Regional drivers of fire regimes in the Brazilian Amazon between 2009 and 2021

Authors Michel Valette ^{1,2*}, Yiannis Kountouris^{1,2}, Anna Freni Sterrantino^{3,4}, Jeremy Woods^{1,2} and Morena Mills^{1,2}

¹ Centre for Environmental Policy, Imperial College London, London SW7 1NE United-Kingdom

² Leverhulme Centre for Wildfires, Environment, and Society, London SW7 2AZ, United-Kingdom

3 The Alan Turing Institute, London NW1 2DB, United-Kingdom

4 MRC Centre for Environment and Health, Department of Epidemiology and Biostatistics, Imperial College London, London W2 1PG, United Kingdom

*Corresponding author. Email: m.valette20@imperial.ac.uk

This manuscript has been submitted for publication. Please note that the manuscript has yet to undergo per-review and be accepted for publication. Subsequent versions of the manuscript may have slightly different content. If accepted, the final version of this manuscript will be available via the 'Peer-reviewed Publication DOI' link on the right-hand side of this webpage

ABSTRACT

Fires are a major source of carbon emissions in the Brazilian Amazon. Climatic and ecological processes affect the flammability of the landscape, while socio-economic processes influence the use of fire. An analysis of the regional drivers of fires used for land clearing, subsequent land management and forest fires is still missing, despite its importance in informing targeted policy interventions for controlling fire regimes. We investigated the social, economic and environmental determinant variables of deforestation, agricultural and forest fires between 2009 and 2021 in the Brazilian Amazon. Pastures were associated with the highest number of deforestation and agricultural fires. Fire occurrence increased in remote locations and forests distant from agriculture between 2009 and 2021. Protected areas were associated with fewer fires but experienced more fire close to their borders. Our results highlight the importance of spatially resolved conservation initiatives and sustainable land management practices to curb fires and reduce environmental degradation.

INTRODUCTION

Either through managed burns for land clearing, subsequent land management or ignitions that have escaped human control, fire places substantial pressure on tropical rainforests (Van Wees et al. 2021). Fires occur in 41% of areas that have experienced tropical rainforest loss, while forest fires in particular contribute an increasingly large proportion of global fire-related carbon emissions (Van Wees et al. 2021; Zheng et al. 2021). Fire-related disturbances can trigger shifts in vegetation composition, enabling woodland conversion to savanna and grassland that host different biodiversity assemblages and are more vulnerable to subsequent cycles of drought and wildfire (Armenteras et al. 2021). Even when forests are not later converted to agricultural

land, fires can prevent their regeneration, hinder the recovery of essential ecosystem functions, and limit their resilience to external disturbances (Drüke et al. 2023; Zheng et al. 2021). The ecological impact of uncontrolled fire use is complemented by its negative effect on local populations through its damaging influence on agricultural assets, infrastructure, access to forest products, and health (Carmenta et al. 2021).

Despite its ecological, environmental and human impacts, fire use is common throughout tropical rainforest landscapes for land clearing and management. <u>Andela et al. (2017)</u> link the global decrease in burned areas to the intensification of agriculture and increased management of the landscape to protect agricultural assets and infrastructure. However, tropical rainforest basins are often characterized by the co-existence of intensified agricultural systems in most accessible areas, alongside extensive agricultural systems in remote areas (Schielein and Börner 2018). For landholders with limited access to capital, fires often represent the most viable tool for land management due to their low cost (Carmenta et al. 2021). Moreover, the prevalence of fires in the landscape may hinder agricultural intensification and the transition toward fire-free agricultural systems due to the risks of accidental fires and their associated damages (Cammelli et al. 2020). Fire regimes are expected to intensify as climate change induces longer and more intense dry periods (Abatzoglou et al. 2019), and tropical rainforests are becoming increasingly fragmented (Ma et al. 2023).

The Brazilian Amazon, which contains more than a quarter of the world's remaining tropical rainforest and harbours an estimated 11,210 tree species, including 3,248 rare species (Hubbell et al. 2008), is severely impacted by fires. Burning, along with other sources of forest degradation including logging, has transformed the region into a carbon source over the last two decades (Tyukavina et al. 2017; Gatti et al. 2021). Between 2001 and 2019, fires affected the distribution range of about 95% of plant and vertebrate species in the Amazon Basin, many of which lack adaptation to fire (Feng et al. 2021; Brando et al. 2012). Nevertheless, fires continue to be used in the Brazilian Amazon for clearing new fields, disposing of crop residues and vegetation regrowth, and managing soil fertility (van Vliet et al. 2013). Deforestation and land management ignitions frequently escape their intended confines and turn into forest fires (Silvério et al. 2013; Cano-Crespo et al. 2015). Fire control measures, including monitoring, fire breaks, and burning under low-risk meteorological conditions are costly, while their effectiveness depends on the collective will and effort of local communities for fire use regulation (Bowman et al. 2008; Morello and Falcão 2020).

The evolving fire crisis in the region has historically been blamed on deforestation patterns. Government efforts to manage it have primarily focused on conservation policy and the criminalization of fire use (Sorrensen 2009). While the rapid decrease in deforestation after 2004 was correlated with a significant decline in satellite-detected fires across the Brazilian Amazon, deforestation rates and fire occurrence later decoupled, suggesting an increasing influence of fire regime drivers unrelated to deforestation (Aragão and Shimabukuro 2010). However, the recent spike in deforestation, driven by the regional weakening of environmental policies, along with a reanalysis of fire trends, again suggests that deforestation remains a key factor in the region's fire regimes (Libonati et al. 2021). The continued use of fires in agricultural landscapes after deforestation, especially in low-intensity agricultural systems, may contribute to the persistence of fires in the Brazilian Amazon (Aragão and Shimabukuro 2010; van Vliet et al. 2013).

Understanding the typology and the drivers behind every type of fire is crucial for assessing the impact of policies focused on reducing deforestation and criminalizing fire use, as well as for bridging the gap between policies targeting deforestation, forest degradation, and integrated fire management (Sorrensen 2009). Identifying areas that are, or will become, susceptible to different types of fires can help prioritize them for wildfire prevention interventions, such as the deployment of fire brigades. Additionally, understanding the drivers of different types of fires provides insights for developing initiatives that address their root causes and mitigate potential harmful impacts on ecosystems, the economy, and human health in the region.

Here we present a typology of fire incidence in the Brazilian Amazon, characterize key drivers for each fire type, and examine their stability over time. Using datasets on deforestation and land use, we begin by classifying fires detected by satellites into deforestation, agricultural, and forest fires. We then use spatio-temporal statistical models to estimate the relationship between each fire type and a series of socio-economic and environmental drivers from 2009 to 2021. This publication contributes to the literature on fire regimes drivers in tropical forests (Fonseca et al. 2017; Silveira et al. 2020; Jones et al. 2022) and the impact of conservation policies on fire regimes in the Brazilian Amazon (Adeney et al. 2009; Sorrensen 2009; Libonati et al. 2021).

Methods

Outcome variables

We derived the response variables by classifying satellite-detected fires into deforestation fires, agricultural fires and forest fires from 2009 to 2021. To obtain fire detections within the Brazilian Amazon, we combined the Thermal Anomalies/Fire Daily datasets from MODIS Terra (MOD14A1 v6.1) and Aqua (MYD14A1 v6.1) satellites which consist of 1 km grids containing the daily occurrences of fires. We removed low-confidence fire detections before creating annual grids with the number of days when thermal anomalies (hereafter referred to as fires) were detected.

Each year, all the grid cells were associated with a percentage of deforestation derived from the PRODES dataset (PRODES 2022), forest cover and pastoral/agricultural land cover derived from Mapbiomas collection 7 (Souza et al. 2020). We classified fires into three categories, excluding fires that didn't fit in any of them:

Deforestation fires: more than 100m² of deforestation (the detection threshold for the MOD14A1/MYD14A1 datasets) detected in the same year than fire. About 14.7% of the fires (221 580 fires) were classified as deforestation fires.

Agricultural fires: less than 100m^2 of deforestation detected on the grid cell in the same year than fire and more than 80% of pastoral/agricultural land cover. About 18.0% of the fires (271 150 fires) were classified as agricultural fires.

Forest fires: less than $100m^2$ of deforestation detected on the grid cell in the same year and more than 80% of forest cover. About 13.2% of the fires (199 287 fires) were classified as forest fires.

In total, 45.87% of the daily fires with medium to high confidence detected were classified as deforestation, agricultural or forest fires (Figure 1). Due to the coarse resolution of satellite products, it was not possible to confirm that all deforestation fires result from burning after vegetation felling, however, they are in proximity to recently deforested areas. Additionally, fires classified as agricultural and forest fires may be associated with deforestation events smaller than 6.5ha, the threshold of detection of the deforestation product used.

We used the pixels centroid as the reference point for the fires detected, thus creating a new dataset of points that was used to fit a point process using the INLA-SPDE approach described later.



Figure 1. Map of the most frequent types of fires detected within 5km cells across the Brazilian Amazon.

Explanatory variables

We identified potential direct and indirect fire drivers in the Brazilian Amazon from a review of 51 relevant papers published between 2004 and 2022. Of these, 24 studies presented results from quantitative analyses of drivers and impacts of fires, 17 presented results from quantitative analyses looking at the driver and impact of other sources of forest degradation. Additionally, 6 publications provided broader context on the link between drivers of deforestation, fires and other sources of forest degradation (see SI1 for more details on the literature review).

This led to the identification of 5 main categories of drivers of fires in the BA and 14 drivers for fire regimes. From these, we identified 22 variables for inclusion in our models and identified associated data sources to model them over the 2009–2021 period, prioritizing the highest possible spatial and temporal resolution. After evaluating redundancy and correlation with other covariates, we only retained 17 variables. The explanatory variables were aggregated into a 1 km grid to correspond to the resolution of our response variable (see Table 1 for the final selection of variables). To address highly skewed distributions of some variables, all explanatory variables were categorized. This categorization helps in the interpretability of the model outputs (see SI2 for more information on data processing and distribution of response variables).

Drivers	Proxy variable	Data sources	Variable categories					
	Climate							
Precipitation Maximum Cumulated Water deficit(MCWD)		CHIRPS	No deficit/1-100mm/101- 200mm/201-300mm/301- 400mm/401mm and more					
	Forest deg	gradation	-					
Fragmentation	Edges density	Mapbiomas collection 7	<1m.Ha ⁻¹ /1-25m.Ha ⁻¹ /25- 50m.Ha ⁻¹ />50m.Ha ⁻¹					
Forest degradation	Distance forest edges	Mapbiomas collection 7	Adjacent to non-forest land/ 0- 1km/1-3km/3-5km/5-10km/10- 25km/>25km					
	Infrastructure a	nd developmen	t					
Access to market	Transport cost for exportation	Victoria et al. (2021)	<5K RU/5-10 RU/10-20RU/20- 30RU/>30 RU					
Rural settlements	Rural settlements	INCRA	Undesignated land/rural settlement					
	Agriculture av	nd pastoralism						
Agriculture	Annual crop cover Annual crop cover increase Perennial crop cover Perennial crop cover increase Domiant agricultural land use	Mapbiomas collection 7	<1%/1-50%/51-100% no increase/ increase <1%/1-50%/51-100% no increase/increase Pasture/annual crops/perennial crops					
Pastoralism	Pastoral land cover Pastoral land cover increase	Mapbiomas collection 7	<1%/1-50%/51-100% No increase/increase					
	Environmei	ntal policies						
Protected areas and Indigenous land	Integral protection areas (IUCN cat. I to III) Sustainable use areas (IUCN cat. IV to VI) Indigenous lands	World Database on Protected Areas FUNAI	Undesignated land/ periphery (<10km from border)/ core (>10km from border)					
Protected areas downsizing or degazettement	Protected areas downsizing or degazettement (PADDD)	PADDD trackers	Undesignated land/ areas no longer protected					
Priority municipalities	List of priority municipalities	Ministry of Environmen t (MMA)	Never on priority list/ on priority list/ on priority list in the past					

Table 1. Drivers and explanatory variables identified, associated data sources and categories used

Statistical Methods

We modelled fire occurrences on a yearly basis, accounting for spatial and temporal dependence. We fitted the model using a Bayesian approach that used Integrated Nested Laplace Approximation (INLA). We defined a Log-Gaussian Cox process and accounted for the spatial component with the stochastic partial differential equation (SPDE) approach. The SPDE provides a Markovian representation of the Matérn covariance (Lindgren et al. 2011). Additionally, we accounted for the temporal component by including a first-order autoregressive random effect across years (AR1).

We developed separate statistical models for each fire type, including the following variables:

- <u>Deforestation fires:</u> MCWD+ edges density + transport cost for exportation + rural settlements + annual crop cover + perennial crop cover + pastoral land cover + annual crop cover increase + perennial crop cover increase + pastoral land cover increase + integral protection areas + sustainable use areas + indigenous land + PADDD + priority list
- <u>Agricultural fires:</u> MCWD + transport cost for exportation + rural settlements + dominant agricultural land cover + annual crop cover increase + perennial crop cover increase + pastoral land cover increase + integral protection areas + sustainable use areas + indigenous land + PADDD + priority list
- <u>Forest fires:</u> MCWD+ distance forest edges + transport cost for exportation + rural settlements + integral protection areas + sustainable use areas + indigenous land + PADDD + priority list

For each fire type, we fit four separate models to investigate the changes in the relationship between variables and fires over time. We decided to use the different phases of the PPCDAm to define our different periods, as each phase is characterized by different deforestation patterns and the deployment of distinct policy instruments to reduce deforestation and environmental degradation in the region (West and Fearnside 2021), as well as a final period from 2019 to 2021, to capture the effects of the weakening of environmental policies and the resulting surge in deforestation rates during this time (Menezes and Barbosa 2021). We defined the following time periods:

- <u>Period 1 (2009-2011)</u>: phase 2 of the PPCDAm, accounting for 5 $640 \pm 297 \text{ km}^2$ of annual deforestation.
- Period 2 (2012-2015): phase 3 of the PPCDAm, accounting for $4\,958\pm725\,\mathrm{km^2}$ of annual deforestation.
- <u>Period 3 (2016-2018)</u>: part of phase 4 of the PPCDAm, accounting for 6 864 ± 169 km² of annual deforestation. We excluded 2019 to ensure this period reflects pre-Bolsonaro administration environmental policies.
- <u>Period 4 (2019-2021)</u>: phase of the dismantlement of environmental policies, accounting for $11\ 020\pm951$ km² of annual deforestation.

We reported results as log-linear posterior means with 95% credible intervals. We used the package inlabru v2.5.2 of the software R 4.3 (R Core Team 2022).



Figure 2. Number of active fires detected by MODIS and annual deforestation detected by PRODES in km2.

Results

Overall, all types of fires were positively associated with droughts and transport costs and negatively associated with the establishment of protected areas and Indigenous land. Different types of agricultural land use were associated with distinct patterns of deforestation fires and agricultural fires, with more fires in pastoral landscapes. Between 2009 and 2021, areas covered by perennial crops and rural settlements were associated with a decreasing number of fires, but areas with high transport costs and forests far from agricultural land were associated with an increasing number of fires.

Climatic factors

More intense droughts, measured by the Maximum Cumulated Water Deficit (MCWD), were associated with increasingly high numbers of agricultural fires and forest fires, up to an MCWD of 300 mm (Figure 3 and 4). A similar pattern was observed for deforestation fires and forest fires but with a lower threshold of 100mm of MCWD (Figures 4 and 5). Areas experiencing extreme droughts (MCWD >400mm) tended to experience the highest number of forest fires from 2009 to 2015. However, after 2016, areas with an MCWD higher than 300 mm saw fewer forest fires than in the earlier period.

Forest degradation

Forest fragmentation was positively associated with deforestation fires for all periods (Figure 3), except in areas with low to moderate forest fragmentation (1-50m edges/ha) between 2012 and 2015. Between 2009 and 2018, areas with low to highly fragmented forest (>1m edges/ha) were associated with similar numbers of deforestation fires. However, between 2019 and 2021, areas with highly fragmented forest cover (>50 m edges/ha) were associated with more deforestation fires.

For all the periods, forests within 1 km of agricultural land were positively associated with forest fires, while forests located more than 1 km away from agricultural land were negatively associated with forest fires (Figure 5). The number of forest fires generally decreased with increasing distance from forest edges, with this trend extending up to five kilometres between 2009 and 2018 and up to ten kilometres from 2019 onward. From 2016, areas situated three to five kilometres from agricultural land experienced more fires than in previous years. This pattern intensified after 2019, when forested areas within one to three kilometres of agricultural land saw a further increase in fire occurrences.



📥 2009-2011 📥 2012-2015 📥 2016-2018 📥 2019-2021

Figure 3. Posterior means and 95% credible intervals for explanatory variables of the models for deforestation fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable negatively associated with deforestation fires, and intervals higher than 0 indicate variables positively associated with deforestation fires.

Infrastructure and development

Overall, all types of fires became increasingly frequent in the areas with higher transport costs between 2009 and 2021. From 2012 to 2021, low transport costs (5-10K RU) were positively associated with deforestation fires, and from 2019 onwards moderate transport costs (10-20K RU) were also positively associated with deforestation fires (Figure 3). Across almost all periods, areas with low to high transport costs (5-30K RU) were associated with similar numbers of agricultural and forest fires (Figures 4 and 5). From 2009 to 2011, areas with high transport costs (>30K RU) were associated with a similar number of deforestation fires, agricultural fires and forest fires as elsewhere. But from 2012 onwards, they became associated with higher numbers of agricultural fires and forest fires.

Rural settlements were positively associated with deforestation fires and agricultural fires from 2009 to 2015 and with forest fires from 2012 to 2015 but were negatively associated with deforestation fires and agricultural fires from 2019 onwards (Figures 3, 4 and 5).



2009-2011 🛃 2012-2015 🗲 2015-2018 🗲 2019-2021

Figure 4. Posterior means and 95% credible intervals for explanatory variables of the models for agricultural fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable negatively associated with agricultural fires, and intervals higher than 0 indicate variables positively associated with agricultural fires.

Agriculture and pastoralism

Pastures were associated with the highest number of deforestation fires regardless of the period, as well as higher numbers of agricultural fires than annual crops from 2009 to 2019, and perennial crops from 2016 onwards (Figures 3 and 4). Areas covered by less than half of perennial crops were negatively associated with deforestation fires from 2016 onwards, along with areas covered by more than half of perennial crops during the 2012-2015 and the 2019-2021 periods. Although areas dominated by perennial crops were associated with similar or fewer agricultural fires than annual crops and pastures from 2016 onwards, they were associated with the highest number of agricultural fires from 2012 to 2015 (Figure 3).

Pasture expansion was associated with the highest number of deforestation and agricultural fires (Figures 3 and 4). While expansions of perennial crops and annual crops were positively associated with deforestation fires from 2009 to 2011, they were either unrelated or negatively associated in all later time periods. Expansions of all types of agricultural land were positively associated with agricultural fires from 2009 to 2015, but from 2016 onwards, only the expansions of pastures and annual crops maintained this association.



Figure 5. Posterior means and 95% credible intervals for explanatory variables of the models for forest fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable negatively associated with forest fires, and intervals higher than 0 indicate variables positively associated with forest fires.

Environmental policies

All types of protected areas were associated with fewer fires than unprotected lands, regardless of the period or fire type. Indigenous lands were associated with the lowest number of agricultural fires and deforestation fires, while integral protection areas were associated with the lowest number of forest fires (Figures 3, 4 and 5). Sustainable use areas were associated with more fires of all types than integral protection areas and Indigenous lands.

The peripheries of all types of protected areas, defined as the portions of their territory within 10km of unprotected lands, were associated with more forest fires than the core of the protected areas (Figure 5). The periphery of Indigenous lands was associated with similar numbers of forest fires to non-protected areas from 2012 to 2018, as did the periphery of integral protection areas from 2012 to 2015.

Periphery of Indigenous lands and integral protection areas were consistently associated with more agricultural fires than their core areas (Figure 4), and more deforestation fires in their periphery than their core from 2016 to 2021, and from 2009 to 2012 for the Indigenous lands (Figure 3). The core of integral protection areas is associated with fewer deforestation fires and forest fires between 2016 and 2021 than previously. Downsizing and degazettement of protected areas were associated with more deforestation fires, agricultural fires and forest fires compared to non-protected areas across all periods (Figures 3, 4 and 5).

Municipalities included on the priority list were associated with higher rate of deforestation fires, agricultural fires and forest fires than other municipalities (Figures 3, 4 and 5). However, once removed from the priority list, these municipalities were associated with similar numbers of deforestation fires as municipalities that were never on the priority list, and from 2016 onwards to lower numbers of agricultural and forest fires than municipalities still on the priority list.

DISCUSSION

This study found that, in the Brazilian Amazon, the relationship between droughts and fires is non-linear and depend on fire type, that agricultural land use is a key driver of fire regimes, that fires are becoming increasingly frequent in the remote areas and forests, and that the network of protected areas and Indigenous lands is essential for safeguarding the remaining forests from fires. By categorizing MODIS Active Fire detections into several fire types, we gain a more nuanced understanding of the relationship between fire use for land clearing, subsequent land management, and forest fires at a regional scale. The three fire types are driven by different processes and, at times, follow distinct dynamics, which can inform policy interventions and help tailor support to either limit fire use or improve fire control measures, ultimately reducing the incidence of forest fires. Additionally, this study sheds light on the increasing spread of fires within the Brazilian Amazon and the exposure of new areas to wildfire risk.

Our analysis shows that droughts were associated with more fires of all types until a certain threshold, depending on the fire types and period. This aligns with other studies that show complex and non-linear relationships between weather and fire regimes across the Amazon, with many fires during relatively wet years (Fonseca et al. 2019; Libonati et al. 2021). The changing relationship across the 4 periods could highlight the fluctuating importance of climate-related drivers. The drought intensity threshold until which deforestation fires and forest fires increased (100mm of maximum water deficit across most periods) was lower than for agricultural fires (300 mm of maximum water deficit). Framed field experiments showed that command and control policies, similar to policies currently used to limit deforestation in

the Brazilian Amazon, could reduce wildfire risks during droughts by promoting the use of fire control measures and alternative land management (Cammelli and Angelsen 2019). A similar dynamic might occur across the Brazilian Amazon, with landholders limiting their use of fires for deforestation and better controlling their agricultural fires during more intense droughts, to avoid escape fires and potential sanctions. A more detailed analysis of the relationship between fire use and climatic conditions throughout the year could provide greater insights into the complex interactions between climate and different fire types than our analysis relying on the driest month.

Our analysis shows that fire use characteristics vary with agricultural land uses, with pastures being more prone to deforestation fires and, to a lesser extent, agricultural fires. The higher number of deforestation fires associated with pastures compared to other land use is consistent with other work (Santos et al. 2021; Nunes et al. 2022). An analysis of fire regimes in the Amazon basin from 2003 to 2005 identified more frequent fires during and after land clearing for cropland than for pastures (Morton et al. 2008). However, after the implementation of the Amazon Soy Moratorium in 2007, direct deforestation related to soy culture, the main annual crop in the Brazilian Amazon, dropped drastically and expanded on already-deforested areas (Gollnow et al. 2018). A similar dynamic was identified in a palm oil expansion frontier in the state of Para: while conversion of primary forest to palm oil was common before 2005, it decreased steeply afterwards when palm oil plantations expanded on already-deforested farmland (De Almeida et al. 2020). Our results, showing continuous use of deforestation fires on pastures, suggest that indirect deforestation due to crop expansions is likely to be still contributing to fire regimes across the Brazilian Amazon.

Our results also highlight the frequent use of fires after initial land clearing, especially in areas with expanding pastures and annual crops. Agricultural fires identified in this study not only include fires purposefully lit for land management but also escaped fires burning on agricultural lands and secondary forests, when they cover less than 20% of a pixel. Across the state of Para in the Brazilian Amazon, all types of ranchers use fires to manage pasture productivity, though large-scale ranchers burn less frequently (Carvalho et al. 2020). In some places, increasing demand for local agricultural products, such as cassava flour, has also led to local intensification of the use of fires and a reduction in fallow periods by smallholders (van Vliet et al. 2013). These agricultural fires could hamper carbon sequestration in the region, by reducing carbon accumulation in soil (Stahl et al. 2017) and preventing the regeneration of secondary forests, a carbon pool that could contribute up to 5.5% of Brazil's 2030 net emissions target (Heinrich et al. 2021).

The decline in deforestation fires, and agricultural fires from 2016 onwards, in areas with perennial crops aligns with previous studies highlighting the antagonism between fire use and perennial crops (Gutiérrez-Vélez et al. 2014; Cammelli et al. 2020). Adopting perennial crops could incentivize landholders to reduce wildfire risks in the landscape to protect valuable assets (Cammelli et al. 2020). In a study in the Peruvian Amazon, Gutiérrez-Vélez et al. (2014) found that contrary to young palm oil plantations, older palm oil plantations were negatively associated with fires, potentially due to changes in vegetation structure and lower susceptibility to escaped fires. A similar dynamic, with ageing perennial crops and reduced risks of roaming fires, could explain the declining number of fires associated with perennial crops after 2016. While potentially limiting the occurrence of fires in the long term, large-scale adoption of perennial crops faces significant constraints, such as the access to necessary output and low

economic return during first years, and some perennial crops monocultures have other harmful ecological impacts (Mendes-Oliveira et al. 2017).

In recent years, our analysis shows all types of fires have occurred more frequently in the areas with higher transport costs of the Brazilian Amazon. Andela et al. (2017) propose agricultural intensification drives a decrease in fire activity for tropical forest regions, due to increased mechanization and the higher value of fire-vulnerable assets. However, the process of agricultural intensification is not uniform across the Brazilian Amazon: well-connected areas have intensified their agricultural systems while marginal areas continue to rely on lowintensity agriculture (Schielein and Börner 2018; Carvalho et al. 2020). Numerous case studies show that limited access to agricultural inputs and mechanization, and a scarcity of firevulnerable assets, could favour the use of fires for land management (Cammelli et al. 2020; Morello and Falcão 2020). Both agricultural intensification increasing the price of alreadydeforested land and frequent regularization of illegal land occupation have encouraged the opening of new deforestation frontiers for land speculation, leading to increased fire risks in increasingly remote areas (Gollnow et al. 2018; Carrero et al. 2022). In an analysis at a coarser scale, Tavares et al. (2022) showed that, between 2012 and 2019 in the Brazilian Amazon, fires occurred more frequently on pixels with higher forest cover and more croplands, potentially indicating the indirect impact of agricultural intensification on fire regimes. The divergent results for the impact of cropland between our study and the study of Tavares et al. (2022) could be due to our finer-scale analysis illustrating a more localized impact of land use change on fire regimes.

Our analysis shows that deforestation fires are occurring increasingly frequently in areas with highly fragmented forests, more vulnerable to escaped fires and conducive to large forest fires (Alencar et al. 2015), while forest fires are burning farther from agricultural lands. The increasing prevalence of fires in remote forests could contribute to the widespread loss of resilience of forests to disturbances already observed across the Amazon basin, especially in areas with higher anthropic disturbance (Boulton et al. 2022). The "interiorization" of fires in the Brazilian Amazon has important implications from an evolutionary ecology perspective: forests that were previously not exposed to fire disturbance, due to wetter climatic conditions and the absence of sources of ignition, are now burning. These ecosystems can experience higher post-fire mortality than seasonally dry Amazonian forests, because of the differences in species composition and lack of selective pressure for fire-resistant traits in the past (Balch et al. 2011). Fires alter species composition and structures of forests, creating favourable conditions for future fires and shifting the vegetal community toward increased dominance of fire-adapted species (Silvério et al. 2013; Balch et al. 2015; Prestes et al. 2020).

The lower number of fires identified in all types of protected areas is consistent with previous analyses of deforestation and fires in the Brazilian Amazon (Adeney et al. 2009; Nolte et al. 2013). Our analysis highlights the increase in all types of fires after the downsizing and degazettement of protected areas, highlighting the importance of maintaining their existence to prevent both deforestation and forest degradation. Indigenous lands, associated with the lowest number of deforestation fires and agricultural fires, serve as a crucial barrier against deforestation, especially in high-pressure frontiers (Soares-Filho et al. 2010). Some of the forest fires identified within Indigenous land could be related to Indigenous land management, including small-scale clearing of secondary forests for food production or burning of other vegetation types (Schwartzman et al. 2013). Extensive traditional knowledge of fire management may allow some Indigenous communities to use fire while preventing accidental large-scale wildfires, such as through the use of controlled fires to reduce fuel load (Bilbao et al. 2010).

When compared to other types of protected areas, the relatively higher frequency of fires in sustainable use areas could be explained by several factors: sustainable use areas are inhabited, livelihood activities relying on fires are allowed, and they generally receive less funding than strictly protected areas for fire management and other activities (Oliveira et al. 2021). While there are legal requirements for conducting fires in sustainable areas, such as the acquisition of burning permits or the clearing of wide fire breaks, many are unrealistic given the constraints met by landholders and are frequently disregarded (Carmenta et al. 2013). Certain sustainable use areas also have loose regulations on land ownership, which can lead to extensive deforestation (Jesus and Catojo 2020). Capitalizing on fire management experience in two sustainable use areas, including the involvement of local communities in fire management, support to community fire-fighters, development of alternative livelihoods to swidden cultivation and better forecasting of wildfire risks.

Our study highlighted a consistently higher occurrence of all types of fires close to the border of protected areas and Indigenous lands throughout the whole Brazilian Amazon. Dos Santos et al. (2021) found that fires within Indigenous lands in the state of Rondônia were partly explained by fire occurrence and land use in their immediate vicinity, while Walker et al. (2020) identified similar dynamics in the state of Mato Grosso. Silva et al. (2022) revealed a higher prevalence of fires in Indigenous lands either cut by highway or located within 10 km of a highway. Complementary measures to avoid forest fires and control fire use around protected areas could help reduce the occurrence of fires within protected areas (Walker et al. 2020). Analysis relying on medium to high-resolution mapping of fires within and close to Indigenous lands and protected areas, like the one done by Walker et al. (2020) in Mato-Grosso, could help shed light on the complex relationship between fires outside and within these areas.

Our analysis also suggests that the Priority List Program, aiming to reduce deforestation at the municipality level through incentives and disincentives, has had positive outcomes on the use of fires, especially regarding deforestation fires and, to a lesser extent, on agricultural and forest fires. This adds to conclusions from previous studies showing that the priority list program was a cost-efficient way to reduce deforestation (Assunção and Rocha 2019). We also identified a general decrease in deforestation and agricultural fire use in rural settlements, a type of land governance covering about 8% of the Brazilian Amazon and supporting the livelihoods of approximately 600,000 families. While part of this decline could be due to a decreasing amount of remaining forest available to burn, we need to better understand what is driving this trend, given that the landscape is often highly fragmented, and landholders rely on low-intensity farming practices on small landholdings.

Conclusion

Climate, forest degradation, infrastructure, agriculture and environmental policies influence agriculture, deforestation and forest fires. Pastures, the most widespread land use in Brazilian Amazon, remain strongly associated with deforestation fires while all agricultural land use contributes to agricultural fires. This showcases the need to not only alleviate deforestation but also support better land management strategies on already-deforested land to prevent fires from escaping further degrading the remaining forests.

Since 2009, fire regimes intensified in remote regions of the Brazilian Amazon and within forests located farther from agricultural lands. This "interiorization" of fires in the Brazilian Amazon, occurring in the context of a drying climate and a loss of resilience of forest to external disturbances, raises concerns about potential forest diebacks in the region.

Protected areas experienced fewer deforestation fires and forest fires than unprotected lands, within protected areas fires were more frequent in areas near unprotected land, and downsizing and degazettement of protected areas were associated with increases in fires. Strengthening environmental policies, ensuring adequate resources for agencies responsible for fire governance, and securing the land rights of traditional and Indigenous communities are crucial for reducing fire pressures and tackling deforestation and forest degradation simultaneously.

Acknowledgement We would like to thank Antonio Oviedo, Rachel Golden Kroner, Yifan He and Bruno Coutinho for initial discussion on forest conservation and fires regimes in the Brazilian Amazon; Lisa Gecchele, Hårvard Rue and Finn Lindgren for the support for data modelling, James Millington and Rafael Chiaravalloti for feedback on early results and Mark Burgman for comments on the manuscript.

Competing interests. Authors declare that they have no competing interest.

References

- Abatzoglou, J. T., A. P. Williams, and R. Barbero. 2019. Global Emergence of Anthropogenic Climate Change in Fire Weather Indices. *Geophysical Research Letters* 46: 326–336. doi:10.1029/2018GL080959.
- Adeney, J. M., N. L. Christensen, and S. L. Pimm. 2009. Reserves Protect against Deforestation Fires in the Amazon. Edited by Rob P. Freckleton. *PLoS ONE* 4. doi:10.1371/journal.pone.0005014.
- Alencar, A. A., P. M. Brando, G. P. Asner, and F. E. Putz. 2015. Landscape fragmentation, severe drought, and the new Amazon forest fire regime. *Ecological Applications* 25: 1493–1505. doi:10.1890/14-1528.1.
- Andela, N., D. C. Morton, L. Giglio, Y. Chen, G. R. Van Der Werf, P. S. Kasibhatla, R. S. DeFries, G. J. Collatz, et al. 2017. A human-driven decline in global burned area. *Science* 356: 1356–1362. doi:10.1126/science.aal4108.
- Aragão, L. E. O. C., and Y. E. Shimabukuro. 2010. The Incidence of Fire in Amazonian Forests with Implications for REDD. *Science* 328: 1275–1278. doi:10.1126/science.1186925.
- Armenteras, D., L. M. Dávalos, J. S. Barreto, A. Miranda, A. Hernández-Moreno, C. Zamorano-Elgueta, T. M. González-Delgado, M. C. Meza-Elizalde, et al. 2021. Fire-induced loss of the world's most biodiverse forests in Latin America. *Science Advances* 7: eabd3357. doi:10.1126/sciadv.abd3357.
- Assunção, J., and R. Rocha. 2019. Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics* 24: 115–137. doi:10.1017/S1355770X18000499.
- Balch, J. K., D. C. Nepstad, L. M. Curran, P. M. Brando, O. Portela, P. Guilherme, J. D. Reuning-Scherer, and O. de Carvalho. 2011. Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management* 261: 68–77. doi:10.1016/j.foreco.2010.09.029.
- Balch, J. K., P. M. Brando, D. C. Nepstad, M. T. Coe, D. Silvério, T. J. Massad, E. A. Davidson, P. Lefebvre, et al. 2015. The Susceptibility of Southeastern Amazon Forests to Fire:

Insights from a Large-Scale Burn Experiment. *BioScience* 65: 893–905. doi:10.1093/biosci/biv106.

- Bilbao, B. A., A. V. Leal, and C. L. Méndez. 2010. Indigenous Use of Fire and Forest Loss in Canaima National Park, Venezuela. Assessment of and Tools for Alternative Strategies of Fire Management in Pemón Indigenous Lands. *Human Ecology* 38: 663–673. doi:10.1007/s10745-010-9344-0.
- Boulton, C. A., T. M. Lenton, and N. Boers. 2022. Pronounced loss of Amazon rainforest resilience since the early 2000s. *Nature Climate Change* 12: 271–278. doi:10.1038/s41558-022-01287-8.
- Bowman, M. S., G. S. Amacher, and F. D. Merry. 2008. Fire use and prevention by traditional households in the Brazilian Amazon. *Ecological Economics* 67: 117–130. doi:10.1016/j.ecolecon.2007.12.003.
- Brando, P. M., D. C. Nepstad, J. K. Balch, B. Bolker, M. C. Christman, M. Coe, and F. E. Putz. 2012. Fire-induced tree mortality in a neotropical forest: the roles of bark traits, tree size, wood density and fire behavior. *Global Change Biology* 18: 630–641. doi:10.1111/j.1365-2486.2011.02533.x.
- Cammelli, F., and A. Angelsen. 2019. Amazonian farmers' response to fire policies and climate change. *Ecological Economics* 165: 106359. doi:10.1016/j.ecolecon.2019.106359.
- Cammelli, F., R. D. Garrett, J. Barlow, and L. Parry. 2020. Fire risk perpetuates poverty and fire use among Amazonian smallholders. *Global Environmental Change* 63. doi:10.1016/j.gloenvcha.2020.102096.
- Cano-Crespo, A., P. J. C. Oliveira, A. Boit, M. Cardoso, and K. Thonicke. 2015. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences* 120: 2095–2107. doi:10.1002/2015JG002914.
- Carmenta, R., S. Vermeylen, L. Parry, and J. Barlow. 2013. Shifting Cultivation and Fire Policy: Insights from the Brazilian Amazon. *Human Ecology* 41: 603–614. doi:10.1007/s10745-013-9600-1.
- Carmenta, R., F. Cammelli, W. Dressler, C. Verbicaro, and J. G. Zaehringer. 2021. Between a rock and a hard place: The burdens of uncontrolled fire for smallholders across the tropics. *World Development* 145: 105521. doi:10.1016/j.worlddev.2021.105521.
- Carrero, G. C., R. T. Walker, C. S. Simmons, and P. M. Fearnside. 2022. Land grabbing in the Brazilian Amazon: Stealing public land with government approval. *Land Use Policy* 120. doi:10.1016/j.landusepol.2022.106133.
- Carvalho, R., A. P. D. de Aguiar, and S. Amaral. 2020. Diversity of cattle raising systems and its effects over forest regrowth in a core region of cattle production in the Brazilian Amazon. *Regional Environmental Change* 20: 44. doi:10.1007/s10113-020-01626-5.
- De Almeida, A. S., I. C. G. Vieira, and S. F. B. Ferraz. 2020. Long-term assessment of oil palm expansion and landscape change in the eastern Brazilian Amazon. *Land Use Policy* 90: 104321. doi:10.1016/j.landusepol.2019.104321.
- Drüke, M., B. Sakschewski, W. Von Bloh, M. Billing, W. Lucht, and K. Thonicke. 2023. Fire may prevent future Amazon forest recovery after large-scale deforestation. *Communications Earth & Environment* 4: 248. doi:10.1038/s43247-023-00911-5.
- Feng, X., C. Merow, Z. Liu, D. S. Park, P. R. Roehrdanz, B. Maitner, E. A. Newman, B. L. Boyle, et al. 2021. How deregulation, drought and increasing fire impact Amazonian biodiversity. *Nature* 597: 516–521. doi:10.1038/s41586-021-03876-7.
- Fonseca, M. G., L. O. Anderson, E. Arai, Y. E. Shimabukuro, H. A. M. Xaud, M. R. Xaud, N. Madani, F. H. Wagner, et al. 2017. Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications* 27: 2514–2527. doi:10.1002/eap.1628.

- Fonseca, M. G., L. M. Alves, A. P. D. Aguiar, E. Arai, L. O. Anderson, T. M. Rosan, Y. E. Shimabukuro, and L. E. O. E. C. De Aragão. 2019. Effects of climate and land-use change scenarios on fire probability during the 21st century in the Brazilian Amazon. *Global Change Biology* 25: 2931–2946. doi:10.1111/gcb.14709.
- Gatti, L. V., L. S. Basso, J. B. Miller, M. Gloor, L. Gatti Domingues, H. L. G. Cassol, G. Tejada, L. E. O. C. Aragão, et al. 2021. Amazonia as a carbon source linked to deforestation and climate change. *Nature* 595: 388–393. doi:10.1038/s41586-021-03629-6.
- Gollnow, F., L. de B. V. Hissa, P. Rufin, and T. Lakes. 2018. Property-level direct and indirect deforestation for soybean production in the Amazon region of Mato Grosso, Brazil. *Land Use Policy* 78: 377–385. doi:10.1016/j.landusepol.2018.07.010.
- Gutiérrez-Vélez, V. H., M. Uriarte, R. DeFries, M. Pinedo-Vásquez, K. Fernandes, P. Ceccato, W. Baethgen, and C. Padoch. 2014. Land cover change interacts with drought severity to change fire regimes in Western Amazonia. *Ecological Applications* 24: 1323–1340. doi:10.1890/13-2101.1.
- Heinrich, V. H. A., R. Dalagnol, H. L. G. Cassol, T. M. Rosan, C. T. De Almeida, C. H. L. Silva Junior, W. A. Campanharo, J. I. House, et al. 2021. Large carbon sink potential of secondary forests in the Brazilian Amazon to mitigate climate change. *Nature Communications* 12: 1785. doi:10.1038/s41467-021-22050-1.
- Hubbell, S. P., F. He, R. Condit, L. Borda-de-Água, J. Kellner, and H. ter Steege. 2008. How many tree species are there in the Amazon and how many of them will go extinct? *Proceedings of the National Academy of Sciences* 105: 11498–11504. doi:10.1073/pnas.0801915105.
- Jesus, S. C. de, and A. M. Z. Catojo. 2020. Deforestation in Conservation Units of the Brazilian Amazon: the case of the Terra do Meio Mosaic. *Ciência e Natura* 42: 1–23. doi:10.5902/2179460X41390.
- Jones, M. W., J. T. Abatzoglou, S. Veraverbeke, N. Andela, G. Lasslop, M. Forkel, A. J. P. Smith, C. Burton, et al. 2022. Global and Regional Trends and Drivers of Fire Under Climate Change. *Reviews of Geophysics* 60. doi:10.1029/2020RG000726.
- Libonati, R., J. M. C. Pereira, C. C. Da Camara, L. F. Peres, D. Oom, J. A. Rodrigues, F. L. M. Santos, R. M. Trigo, et al. 2021. Twenty-first century droughts have not increasingly exacerbated fire season severity in the Brazilian Amazon. *Scientific Reports* 11: 4400. doi:10.1038/s41598-021-82158-8.
- Lindgren, F., H. Rue, and J. Lindström. 2011. An explicit link between Gaussian fields and Gaussian Markov random fields: the stochastic partial differential equation approach: Link between Gaussian Fields and Gaussian Markov Random Fields. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 73: 423–498. doi:10.1111/j.1467-9868.2011.00777.x.
- Ma, J., J. Li, W. Wu, and J. Liu. 2023. Global forest fragmentation change from 2000 to 2020. *Nature Communications* 14: 3752. doi:10.1038/s41467-023-39221-x.
- Mendes-Oliveira, A. C., C. A. Peres, P. C. R. D. A. Maués, G. L. Oliveira, I. G. B. Mineiro, S. L. S. De Maria, and R. C. S. Lima. 2017. Oil palm monoculture induces drastic erosion of an Amazonian forest mammal fauna. Edited by Danilo Russo. *PLOS ONE* 12: e0187650. doi:10.1371/journal.pone.0187650.
- Menezes, R. G., and R. Barbosa. 2021. Environmental governance under Bolsonaro: dismantling institutions, curtailing participation, delegitimising opposition. Zeitschrift für Vergleichende Politikwissenschaft 15: 229–247. doi:10.1007/s12286-021-00491-8.
- Morello, T., and L. Falcão. 2020. The Fire Management Dilemma in the Brazilian Amazon: Synthesizing Pathways of Causality across Five Case Studies in the State of Pará. *Human Ecology* 48: 397–409. doi:10.1007/s10745-020-00166-0.

- Morton, D. C., R. S. Defries, J. T. Randerson, L. Giglio, W. Schroeder, and G. R. Van Der Werf. 2008. Agricultural intensification increases deforestation fire activity in Amazonia: Deforestation Fires in Amazonia. *Global Change Biology* 14: 2262–2275. doi:10.1111/j.1365-2486.2008.01652.x.
- Nóbrega Spínola, J., M. J. Soares da Silva, J. R. Assis da Silva, J. Barlow, and J. Ferreira. 2020. A shared perspective on managing Amazonian sustainable-use reserves in an era of megafires. Edited by Alexandro B. Leverkus. *Journal of Applied Ecology* 57: 2132– 2138. doi:10.1111/1365-2664.13690.
- Nolte, C., A. Agrawal, K. M. Silvius, and B. S. Soares-Filho. 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 110: 4956–4961. doi:10.1073/pnas.1214786110.
- Nunes, C. A., E. Berenguer, F. França, J. Ferreira, A. C. Lees, J. Louzada, E. J. Sayer, R. Solar, et al. 2022. Linking land-use and land-cover transitions to their ecological impact in the Amazon. *Proceedings of the National Academy of Sciences* 119: e2202310119. doi:10.1073/pnas.2202310119.
- Oliveira, A. S., B. S. Soares-Filho, U. Oliveira, R. Van der Hoff, S. M. Carvalho-Ribeiro, A. R. Oliveira, L. C. Scheepers, B. A. Vargas, et al. 2021. Costs and effectiveness of public and private fire management programs in the Brazilian Amazon and Cerrado. *Forest Policy and Economics* 127. doi:10.1016/j.forpol.2021.102447.
- Prestes, N. C. C. D. S., K. G. Massi, E. A. Silva, D. S. Nogueira, E. A. De Oliveira, R. Freitag, B. S. Marimon, B. H. Marimon-Junior, et al. 2020. Fire Effects on Understory Forest Regeneration in Southern Amazonia. *Frontiers in Forests and Global Change* 3: 10. doi:10.3389/ffgc.2020.00010.
- PRODES. 2022. Coordenação-Geral de Observação da Terra.
- R Core Team. 2022. R: A language and environment for statistical computing (version V4.1). Vienna, Austria: R Foundation for Statistical Computing.
- Santos, A. M. D., C. F. A. D. Silva, P. M. D. Almeida Junior, A. P. Rudke, and S. N. D. Melo. 2021. Deforestation drivers in the Brazilian Amazon: assessing new spatial predictors. *Journal of Environmental Management* 294: 113020. doi:10.1016/j.jenvman.2021.113020.
- Santos, A. M. dos, C. F. A. da Silva, A. P. Rudke, and D. de Oliveira Soares. 2021. Dynamics of active fire data and their relationship with fires in the areas of regularized indigenous lands in the Southern Amazon. *Remote Sensing Applications: Society and Environment* 23. doi:10.1016/j.rsase.2021.100570.
- Schielein, J., and J. Börner. 2018. Recent transformations of land-use and land-cover dynamics across different deforestation frontiers in the Brazilian Amazon. *Land Use Policy* 76: 81–94. doi:10.1016/j.landusepol.2018.04.052.
- Schwartzman, S., A. V. Boas, K. Y. Ono, M. G. Fonseca, J. Doblas, B. Zimmerman, P. Junqueira, A. Jerozolimski, et al. 2013. The natural and social history of the indigenous lands and protected areas corridor of the Xingu River basin. *Philosophical Transactions of the Royal Society B: Biological Sciences* 368: 20120164. doi:10.1098/rstb.2012.0164.
- Silva, C. F. A., S. T. Alvarado, A. M. Santos, M. O. Andrade, and S. N. Melo. 2022. Highway Network and Fire Occurrence in Amazonian Indigenous Lands. *Sustainability* 14: 9167. doi:10.3390/su14159167.
- Silveira, M. V. F., C. A. Petri, I. S. Broggio, G. O. Chagas, M. S. Macul, C. C. S. S. Leite, E. M. M. Ferrari, C. G. V. Amim, et al. 2020. Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land* 9: 516. doi:10.3390/land9120516.

- Silvério, D. V., P. M. Brando, J. K. Balch, F. E. Putz, D. C. Nepstad, C. Oliveira-Santos, and M. M. C. Bustamante. 2013. Testing the Amazon savannization hypothesis: fire effects on invasion of a neotropical forest by native cerrado and exotic pasture grasses. *Philosophical Transactions of the Royal Society B: Biological Sciences* 368. doi:10.1098/rstb.2012.0427.
- Soares-Filho, B., P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, et al. 2010. Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences* 107: 10821–10826. doi:10.1073/pnas.0913048107.
- Sorrensen, C. 2009. Potential hazards of land policy: Conservation, rural development and fire use in the Brazilian Amazon. *Land Use Policy* 26: 782–791. doi:10.1016/j.landusepol.2008.10.007.
- Souza, C. M., J. Z. Shimbo, M. R. Rosa, L. L. Parente, A. A. Alencar, B. F. T. Rudorff, H. Hasenack, M. Matsumoto, et al. 2020. Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. *Remote Sensing* 12: 2735. doi:10.3390/rs12172735.
- Stahl, C., S. Fontaine, K. Klumpp, C. Picon-Cochard, M. M. Grise, C. Dezécache, L. Ponchant, V. Freycon, et al. 2017. Continuous soil carbon storage of old permanent pastures in Amazonia. *Global Change Biology* 23: 3382–3392. doi:10.1111/gcb.13573.
- Tavares, P. A., J. Ferreira, C. V. J. Silva, E. Berenguer, and J. Barlow. 2022. Exploring the Role of Deforestation and Cropland Expansion in Driving a Fire-Transition in the Brazilian Amazon. *Land* 11: 2274. doi:10.3390/land11122274.
- Tyukavina, A., M. C. Hansen, P. V. Potapov, S. V. Stehman, K. Smith-Rodriguez, C. Okpa, and R. Aguilar. 2017. Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science Advances* 3. doi:10.1126/sciadv.1601047.
- Van Wees, D., G. R. Van Der Werf, J. T. Randerson, N. Andela, Y. Chen, and D. C. Morton. 2021. The role of fire in global forest loss dynamics. *Global Change Biology* 27: 2377– 2391. doi:10.1111/gcb.15591.
- van Vliet, N., C. Adams, I. C. G. Vieira, and O. Mertz. 2013. "Slash and Burn" and "Shifting" Cultivation Systems in Forest Agriculture Frontiers from the Brazilian Amazon. *Society* & *Natural Resources* 26: 1454–1467. doi:10.1080/08941920.2013.820813.
- Walker, W. S., S. R. Gorelik, A. Baccini, J. L. Aragon-Osejo, C. Josse, C. Meyer, M. N. Macedo, C. Augusto, et al. 2020. The role of forest conversion, degradation, and disturbance in the carbon dynamics of Amazon indigenous territories and protected areas. *Proceedings of the National Academy of Sciences* 117: 3015–3025. doi:10.1073/pnas.1913321117.
- West, T. A. P., and P. M. Fearnside. 2021. Brazil's conservation reform and the reduction of deforestation in Amazonia. *Land Use Policy* 100. doi:10.1016/j.landusepol.2020.105072.
- Zheng, B., P. Ciais, F. Chevallier, E. Chuvieco, Y. Chen, and H. Yang. 2021. Increasing forest fire emissions despite the decline in global burned area. *Science Advances* 7: eabh2646. doi:10.1126/sciadv.abh2646.

Supporting information 1: Framework of potential drivers of fires regimes

At the initial stage of this research, we conducted a non-systematic literature review to investigate the potential theoretical framework of drivers of fire regimes in the region and identify relevant data sources. This non-systematic literature review encompasses 51 publications ranging from 2004 to 2022 and focusing on the Brazilian Amazon region. Out of these publications, 24 present results from quantitative analysis of drivers and impacts of fires, 17 results from quantitative analysis of drivers and impacts of forest degradation, a well as 6 other publications providing richer context on the link between drivers of deforestation, fires and other sources of forest degradation. The following paragraphs describe the main categories of drivers of fire regimes that were identified through the literature review, while table S1 details different links identified between potential variables and fires regimes in the Brazilian Amazon.

Climate

There is a strong association between annual precipitation and fire occurrence within the Brazilian Amazon (Aragão et al. 2007; Arima et al. 2007; Soares-Filho et al. 2012; Fonseca et al. 2016; Fonseca et al. 2017; Silveira et al. 2020). While most of the rainforests in the region are too humid to burn, El-Nino events, Pacific Decadal Oscillation and Atlantic Multidecadal oscillations are triggering periodic droughts increasing considerably the number of active fires detected across Amazonian landscapes (Aragão et al. 2007; Fonseca et al. 2017; Aragão et al. 2018). Prolonged droughts lead Amazonian trees to lose part of their branches and leaves, resulting in an accumulation of fuel, an opening of the canopy, an increased penetration of solar radiation and ultimately more intense fire and higher post-fire mortality than in normal climatic conditions (Nepstad et al. 2008; Brando et al. 2014) However, chronic water deficit limits the regrowth of the vegetation a contributing to fuel scarcity (Silveira et al. 2020).

Agriculture and pastoralism

Increasing the profitability of ranching or crop farming might incentivize landholders to clear more land, using fires in the process, especially when cleared land is intended for crop cultivation. Fires is used more intensely for land clearing associated with crop cultures than ranching (Morton et al. 2008; Aragão et al. 2018). After land clearing, fires continue to be used, especially in low-intensity farming systems and pastures, for getting rid of the regrowing vegetation, creating many ignition points that frequently escape into nearby forests (Cano-Crespo et al. 2015). However, mechanization and intensification of agriculture reduce the need to use fires and increase the value of fire-vulnerable assets on agricultural land, sending incentives for better fire management (Morello and Falcão 2020).

Forest degradation

Before deforestation and conversion to agricultural land, Amazonian forests might face several types of disturbance (Tyukavina et al. 2017). In the early stage of frontier expansions, logging is an important source of pressure, leading to an accumulation of fuelwood due to vegetation disturbance, damage to the canopy increasing the penetration of solar radiation and fragmentation of the landscape making the forest more prone to fires (Asner et al. 2005; Asner et al. 2006; Broadbent et al. 2008). The road opened during the logging process fragment the forest cover, improve the accessibility of forested areas and profitability of ranching/farming venture: significant parts of logged forests are deforested within the next years (Asner et al. 2006).

Fragmentation of the forest cover has several impacts on the fire regime: edges are favoring drier microclimate, increase mortality rates and impact the vegetal communities and thus fuel structure (Balch et al. 2015). It also increases the interface between the agricultural landscape, on which fire is frequently used, and forests, thus increasing the possibility of escaped fires (Cano-Crespo et al. 2015). Understory fires also influence future fires: even low-intensity burn results in tree mortality, fuel accumulation, damage of the canopy and invasion of the forest by grass species, all processes that increase the intensity of future fires (Barlow and Peres 2008; Balch et al. 2011; Balch et al. 2015). Finally, deforestation is one of the most important drivers of fire regimes in the region: after felling the trees, they are left on the ground to dry before being lit on fires several times for getting rid of the biomass and allow agriculture (Morton et al. 2008).

Infrastructures and development

The Brazilian Amazon has a limited road network and many areas that are distant from densely populated areas, markets and governmental infrastructure. The distance from the road and port destined for exportation determine the potential profitability of deforestation and agricultural ventures, as well as access to labor and agricultural inputs. Most deforestation in the Brazilian Amazon and associated fires, occurred close to roads and rivers (Barber et al. 2014; Fonseca et al. 2017). However, areas close to major roads have better access to agricultural inputs and labour and could have a higher degree of mechanization and/or intensification of their agricultural system, which incentive landholders to invest more into firerisk reduction and/or find alternative land management technics, while reducing the need to use fires for agricultural production due to better market prices (Bowman et al. 2008).

The relationship between fire and population density appears non-linear: while initially increase in population is accompanied by an increase in fire use for land clearing and agriculture, it seems that the relationship reverses after a threshold is reached (Silveira et al. 2020). This could be explained by the consolidation of agricultural frontiers in densely populated areas and the increase of fire-vulnerable assets on the land, encouraging local stakeholders to reach better fire governance, as well as a higher degree of mechanization of agriculture (Morello and Falcão 2020).

The rural settlement, areas designated by the INCRA to be exploited by landless farmers and smallholders coming from other regions of Brazil, are of particular interest. Farmers can gain land titles from the INCRA, the governmental institution implementing the agrarian reform in Brazil, on the condition that they prove a "productive" use of the land. Thus rural settlements tend to have higher rates of deforestation and fire occurrence than other areas (Schneider and Peres 2015; Yanai et al. 2017). These areas, open for occupation, also concentrate tensions around land tenure: while part of the landholders wants to keep modest landholdings, part of settlers clear vegetation (thus increasing the value of the land plot) and sell their land to capitalized farmers (Carrero et al. 2020; Yanai et al. 2020).

Environmental policies

Over the 2005-2015 period, the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDam), coordinated the action of different Brazilian ministries aimed to decrease deforestation by more than 80%. While initially focusing on the improvement of satellite monitoring and law enforcement capacities as well as the demarcation of new protected areas, the latter phases emphasized the promotion of sustainable economic development and reducing deforestation on private lands (West and Fearnside 2021). Delimitation of new protected areas has succeeded in reducing deforestation rate and fire frequency, but their effectiveness depends on the type of protection system, deforestation pressures faced and managing authorities (Soares-Filho et al. 2010; Nolte et al. 2013; Carmenta et al. 2016; Herrera et al. 2019). Indigenous land, often located in high-pressure areas, tend to be the most efficient protection regime, followed by strictly protected areas and then sustainable use area, allowing many types of human activities (Soares-Filho et al. 2010; Nolte et al. 2013). Many fires in the protected areas are occurring in places closes to road and border with unprotected land (Adeney et al. 2009; Santos et al. 2021; Walker et al. 2022).

The creation of a near real-time satellite monitoring system of deforestation to guide law enforcement on the ground was also a crucial point of the PPCDAm (Assunção et al. 2015; Börner et al. 2015). However, the size of the average deforestation patch has decreased over the 2005-2014 period to avoid detection and subsequent punishment by environmental authorities (Rosa et al. 2012; Richards et al. 2017; Kalamandeen et al. 2018). The dismantlement of IBAMA and INPE, the governmental agency responsible for respectively the law enforcement efforts and the satellite monitoring of deforestation, has led to a lower probability of punishment and an increase in deforestation patch size in recent years (de Area Leão Pereira et al. 2019; Carvalho et al. 2019; Ferrante and Fearnside 2019). Land conflicts, the creation of rural settlements and infrastructure projects also led to the downgrading, downsizing or degazettement of around 90 000 km2 of protected areas in the Brazilian Amazon, even though there is mixed evidence of a short-term increase in deforestation rates in these areas (Pack et al. 2016; Keles et al. 2020).

In 2008, the critical county program (also called "priority list program" in certain instances) started to publish a "blacklist" of municipalities experiencing an increase in deforestation. The first list published included the 36 Brazilian municipalities responsible for 45% of the deforestation detected by PRODES in 2007 (Assunção and Rocha 2019). The blacklisted municipalities are subject to stricter administrative requirements for further forest clearing, suffer from a bad reputation, which could reduce business opportunities, and increase monitoring and enforcement actions by the IBAMA. Further restrictions can be adopted by state government such as restricted access to government-sponsored agricultural credits. However, they also benefit from increased support from state actors and NGOs to reduce their deforestation rate. The critical counties program has been efficient to reduce the deforestation rate of blacklisted counties and has a low cost of implementation (Cisneros et al. 2015).

Drivers	Relationship			
	Climate			
Temperature	High temperatures favour fires (Morello 2020; Ferreira Barbosa et al. 2021)			
	Water deficit triggered by major drought increases the frequency of fires (Aragão et al. 2007; Morton et al. 2008; Adeney et al. 2009; Soares-Filho et al. 2012; Fonseca et al. 2017)			
Precipitations	Areas with higher precipitations tend to have less frequent fires (Arima et al. 2007; Fonseca et al. 2016; Morello 2020)			
	Increasing water deficits are increasing and then decreasing the probability of having fires (Silveira et al. 2020)			
	Agriculture and pastoralism			
	Crop production encourages the use of fires (Morton et al. 2008; Xu et al. 2021)			
Agriculture	Non-linear relationship between crop production and fire occurrences (Arima et al. 2007; Aragão and Shimabukuro 2010; Silveira et al. 2020)			
	No significant effect (Morello 2020)			
	Frequent agricultural fires escaping in nearby forest edges (Cano-Crespo et al. 2015)			
	Beef production increases the use of fires (Arima et al. 2007; Fonseca et al. 2016)			
	No significant effect (Morello 2020)			
Pastoralism	Lower counts of fires when land clearing is related to ranching rather than crop production, but higher fire counts after land clearing (Morton et al. 2008; Aragão and Shimabukuro 2010)			
	Increase in the number of fires until pasture covers more than 56% of the cell (Silveira et al. 2020)			
	Frequent agricultural fires escaping in nearby forest edges (Cano-Crespo et al. 2015)			

Drivers	Relationship					
Ecosystem integrity						
Fragmentation	Forest fragmentation favours forest fires (Soares-Filho et al. 2012; Armenteras et al. 2013; Silveira et al. 2020)					
	Marginal effect on fires (Fonseca et al. 2016)					
Forest	Past forest degradation favours fires (Morello 2020)					
degradation	Past fires favour fires (Barlow and Peres 2008; Balch et al. 2011; Brando et al. 2014; Balch et al. 2015; Silveira et al. 2020)					
	Infrastructure and Development					
	Proximity to roads and rivers favours fires (Adeney et al. 2009; Fonseca et al. 2017; Xu et al. 2021)					
Access to market	Proximity to roads favours fire prevention activities and reduces the need to use fires (Bowman et al. 2008)					
	Distance to road increases and then decreases the risk of fires (Arima et al. 2007; Silveira et al. 2020)					
Rural settlements	Proportion of settlements raises the probability of fires (Fonseca et al. 2017)					
Population	Increase and then decrease the probability of fires (Silveira et al. 2020)					
	Environmental policies					
	Limit the number of fires, especially in areas with high deforestation pressure (Nepstad et al. 2006; Arima et al. 2007; Adeney et al. 2009)					
Protected areas	Fires within protected areas occurs mainly close to their border with unprotected land or close to roads (Adeney et al. 2009; Santos et al. 2021; Walker et al. 2022)					
	High number of fires within municipalities with lots of protected areas/certain types of protected areas (Morello 2020; Silveira et al. 2020)					
	No significant effect (Carmenta et al. 2016; Fonseca et al. 2016)					
PADDD	No increase in deforestation in protected areas that were downsized or degazetted (Pack et al. 2016)					
Blacklisting	Blacklisting program could reduce the deforestation rate of blacklisted counties (Cisneros et al. 2015).					
Law enforcement	Field-based enforcement operations can reduce deforestation (Börner et al. 2015)					

Table S1. Potential drivers of the fire regimes identified through literature review and relationship with the fires regimes identified. To be included in the table, a publication should be analyzing fire regime using quantitative analysis, or deforestation if there are no data available on fire regimes, conduct an analysis in the Brazilian Amazon and include a spatial component

References

- Adeney, J. M., N. L. Christensen, and S. L. Pimm. 2009. Reserves Protect against Deforestation Fires in the Amazon. Edited by Rob P. Freckleton. *PLoS ONE* 4. doi:10.1371/journal.pone.0005014.
- Aragão, L. E. O. C., and Y. E. Shimabukuro. 2010. The Incidence of Fire in Amazonian Forests with Implications for REDD. *Science* 328: 1275–1278. doi:10.1126/science.1186925.
- Aragão, L. E. O. C., Y. Malhi, R. M. Roman-Cuesta, S. Saatchi, L. O. Anderson, and Y. E. Shimabukuro. 2007. Spatial patterns and fire response of recent Amazonian droughts. *Geophysical Research Letters* 34. doi:10.1029/2006GL028946.
- Aragão, L. E. O. C., L. O. Anderson, M. G. Fonseca, T. M. Rosan, L. B. Vedovato, F. H. Wagner, C. V. J. Silva, C. H. L. Silva Junior, et al. 2018. 21st Century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications* 9: 536. doi:10.1038/s41467-017-02771-y.
- de Area Leão Pereira, E. J., P. J. Silveira Ferreira, L. C. de Santana Ribeiro, T. Sabadini Carvalho, and H. B. de Barros Pereira. 2019. Policy in Brazil (2016–2019) threaten conservation of the Amazon rainforest. *Environmental Science & Policy* 100: 8–12. doi:10.1016/j.envsci.2019.06.001.
- Arima, E. Y., C. S. Simmons, R. T. Walker, and M. A. Cochrane. 2007. Fire in the Brazilian Amazon: a Spatially Explicit Model for Policy Impact Analysis. *Journal of Regional Science* 47: 541–567. doi:10.1111/j.1467-9787.2007.00519.x.
- Armenteras, D., T. M. González, and J. Retana. 2013. Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests. *Biological Conservation* 159: 73–79. doi:10.1016/j.biocon.2012.10.026.
- Asner, G. P., D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, and J. N. Silva. 2005. Selective Logging in the Brazilian Amazon. *Science* 310: 480–482. doi:10.1126/science.1118051.
- Asner, G. P., E. N. Broadbent, P. J. C. Oliveira, M. Keller, D. E. Knapp, and J. N. M. Silva. 2006. Condition and fate of logged forests in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 103: 12947–12950. doi:10.1073/pnas.0604093103.
- Assunção, J., and R. Rocha. 2019. Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics* 24: 115–137. doi:10.1017/S1355770X18000499.
- Assunção, J., C. Gandour, and R. Rocha. 2015. Deforestation slowdown in the Brazilian Amazon: prices or policies? *Environment and Development Economics* 20: 697–722. doi:10.1017/S1355770X15000078.
- Balch, J. K., D. C. Nepstad, L. M. Curran, P. M. Brando, O. Portela, P. Guilherme, J. D. Reuning-Scherer, and O. de Carvalho. 2011. Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management* 261: 68–77. doi:10.1016/j.foreco.2010.09.029.
- Balch, J. K., P. M. Brando, D. C. Nepstad, M. T. Coe, D. Silvério, T. J. Massad, E. A. Davidson,
 P. Lefebvre, et al. 2015. The Susceptibility of Southeastern Amazon Forests to Fire: Insights from a Large-Scale Burn Experiment. *BioScience* 65: 893–905. doi:10.1093/biosci/biv106.
- Barber, C. P., M. A. Cochrane, C. M. Souza, and W. F. Laurance. 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. *Biological Conservation* 177: 203–209. doi:10.1016/j.biocon.2014.07.004.
- Barlow, J., and C. A. Peres. 2008. Fire-mediated dieback and compositional cascade in an Amazonian forest. *Philosophical Transactions of the Royal Society B: Biological Sciences* 363: 1787–1794. doi:10.1098/rstb.2007.0013.

- Börner, J., K. Kis-Katos, J. Hargrave, and K. König. 2015. Post-Crackdown Effectiveness of Field-Based Forest Law Enforcement in the Brazilian Amazon. Edited by Ricardo Bomfim Machado. *PLOS ONE* 10: e0121544. doi:10.1371/journal.pone.0121544.
- Bowman, M. S., G. S. Amacher, and F. D. Merry. 2008. Fire use and prevention by traditional households in the Brazilian Amazon. *Ecological Economics* 67: 117–130. doi:10.1016/j.ecolecon.2007.12.003.
- Brando, P. M., J. K. Balch, D. C. Nepstad, D. C. Morton, F. E. Putz, M. T. Coe, D. Silverio, M. N. Macedo, et al. 2014. Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proceedings of the National Academy of Sciences* 111: 6347– 6352. doi:10.1073/pnas.1305499111.
- Broadbent, E. N., G. P. Asner, M. Keller, D. E. Knapp, P. J. C. Oliveira, and J. N. Silva. 2008. Forest fragmentation and edge effects from deforestation and selective logging in the Brazilian Amazon. *Biological Conservation*: 13.
- Cano-Crespo, A., P. J. C. Oliveira, A. Boit, M. Cardoso, and K. Thonicke. 2015. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences* 120: 2095–2107. doi:10.1002/2015JG002914.
- Carmenta, R., G. A. Blackburn, G. Davies, C. de Sassi, A. Lima, L. Parry, W. Tych, and J. Barlow. 2016. Does the Establishment of Sustainable Use Reserves Affect Fire Management in the Humid Tropics? Edited by Clinton N. Jenkins. *PLOS ONE* 11. doi:10.1371/journal.pone.0149292.
- Carrero, G. C., P. M. Fearnside, D. R. do Valle, and C. de Souza Alves. 2020. Deforestation Trajectories on a Development Frontier in the Brazilian Amazon: 35 Years of Settlement Colonization, Policy and Economic Shifts, and Land Accumulation. *Environmental Management* 66: 966–984. doi:10.1007/s00267-020-01354-w.
- Carvalho, W. D., K. Mustin, R. R. Hilário, I. M. Vasconcelos, V. Eilers, and P. M. Fearnside. 2019. Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed. *Perspectives in Ecology* and Conservation 17: 122–130. doi:10.1016/j.pecon.2019.06.002.
- Cisneros, E., S. L. Zhou, and J. Börner. 2015. Naming and Shaming for Conservation: Evidence from the Brazilian Amazon. Edited by Edward Webb. *PLOS ONE* 10. doi:10.1371/journal.pone.0136402.
- Ferrante, L., and P. M. Fearnside. 2019. Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate. *Environmental Conservation* 46: 261–263. doi:10.1017/S0376892919000213.
- Ferreira Barbosa, M. L., R. C. Delgado, C. Forsad de Andrade, P. E. Teodoro, C. A. Silva Junior, H. S. Wanderley, and G. F. Capristo-Silva. 2021. Recent trends in the fire dynamics in Brazilian Legal Amazon: Interaction between the ENSO phenomenon, climate and land use. *Environmental Development* 39. doi:10.1016/j.envdev.2021.100648.
- Fonseca, M. G., L. E. O. C. Aragão, A. Lima, Y. E. Shimabukuro, E. Arai, and L. O. Anderson. 2016. Modelling fire probability in the Brazilian Amazon using the maximum entropy method. *International Journal of Wildland Fire* 25: 955–969. doi:10.1071/WF15216.
- Fonseca, M. G., L. O. Anderson, E. Arai, Y. E. Shimabukuro, H. A. M. Xaud, M. R. Xaud, N. Madani, F. H. Wagner, et al. 2017. Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications* 27: 2514–2527. doi:10.1002/eap.1628.
- Herrera, D., A. Pfaff, and J. Robalino. 2019. Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian

Amazon. *Proceedings of the National Academy of Sciences* 116: 14916–14925. doi:10.1073/pnas.1802877116.

- Kalamandeen, M., E. Gloor, E. Mitchard, D. Quincey, G. Ziv, D. Spracklen, B. Spracklen, M. Adami, et al. 2018. Pervasive Rise of Small-scale Deforestation in Amazonia. *Scientific Reports* 8: 1600. doi:10.1038/s41598-018-19358-2.
- Keles, D., P. Delacote, A. Pfaff, S. Qin, and M. B. Mascia. 2020. What Drives the Erasure of Protected Areas? Evidence from across the Brazilian Amazon. *Ecological Economics* 176: 106733. doi:10.1016/j.ecolecon.2020.106733.
- Morello, T., and L. Falcão. 2020. The Fire Management Dilemma in the Brazilian Amazon: Synthesizing Pathways of Causality across Five Case Studies in the State of Pará. *Human Ecology* 48: 397–409. doi:10.1007/s10745-020-00166-0.
- Morello, T. F. 2020. Predicting fires for policy making: Improving accuracy of fire brigade allocation in the Brazilian Amazon. *Ecological Economics* 169: 14.
- Morton, D. C., R. S. Defries, J. T. Randerson, L. Giglio, W. Schroeder, and G. R. Van Der Werf. 2008. Agricultural intensification increases deforestation fire activity in Amazonia: Deforestation Fires in Amazonia. *Global Change Biology* 14: 2262–2275. doi:10.1111/j.1365-2486.2008.01652.x.
- Nepstad, D., S. Schwartzman, B. Bamberger, M. Santilli, D. Ray, P. Schlesinger, P. Lefebvre, A. Alencar, et al. 2006. Inhibition of Amazon Deforestation and Fire by Parks and Indigenous Lands: Inhibition of Amazon Deforestation and Fire. *Conservation Biology* 20: 65–73. doi:10.1111/j.1523-1739.2006.00351.x.
- Nepstad, D. C., C. M. Stickler, B. S.- Filho, and F. Merry. 2008. Interactions among Amazon land use, forests and climate: prospects for a near-term forest tipping point. *Philosophical Transactions of the Royal Society B: Biological Sciences* 363: 1737– 1746. doi:10.1098/rstb.2007.0036.
- Nolte, C., A. Agrawal, K. M. Silvius, and B. S. Soares-Filho. 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 110: 4956–4961. doi:10.1073/pnas.1214786110.
- Pack, S. M., M. N. Ferreira, R. Krithivasan, J. Murrow, E. Bernard, and M. B. Mascia. 2016. Protected area downgrading, downsizing, and degazettement (PADDD) in the Amazon. *Biological Conservation* 197: 32–39. doi:10.1016/j.biocon.2016.02.004.
- Richards, P., E. Arima, L. VanWey, A. Cohn, and N. Bhattarai. 2017. Are Brazil's Deforesters Avoiding Detection? *Conservation Letters* 10: 470–476. doi:10.1111/conl.12310.
- Rosa, I. M. D., C. Souza, and R. M. Ewers. 2012. Changes in Size of Deforested Patches in the Brazilian Amazon: Dynamics of Amazonian Deforestation. *Conservation Biology* 26: 932–937. doi:10.1111/j.1523-1739.2012.01901.x.
- Santos, A. M. dos, C. F. A. da Silva, A. P. Rudke, and D. de Oliveira Soares. 2021. Dynamics of active fire data and their relationship with fires in the areas of regularized indigenous lands in the Southern Amazon. *Remote Sensing Applications: Society and Environment* 23. doi:10.1016/j.rsase.2021.100570.
- Schneider, M., and C. A. Peres. 2015. Environmental Costs of Government-Sponsored Agrarian Settlements in Brazilian Amazonia. Edited by RunGuo Zang. *PLOS ONE* 10. doi:10.1371/journal.pone.0134016.
- Silveira, M. V. F., C. A. Petri, I. S. Broggio, G. O. Chagas, M. S. Macul, C. C. S. S. Leite, E. M. M. Ferrari, C. G. V. Amim, et al. 2020. Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land* 9: 516. doi:10.3390/land9120516.
- Soares-Filho, B., P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, et al. 2010. Role of Brazilian Amazon protected areas in climate change

mitigation. *Proceedings of the National Academy of Sciences* 107: 10821–10826. doi:10.1073/pnas.0913048107.

- Soares-Filho, B., R. Silvestrini, D. Nepstad, P. Brando, H. Rodrigues, A. Alencar, M. Coe, C. Locks, et al. 2012. Forest fragmentation, climate change and understory fire regimes on the Amazonian landscapes of the Xingu headwaters. *Landscape Ecology* 27: 585–598. doi:10.1007/s10980-012-9723-6.
- Tyukavina, A., M. C. Hansen, P. V. Potapov, S. V. Stehman, K. Smith-Rodriguez, C. Okpa, and R. Aguilar. 2017. Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. Science Advances 3. doi:10.1126/sciadv.1601047.
- Walker, K., A. Flores-Anderson, L. Villa, R. Griffin, M. Finer, and K. Herndon. 2022. An analysis of fire dynamics in and around indigenous territories and protected areas in a Brazilian agricultural frontier. *Environmental Research Letters* 17: 084030. doi:10.1088/1748-9326/ac8237.
- West, T. A. P., and P. M. Fearnside. 2021. Brazil's conservation reform and the reduction of deforestation in Amazonia. Land Use Policy 100. doi:10.1016/j.landusepol.2020.105072.
- Xu, W., Y. Liu, S. Veraverbeke, W. Wu, Y. Dong, and W. Lu. 2021. Active Fire Dynamics in the Amazon: New Perspectives From High-Resolution Satellite Observations. *Geophysical Research Letters* 48. doi:10.1029/2021GL093789.
- Yanai, A. M., E. M. Nogueira, P. M. L. de Alencastro Graça, and P. M. Fearnside. 2017. Deforestation and Carbon Stock Loss in Brazil's Amazonian Settlements. *Environmental Management* 59: 393–409. doi:10.1007/s00267-016-0783-2.
- Yanai, A. M., P. M. L. de A. Graça, M. I. S. Escada, L. G. Ziccardi, and P. M. Fearnside. 2020. Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration. *Journal of Environmental Management* 268. doi:10.1016/j.jenvman.2020.110555.

Supporting information 2: Explanatory variables selection and preprocessing

Explanatory variables selection

Computation of large-scale models with many variables and interpretation of their results can prove challenging, especially if some of the variables rely on poor-quality data. Thus, after the identification of potential drivers of fire regimes and data sources that could be used to derive variables, we removed some variables based on:

- **Quality of the datasets:** some datasets were collected in ways that could make their interpretation challenging
- **Redundancy between variables:** several variables could be proxies for the same underlying drivers of fire regimes and/or are highly correlated to other variables
- **Distribution of the data:** some variable's distribution are skewed over few values and would bring little information in the large-scale models

The following variables, initially considered, have been removed from the models:

- **Temperature and precipitations:** these two climatic factors affect the flammability of the ecosystems by determining the balance between the input of water through precipitations and the output of water through evaporation and evapotranspiration. We used the Maximum Cumulated Water Deficit, a drought index that accounts for both phenomena (see next section for more details) and determined the amount of hydric stress vegetation is exposed to throughout a year.
- **Past fires:** while initially thought of as a potential proxy for past degradation of the forest, the interpretation of this variable could be quite challenging as fire tends to repeat over the same pixels and past fires could be a proxy for other phenomena driving fire occurrences. Moreover, it is challenging to know if a fire is burning over the same area as in the past, or other places across the pixel.
- Law enforcement efforts A list of embargos issued by the IBAMA for environmental infractions was available, but the data was aggregated at a municipality level. Moreover, the distribution of the data was highly skewed, concerns mainly a few municipalities and is highly correlated to municipalities on the priority list.
- **Population** the data available were projections from the IBGE aggregated at a municipality level. The population is a proxy of human pressures, which is modelled by other explanatory variables in the model such as the transport cost or the presence of different agricultural land use. Moreover, the distribution was highly skewed with few small municipalities regrouping huge proportions of the populations, corresponding to the major urban centres.

Explanatory variables Preprocessing

Maximum cumulated water deficit: The algorithm used for deriving the maximum cumulated water deficit is similar to the one described in Aragão et al (2007) and provides an indication of the severity of drought reach over a year. For each pixel, a Cumulated Water Deficit (CWD) was calculated for each month (n) using these rules:

if CWD
$$_{n-1}$$
 - evapotranspiration $_n$ + precipitation $_n < 0$,
then CWD $_n = CWD_{n-1} - 100 + Precipitation_n$,
else CWD $_n = 0$

Then, for each pixel the lowest CWD value for each year was kept, representing the intensity of hydric stress over a year. A raster stack has been created with the Maximum cumulated water deficit for each year of the study period, before being divided into 6 categories. The data used for precipitations were from CHIRPS dataset ¹.

Maximum Cumulated Water Deficit	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
category				
0 mm	9.1%	11%	7.4%	9.4%
1-100mm	23%	24%	22%	28%
101-200mm	21%	19%	29%	24%
201-300mm	24%	25%	22%	18%
301-400mm	15%	17%	13%	15%
401mm and more	8.4%	4.0%	6.1%	6.7%



Table S2. Summary of the percentage of pixels in each category over the 4 period of analysis.

Agricultural land use Mapbiomas collection 7 was used to look at land uses. The land use map was reclassified to create the following explanatory variables:

Figure S2. Map of the categorized MCWD in 2021.

- <u>Pasture:</u> pasture and mosaic agriculture and pasture (ID 15+21)
- <u>Annual crops:</u> soybean, sugarcane, rice, cotton and other annual crops (ID 39+20+40+41+62)
- <u>Perennial crops:</u> Forest plantations, coffee, citrus and other perennial crops (ID 9, 46, 47, 48)

The coverage of each agricultural land was calculated for each 1km pixels and include into raster stacks, before being classified as covering less than 1%, 1 to 50% or 51 to 100% of the pixel. For the models on agricultural fires, we started by calculating areas with a coverage of >90% of agricultural land, and then derive the type of agricultural land covering the highest proportion of the pixel.





Figure S3. Map of the categorized agricultural land uses in 2021.

Agricultural land use	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
pasture				
0%	70%	70%	69%	68%
1-50%	19%	19%	20%	20%
51-100%	12%	12%	12%	12%
annual crop				
0%	98%	98%	97%	96%
1-50%	1.1%	1.6%	2.2%	2.8%
51-100%	0.4%	0.6%	0.9%	1.0%
perennial crop				
0%	99%	99%	99%	99%
1-50%	0.5%	0.5%	0.5%	0.6%
51-100%	<0.1%	<0.1%	<0.1%	<0.1%
dominant agricultural land use				
<80% of agricultural land	95%	95%	95%	95%
pasture	4.6%	4.5%	4.4%	4.6%
annual crop	0.2%	0.3%	0.5%	0.6%
perennial crop	<0.1%	<0.1%	<0.1%	<0.1%

Table S3. Summary of the percentage of pixels in each category over the 4 period of analysis

Agricultural land use increases Mapbiomas collection 7 was used to look at the expansions of pastures, annual crops and perennial crops. The percentage of each agricultural land category was compared to the previous year, and pixels with an increase >1% of the identified land category was classified as having increasing cover.





Figure S4.	Map of t	the categori	zed agricul	tural land	uses chan	ges in 2021.

Increase agricultural land use	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
increase pasture				
increase	6.0%	6.3%	7.5%	8.5%
no increase	94%	94%	93%	92%
increase annual crop				
increase	0.6%	1.0%	1.1%	1.4%
no increase	99%	99%	99%	99%
increase perennial crop				
increase	<0.1%	0.1%	<0.1%	<0.1%
no increase	100%	100%	100%	100%

Table S4. Summary of the percentage of pixels in each category over the 4 period of analysis

Forest fragmentation Using the forest category of Mapbiomas 7 (ID 3) and the *landscapemetrics* packages in R, edge density was calculated for every year at a 1 km resolution, a raster stack was created with the edge density values and was categorized.



Figure S5. Map of the categorized edges density in 2021.

Fragmentation	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
edges density				
>50m/ha	6.1%	6.3%	6.9%	7.5%
1 - 25m/ha	22%	22%	22%	22%
25-50m/ha	14%	14%	15%	16%
no edges	58%	58%	57%	55%

Table S5. Summary of the percentage of pixels in each category over the 4 period of analysis

Distance agricultural edges Mapbiomas collection 7 was used to identify 1 km pixels which contain any type of agricultural land use, before deriving between the centroid of these pixels and any 1 km pixels without any agricultural land. Then, the resulting raster stack was divided into 7 categories: pixels adjacent to agricultural edges, 0 to 1km, 1 to 2km, 2 to 5km, 5 to 10km, 10 to 25km and more than 25km.



period 2 (2012-2015) period 3 (2016-2018) period 1 (2009-2011) period 4 (2019-2021) Distance from agricultural land category 28% 28% 29% 30% Adjacent 0-1km 19% 19% 19% 20% 1-3km 16% 16% 15% 16% 3-5km 9.2% 9.2% 9.1% 8.9% 5-10km 12% 12% 12% 11% 10-25km 9.8% 9.6% 9.3% 9.5% 6.7% 6.6% 25km and more 6.4% 5.4%

Figure S6. Map of the categorized distance to agricultural lands in 2021.

Table S6. Summary of the percentage of pixels in each category over the 4 period of analysis

Remoteness The transport costs to port dataset developed by Victoria et al. 2021^{2} was used, as it takes into account the evolution of the road network in the region, but also the presence of ports to export agricultural commodities. Since transport cost information was only available for 2005, 2010 and 2017, the transport cost of 2005 was used for 2009, the transport cost of 2010 was used for the 2011-2016 period and the transport cost of 2017 was used for the 2017-2020 period. The values for transport costs to port were scaled by the mean standard deviations and compiled into a raster stack.



Figure S7. Map of the categorized transport costs in 2021.

Transport cost	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
Relative transport cost				
>5K RU	7.4%	7.9%	7.9%	7.9%
5-10K RU	17%	18%	18%	18%
10-20K RU	39%	39%	39%	39%
20-30K RU	26%	26%	26%	26%
more than 30K	9.9%	9.5%	9.4%	9.4%

Table S7. Summary of the percentage of pixels in each category over the 4 period of analysis

Governance protected areas data have been collected from the WDPA which includes both the spatial delimitation of protected areas, their categories according to the Brazilian classification system and the year of creation. The protected areas have been classified into the following categories:

- <u>Sustainable use areas:</u> include forests, environmental protection areas, sustainable development reserves, extractive reserves, areas of relevant ecological interest and natural heritage private reserves
- <u>Strictly protected areas:</u> include biological reserves, parks, ecological stations, wildlife refuges, and natural monuments.
- <u>Indigenous lands</u>: including only indigenous land that has finished the delimitation process

These protected areas have been divided between periphery areas, corresponding to the first five kilometres between the protected areas and unprotected areas (thus not creating a buffer between two different protected areas), and core areas, more than 5km from the protected areas or indigenous land border with unprotected areas.

Additionally, the database of PADDD events in the Brazilian Amazon was downloaded on padddtracker website ³, and the downgrading of protected areas was excluded as they might not necessarily represent a weaker protection effort in the region. A raster stack has been created with the proportions of pixels covered by PADDD events before or during each year of the period of study. Rural settlement polygons have been downloaded from the INCRA websites and then filtered to remove sustainable use areas that were included in the sustainable use areas.

For each year, we derived a raster with the dominant types of land governance on each pixel, corresponding to the 10 categories.



Figure S8. Map of the categorized land governance, including the rural settlements, protected areas and indigenous lands in 2021.

Land governance	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
category				
no protection	47%	46%	45%	45%
indigenous land periphery	6.4%	6.5%	6.5%	6.5%
indigenous land core	15%	16%	16%	16%
sustainable use periphery	6.1%	6.0%	6.0%	6.0%
sustainable use core	10%	10%	11%	11%
strictly protected periphery	2.5%	2.5%	2.5%	2.5%
strictly protected core	6.0%	6.0%	6.4%	6.4%
protected area downsizing and degazettement	1.5%	1.7%	1.7%	1.7%
rural settlement	5.1%	5.2%	5.3%	5.3%

Table S8. Summary of the percentage of pixels in each category over the 4 period of analysis

Priority list

The list of priorities municipalities published by the ministry of the environment has been used to create a raster stack with values indicating if the municipality is currently on the blacklist or if it used to be on the blacklist but has been removed, indicating decreasing deforestation pressure and fulfilment of certain conditions such as the registration in the rural land registry.



Figure S9. Map of the municipalities on the priority list in 2021.

Municipalities on priority list	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2021)
category				
never on priority list	80%	79%	75%	73%
priority list	19%	20%	23%	24%
removed from priority list	0.2%	1.2%	2.1%	3.3%

Table S9. Summary of the percentage of pixels in each category over the 4 period of analysis

Supporting Information 3: Bayesian spatio-temporal modelling approach for understanding Active-Fires occurrence

Compared to previous work for understanding the drivers of fire regimes in the Brazilian Amazon, one major difference in our analysis was the inclusion of a spatio-temporal component. A careful design of the models attempts to include most of the important drivers of the fire regimes, but some drivers can hardly be captured by numerical variables (e.g. fine-scale governance process), while for other drivers no data sources could be identified (e.g. logging and forest degradation). According to Tobler's first law, "everything is related to everything else, but near things are more related than distant things" ⁵⁴ and fires close to each other are more likely to be influenced by similar underlying processes than distant fires. Moreover, Actives-Fires detection is not completely independent: one large fire can lead to many active-fires detections clustered in space and time. In this annex, we provide a brief overview of the Bayesian statistical foundations of our modelling approach.

Log Gaussian Cox Process

Log Gaussian Cox Process is a class of models for modelling non-stationary point processes ^{55,56}. The Cox Process represents a Poisson process for the distribution of the points with an intensity function varying across the mathematical space, in this case across space and time. The intensity function of the Cox Process depends on a Gaussian Process that includes both the contribution of the explanatory variables and spatiotemporal dependence structure.

Number Active Fires (st) ~ Poisson (Intensity process (st))

Intensity process $(st) = exp(\sum_{i=1}^{i=1} cov_{i(st)} * \beta_i + Y_{(st)})$

Considering that *st* represents a defined space and time for observation of the fire patterns, *n* represents the total number of covariates, *cov* the values of the covariate, β the coefficient attributed to the covariate and Y the residual process explained by spatiotemporal correlations.

Bayesian inferences

In Bayesian statistics, the posterior distribution of a model parameter, in our case indicative of the impact of covariates on fire occurrence, is proportional to the density function of a model (likelihood) and a set of prior beliefs on the hyper-parameters. The objective of the approach is to estimate the posterior marginals of model effects and hyperparameters, that could be used to investigate both the impact of covariates on the response variables. Two approaches can be used to estimate the posterior joint distribution of the model parameters:

- Markov Chain Monte Carlo (MCMC)
- Integrated Nested Laplace Approximation (INLA)

The Integrated Nested Laplace Approximation, thanks to the use of computational properties of latent Gaussian models, reduce drastically the computation time compared to a classic MCMC algorithm with a moderate decline in precision ⁵⁷. We fitted our LGCP model using inlabru ⁵⁸, a wrapper R package for R-INLA.

Stochastic Partial Differential Equation (SPDE) approach

To represent the spatial correlation, we rely on the Matérn covariance function that determines the correlation between two predictors according to their distance. To embed this into INLA, the Stochastic Partial Differential Equation approach is used to represent the spatial autocorrelation into the model by simplifying a continuous Gaussian field into a more sober Gaussian Markov Random Field thanks to a discretization into non-intersecting triangles. A projector matrix is then created to associate each observation with three nodes of the mesh in which it is located, thus creating a sparse matrix with only three non-zero values per row. The spatial covariance function and the dense covariance matrix of a Gaussian Field are represented by a neighbourhood structure and a sparse precision matrix, graphically defined by a mesh ⁵⁹. Briefly, the spatial process can be represented by the basic function:

 $U_{(s)} = \sum k = 1 m \psi k(s) w k$

where ψk are basis function, Wk are Gaussian distributed weight, m being the number of vertices in the mesh. The joint distribution for the weights determines the full distribution in the continuous domain.

Mesh creation

For each model, we generated a mesh based on the locations of the observation points. A minimal value of triangles edges of 1 kilometres has been set, to assure efficient computation of spatial autocorrelations even with a range value of around 5 kilometres. Other constraints on the angles of the triangles and the maximum number of triangles within the border have been imposed for having a fine mesh around active fires and a coarser mesh in areas with few active fires (Fig. S5). The border of the mesh has been simplified using the *inla.nonconvex.hull* function: to ensure all observed points are in triangles within the border of the mesh, and the mesh has been extended outside the border to compute spatial autocorrelations on the edges of the model.

Priors' distribution

We specified penalized complexity priors frameworks, a class of weakly informative priors ⁶⁰, for the spatial and temporal component and temporal components.

The penalized complexity priors of the Matérn-SPDE model can be controlled by two parameters:

Spatial range: The user defines a spatial range p_0 and a lower tail quantile p_p for which spatial interactions will be smaller than the determined spatial range, such as $P(p < p_0) = p_p$. Specification used: prior.range=c(10,0.5) correspond to a 50% chance that spatial interactions is less than 10 kilometers

Sigma: The user defines a standard deviation σ_0 and an upper tail quantile p_σ for which the effective standard deviation of the spatial field will be higher than the determined standard deviation, such as $P(\sigma > \sigma_0) = p_\sigma$. Specification used: prior.sigma=c(15,0.05) correspond to a 5% chance that spatial interactions will have a deviation of more than 15 km.



Figure S10. Mesh created for the 2009-2011 deforestation fires model.

Supporting Information 4: Comparison of the residuals and observed fires for all of the models



Number of deforestation fires predicted in 10km pixel





Number of deforestation fires detected in 10km pixel



Figure S11. Map of the number of median numbers of deforestation fires predicted by the models (left column) and observed right column) in 10km2 pixels for the four periods.





Number of agricultural fires predicted in 10km pixel



Number of agricultural fires detected in 10km pixel



Figure S12. Map of the number of median numbers of agricultural fires predicted by the models (left column) and observed right column) in 10km2 pixels for the four periods.









Number of forest fires detected in 10km pixel



Figure S13. Map of the number of median numbers of forest fires predicted by the models (left column) and observed right column) in 10km2 pixels for the four periods.