter. For the discrete lognormal, $\frac{\mu}{\sigma}$ is the shape parameter, and e^μ is the scale parameter.

Continuous Weibull			Discrete Weibull			Discrete Lognormal		
b	c	Log-Likelihood	b	c	Log-Likelihood	$\frac{\mu}{\sigma}$	e^μ	Log-Likelihood
5.72	0.95	1,526,086	4.83	0.69	1,422,611	0.67	2.62	1,389,232

4.4 Discussion

Daldegan et al. (2019) demonstrated that remnant patches of native vegetation within the extensively fragmented Amazon-Cerrado transition zone are subject to recurrent burning. In this study, we focused our analyzes in the Paresi plateau, one of the last areas of continuous Cerrado ecosystems in Mato Grosso state. Our results corroborate previous studies that have found the mean fire interval in protected areas of the Cerrado is equal to 3 years (Ramos-Neto & Pivello, 2000; Daldegan et al., 2014; Pereira Júnior et al., 2014), which is an unsustainable fire return interval even in pyrophilic landscapes, given that the natural fire frequency in the Cerrado biome is thought to had been considerably longer (every 10 to 20 years) prior to human settlements. This very short fire return internal favors herbaceous species and promotes vegetation shifts to less-denser physiognomies (Pivello, 2011). Consequently, remnant patches of Cerrado are potentially exposed to impoverishment and degradation due to high fire frequency over long periods (Miranda et al., 2010). Natural landscapes distressed by disturbance regimes have their structures and compositions modified, as well as their natural processes (White, 2006; Fischer and Lindenmayer, 2007). Further, the synergy among natural and human-driven disturbance regimes seriously threatens biodiversity (Davidson et al., 2012; Klink & Machado, 2005). Quantitatively characterizing the spatiotemporal dynamics of burned area and statistically exploring the fire return interval of the anthropogenic burning regime over a long term is of fundamental importance for the study region.

Our analysis focused on a region dominated by grasslands showing elevated fire activity since 1985 (Daldegan et al., 2019). Fire incidence was highest in the Paresi indigenous land, followed by Utiariti and Tirecatinga indigenous lands, and Juinhã indigenous land shows the lowest observed fire activity over the 32-year time-series. These discrepancies are likely an effect of the diverse traditional burning practices among indigenous populations. Consequently, fire recurrence analysis mirrors the same pattern, returning frequently burned pixels within Paresi, Utiariti and Tirecatinga (**Figure 4.6**).

Very large extents of burned area were observed within the Paresi and the Utiariti indigenous lands (**Figures 4.3** and **4.4**), mostly spread over grassland ecosystems. Murphy et al. (2015) and Schmidt et al. (2018) associate large burned area in fire-prone ecosystems to fires occurring in late-dry season, when ground fuel is thoroughly cured. Small burned patches were found in savannas and the forest ecosystems showed very small burned area (**Figure 4.7**). Forest burning patterns are in accordance to the traditional use of fire by the Haliti-Paresi people, who use fire for clearing small patches of forest for subsistence farming, mainly for cassava (*Manihot esculenta*: Moura et al., 2019). Avoiding very large burnings is one of the main objectives of the Integrated Fire Management plan implemented by PrevFogo in the indigenous lands that occupy the Paresi plateau (Rodrigo Falleiro, personal communication); an anticipated outcome is to observe shifts in vegetation density, as demonstrated by Miranda et al. (2010).

Fidelis et al. (2018) assessed how the implementation of Integrated Fire Management plans led to changes in spatiotemporal patterns of burnings in five

protected areas of the Cerrado biome. According to the authors, 2017 was a megafire year, in which long-lasting fires occurred in different continents: Brazil, California, Portugal, and Spain registered record fires, either in severity or fire-affected extent. Several regions of the Cerrado biome also experienced large-scale fires in 2017, due to the combination of anthropogenic activities and climate change (Fidelis et al., 2018). However, our results show that the Paresi plateau did not follow this worldwide trend, as 2017 was one of the years with the least fire activity within the study area, with a total of 22,732 ha burned. This is most likely a result of the Integrate Fire Management plan, which began to be implemented in that year.

Likewise, implementation of an Integrate Fire Management plan in the Estação Ecológica Serra Geral do Tocantins (ESEC-SGT), one of the largest protected areas in the Cerrado, also led to immediate changes in the spatiotemporal patterns of fire (Fidelis et al., 2018; Schmidt et al., 2018). PrevFogo and the Haliti-Paresi people are applying the same strategy adopted in the ESEC-SGT: burning several small patches of open physiognomies of the Cerrado, i.e., grasslands and open savannas physiognomies (Pivello, 2011; Ribeiro & Walter, 2008), in the early dry season, a management practice that tend to increase the number of individual fire and to reduce the total annual burned area. This model was built upon the Australian experience on managing fire in savannas (Schmidt et al., 2018). Therefore, spatiotemporal patterns reported in **Table 4.2** would help to keep track of the results of the Integrate Fire Management plan in the Paresi plateau.

By selecting a large land mostly covered with remnant grasslands ecosystems and featuring an elevated fire activity over the time-series, we assumed that the fire

frequency modelling analysis was constrained to an area of relatively homogenous fire return interval (Moritz et al., 2009). Nevertheless, the shape parameter c estimated using the maximum likelihood approach to be used as input to the continuous Weibull model is <1 , a value that, according to Johnson and van Wagner (1984), makes little sense in fire ecology. We believe that this unusual value for the c parameter is due to the failed assumption made regarding the stability of the fire history of the study area. Fire activity in the Paresi plateau is strongly influenced by the Hailiti-Paresi traditional use of fire, which is likely to have had a heterogeneous pattern amongst the indigenous lands over the time-series. Thus, we recommend that this assessment should be subject of further detailed studies, looking into ways to stratify the samples by periods and geographies of homogenous fire frequency.

4.5 Conclusion

Fine-scale burned area mapped over long time-series allowed us to quantitatively estimate descriptive statistics regarding spatiotemporal dynamics of burnings and to assess the fire frequency in the Paresi plateau. Our results found similar mean fire interval as previously reported by other studies for different parts of the Cerrado. Further, they demonstrated that the study area is under constant anthropogenic use of fire, identifying areas and vegetations types that are frequently burned. Spatiotemporal patterns reported here would aid in the process of monitoring how the Integrated Fire Management plan is modifying fire activity and vegetation in the study region.

The fire frequency modelling analysis did not work as expected, returning unusual values for the c parameter when compared to results reported by Oliveira et al. (2013) and Pereira Júnior et al. (2014) for protected areas of the Cerrado. Considering that the fire recurrence analysis returned deviating patterns among the indigenous lands, it is likely that these have varied traditional burning practices. Hence, further studies must be conducted to better understand the human-fire relationship in this pyrophilic region; subdividing the fire frequency modelling into each of the indigenous lands could potentially return better results.

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Chapter 5: Conclusions

In this study, I aimed to assess the spatiotemporal dynamics of anthropogenic fire activity in a large subset of a neotropical rainforest and savanna. Below I review the overarching questions that guided the study and present the conclusions reached based on the methodologies applied and results found.

Research question 1 – *Can fire scars be mapped semi-automatically at high accuracy over an extended time series and large geographic extent using spectral mixture analysis and cloud-based analysis tools?*

In Chapter Two, I presented the Burned Area Spectral Mixture Analysis (BASMA), a semi-automatic burned area mapping algorithm developed in Google Earth Engine to SMA in Landsat time-series. Here, I tested whether SMA is a robust means for mapping fire scars present in Landsat imagery for the Amazon-Cerrado transition zone that is stable over time and over space. Results showed that BASMA successfully identified char fractions and delineated burned area in Landsat imagery collected from 1985 to 2017 for an area of 36 million hectares. Imagery from Landsat 5 TM, Landsat 7 ETM +, and Landsat 8 OLI were digitally processed and burned area was consistently modeled by a single fire scar image endmember and a single fraction threshold. Validation of BASMA-derived burned area was performed against independent burned area products extracted from finer spatial resolution imagery for several years. Accuracy assessment returned high Dice coefficients (varying from 0.83 to 0.90, with 0.86 of average). Thus, I reached the

conclusion that BASMA is an effective algorithm to map fire scars for a large extent over long time-series analysis using imagery acquired from sensors with similar spatial and spectral resolution

Previous studies reported that it is challenging to develop a generic and optimal context-independent method to map burned area, given the spectral signal captured by spaceborne sensors (Bastarrika et al., 2014, 2011; Hawbaker et al., 2017; Pereira et al., 1997). BASMA was shown to be a consistent burned area mapping algorithm, given that the image fire scar endmembers applied has the advantage of having been measured at the same scale as the input image data. Nevertheless, the product reported in Chapter Two does not provide a complete record of the annual burned area within the study region, given that some burned pixels are likely to be excluded when generating the multi-temporal mosaics. Hence, it is necessary to further explore approaches on how to build the annual mosaics, aiming to identify char pixels that better express fire-affected areas.

Research question 2 – *How has the distinct phases of human occupation influenced the fire activity between 1985 and 2017? Did the spatiotemporal burning pattern follow a pyric transition as proposed by Pyne (2001)?*

In Chapter Three, I tested the hypothesis that fire activity follows a pyric transition (Pyne, 2001) in the most productive agricultural region in Mato Grosso state, accounting for the land-use trajectory over time, which reflects the different colonization stages of the region over the last 30+ years.

People have long used fire to manage lands for food and forage production (Cochrane, 2009; Pivello, 2011; Pyne, 1997; Schmidt et al., 2011). Anthropogenic activities directly influence ignition sources and suppression efforts; modify the type, load, structure and continuity of fuel; alter microclimates; and burn biomass in different seasons than non-anthropogenic fire regimes (Bowman et al., 2011). To test the pyric transition hypothesis, I analyzed a burned area and a LULCC spatially-explicit datasets derived from Landsat imagery to characterize fire activity during the annual dry season in a 108,210 km² extent spanning the Amazon-Cerrado transition zone. Both spatial datasets share the same long-term (1985 to 2017) and fine-scale (30-meter spatial resolution).

Spatiotemporal dynamics of burned area and LULCC demonstrated that fire activity increased in the study area as more land was opened for economic use during the intermediary period of the analyzed time-series, and that burning was dramatically reduced towards the end of the period. At the very beginning of the analyzed time-series, human and natural ignitions co-occurred given the low fraction of the landscape modified by anthropogenic forces. Next, fire activity increased considerably reflecting the high deforestation rates observed in the region, mostly driven by agribusiness interests. Lastly, a shift in fire regime was noticed due to official deforestation monitoring programs and policies designed to incentive environmental compliancy of rural properties. Therefore, analyzing the anthropogenic use of fire in the study area, pyric transitions as described by Bowman et al. (2011) were observed: from 'wildland anthropogenic fire' to 'agricultural anthropogenic fire', and then to 'fire suppression and wildfires' phase.

Based on the evidences found, I concluded that anthropogenic dynamics had a direct influence over the pyrogeography of our study area, confirming the pyric transition hypothesis. Yet, this hypothesis should be tested in other active agricultural frontiers in the tropics, including further developing the conceptual methodological approach I used here. A substantial improvement would be the inclusion of land use classes representing degraded and secondary forests.

Research question 3 – *What are the current spatiotemporal dynamics and the fire return interval in remnants patches of natural vegetation which have been traditionally under indigenous people fire management?*

In Chapter Four, I aimed to characterize the spatiotemporal distribution of burned area prior the establishment of an Integrated Fire Management plan in remnants areas of the Cerrado biome under traditional burnings, testing if there is a fire frequency statistical model that best model the observed fire-return interval.

In a review of the vegetation-fire relationship across several environments, Myers (2006) proposed that many tropical pyrophilic ecosystems are currently threatened by human-induced fire regimes. The author reported an overall lack of knowledge regarding the nature and the ecological appropriateness of present fire frequency in many of those environments. To assess how vegetation is responding to contemporary fire activity, detailed characterization of the spatiotemporal patterns of burnings in pyrophilic ecosystems is needed.

In this chapter, I used focused on a subset of the fine-scale BASMA-derived burned area dataset to analyze how frequently fire events occur in the Paresi plateau, one of the last continuous remnant areas of Cerrado in Mato Grosso state. The results were in agreement with previous studies, finding a mean fire interval equal to 3 years, similar to metrics estimated in other protected areas of the Cerrado (Ramos-Neto & Pivello, 2000; Daldegan et al., 2014; Pereira Júnior et al., 2014). Such a short which fire return interval is supposed to be unsustainable even in pyrophilic landscapes (Myers, 2006; Pivello, 2011).

The fire frequency modelling analysis returned relatively high values for the C test used to evaluate the goodness-of-fit, indicating that further studies must be conducted to better understand the human-fire relationship in the fire-prone ecosystems present in the Paresi plateau. Given that the fire recurrence assessment indicated deviating patterns among the indigenous lands, likely an effect of the diverse traditional burning practices among indigenous lands, subdividing the study area by indigenous lands could improve the fire frequency modelling analysis. Lastly, I am confident that the spatiotemporal patterns reported here would aid in the process of monitoring how the Integrated Fire Management plan is modifying fire activity and vegetation in the Paresi plateau.

5.1 Future Research

The subsequent development phase of the Burned Area Spectral Mixture Analysis (BASMA) algorithm has already began. Currently, I am adapting BASMA to run with Sentinel 2 MultiSpectral Instrument (MSI) imagery, which feature a spatial resolution of 20 meters, spectral resolution of 13 bands, and a revisiting time of five

days. Preliminary results demonstrate great potential of BASMA to efficiently and accurately delineate burned areas using a different collection of multispectral imagery and in a different geography. As fire is present in many parts of the world, there are plenty of opportunities to apply BASMA in studies involving not only tropical regions. For instance, BASMA is returning great results for mapping paddy-rice related burns in the Punjab state, India, at the 20-meter spatial resolution featured by Sentinel 2 imagery.

Moreover, I will keep exploring the Pyric Transition concept, by monitoring how the human-fire relationship unfolds in the existing study region in the years to come, and by further testing this hypothesis in other regions of Brazil and around the world. As demonstrated in Chapter 3, changes in policies and/or political regimes have a direct influence on how humans perceive their relationship with vegetation burns. The ongoing burns happening in the Amazon basin during the 2019 dry season are a clear outcome of the political shift Brazil is experiencing under the new federal administration that took power in January 2019. As new lands are cleared for anthropogenic activities and expands the agricultural frontier into the rainforest, the opportunity to further test the phases of pyric transition hypothesis is offered. Besides, such methodological approach should be tested in other active agricultural frontiers. Currently, the MATOPIBA region located in the intersection of Maranhão, Tocantins, Piauí, and Bahia, in central-northeastern Brazil, is foci of intensive land use and land cover change (Araújo et al., 2019; Graesser et al., 2015) offering the opportunity to further test the relationship between pyrogeography and anthropogenic activities. However, the conceptual model developed in Chapter 3

must need to go through modification in case secondary and degraded forest were mapped separately.

Finally, I have just started to explore the subject of testing statistical models to describe fire return interval. The fire frequency analysis for the Paresi Plateau presented in Chapter 4 indicated that the fire regime in the selected study area is not homogeneous. Thus, I am currently exploring methods to stratify the sampling points that would potentially lead to more appropriate results regarding which probabilistic model best fit the timing of burns in these pyrophilic ecosystems. Nevertheless, the methodology applied here was successful to create a spatiotemporal baseline for burns that happened in the four indigenous lands prior the establishment of the Integrated Fire Management plan in 2017. However, it is challenging to predict how the identified patterns might change in the mid to long term given the uncertainty related to the continuity of the Brazilian environmental policies.

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