Spatially explicit analysis of drivers of fire in the Brazilian Amazon from 2011-2020

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Abstract:

Fires in the Brazilian Amazon jeopardize forest resilience and the ecosystem services they provide. They are driven by climatic, ecological and socio-economic processes. After classifying fires into deforestation, forest and agricultural fires, we fitted Bayesian spatiotemporal models for the 2011-2015 and 2016-2020 periods to estimate the association between each type of fire and potential drivers. Different types of agricultural land use were associated with distinct use of fires for land management, and isolated areas were associated with more fires over the last period. Protected areas were associated with fewer deforestation fires and forest fires, especially indigenous lands and integral protection areas. Reducing fires in the region will require changes in agricultural systems and reinforcement of existing environmental policies.

Introduction

In 2004, the Brazilian government adopted the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon, which, associated with decrease in soy and beef prices and sustainability commitments in their supply chain, reduced deforestation drastically in the following decade (*1*). Meanwhile, forest degradation, mainly linked with logging and forest fires, became the major driver of above-ground biomass loss in the region, turning the Brazilian Amazon (BA) into a carbon source (*2*, *3*). Forest degradation, precipitation and fire regimes are closely linked, and feedback between these processes can transform large tracts of rainforest into savanna, emitting considerable quantities of carbon into the atmosphere (*4*). Moreover, since 2016, weakened environmental policies by the federal government coincide with a surge in deforestation and associated fires (*5*).

Fires are widely used for deforestation and land management in the BA: deforestation fires occur during the dry seasons to clear new fields, while agricultural fires are employed to remove crop residues and regrowing vegetation as well as manage agricultural soil fertility (*6*). Both types of fires frequently escape into nearby forests (*7*). Thus, fire occurrence in the BA is affected by socio-economic factors determining the expansion of different agricultural systems and associated deforestation, as well as the post-clearing use of fire in agricultural lands (*8*, *9*). Fire management measures, such as the creation of fire breaks or monitoring the burning until extinguishment, can help to prevent the spread of fires to nearby forests, but are costly to implement for landholders and can only succeed if there is collective will and efforts to control fires (*10*). However, forest degradation is also affecting the flammability of remaining forest and the likelihood that deforestation fires and agricultural fires spread into the forested areas (*11*).

In this study, we examine the drivers of deforestation, agricultural and forest fires in the BA over the 2011-2020 period, and the evolution of their influence following the shift in forest resources governance that took place in 2016 (*12*). We classify Amazon wildfires into deforestation, agricultural and forest fires, using land cover maps and deforestation polygons, to have a precise understanding of their respective drivers. We then fit Bayesian spatio-temporal models, using a Log Cox Gaussian Process to assess the relationship between fire frequency and 13 variables capturing climatic conditions, agricultural land use, infrastructure, ecosystem integrity and governance of forest resources, aggregated in 1km pixels, the resolution of our response variables. We fitted the models for two time periods (i) 2011-2015, the phase of strong implementation of anti-deforestation policies, and (ii) 2016-2020, the phase of weakening anti-deforestation policies.

Materials and Methods

Data

We undertook a literature review to identify the potential drivers of fires, forest degradation and deforestation in the BA (see SI1 for details). After identification of the potential variables of interest, we determined data sources that could be used to model them over the 2011-2020 period, favouring the highest spatial and temporal resolution possible (see SI2 for details on data pre-processing).

The response variable is the fire occurrences derived from the MODIS Active-Fire dataset (MCD14ML) for the 2011-2020 period, a collection of points indicating thermal anomalies (most often fires) within a 1-kilometre pixel. Active-Fires products have been used rather than burned areas products as they perform better for identifying small fires, especially in tropical rainforests. Data have been filtered to remove observations under 30% of confidence and multiple observation occurring on the same day within the same pixel, which could result from multiple detections of the same fire. Then, PRODES deforestation polygons and Mapbiomas collection 6 land use maps were used to classify actives-fires: active-fires within 500 meters of a deforestation event in the same year were tagged as deforestation fires, while fires on pixels with >90% of forest or agricultural land (including pastures) and more than 500 meters from a deforestation event the same year have been tagged as forest fires and agricultural fires respectively (see SI3 for more details). While imperfect, this classification allows an understanding of the drivers of the three major types of fires in the region, which have different impacts on ecosystems and society.

Statistical Methods

We model fire occurrences under the assumption that a latent structure drives all the trends and dependence patterns we observe in our data. We fitted the model by adopting a Bayesian approach that used Integrated Nested Laplace Approximation (INLA) for inference. We defined a Log-Gaussian Cox process and accounted for the spatial component at the latent level by using the stochastic partial differential equation (SPDE) approach that provides accurate Markovian representations of the flexible Matérn covariance (*13*, *14*). Additionally, we accounted for the temporal component by including an auto-regressive random effect. For deforestation fires, we included the following covariates: maximum cumulated water deficit, pasture, annual crops, perennials crops, pasture increase, annual crop increase, perennial crop increase, forest, fragmentation, transport cost, governance regimes (including protected areas, settlements areas and protected areas downgrading, downsizing and degazettements events) and blacklisting. For agricultural fires, we removed the variable associated with forest cover as they occur only on pixels with >90% of agricultural land use, and for forest fires, we removed variables related to forest cover and agricultural land use, as they occur only on pixels with >90% forest cover but we added a variable on the distance from agricultural edges. Finally, we fitted each type of fire (forest, agricultural, deforestation) with two separate models for time periods: 2011-2015 (corresponding to a good governance of forest resources), and 2016-2020 corresponding to a degrading governance of forest resources), to assess potential shifts in the drivers of the different types of fires (see SI4 for details on the modelling). For the two time periods, we have included a temporal component to account for correlation among the years within the time-periods, using an autoregressive random effect. We reported results as log linear estimates with 95% credible intervals (see SI5 for full results). We used the package inlabru v2.5.2 (*15*) of the software R V4.1 (*16*).

Landscape configuration and fires regimes

Climate, distance from agricultural edges and, for the 2016-2020 period, forest fragmentation were linked to forest fires. Maximum cumulated water deficit was associated with a higher number of forest fires (figure 1). During the 2016-2020 period, areas with higher edges density and more isolated (pixels with higher transport costs) were associated with more forest fires than during the 2011-2015 period (figure 1). Forest fires in the Amazon are driven not only by climatic conditions, but also other drivers related to land cover and land use change, especially during non-drought years (*17*). Deforestation is fragmenting the remaining forest cover and increasing the susceptibility of rainforests to fires (*18*). It also influences the proximity between forest edges and managed fires, as well as accessibility of forest to loggers and subsequent degradation, increasing vulnerability of forest to fires (*7*, *19*).

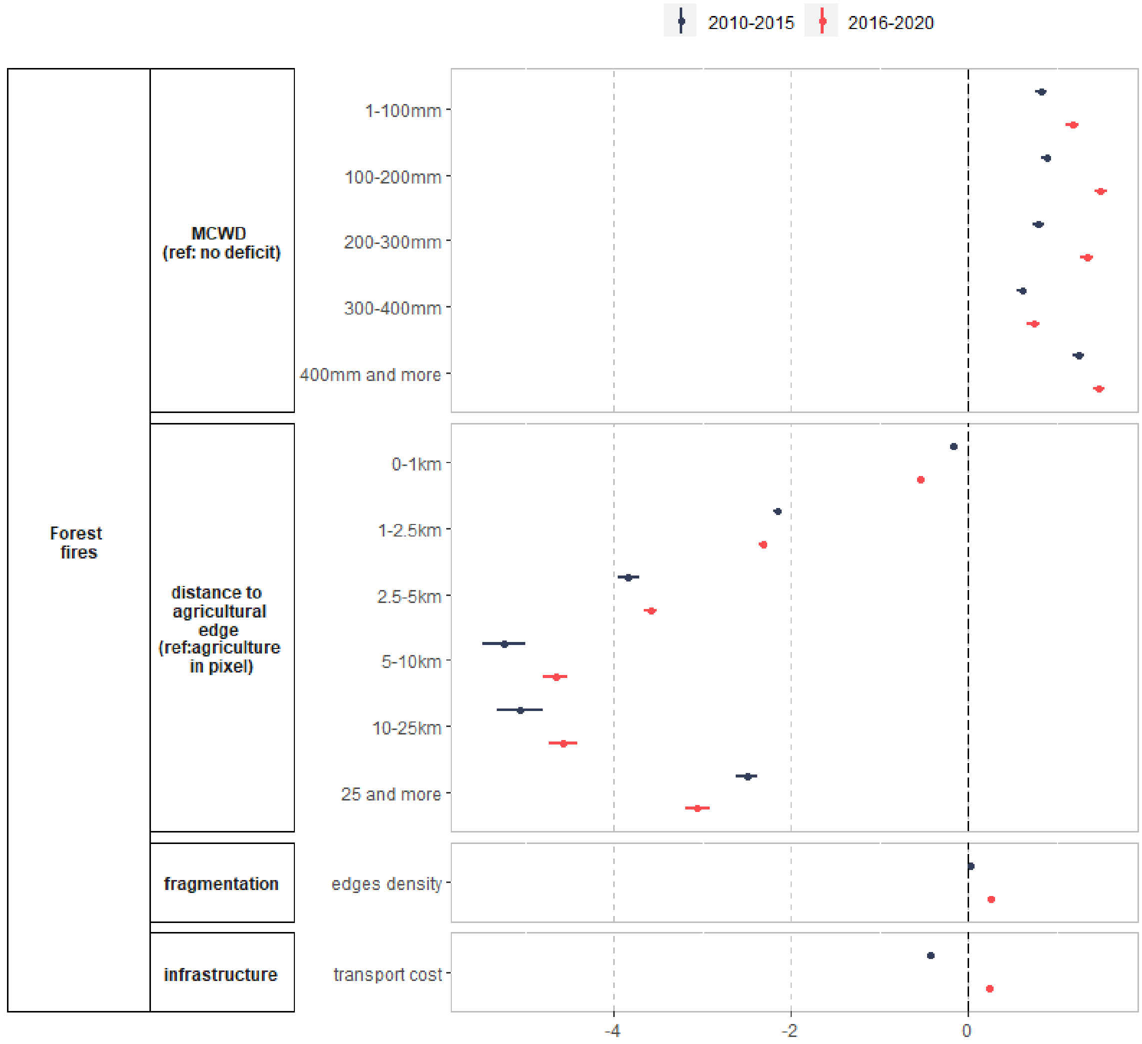

Figure 1. Posterior means and 95% credible intervals for explanatory variables related to climate and ecosystem integrity for forest fires in the Brazilian Amazon. Intervals lower than 0 indicate a variable that decreases the occurrence of fires in 1 kilometer pixel, and intervals higher than 0 indicate variables that increase fire occurrence. See annex 5 for the credible intervals of all the explanatory variables.

Divergent fire regimes across agricultural systems in the region

Different land uses and land use changes were associated with distinct use of fires. Pastures were the agricultural land use most associated with deforestation fires, as well as agricultural fires over the 2011-2015 period (figure 2). The majority of smallholders in the BA dedicate an important proportion of their land to ranching, partly due to the resilience of pasture to accidental fires and lack of technical support for crop farming (*20*, *21*). The use of fires for pastoralism and shifting cultivation is common, especially in remote parts where access to fertilizers and labour, essential for the adoption of fire-free agriculture, is limited (*6*, *22*). However as cattle ranching intensifies, supported by recent public policies, an increasing proportion of pastures are managed without agricultural fires (*23*). Certain parts of the BA have also seen an increase in the demand for local agricultural products, such as cassava flour, which can lead to local intensification of the use of fires and reduction of fallow periods by smallholders (*6*).

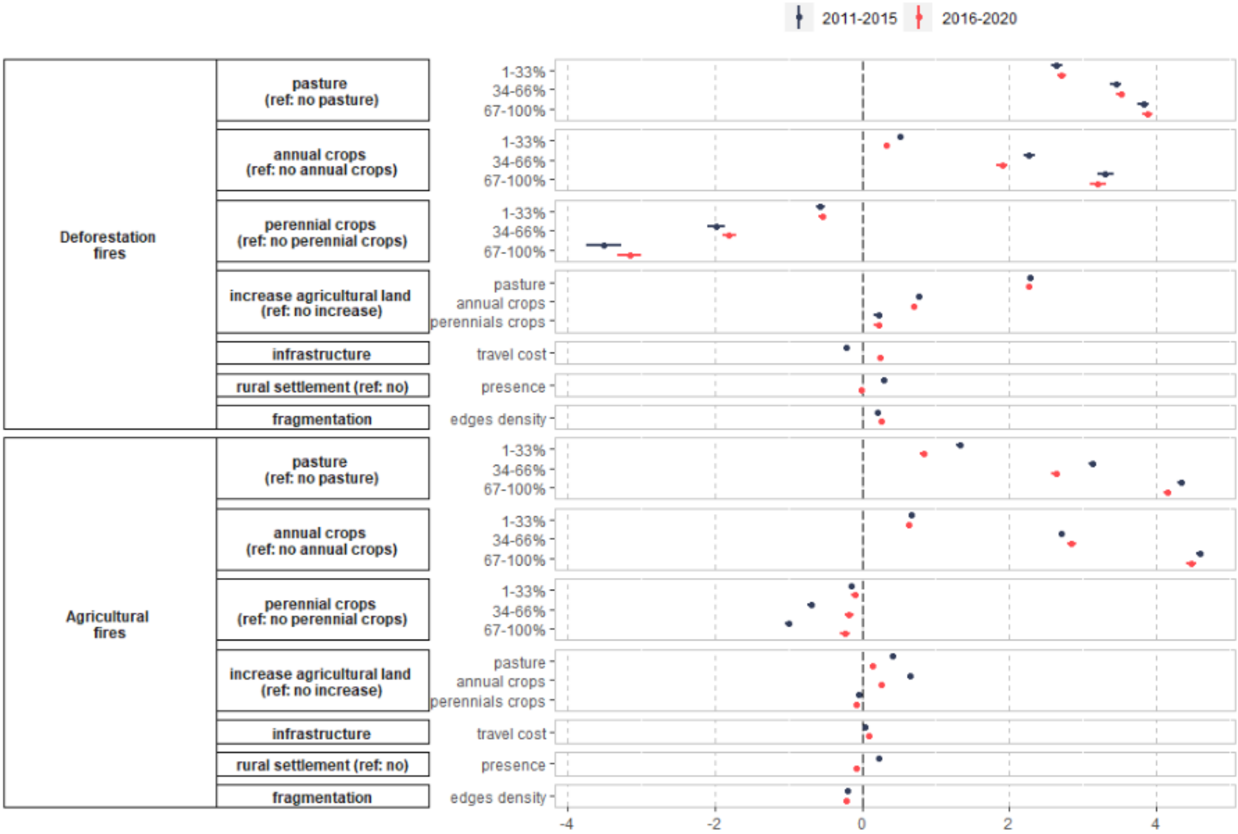

Figure 2. Posterior means and 95% credible intervals for explanatory variables related to agricultural expansions for deforestation and agricultural fires in the Brazilian Amazon. Intervals lower than 0 indicates a variable that decreases occurrence of fires in 1 kilometer pixel, and intervals higher than 0 indicate variables that increase fire occurrence. See annex 5 for the credible intervals of all the explanatory variables.

Annual crops (including cash crops and crops related to subsistence farming) were associated with smaller increases in deforestation fires, while perennial crops were linked to a decrease in agricultural and deforestation fires. Expansions of pastures and annual crops were associated with an increased number of agricultural and deforestation fires, while expansion of perennial crops was associated with a modest increase in deforestation fires and a decrease in agricultural fires (figure 2). Large-scale farming of annual crops (mainly soy in the BA) is characterized by intense fire activity during initial land clearing but often relies less on the use of fires for subsequent land management due to the mechanisation of agriculture, and a significant part of soy expansion occurred on pastoral land (*8*, *24*). The reduced occurrence of deforestation and agricultural fires in pixels with perennial crops is concordant with previous studies highlighting the antagonism between fire use and perennial crops: fire risk and associated damage to crops are a major bottleneck to the adoption of perennial crops and need to be addressed at a community level before perennials crops cultivation is economically viable (*20*, *25*).

Over the 2016-2020 period, isolated areas (represented by pixels with higher transport cost) were associated with more deforestation and agricultural fires than over the 2011-2015 period (figure 2). Over the same period, pixels with annual crops were associated with fewer deforestation fires than during the 2011-2015 period (figure 2). Scarce law enforcement efforts, lack of access to agricultural inputs and the presence of few fire-vulnerable assets increase the profitability of using fires for land management in remote areas of the BA (*10*, *20*, *25*). Landholders in the new deforestation frontiers are also less affected by sustainability engagements from the beef sector: they can sell cattle to non-signatory slaughterhouses or intermediary fattening ranches, thus their land use practices are not monitored by signatory slaughterhouses (*26*). Thus, landholders are less likely to adapt their land use practices to fit international market expectations. Moreover, extensive pastoralism and the use of fires for land clearing and maintenance is a cost-effective way to get land titles and increase the profitability of ranching in the remote part of the BA (*27*). Frequent regularisation of illegal land occupation encourage the opening of new deforestation frontiers, especially in undesignated public forests (*27*). The expansions and intensification of cash crops cultivation can have indirect impacts on land use in the region: strong linkages between expansions of soy farming frontiers, price of land and movement of small landholders and traditional communities into the remotest part of the region have been highlighted in the literature (*24*). These dynamics became especially strong under Temer’s and Bolsonaro’s administrations, which prioritized infrastructure development and agribusiness expansion for the economic development of the region, regardless of the environmental cost and risks of land grabbing (*28*).

Environmental policies and reduction in fires occurrence

All types of protected areas were associated with fewer forest and deforestation fires, with indigenous land and strictly protected areas being the protection regimes associated with the lower number of fires (figure 3). These results are consistent with previous analyses of deforestation and fires rate in the BA (*29*, *30*). While initially implemented to give territory sovereignty to indigenous people, indigenous land proved a pivotal instrument for reducing deforestation, especially in high-pressure frontiers (*31*). Extensive traditional knowledge of fire management allows some indigenous communities to widely use fire while preventing accidental large-scale wildfires and their deleterious impact on the environment, for example through prescribed fires to control fuel load (*32*). Cooperation between conservation agencies and indigenous communities is a cost-effective strategy for reducing environmental degradation, especially in large and remote landscapes which are costly to monitor (*33*).

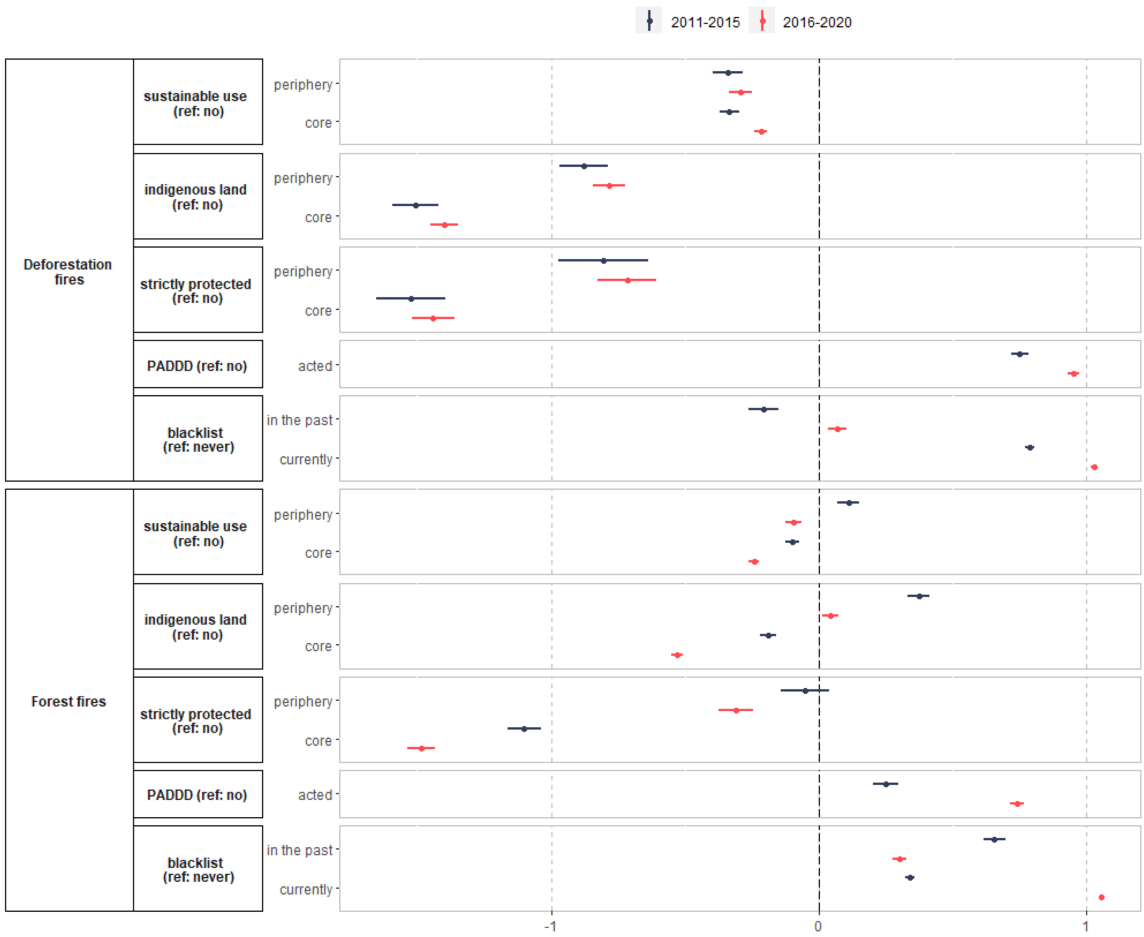

Figure 3. Posterior means and 95% credible intervals for explanatory variables related to environmental policies for deforestation and forest fires in the Brazilian Amazon. Intervals lower than 0 indicates a variable that decreases occurrence of fires in 1 kilometer pixel, and intervals higher than 0 indicate variables that increase fire occurrence. See annex 5 for the credible intervals of all the explanatory variables.

Sustainable use areas receive less funding than strictly protected areas, including for fire management , which prove efficient only in strictly protected areas (*34*). Sustainable use areas are inhabited and some livelihood activities relying on fires are allowed. While there are legal requirements for conducting fires, such as the acquisition of burn permits or clearing of large fire breaks, many of these are unrealistic given the constraints met by landholders in these remote areas (*35*). Certain sustainable use areas, such as environmental protection areas, have loose regulations on land ownership, which can lead to extensive deforestation (*36*). However, the exclusion of environmental protection areas from our analysis didn't change the outcomes and sustainable use areas were still the least efficient protection regimes.

The peripheries of all types of protected areas (first 5km adjacent to non-protected areas) were associated with higher numbers of deforestation and forest fires than core areas, but the difference was smaller for sustainable use areas (figure 3). Santos et al. (*37*) found that part of the fires within indigenous land in the state of Rondônia was in part explained by fire occurrence and land use in their immediate vicinity. Additionally, Kauano et al. (*38*) showed that environmental offences, including activities that are linked to fire use such as small-scale clearing or logging, are common in all types of protected areas, especially if they are easily accessible and close to areas with high populations. Complementary measures to avoid forest fires and control fire use around protected areas could be important to reduce the occurrence of fires within the protected areas and associated carbon emissions (*39*).

Sustainable use areas and indigenous land were associated with more deforestation fires (close to deforestation events) and fewer forest fires (far from deforestation events) over the 2016-2020 period than the 2011-2015 period. Protected areas that have been downsized or degazetted (hereafter PADDD events) were associated with higher numbers of deforestation and forest fires, especially over the last period (figure 3). This is consistent with work showing recent peaks of deforestation in protected areas and land grabbing in indigenous lands (*40*). Our result on the impact of PADDD events differs from Pack et al. (*41*) who didn't find short-term peaks in deforestation after PADDD events in the BA. This could be explained by a different period of analysis, the exclusion of downgrading of protected areas from our dataset (likely to have only a minimal impact) and divergent trends between short-term deforestation rates and long-term use of fires in these areas. Increasing numbers of deforestation fires associated with PADDD events and protected areas over the 2016-2020 period highlight the importance of continuous management efforts for assuring the efficiency of area-based conservation initiatives. However, the majority of protected areas in the BA are increasingly underfunded and federal institutions controlling land use in and around protected areas have been weakened over the last phase of forest governance (*42*).

Municipalities on the blacklist (sometimes called priority list) were associated with more deforestation and forest fires, particularly over the 2016-2020 period (figure 3). However, once removed from the blacklist, the municipalities were no longer associated with more deforestation fires than municipalities that were never on the list and fewer forest fires than municipalities still on the blacklist. The blacklist is a governmental program consisting of regular publication of lists of municipalities with the highest deforestation rates, resulting in reputational risks for local farmers, higher administrative burdens associated with land clearing, increased scrutiny by law enforcement and support from external stakeholders for improving landscape governance (*43*). To be removed from the blacklist, municipalities need to reduce their deforestation rate and register in the land registry system, which is then used to assure compliance with the forest code. Our result seems to indicate that not only municipalities removed from the blacklist experience drop in deforestation, but also a more parsimonious use of fires on agricultural land. Cisneros et al. (*44*) showed that the blacklist program was a cost-efficient way to reduce deforestation, and Assunçao found that law enforcement was an important part of the success of the blacklist (*43*).

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Analysis: MV, AFS

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Writing – original draft: MV, MM

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Data and materials availability: The code used for performing the analysis are available on the public repository https://github.com/michel-va/INLA_SPDE_fire_BA.git . The processed data and code for their processing are available from the corresponding author upon request.

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Supplementary Text

Supporting information 1: Framework of potential drivers of fires regimes

At the initial stage of this research, we conducted a literature review to investigate the potential theoretical framework of drivers of fire regimes in the region and identify relevant data sources. We reviewed articles presenting quantitative or qualitative analyses of fire regimes drivers in the Brazilian Amazon, as well as quantitative analysis of drivers of deforestation in the Brazilian Amazon (table S1). The following paragraphs describe the main categories of drivers of fire regimes that were identified through the literature review.

Climatic factors

There is a strong association between annual precipitation and fire occurrence within the Brazilian Amazon(*9*, *45*–*49*). 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 (*46*, *48*, *50*). 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 (*51*, *52*) However, chronic water deficit limits the regrowth of the vegetation a contributing to fuel scarcity (*9*).

Agriculture

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 . 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 (*7*). 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 (*10*).

Ecosystem integrity

Before deforestation and conversion to agricultural land, Amazonian forests might face several types of disturbance (*3*). 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 (*53*–*55*). 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 (*55*). Fragmentation of the forest cover has several impacts on the fire regime: edges are favouring drier microclimate, increase mortality rates and impact the vegetal communities and thus fuel structure (*56*). It also increases the interface between the agricultural landscape, on which fire is frequently used, and forests, thus increasing the possibility of escaped fires (*7*). 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 (*56*–*58*). 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 (*8*). Abandoned fields and pastures on which trees are regrowing as well as grasslands and savannas are also prone to fires (*9*, *46*, *49*).

Infrastructure and population

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 labour and agricultural inputs. Most deforestation in the Brazilian Amazon and associated fires, occurred close to roads and rivers (*46*, *59*). 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 fire-risk reduction and/or find alternative land management technics (*22*). 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 (*9*). 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 mechanisation of agriculture (*10*). 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 (*60*, *61*). 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 (*62*, *63*).

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 (*1*). 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 (*30*, *31*, *64*, *65*). 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 (*30*, *31*). 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 (*66*, *67*). However, the size of the average deforestation patch has decreased over the 2005-2014 period to avoid detection and subsequent punishment by environmental authorities (*68–70*). 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 (*71–73*). 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 (*41*, *74*). In 2008, the critical county program 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 (*43*). 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 (*44*).

Land conflict

Certain regions of the Amazon, such as the South-East of the state of Para, have seen many (violent) land conflicts since the beginning of the agrarian reform in the 1970s. To reduce land concentrations that occur during the military dictatorship, Brazil implemented a large agrarian reform allowing poor farmers to occupy “unused” land in the Brazilian Amazon. If farmers prove a ‘productive use’ for 5 years of previously unoccupied land, they can gain a land title even if the land was owned by another farmer. This creates a need to demonstrate productive use of the land both for new migrants and established large landholders, ultimately resulting in higher rates of deforestation and wide use of fires to open and maintain pastures and farmland at a low cost (*75*). Land conflicts are concentrated in places with good market access (through roads) and high landholding size disparity (*76*, *77*). Development projects and the opening of new roads can also bring illegal loggers, deforesters and land grabbers close to indigenous land, either established or in the process of demarcation, and pose important risks of land conflicts and land grabs (*78*). These pressures can result in the demarcation of new indigenous land, a long process that could be blocked by the administration (*79*). However, these places might crystallize tensions between indigenous and non-indigenous communities and lead to the use of fire for intentionally damaging the ecosystems.

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, conduct an analysis in the Brazilian Amazon and include a spatial component.

Drivers	Relationship
Climat	
Temperature	High temperature favorise fires (*17*, *80*)
Precipitations	Water deficit triggered by major drought increase frequency of fires (*8*, *29*, *46–48*, *50*) Areas with higher precipitations tend to have less frequent fires (*45*, *49*, *80*) Increasing water deficits are increasing and then decreasing the probability of having fires (*9*)
Agricultural expansions	
Agriculture	Crop production encourages the use of fires (*8*, *81*) Non-linear relationship between crops production and fires occurrences (*9*, *45*, *82*) No significant effect (*80*)
Pastoralism	Beef production increase the use of fires (*45*, *49*) No significant effect (*80*) Lower count of fires when land clearing related to ranching rather than crop production (*8*, *82*) Nonlinear relationship between pasture and fire (*9*)

Drivers	Relationship
Ecosystem integrity	
Deforestation	Deforestation has a marginal effect on fires (*46*) Deforestation and fires are tightly coupled (*8*, *9*, *29*, *47*, *49*, *80*, *81*, *83*) Deforestation is decoupling from fire regimes (*48*, *50*, *82*)
Fragmentation	Forest fragmentation favour forest fires (*47*, *84*) Forest fragmentation increase and then decrease the probability of fires (*9*)
Past forest degradation	Marginal effect on fires (*49*) Favorize fires (*9*, *80*)
Other vegetation	Secondary vegetation and non-forested land use favour fires (*9*, *17*, *46*, *47*, *49*, *81*) Fallow don't impact fire probability at municipality level (*80*)
Infrastructure and population	
Access to market	Proximity to roads and river favorize fires (*29*, *46*, *81*) Distance to road increase and then decreases the risk of fires (*9*, *45*)
Settlements	Proportion of settlements raises the probability of fires (*46*)
Population	Increase and then decrease the probability of fires (*9*)
Environmental policies	
Protected areas	Limit the number of fires, especially in areas with high deforestation pressure (*29*, *45*) High number of fires within municipalities with lots of protected areas/certains protected areas (*9*, *80*) No significant effect (*49*)

Supporting information 2: Response variables preprocessing

MODIS data processing.

To obtain the fires occurence within the Brazilian Amazon, we used MCD14DL, a dataset consisting of a collection of points (called Active-Fires or AF) recorded by the Aqua and Terra satellite indicating the centre of a 1km pixel with at least one thermal anomalies,

An algorithm was developed to filter multiple Actives-Fires detected within 1 km during the same day, thus limiting multiple detection of fires burning over a day while retaining as many AF as possible. This filtering kept 78% of the fires observed and filtered higher number of duplicates in the open landscape of the deforestation frontiers than in the other regions of the Brazilian Amazon. Algorithm used for MODIS AF filtering is available there: https://github.com/michel-va/filter_duplicate_modis .

In a second step, active fires were classified into three categories: deforestation fires (use for clearing biomass after forest clearing), agricultural/pastoral fires (use for getting rid of regrowing vegetation on pastures and croplands and fertilize soils) and forest fires (uncontrolled burning of forests). Our classification used two complementary datasets:

- **PRODES:** deforestation dataset compiled through automatic processing and human interpretation of high-resolution images from Landsat and other satellites. Comprise deforestation polygons for deforestation events over 6.25 hectares but overlooked small deforestation events.
- **Mapbiomas (Collection 6):** land cover and land use map of 30 meters resolution compiled through automatic processing of Landsat images. Comprise 30 meters pixels classified into 25 categories.

The classification of actives-fires was done in two steps (see figure S1):

1. Active Fires detected less than **500 meters** from a deforestation event in the same year were classified as deforestation fires (350 017 active fires, ~ 17%)
2. Remaining Active Fires detected on pixels with more than **90% of agricultural land cover** (including all agricultural land cover of Mapbiomas collection 6) were classified as agricultural/pastoral fires (320 327 active fires, ~16%) while active fires detected on pixels with more than **90% of forest** were classified as forest fires (290 379 active fires, ~ 14%)

Around 54% of the filtered MODIS Active-Fires have been classified as either a deforestation, agricultural/pastoral or forest fires by this algorithm. Figure S2 show temporal trends of the different types of fires, while figure S3 show the location of the three types of fires for the three periods of analysis. The high number of deforestation fires and coarse resolution of actives fires data suggest that some of the “deforestation fires” might not result directly from the use of fires after vegetation felling. However, these actives-fires are associated with areas of actives deforestation and associated explanatory variables values. The fires classified as forest fires could be either associated to deforestation events less than 6.5ha, the threshold of detection of the deforestation product used, or to understory forest fires that escaped from agricultural maintenance or deforestation fires. The error induced by the absence of data from small-scale deforestation events is expected to be especially important during the second period, as the average size of deforestation events decreased during this period (*85*). Thus, interpretation from further analysis discriminating the three types of fires should be done carefully. More recent Active fire products, such as the one derived from VIIRS and Sentinel imagery, have finer resolution and could be more confidently attach to a specific land use or land use change. However, we used MODIS active fires dataset as it allows us to have a consistent dataset for longer period.

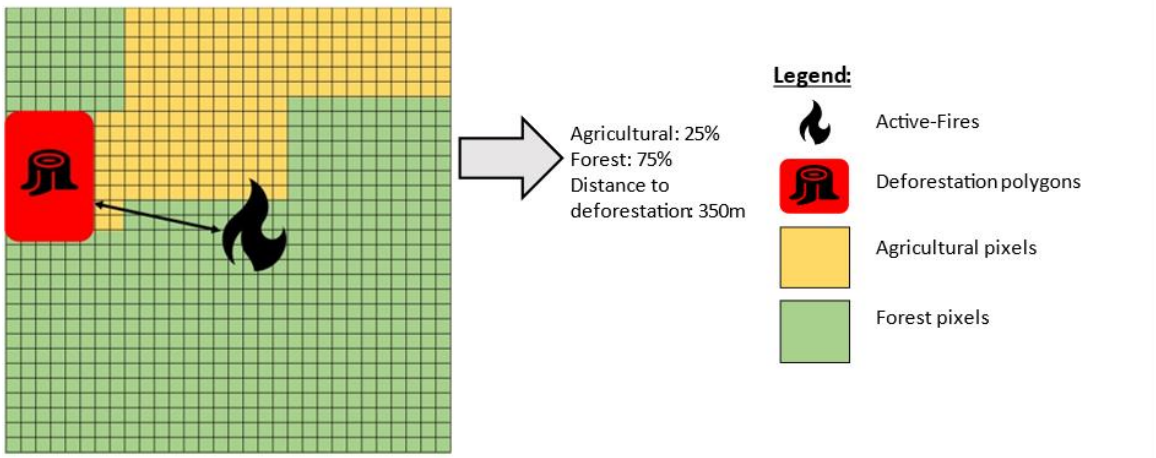


Fig. S1. Classification strategy of Active-Fires based on deforestation and land use information available

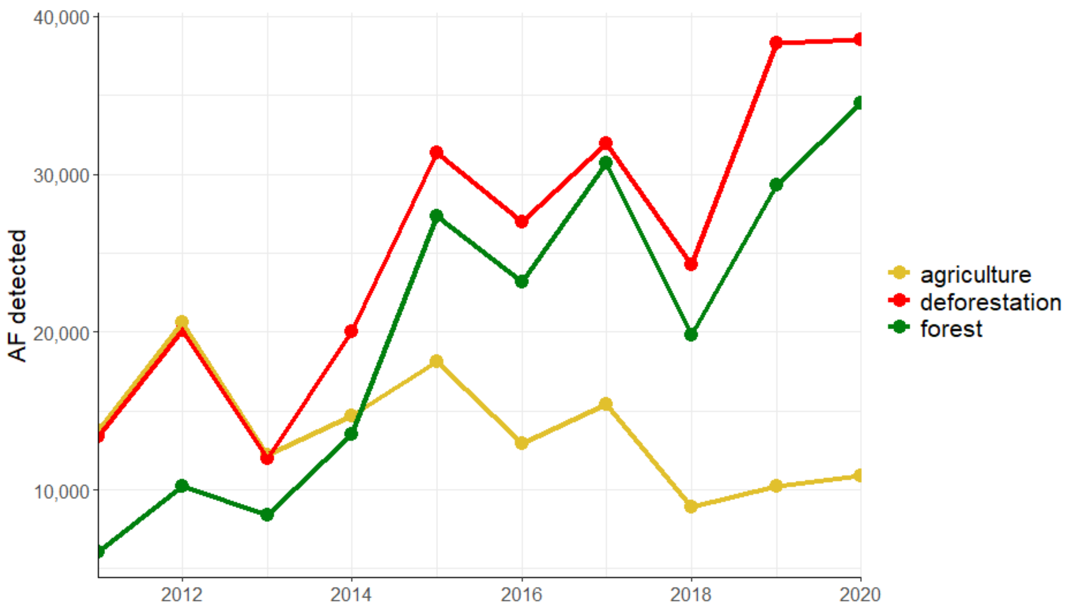


Fig. S2. Number of Active-Fires classified into each category for the 2011-2020 period in the Brazilian Amazon biome

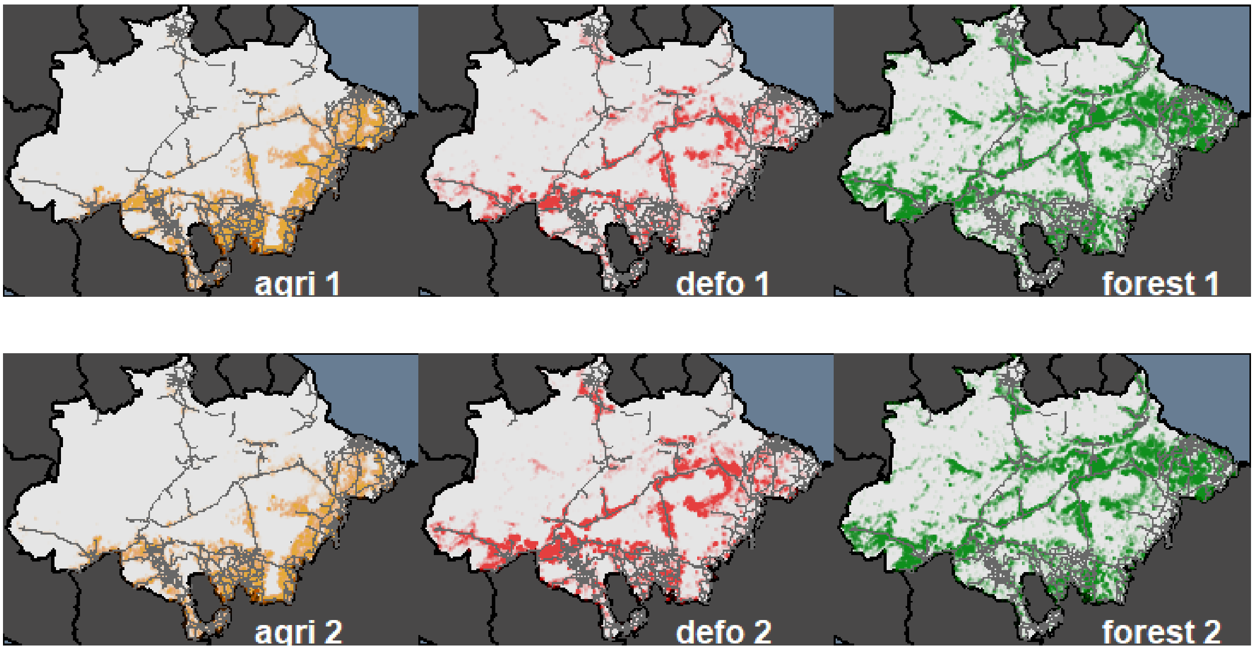


Fig. S3. Number of Active-Fires classified into each category for the 2011-2020 period in the Brazilian Amazon biome

Supporting information 3: 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 data sources that could be used to represent the different drivers from our theoretical framework, we removed some variables to simplify the models and interpretation of their results based on:

- **Quality of the datasets:** some datasets were aggregated at a municipality level and/or have been collected in ways that don't adequately represent our drivers.
- **Theoretical redundancy between variables:** several variables could be proxies for the same underlying drivers of fire regimes
- **Distribution of the data:** some variables, while theoretically interesting, were having distribution 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 droughtiness index that accounts for both phenomena (see next section for more details) and determine the amount of hydric stress vegetation is exposed to throughout a year.
- **Beef and soy productivity:** data on beef and soy production are aggregated at a municipality level. Data on beef production don't differentiate beef production from intensive and extensive ranching, leading to a few outliers with especially high productivity due to the presence of large estates doing intensive ranching. The degree of intensification of agricultural systems is already accounted for to a certain extent by the presence of annuals and perennial crops. The municipalities with higher beef or soy production are located along the arc of deforestation and are correlated to other variables such as hydric stress.
- **Past fires:** while initially thought as a potential proxy for past degradation of the forest, the interpretation of this variable could be quite challenging as fire tend to repeat over the same pixels and past fires could be a proxy for other phenomena driving fire occurrences.
- **Other natural vegetation:** The presence of other vegetation (savannas and grassland) could only be included in the model on the occurrence of deforestation fires, as other mutually exclusive land use categories were used to classify agricultural and forest fires. Mapbiomas collection 6, while being relatively precise, can have difficulties to differentiate grasslands, savannas and abandoned pastures, thus introducing new sources of errors.
- **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. Municipalities aimed by law enforcement efforts were mainly located in the arc of

deforestation and were on the blacklist, and the inscription on the blacklist is also affecting law enforcement efforts, thus there was strong theoretical redundancy between these variables. Moreover, the distribution of the data was highly skewed.

- **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.
- **Indigenous land under the process of demarcation** represents a small sample of indigenous lands, generally smaller than indigenous land already demarcated. The highly skewed distribution of the variable could affect the reliability of the models.
- **Land conflicts:** The data were aggregated at a municipality level and represented a low number of events compared to the surface of the different municipalities. These conflicts tend to aggregate in the municipalities along the deforestation arc and there is a risk of collinearity with other variables such as the transport cost or the blacklist programs.

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. However, instead of using a constant evapotranspiration rate of 100 mm, monthly evapotranspiration rates were derived from MOD16A2 satellite product and used in the algorithm. For each pixel, a Cumulated Water Deficit (CWD) was calculated for each month (n) using these rules:

if $CWD_{n-1} - evapotranspiration_n + precipitation_n < 0,$

$\quad$ *then* $CWD_n = CWD_{n-1} - evapotranspiration_n + Precipitation_n,$

$\quad$ *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.

Agricultural land use Mapbiomas collection 6 was used to look at land uses. The land use map was reclassified to create the following explanatory variables:

- Pasture: pasture and mosaic agriculture and pasture (ID 15+21)
- Annual crops: soya bean, sugarcane, rice and other annual crops (ID 39+20+40+41)
- Perennial crops: Forest plantations, coffee, citrus and other perennial crops (ID 9, 46, 47, 48)

The 30 metres pixels of Mapbiomas were used to calculate the proportions of 1 km pixels that were covered by the different land use for each year and include them into raster stacks, before being divided into 4 categories.

Agricultural land use increases Mapbiomas collection 6 was used to look at the evolution of the three categories of agricultural land use created. The percentage of each agricultural land use was compared to the previous year, and resulting raster stacks were divided into 2 categories.

Forest cover Mapbiomas collection 6 was used to look at the forest cover on each pixel. The 30 metres pixels of Mapbiomas were used to calculate the proportions of 1 km pixels that were covered by forest. Then, the resulting raster stack was divided into 5 categories.

Forest fragmentation Using the forest categories of Mapbiomas and the *landscapemetrics* packages in R, edge density was calculated for every year at a 1 km resolution, and a raster stack was created with the edge density values for each year and scaled by the mean standard deviation of the same year.

Distance agricultural edges Mapbiomas collection 6 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. Then, the resulting raster stack was divided into 7 categories.

Access to market The transport costs dataset developed by Victoria et al. 2021 (*86*) 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 2010 and 2017, 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 market were scaled by the mean standard deviations of the same year and compiled into a raster stack.

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:

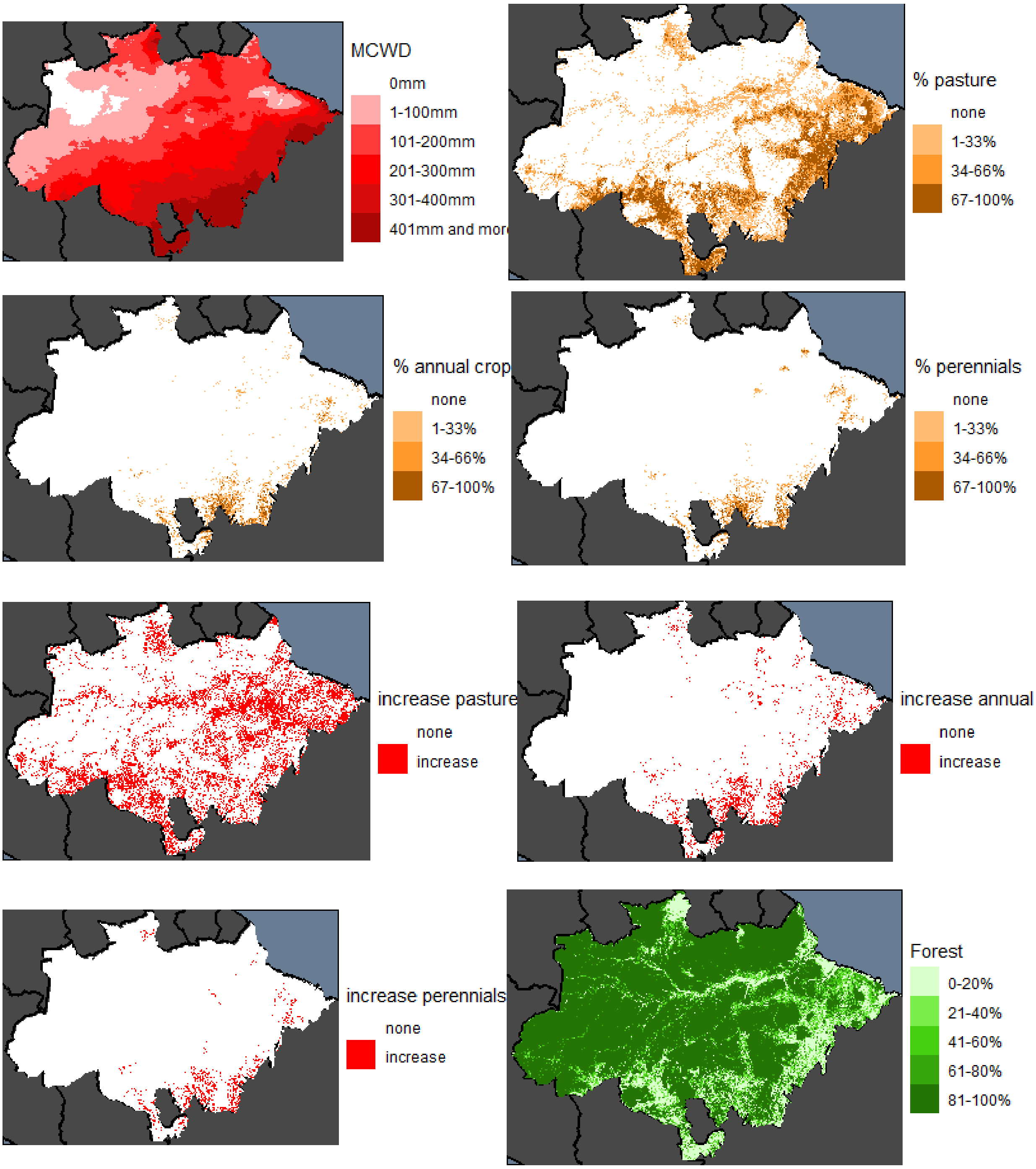
- Sustainable use areas: include forests, environmental protection areas, sustainable development reserves, extractive reserves, areas of relevant ecological interest and natural heritage private reserves
- strictly protected areas: include biological reserves, parks, ecological stations, wildlife refuges, and natural monuments.
- Indigenous lands: 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.

Additionally, the database of PADDD events in the Brazilian Amazon was downloaded on padddtracker website (*87*), and the downgradings of protected areas were 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 governance variables of the model. A raster stack has been created with the proportions of pixels covered by rural settlements opened before or during each year of the period of study.

Blacklisting 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.


MCWD
0mm
1-100mm
101-200mm
201-300mm
301-400mm
401mm and more
% pasture
none
1-33%
34-66%
67-100%
% annual crop
none
1-33%
34-66%
67-100%
% perennials
none
1-33%
34-66%
67-100%
increase pasture
none
increase
increase annual
none
increase
increase perennials
none
increase
Forest
0-20%
21-40%
41-60%
61-80%
81-100%

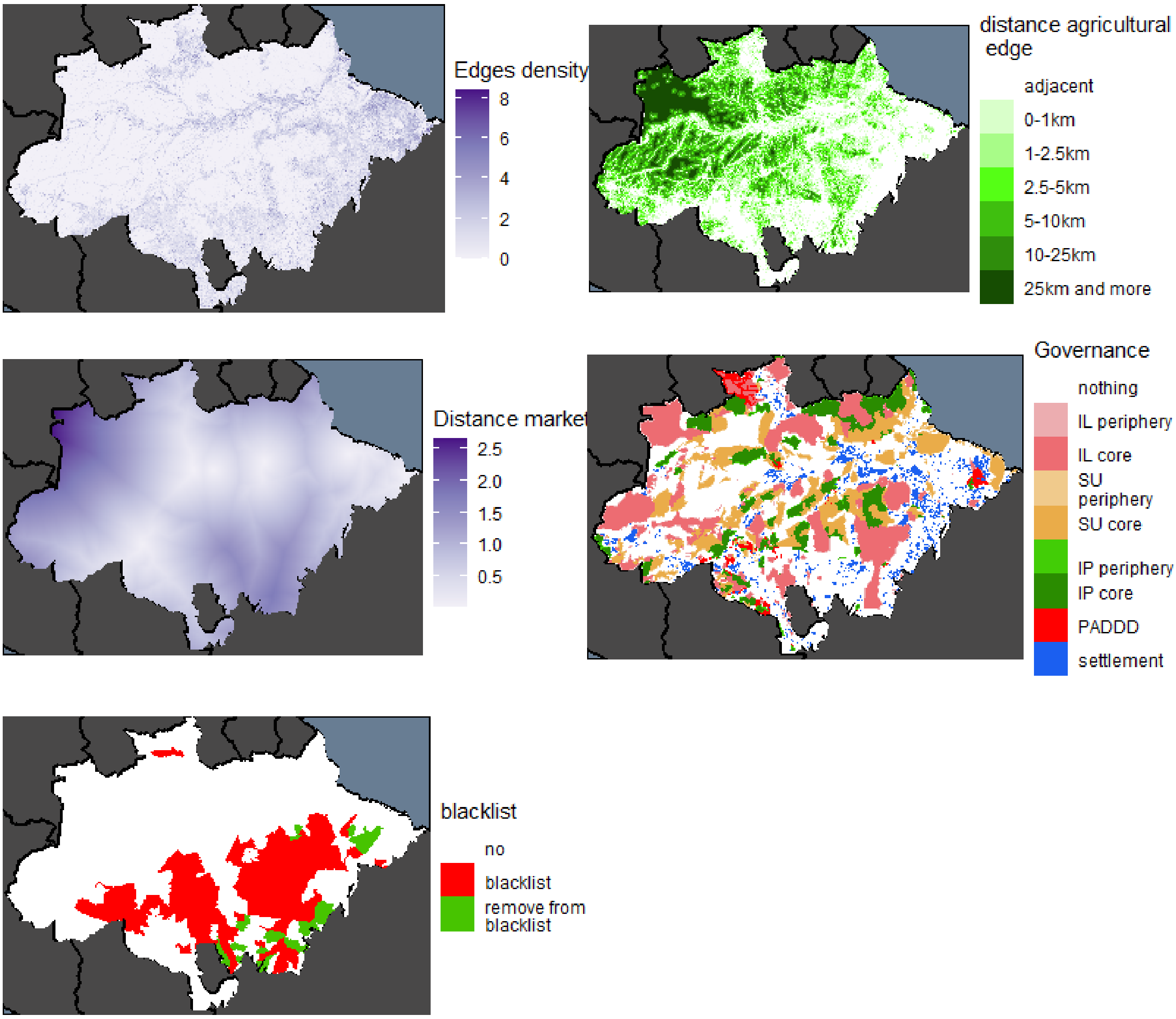


Fig. S4. Map of the processed explanatory variables included in the model for 2020

Table S2. Summary table of the value of the explanatory variables for the two period of analysis

Variable	2011-2015	2016-2020
Maximum cumulated Water Deficit		
none	2,220,269 (10%)	1,570,748 (7.2%)
1-100mm	5,103,480 (23%)	4,520,389 (21%)
101-200mm	4,286,572 (20%)	5,517,561 (25%)
201-300mm	5,401,597 (25%)	5,013,411 (23%)
301-400mm	3,755,464 (17%)	3,459,201 (16%)
401mm and more	1,156,883 (5.3%)	1,842,955 (8.4%)
Pasture		
none	15,244,512 (70%)	14,882,379 (68%)
1-33%	3,303,554 (15%)	3,509,174 (16%)
34-66%	1,369,923 (6.2%)	1,454,630 (6.6%)
67-100%	2,006,276 (9.2%)	2,078,082 (9.5%)
Annual crop		
none	21,303,740 (97%)	21,077,297 (96%)
1-33%	398,076 (1.8%)	518,622 (2.4%)
34-66%	107,604 (0.5%)	161,172 (0.7%)
67-100%	114,845 (0.5%)	167,174 (0.8%)
Perennial crop		
none	21,456,261 (98%)	21,208,442 (97%)
1-33%	280,189 (1.3%)	406,381 (1.9%)
34-66%	95,063 (0.4%)	157,322 (0.7%)
67-100%	92,752 (0.4%)	152,120 (0.7%)
Pasture change		
none	18,643,275 (85%)	17,957,389 (82%)
increase	3,280,990 (15%)	3,966,876 (18%)

Variable	2011-2015	2016-2020
Perrenial crop change		
none	21,613,180 (99%)	21,498,159 (98%)
increase	311,085 (1.4%)	426,106 (1.9%)
Forest		
0-20%	2,744,974 (13%)	2,866,405 (13%)
20-40%	1,281,547 (5.8%)	1,366,387 (6.2%)
40-60%	1,112,104 (5.1%)	1,157,787 (5.3%)
60-80%	1,282,340 (5.8%)	1,308,255 (6.0%)
80-100%	15,503,300 (71%)	15,225,431 (69%)
Edges density	0.06 (0.00, 0.87)	0.08 (0.00, 0.89)
Distance edge		
adjacent	6,998,985 (32%)	7,333,499 (33%)
0-1km	3,459,314 (16%)	3,474,735 (16%)
1-2.5km	2,636,923 (12%)	2,610,395 (12%)
2.5-5km	2,678,558 (12%)	2,625,838 (12%)
5-10km	2,625,895 (12%)	2,517,354 (11%)
10-25km	2,088,256 (9.5%)	2,051,489 (9.4%)
25km and more	1,436,334 (6.6%)	1,310,955 (6.0%)

Variable	2011-2015	2016-2020
Transport cost	0.81 (0.50, 1.18)	0.81 (0.50, 1.18)
Blacklist		
no	17,342,476 (79%)	16,235,189 (74%)
currently	4,342,679 (20%)	5,122,115 (23%)
in the past	239,110 (1.1%)	566,961 (2.6%)
Governance		
none	10,136,284 (46%)	9,993,056 (46%)
settlements	1,148,662 (5.2%)	1,153,930 (5.3%)
sustainable use periphery	660,904 (3.0%)	650,488 (3.0%)
sustainable use core	2,986,601 (14%)	2,930,374 (13%)
indigenous land periphery	636,357 (2.9%)	639,476 (2.9%)
indigenous land core	3,917,929 (18%)	4,016,123 (18%)
integral protection periphery	239,877 (1.1%)	242,808 (1.1%)
integral protection core	1,840,271 (8.4%)	1,920,641 (8.8%)
PADDD	357,380 (1.6%)	377,369 (1.7%)

Supporting Information 4: 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" (*88*) 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 (*89*, *90*). 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=1n $cov_{i(st)}*\beta_i + Y_{(st)}$)

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 (*91*).We fitted our LGCP model using inlabru (*15*), 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 (*92*). Briefly, the spatial process can be represented by the basic function:

$U_{(s)}$ = ∑k=1mψk(s)wk

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 (*93*), 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(σ> σ_0)=p_ σ. 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.

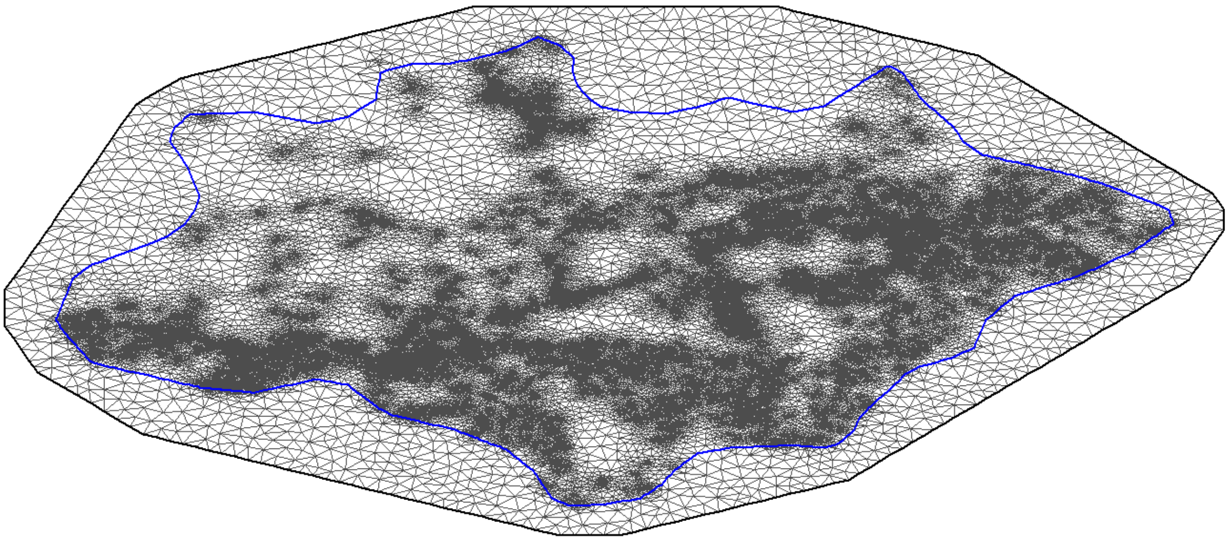


Fig. S5. Mesh created for the 2016-2020 deforestation fires model.

Supporting Information 5: Detailed results for all the models

Model deforestation fires

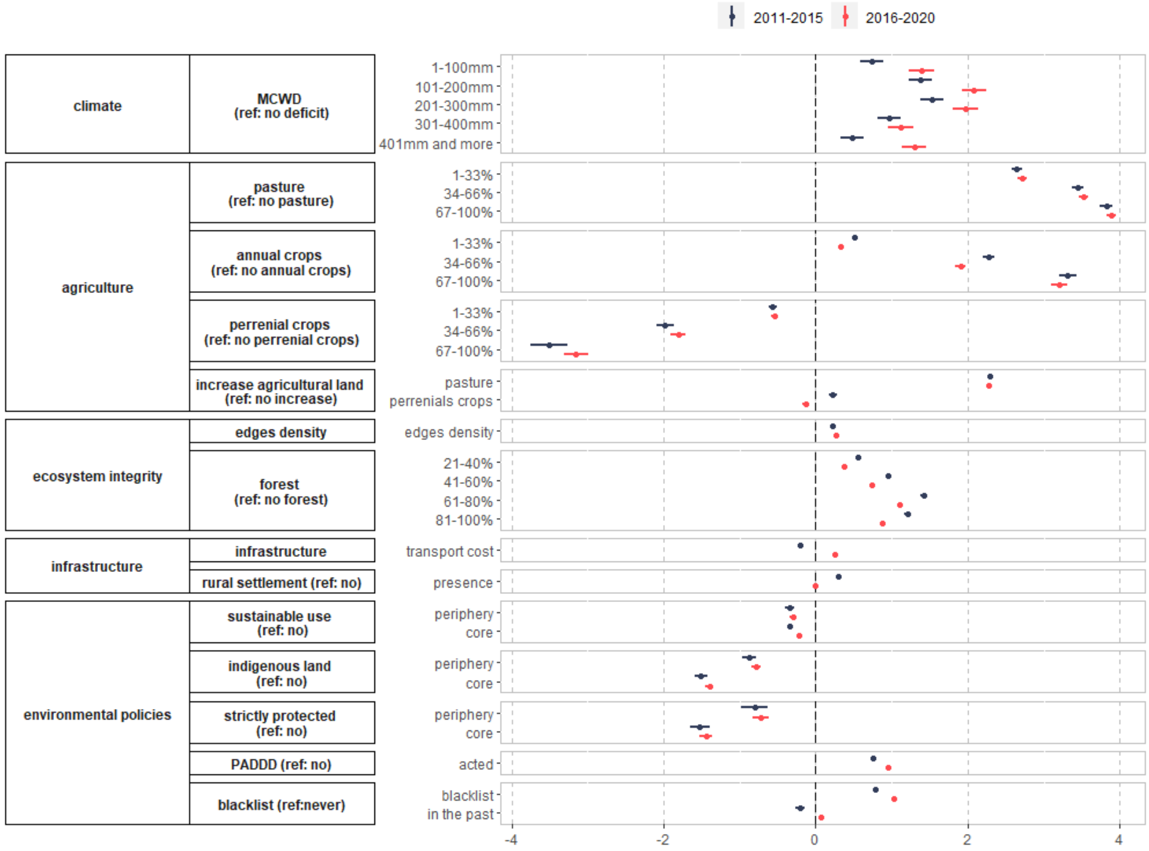


Fig.

Fig. S6. Posterior means and 95% credible intervals of explanatory variables for deforestation fires in the Brazilian Amazon

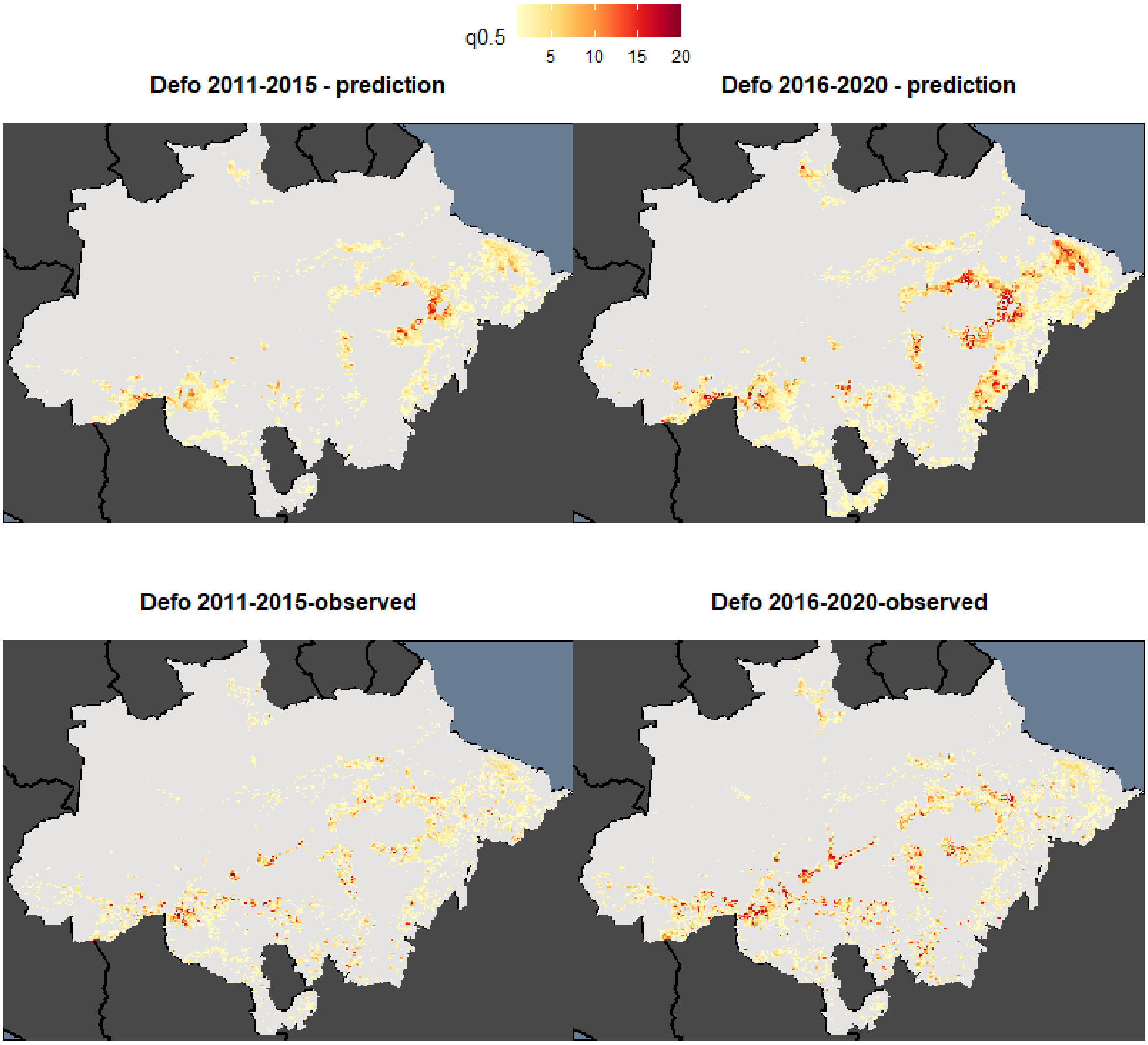


Fig. S7. Map of the number of median numbers of deforestation fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.

Model forest fires

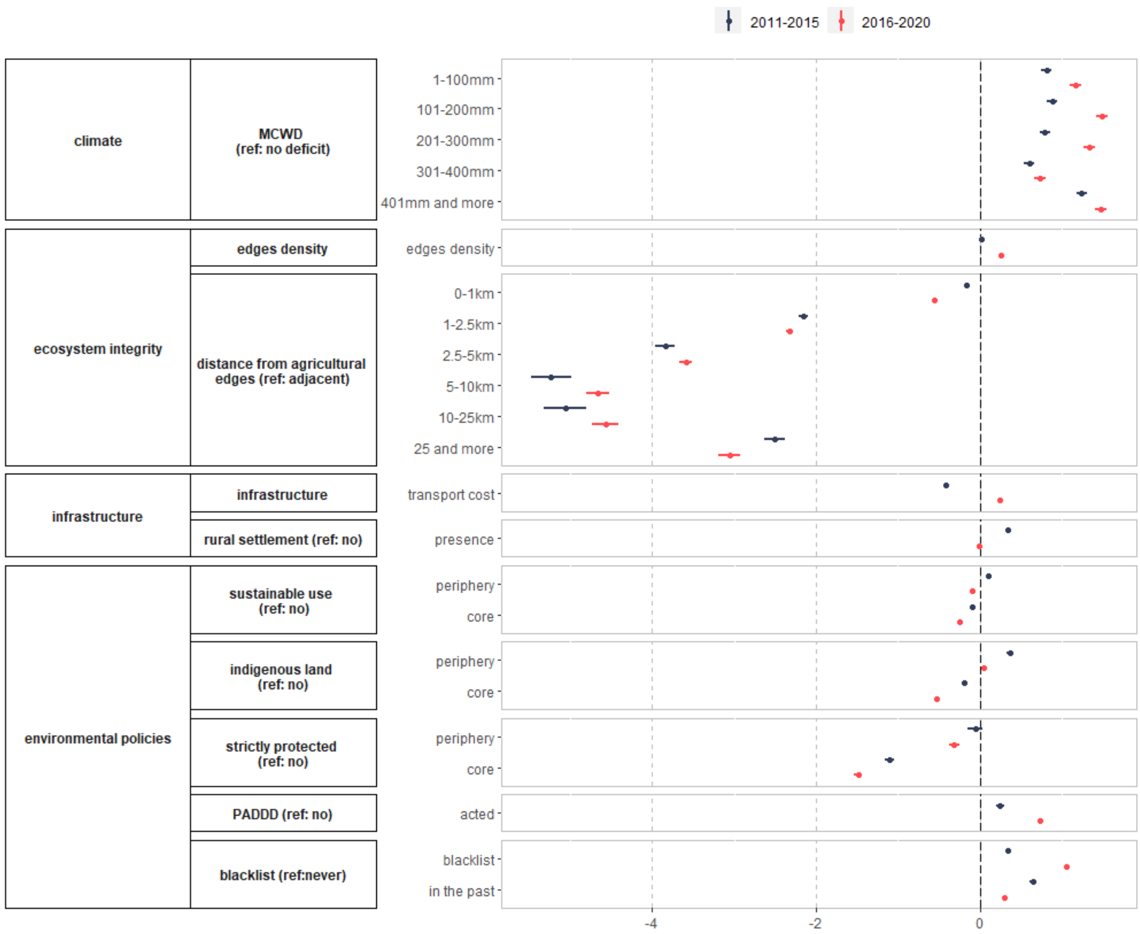


Fig. S8. Posterior means and 95% credible intervals of explanatory variables of explanatory variables for forest fires in the Brazilian Amazon

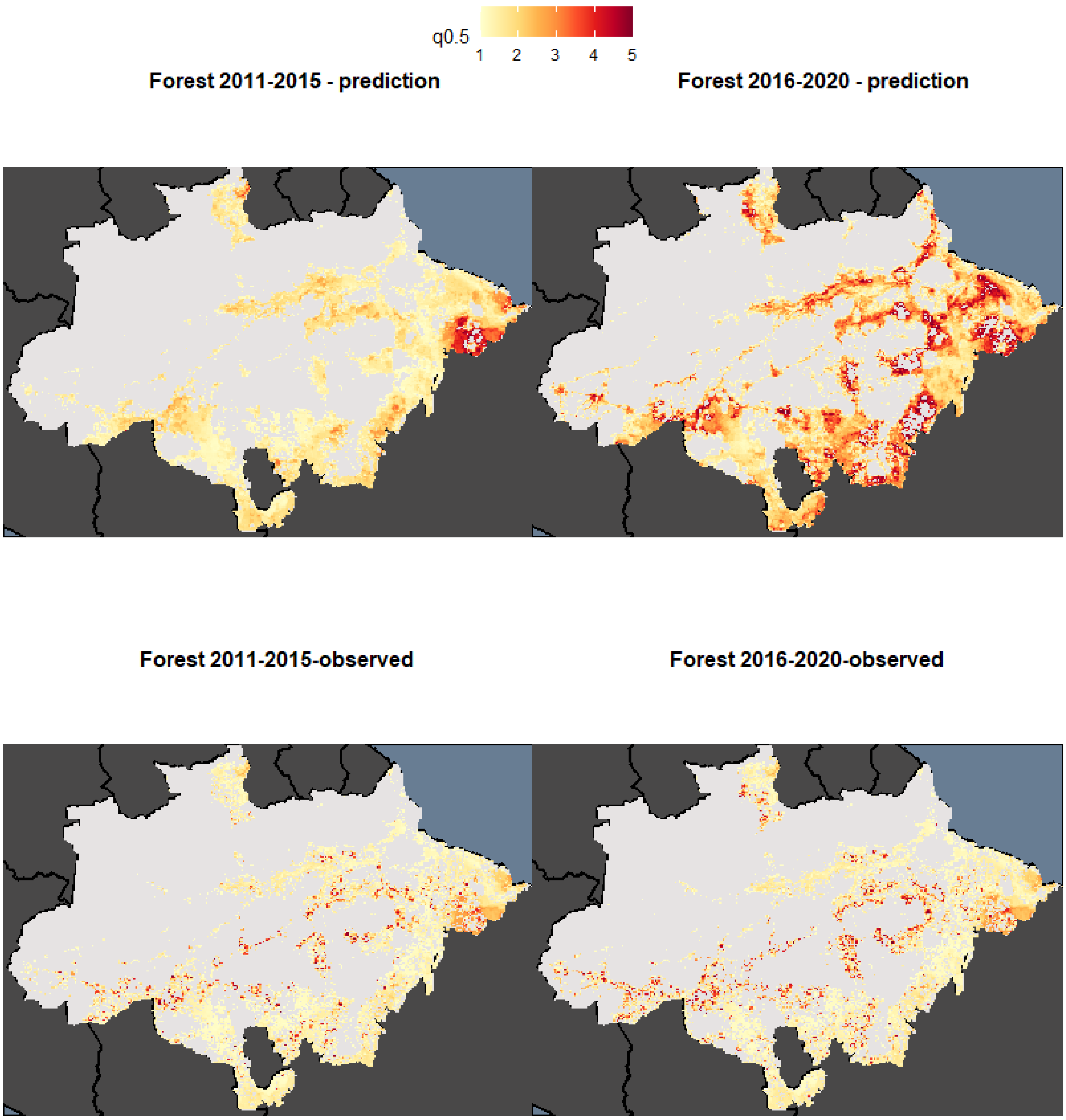


Fig. S9. Map of the number of median numbers of forest fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.

Model agricultural fires

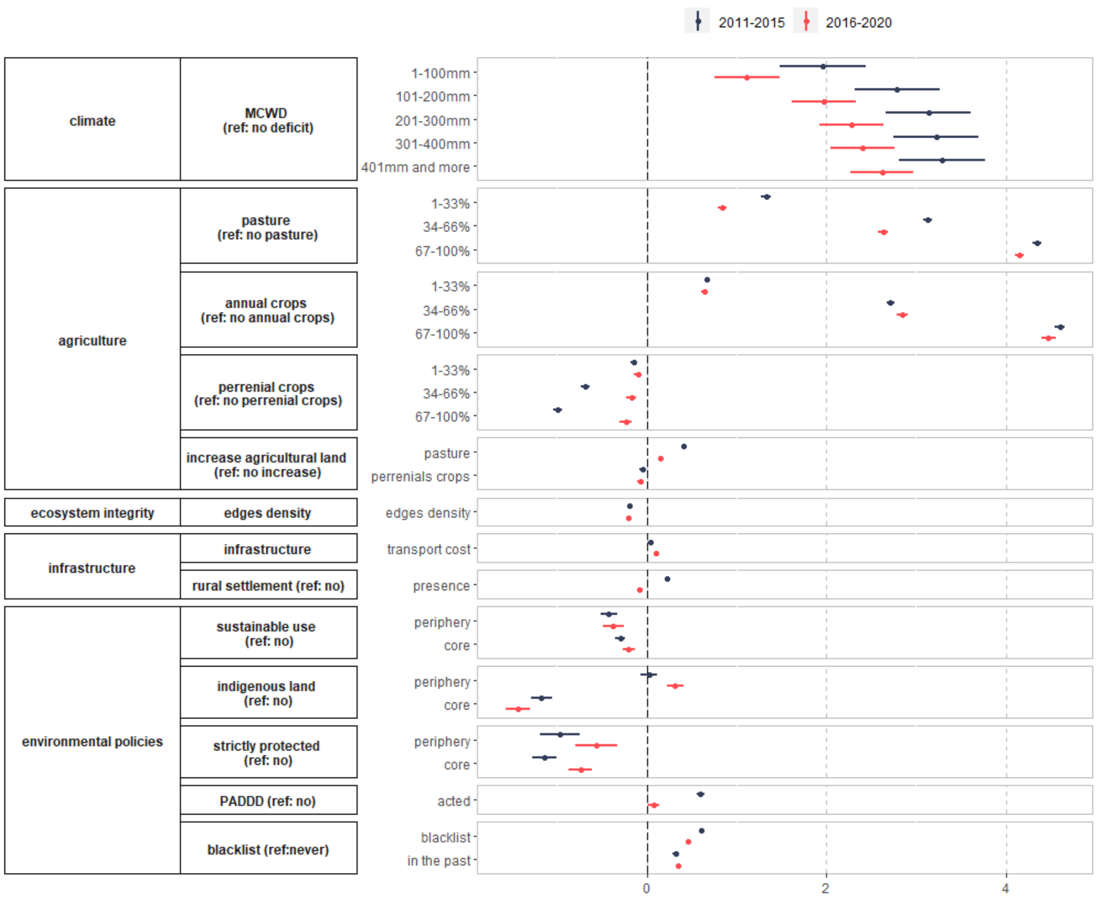


Fig. S10. Posterior means and 95% credible intervals of posterior distribution of explanatory variables for agricultural fires in the Brazilian Amazon

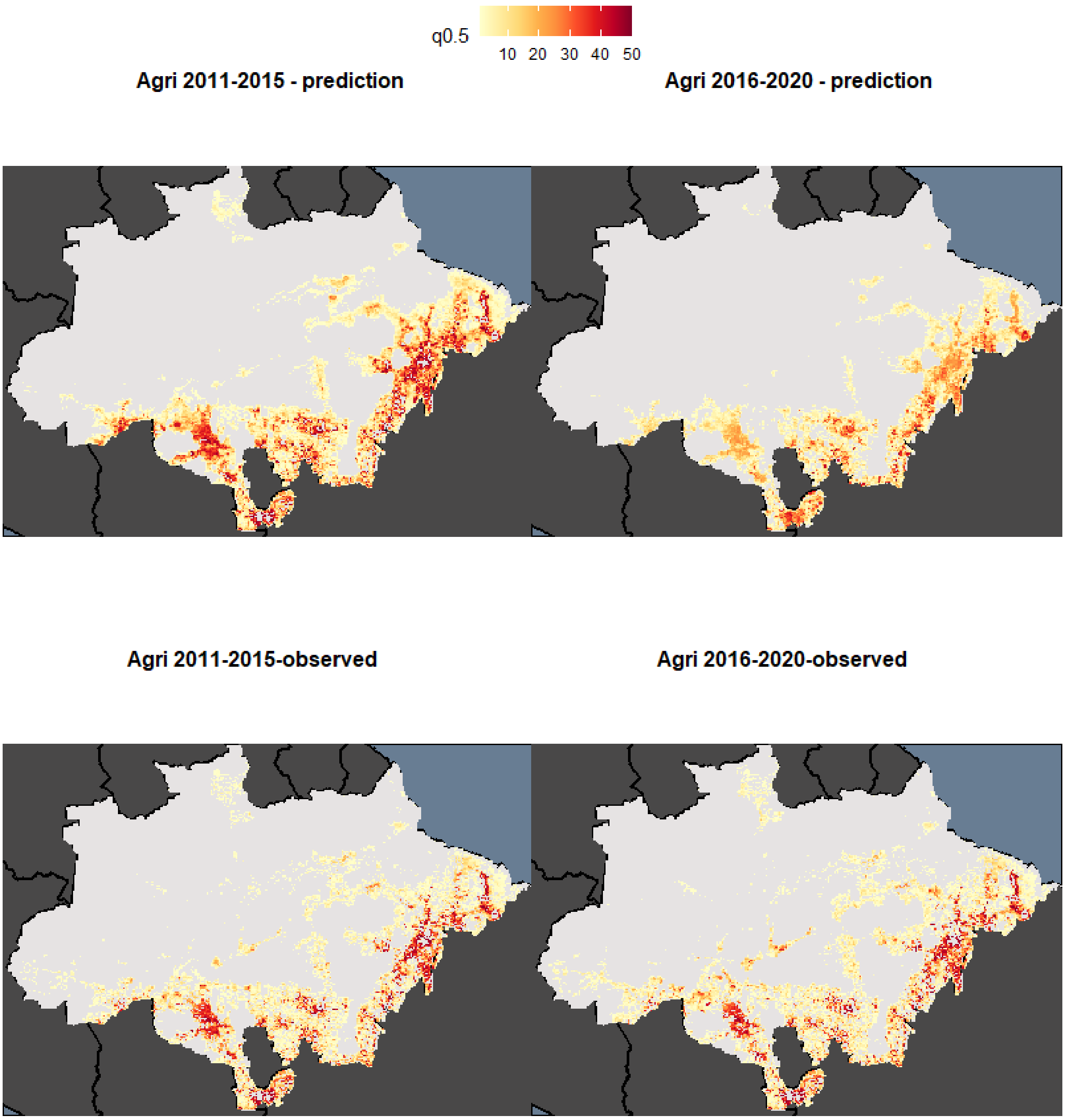


Fig. S11. Map of the number of median numbers of agricultural fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.