Drivers of fire regimes in the Brazilian Amazon from 2011-2020

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Abstract.

Over the last decade, carbon emissions due to forest degradation in the Brazilian Amazon, linked mainly to logging and wildfires, became larger than carbon emissions due to deforestation. Climatic and ecological processes affect the landscape's flammability, while socio-economic processes influence the use of fire for deforestation and agricultural land management. However, a comprehensive spatially explicit analysis of the relative influence of these processes on deforestation, agricultural and forest fires in the Brazilian Amazon, as well as how their influences changed during the recent weakening of environmental governance, was still missing. Here we show how the climate, land use and anti-deforestation policies are affecting all types of fires, which are increasingly affecting the remote part of the region. Among agricultural land, pastures are associated with the highest number of deforestation and agricultural fires, while perennials crops are associated with the smallest. All types of protected areas are associated with fewer forest and deforestation fires, especially integral protection and indigenous lands, but they are facing increasing pressures from their surroundings and fires are becoming more frequent on their peripheries. Our results show both agricultural and environmental policies are critical to prevent deforestation and forest degradation and highlight the importance of area-based conservation initiatives to curb fire and reduce environmental degradation within tropical rainforests.

Introduction

In 2004, the Brazilian government adopted the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), which, associated with a decrease in soy and beef prices and sustainability commitments in their supply chain, helped to reduce deforestation rates by more than 80% in the following decade [1,2]. The PPCDAm focused initially on the delimitation of new protected areas and indigenous land along active deforestation frontiers, as well as the use of satellite monitoring of deforestation to guide law enforcement on the ground [1]. Since 2006, these initial efforts were complemented by policies to address deforestation in agricultural lands through partnerships with the private sector, the creation of a rural land registry, and the regular publication of blacklists of municipalities with high deforestation rates, prioritizing the efforts of law enforcement and support services in these municipalities [3,4]. The rapid decrease in deforestation observed during the initial phase of implementation of the PPCDAm was correlated with an important decrease in satellite-detected fires in the BA[5]. However, the decline in fires observed was slower than the decline in deforestation rates, highlighting the increasing contribution of non-deforestation drivers on fire regimes [6]. Between 2016 and 2022, weakened environmental policies by the federal government, through legislative changes, pro-deforestation rhetoric and disempowerment of institutions controlling deforestation, coincided with a surge in deforestation and associated fires [7,8]. During the last decade, forest degradation, primarily linked with logging and fires, became the major driver of above-ground biomass loss in the region, turning the Brazilian Amazon (BA) into a carbon source [9–11]. 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 [12]. While the reduction of precipitation due to climate change alone is unlikely to result in massive forest dieback over the next century, fires can catalyse this process by increasing the mortality of rainforest trees and their replacement by other species [13,14].

Fires are widely used for deforestation and land management in the BA: deforestation fires are lit during the dry season to clear new fields, while agricultural fires are used to remove crop residues and regrowth, and manage soil fertility [15]. Both types of fires frequently escape and become forest fires, sometimes burning over large areas, which results in high tree mortality and transforms rainforests into savannas [16–18]. 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 a collective will and efforts to control fires [19]. Forest degradation also affects the flammability of remaining forest and the likelihood that deforestation fires and agricultural fires spread into the forested areas [20]. Thus, fire occurrence in the BA is affected by socio-economic factors determining the expansion of different agricultural systems, associated deforestation and forest degradation, as well as the post-clearing use and control of fire in agricultural lands [7,21]. Due to the close connections between the three types of fires, understanding their respective drivers could help to identify adequate interventions for each type of fire and limit the risks of forest fires and resulting degradation in the Brazilian Amazon.

In this study, we examine the drivers of deforestation, agricultural and forest fires in the BA over the 2011-2020 period, and how they changed with the weakening of forest resource governance in 2016 [22]. We classify fires into deforestation, agricultural and forest fires, using information on land cover and deforestation. 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 development, ecosystem integrity and governance of forest resources, aggregated in 1km pixels. We fitted the models for two time periods (i) 2011-2015, representing strong implementation of anti-deforestation policies, and (ii) 2016-2020, representing weakening anti-deforestation policies. We divided the results into three sections: first, the relationship between agriculture and associated land use change with agricultural and deforestation fires; second, the association of climate and landscape configuration with forest fires and; last, the influence of anti-deforestation policies on deforestation and forest fires.

Divergent fire regimes across agricultural systems

We found different land uses and land use changes were associated with distinct use of fires. We show that pastures were associated with higher numbers of deforestation fires, as well as agricultural fires between 2011 and 2015 (Figure 1). Expansions of pastures were also associated with an increased number of agricultural and deforestation fires. The majority of smallholders in the BA dedicate an important proportion of their land to ranching or shifting cultivation, partly due to the resilience of pasture to accidental fires as well as lack of technical support and agricultural inputs [15,23,24]. However as cattle ranching intensifies, an increasing proportion of pastures are managed with alternative approaches to agricultural fires [25].

Our study shows that expansions and cultivations of annual crops (including cash crops and crops related to subsistence farming) were associated with an increased number of agricultural and deforestation fires (Figure 1). The expansion of annual crops was associated with fewer deforestation fires than expansions of pastures, but the numbers of agricultural fires were comparable between these land use changes. Large-scale farming of annual crops (mainly soy in the BA) is characterized by intense fire activity during initial land clearing [21]. However, in recent years, a significant part of soy expansions occurred on pastoral land, in agreement with the zero-deforestation commitment from the soy sectors [26]. An increase in the demand for local agricultural products, such as cassava flour, has also led to an intensification of the use of fires and a reduction of fallow periods by smallholders in some places [15].

We observed that, in contrast to annual crops, perennial crops were linked to a decrease in agricultural and deforestation fires. The expansion of perennial crops was associated with a modest increase in deforestation fires and a decrease in agricultural fires (Figure 1). The reduced occurrence of deforestation and agricultural fires in areas with perennial crops is concordant with previous studies highlighting the antagonism between fire use and perennial crops: fire risk and potentials damage to crops need to be addressed at the community level prior to the adoption of perennials crops [23,27].

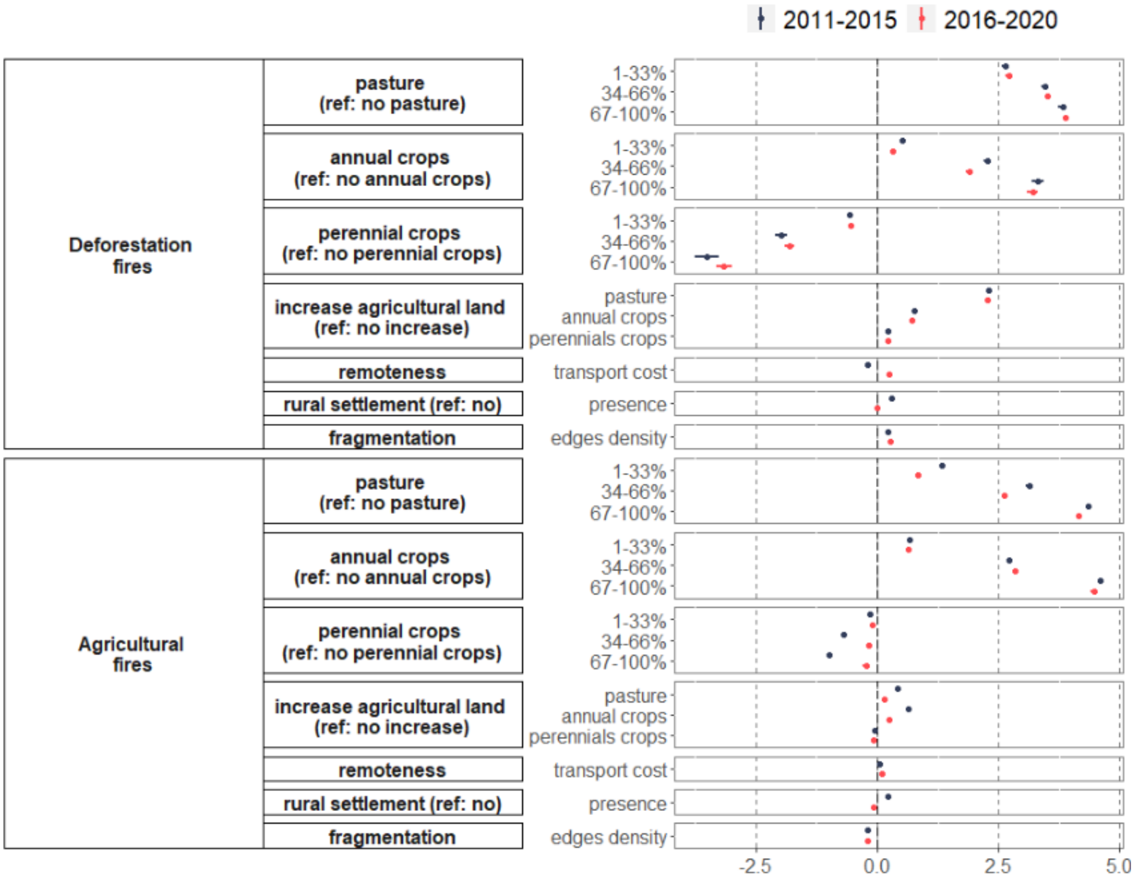

Figure 1. Posterior means and 95% credible intervals for explanatory variables related to agricultural expansions for deforestation and agricultural fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicates a variable that decreases occurrence of fires in 1 kilometer pixel, and intervals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

Our study shows that over the 2016-2020 period, remoteness is associated with more deforestation and agricultural fires than over the 2011-2015 period (Figure 1). Lack of access to agricultural inputs, the presence of few fire-vulnerable assets, and lower accountability of landholders for their land use practices increase the likelihood that fires are used for land management in remote areas of the BA [19,23,27]. Landholders in the new deforestation frontiers are less affected by fire restrictions associated with zero-deforestation commitments from the beef sector than landholders in old deforestation frontiers: they can sell cattle to non-signatory slaughterhouses or intermediary fattening ranches and thus avoid being monitored by signatory slaughterhouses [28]. The use of fires for land clearing and maintenance is also a cost-effective way to get land titles in the remote part of the BA [29]. Frequent regularisation of illegal land occupation encourages the opening of new deforestation frontiers, especially in undesignated public forests, and has been linked with the expansions of soy farming frontiers and increase in the price of already-deforested lands [26,29]. Fire moved deeper into the BA 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 [30].

Climate, fragmentation, and remoteness impact fire regimes

We found that forest fires in the BA are driven both by climatic conditions and landscape characteristics (Figure 2). Concomitant with previous research, our results show that a higher maximum cumulated water deficit was generally associated with more forest fires (Figure 2) [7,31]. Forest fires during drought years lead to particularly high tree mortality rates and subsequent degradation of the forest, raising concerns about the potential cumulative impact of drought episodes [17]. We also show that areas at a greater distance from agricultural edges are associated with fewer fires (Figure 2), as expected given that forest fires are mostly fires ignited on farmlands that escaped [16].

We found that the association between fragmentation and remoteness with forest fires changed according to the period examined, suggesting a recent increase in fire within remote and degraded forests of the BA. Fragmentation was associated with more forest fires from 2016 to 2020 than 2011 to 2015, (Figure 2), when the association was negligible. Remoteness followed a similar pattern: more isolated areas were positively associated with forest fires from 2016 to 2020 while this association was previously negative (Figure 2). Fires associated with deforestation and agriculture were also increasingly associated with the remote part of the BA (Figure 1), increasing risks of escaped fires in nearby forests [16]. Previous studies have shown higher post-fire tree mortalities in the humid Amazonian forest than within the seasonally dry Amazonian forest, potentially due to differences in species composition and selection of fire-resistant traits [14,32]. Increasing forest fires occurring within the remote parts of the BA, often characterized by wetter climate, could induce quicker and more severe responses of forest to fire disturbances.

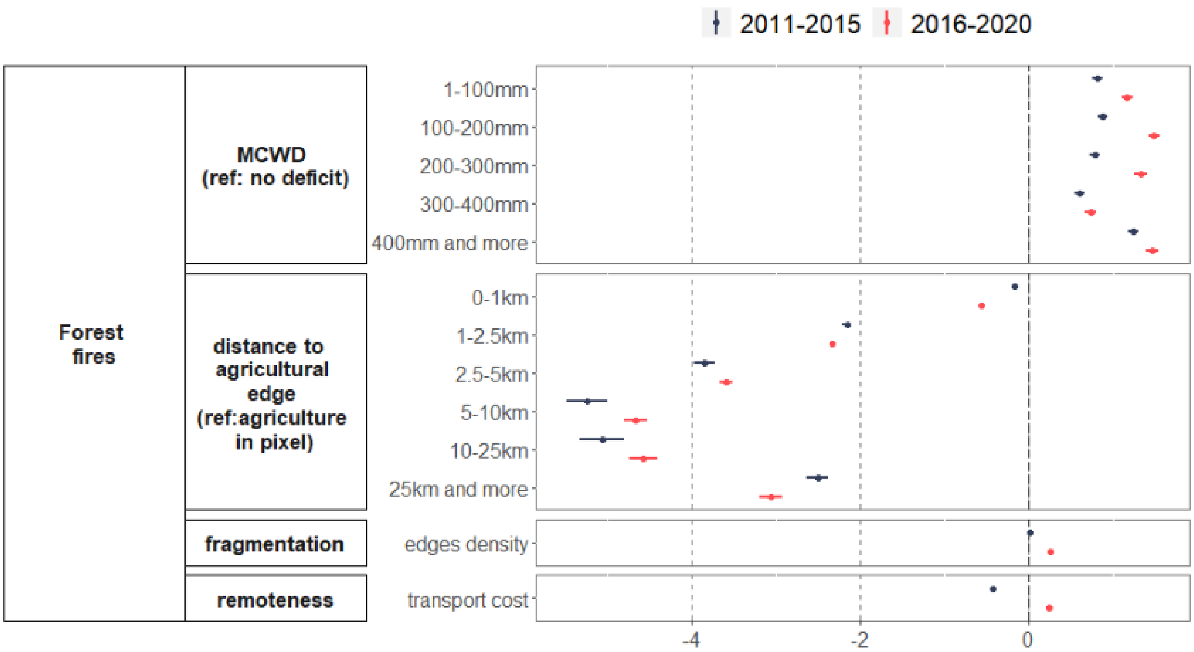

Figure 2. Posterior means and 95% credible intervals for explanatory variables related to climate and ecosystem integrity for forest fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable that decreases the occurrence of fires in 1 kilometer pixel, and intervals higher than 0 indicate variables that increase fire occurrence. See annex 5 for the credible intervals of all the explanatory variables.

Anti-deforestation policies and reduction in fires occurrence

We found that 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 in the BA [33,34]. While initially implemented to give territory sovereignty to indigenous people, indigenous land proved a pivotal instrument for reducing deforestation, especially in high-pressure frontiers [35]. Extensive traditional knowledge of fire management allows some indigenous communities to use fire while preventing accidental large-scale wildfires and their deleterious impact on the environment, for example through prescribed fires to control fuel load [36]. 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 [37].

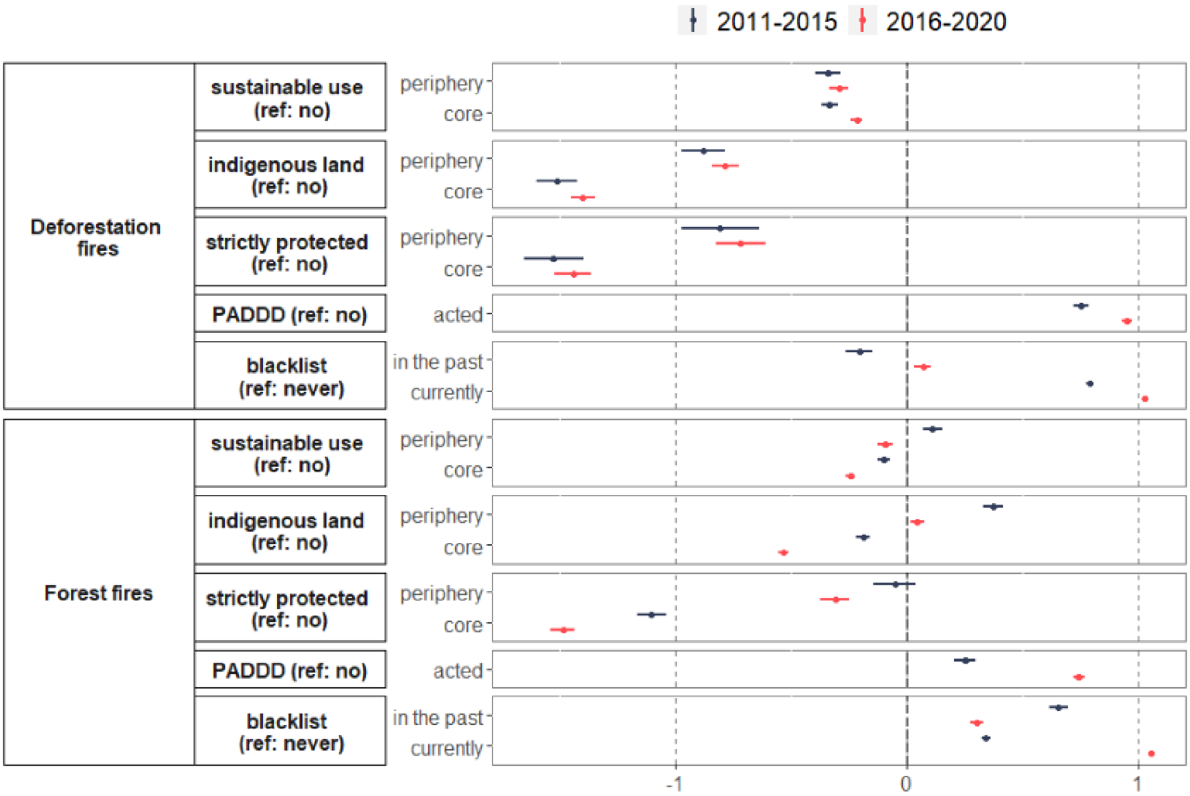

Figure 3. Posterior means and 95% credible intervals for explanatory variables related to anti-deforestation policies for deforestation and forest fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicates a variable that decreases occurrence of fires in 1 kilometer pixel, and intervals 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 [38]. Sustainable use areas are inhabited and 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 [39]. Certain sustainable use areas also have loose regulations on land ownership, which can lead to extensive deforestation [40].

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. [41] found that fires within indigenous land in the state of Rondônia were partly explained by fire occurrence and land use in their immediate vicinity. Additionally, Kauano et al [42] 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 are important to reduce the occurrence of fires within the protected areas [43].

We found sustainable use areas and indigenous land were associated with more deforestation fires (close to deforestation events) and fewer forest fires (far from deforestation events) from 2016-2020 than from 2011-2015. This is consistent with work showing recent peaks of deforestation in protected areas and land grabbing in indigenous lands [44]. We also found that protected areas that have been downsized or degazetted (hereafter PADDD events) were associated with more deforestation and forest fires, especially over the last period (Figure 3). Our result contrasts with a recent study showing no short-term peaks in deforestation after PADDD events in the BA [45]. We believe this difference could be a result of us investigating fire occurrence over a longer period and thus capturing a gradual process of land-use change. Increasing numbers of deforestation fires associated with PADDD events and protected areas between 2016 and 2020 highlight the importance of continuous management efforts to assure the effectiveness of area-based conservation initiatives. Unfortunately, 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 [46].

To curb deforestation, the Brazilian government has implemented a blacklist program. This involves regular publication of lists of municipalities with the highest deforestation rates, resulting in increased scrutiny by law enforcement, higher administrative burdens associated with land clearing, reputational risks for local farmers and support from external stakeholders for reducing deforestation [4]. We found that municipalities on the blacklist were associated with more deforestation and forest fires, particularly between 2016 and 2020 (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. 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 suggests that the blacklist drives a more parsimonious use of fires on agricultural land, strengthening conclusions from previous studies showing that the blacklist program was a cost-efficient way to reduce deforestation [4,47].

Conclusion

Fires in the Brazilian Amazon are contributing to forest degradation, carbon emissions and increase the risk of large-scale rainforest die-off. Understanding the drivers of agricultural, deforestation and forest fires, as well as how their influence evolved, is critical for identifying appropriate interventions to reduce fire occurrence and their detrimental impact on the ecosystems, economy, and human health.

We found that climate, agriculture, landscape configuration and anti-deforestation policies are affecting agricultural, deforestation and forest fires. Generally, while fire regimes became less intense in the well-connected areas of the BA, an opposite trend is observed in the most remote part of the region, threatening the remaining forests.

We found deforestation fires are most prevalent in pastoral lands, especially in the new deforestation frontiers expanding through the remote parts of the BA. Annual crops are associated with comparatively fewer deforestation fires, and perennial crops are associated with a reduction of deforestation and agricultural fires. To diminish the deleterious impact of fires in the region, mechanisms that support the transition from extensive pastoralism to other agricultural land uses, especially perennial crop cultivation, should be adopted and complemented by measures to improve fire management within new deforestation frontiers.

We found that protected areas experienced fewer deforestation fires and forest fires than unprotected lands. The downsizing and degazettement of protected areas in the region increased these areas' propensity for deforestation and forest fires. Strengthening indigenous land rights and the management of protected areas in the Amazon will reduce fires in remaining forests, tackling simultaneously deforestation and forest degradation. Sustainable use areas and indigenous land also experienced more fire in their periphery compared to their core, showing they are facing increasing pressure from their surrounding. Anti-deforestation policies have played a major role in reducing fire occurrence in the region, but their effectiveness in addressing fire was weakened in the face of faltering national and regional support. Strengthening environmental policies and resourcing responsible agencies adequately has never been more critical.

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 explanatory variables have then been aggregated into 1km grid to correspond to the resolution of our response variables (Table 1).

The response variable is the fire occurrences derived from the MODIS Active-Fire dataset (MCD14ML) for the 2011-2020 period, consisting of a collection of points indicating thermal anomalies (most often fires) within a 1-kilometre pixel. Active-Fires have been used rather than Burned Areas as they identify small fires more accurately, especially in tropical rainforests. Data have been filtered to remove observations under 30% of confidence and multiple observations 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 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 (350 016 Active-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 (290 376 Active-Fires) and agricultural fires (320 324 Active-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.

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 [48,49]. We generated a mesh based on the locations of observed points, using constraints on the angles of the triangles and the maximum number of triangles to have a fine mesh around active fires and a coarser mesh in areas with few active fires (see SI4). 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 and prior specification). 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 [50] of the software R V4.1 [51].

References.

1. West, T. A. P. & Fearnside, P. M. Brazil's conservation reform and the reduction of deforestation in Amazonia. *Land Use Policy* **100**, (2021).
2. Assunção, J., Gandour, C. & Rocha, R. Deforestation slowdown in the Brazilian Amazon: prices or policies? *Environment and Development Economics* **20**, 697–722 (2015).
3. Costa, M. A., Rajão, R., Stabile, M. C. C., Azevedo, A. A. & Correa, J. Epidemiologically inspired approaches to land-use policy evaluation: The influence of the Rural Environmental Registry (CAR) on deforestation in the Brazilian Amazon. *Elementa: Science of the Anthropocene* **6**, 1 (2018).
4. Assunção, J. & Rocha, R. Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics* **24**, 115–137 (2019).
5. Libonati, R. *et al.* Twenty-first century droughts have not increasingly exacerbated fire season severity in the Brazilian Amazon. *Scientific Reports* **11**, 4400 (2021).
6. Morgan, W. T., Darbyshire, E., Spracklen, D. V., Artaxo, P. & Coe, H. Non-deforestation drivers of fires are increasingly important sources of aerosol and carbon dioxide emissions across Amazonia. *Sci Rep* **9**, 16975 (2019).
7. Silveira, M. V. F. *et al.* Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land* **9**, 516 (2020).
8. Silva Junior, C. H. L. *et al.* The Brazilian Amazon deforestation rate in 2020 is the greatest of the decade. *Nature Ecology & Evolution* **5**, 144–145 (2021).
9. Qin, Y. *et al.* Carbon loss from forest degradation exceeds that from deforestation in the Brazilian Amazon. *Nature Climate Change* **11**, 442–448 (2021).
10. Matricardi, E. A. T. *et al.* Long-term forest degradation surpasses deforestation in the Brazilian Amazon. *Science* **369**, 1378–1382 (2020).
11. Tyukavina, A. *et al.* Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science Advances* **3**, (2017).
12. Amigo, I. When will the Amazon hit a tipping point? *Nature* **578**, 505–507 (2020).
13. Malhi, Y. *et al.* Exploring the likelihood and mechanism of a climate-change-induced dieback of the Amazon rainforest. *Proceedings of the National Academy of Sciences* **106**, 20610–20615 (2009).
14. Barlow, J., Lagan, B. O. & Peres, C. A. Morphological correlates of fire-induced tree mortality in a central Amazonian forest. *Journal of Tropical Ecology* **19**, 291–299 (2003).
15. van Vliet, N., Adams, C., Vieira, I. C. G. & Mertz, O. "Slash and Burn" and "Shifting" Cultivation Systems in Forest Agriculture Frontiers from the Brazilian Amazon. *Society & Natural Resources* **26**, 1454–1467 (2013).
16. Cano-Crespo, A., Oliveira, P. J. C., Boit, A., Cardoso, M. & Thonicke, K. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences* **120**, 2095–2107 (2015).
17. Brando, P. M. *et al.* Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proceedings of the National Academy of Sciences* **111**, 6347–6352 (2014).
18. Silvério, D. V. *et al.* 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**, (2013).
19. Morello, T. & Falcão, L. 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 (2020).
20. Silva-Junior, C. H. L. *et al.* Forest Fragmentation and Fires in the Eastern Brazilian Amazon–Maranhão State, Brazil. *Fire* **5**, 77 (2022).
21. Morton, D. C. *et al.* Agricultural intensification increases deforestation fire activity in Amazonia: Deforestation Fires in Amazonia. *Global Change Biology* **14**, 2262–2275 (2008).

22. Pokorny, B., Pacheco, P., de Jong, W. & Entenmann, S. K. Forest frontiers out of control: The long-term effects of discourses, policies, and markets on conservation and development of the Brazilian Amazon. *Ambio* **50**, 2199–2223 (2021).
23. Cammelli, F., Garrett, R. D., Barlow, J. & Parry, L. Fire risk perpetuates poverty and fire use among Amazonian smallholders. *Global Environmental Change* **63**, (2020).
24. Pereira, R., Simmons, C. & Walker, R. Smallholders, Agrarian Reform, and Globalization in the Brazilian Amazon: Cattle versus the Environment. *Land* **5**, 24 (2016).
25. Carvalho, R., de Aguiar, A. P. D. & Amaral, S. 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 (2020).
26. Gollnow, F., Hissa, L. de B. V., Rufin, P. & Lakes, T. Property-level direct and indirect deforestation for soybean production in the Amazon region of Mato Grosso, Brazil. *Land Use Policy* **78**, 377–385 (2018).
27. Carmenta, R., Coudel, E. & Steward, A. M. Forbidden fire: Does criminalising fire hinder conservation efforts in swidden landscapes of the Brazilian Amazon? *The Geographical Journal* **185**, 23–37 (2019).
28. Gibbs, H. K. *et al.* Did Ranchers and Slaughterhouses Respond to Zero-Deforestation Agreements in the Brazilian Amazon?: Brazil's zero-deforestation pacts. *Conservation Letters* **9**, 32–42 (2016).
29. Bowman, M. S. *et al.* Persistence of cattle ranching in the Brazilian Amazon: A spatial analysis of the rationale for beef production. *Land Use Policy* **29**, 558–568 (2012).
30. Ferrante, L., Andrade, M. B. T. & Fearnside, P. M. Land grabbing on Brazil's Highway BR-319 as a spearhead for Amazonian deforestation. *Land Use Policy* **108**, (2021).
31. Fonseca, M. G. *et al.* Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications* **27**, 2514–2527 (2017).
32. Balch, J. K. *et al.* Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management* **261**, 68–77 (2011).
33. Adeney, J. M., Christensen, N. L. & Pimm, S. L. Reserves Protect against Deforestation Fires in the Amazon. *PLoS ONE* **4**, (2009).
34. Nolte, C., Agrawal, A., Silvius, K. M. & Soares-Filho, B. S. 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 (2013).
35. Soares-Filho, B. *et al.* Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences* **107**, 10821–10826 (2010).
36. Mistry, J., Bilbao, B. A. & Berardi, A. Community owned solutions for fire management in tropical ecosystems: case studies from Indigenous communities of South America. *Philosophical Transactions of the Royal Society B: Biological Sciences* **371**, (2016).
37. Lessmann, J., Fajardo, J., Bonaccorso, E. & Bruner, A. Cost-effective protection of biodiversity in the western Amazon. *Biological Conservation* **235**, 250–259 (2019).
38. Oliveira, A. S. *et al.* Costs and effectiveness of public and private fire management programs in the Brazilian Amazon and Cerrado. *Forest Policy and Economics* **127**, (2021).
39. Carmenta, R., Vermeylen, S., Parry, L. & Barlow, J. Shifting Cultivation and Fire Policy: Insights from the Brazilian Amazon. *Human Ecology* **41**, 603–614 (2013).
40. Jesus, S. C. de & Catojo, A. M. Z. Deforestation in Conservation Units of the Brazilian Amazon: the case of the Terra do Meio Mosaic. *Ciência e Natura* **42**, 1–23 (2020).
41. Santos, A. M. dos, Silva, C. F. A. da, Rudke, A. P. & Oliveira Soares, D. de. 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**, (2021).
42. Kauano, É. E., Silva, J. M. C. & Michalski, F. Illegal use of natural resources in federal protected areas of the Brazilian Amazon. *PeerJ* **5**, (2017).

43. Walker, W. S. *et al.* 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 (2020).
44. Conceição, K. V. *et al.* Government policies endanger the indigenous peoples of the Brazilian Amazon. *Land Use Policy* **108**, (2021).
45. Pack, S. M. *et al.* Protected area downgrading, downsizing, and degazettement (PADDD) in the Amazon. *Biological Conservation* **197**, 32–39 (2016).
46. Silva, J. M. C. da, Dias, T. C. A. de C., Cunha, A. C. da & Cunha, H. F. A. Funding deficits of protected areas in Brazil. *Land Use Policy* **100**, (2021).
47. Cisneros, E., Zhou, S. L. & Börner, J. Naming and Shaming for Conservation: Evidence from the Brazilian Amazon. *PLoS ONE* **10**, (2015).
48. Rue, H., Martino, S. & Chopin, N. Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* **71**, 319–392 (2009).
49. Lindgren, F., Rue, H. & Lindström, J. 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 (2011).
50. Bachl, F. E., Lindgren, F., Borchers, D. L. & Illian, J. B. inlabru: an R package for Bayesian spatial modelling from ecological survey data. *Methods in Ecology and Evolution* **10**, 760–766 (2019).
51. R Core Team. R: A language and environment for statistical computing. (2022).

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Author contributions.

MV contributed to the conceptualization, methodology, analysis, interpretation and visualization of the results, and writing the original draft and edited version of the manuscript

YK contributed to the conceptualization, interpretation of the results, and writing the edited version of the manuscript

AFS contributed to the methodology, analysis, supervision of Bayesian modelling, interpretation and visualization of the results, and writing the edited version of the manuscript

JW contributed to the conceptualization, interpretation of the results, and writing the edited version of the manuscript

MM contributed to the conceptualization, methodology, interpretation of the results, and writing the original draft and edited version of the manuscript

Competing interests. Authors declare that they have no competing interests

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Tables.

Explanatory variables	**Data source used**
Maximum Cumulated Water Deficit	CHIRPS and MOD16A2
Pasture	Mapbiomas Collection 6
Annual crops	Mapbiomas Collection 6
Perennial crops	Mapbiomas Collection 6
Pasture increase	Mapbiomas Collection 6
Annual crops increase	Mapbiomas Collection 6
Perennial crops increase	Mapbiomas Collection 6
Forest cover	Mapbiomas Collection 6
Forest fragmentation	Mapbiomas Collection 6
Distance agricultural edges	Mapbiomas Collection 6
Access to market	Victoria et al. (2006)
Governance	WDPA + PADDDtracker+ INCRA
Blacklisting	MMA

Table 1. Data sources used for the explanatory variables

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(*5–10*). 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 (*7*, *9*, *11*). 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 (*12*, *13*) However, chronic water deficit limits the regrowth of the vegetation a contributing to fuel scarcity (*5*).

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 (*15*). 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 (*16*).

Ecosystem integrity

Before deforestation and conversion to agricultural land, Amazonian forests might face several types of disturbance (*17*). 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 (*18–20*). 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 (*20*). 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 (*21*). It also increases the interface between the agricultural landscape, on which fire is frequently used, and forests, thus increasing the possibility of escaped fires (*15*). 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 (*21–23*). 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 (*14*). Abandoned fields and pastures on which trees are regrowing as well as grasslands and savannas are also prone to fires (*5*, *7*, *10*).

Remoteness

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 (*7*, *24*). 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 (*25*). 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 (*5*). 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 (*16*). 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 (*26*, *27*). 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 (*28*, *29*).

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 (*30*). 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 (*31–34*). 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 (*32*, *33*). 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 (*35*, *36*). However, the size of the average deforestation patch has decreased over the 2005-2014 period to avoid detection and subsequent punishment by environmental authorities (*37–39*). 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 (*40–42*). 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 (*43*, *44*). 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 (*45*). 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 (*46*).

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 (*47*). Land conflicts are concentrated in places with good market access (through roads) and high landholding size disparity (*48*, *49*). 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 (*50*). These pressures can result in the demarcation of new indigenous land, a long process that could be blocked by the administration (*51*). 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 (*52*, *53*)
Precipitations	Water deficit triggered by major drought increase frequency of fires (*7–9*, *11*, *14*, *54*) Areas with higher precipitations tend to have less frequent fires (*6*, *10*, *53*) Increasing water deficits are increasing and then decreasing the probability of having fires (*5*)
Agricultural expansions	
Agriculture	Crop production encourages the use of fires (*14*, *55*) Non-linear relationship between crops production and fires occurrences (*5*, *6*, *56*) No significant effect (*53*)
Pastoralism	Beef production increase the use of fires (*6*, *10*) No significant effect (*53*) Lower count of fires when land clearing related to ranching rather than crop production (*14*, *56*) Nonlinear relationship between pasture and fire (*5*)

Drivers	Relationship
Ecosystem integrity	
Deforestation	Deforestation has a marginal effect on fires (*7*) Deforestation and fires are tightly coupled (*5*, *8*, *10*, *14*, *53–55*, *57*) Deforestation is decoupling from fire regimes (*9*, *11*, *56*)
Fragmentation	Forest fragmentation favour forest fires (*8*, *58*) Forest fragmentation increase and then decrease the probability of fires (*5*)
Past forest degradation	Marginal effect on fires (*10*) Favorize fires (*5*, *53*)
Other vegetation	Secondary vegetation and non-forested land use favour fires (*5*, *7*, *8*, *10*, *52*, *55*) Fallow don't impact fire probability at municipality level (*53*)
Remoteness	
Access to market	Proximity to roads and river favorize fires (*7*, *54*, *55*) Distance to road increase and then decreases the risk of fires (*5*, *6*)
Settlements	Proportion of settlements raises the probability of fires (*7*)
Population	Increase and then decrease the probability of fires (*5*)
Environmental policies	
Protected areas	Limit the number of fires, especially in areas with high deforestation pressure (*6*, *54*) High number of fires within municipalities with lots of protected areas/certains protected areas (*5*, *53*) No significant effect (*10*)

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 (*59*). 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.

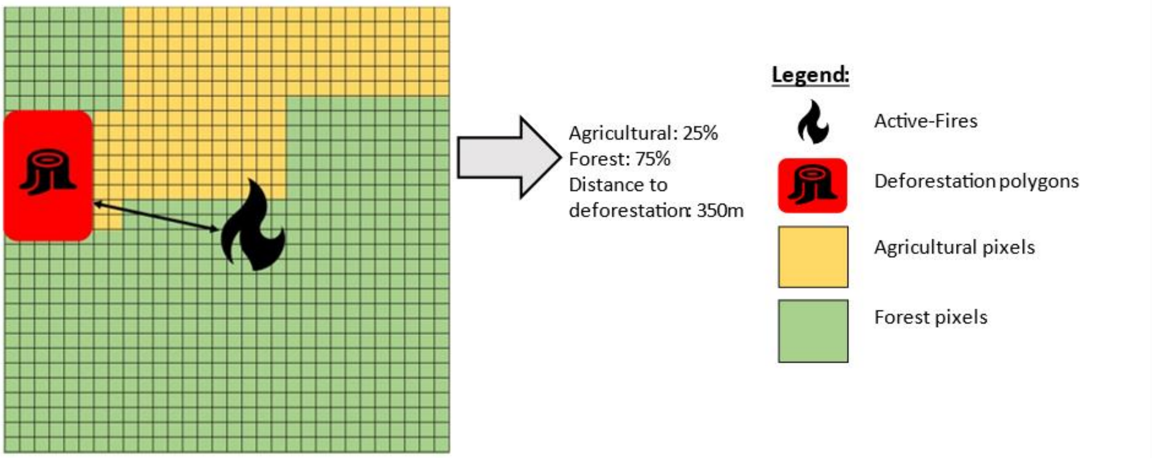


Fig. S1. Classification strategy of Active-Fires based on deforestation and land use information available

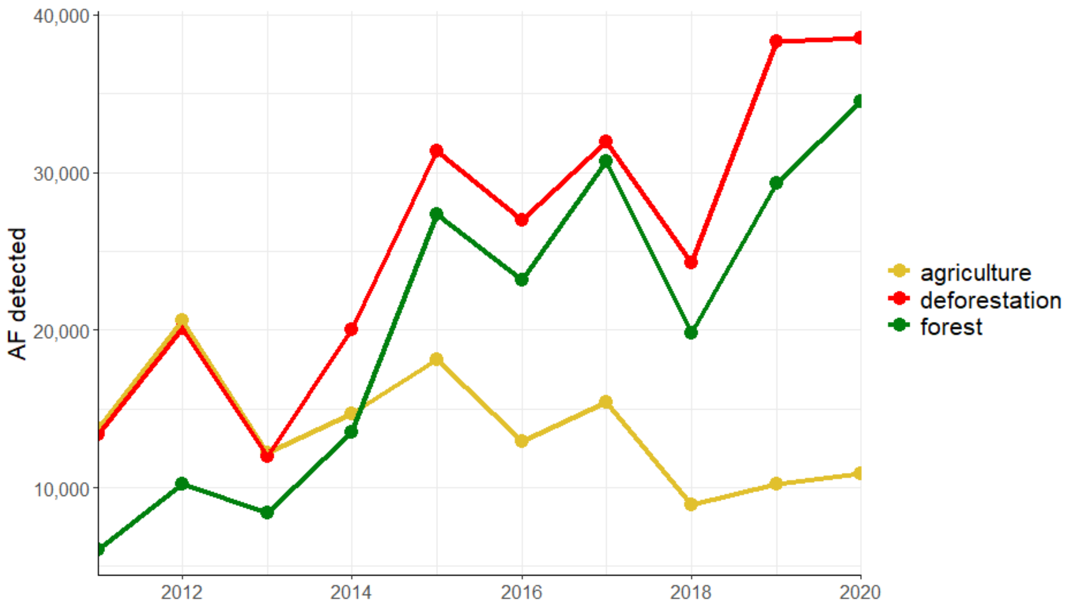


Fig. S2. Number of Active-Fires classified into each category for the 2011-2020 period in the Brazilian Amazon biome

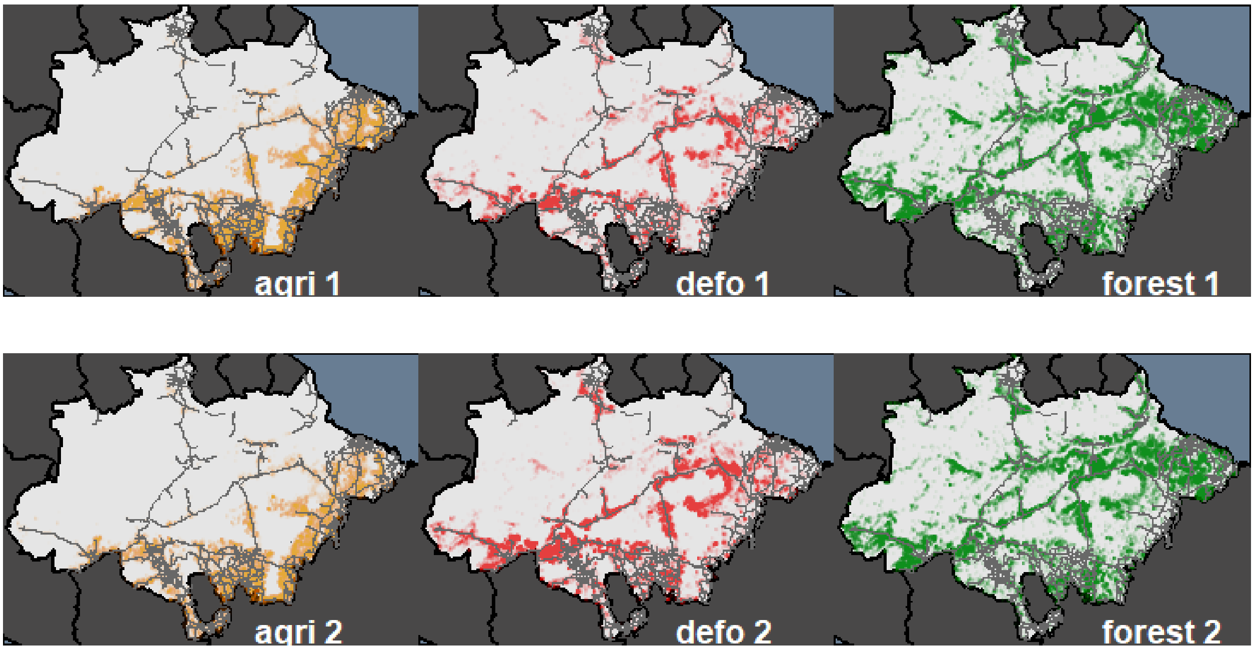


Fig. S3. Map of the Active-Fires classified into each category for the 2011-2020 period in the Brazilian Amazon biome

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

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

$else\ CWD_n = 0$

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.

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:

- <u>Pasture:</u> pasture and mosaic agriculture and pasture (ID 15+21)
- <u>Annual crops:</u> soya bean, sugarcane, rice and other annual crops (ID 39+20+40+41)
- <u>Perennial crops:</u> 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.

Remoteness The transport costs dataset developed by Victoria et al. 2021 (*60*) 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:

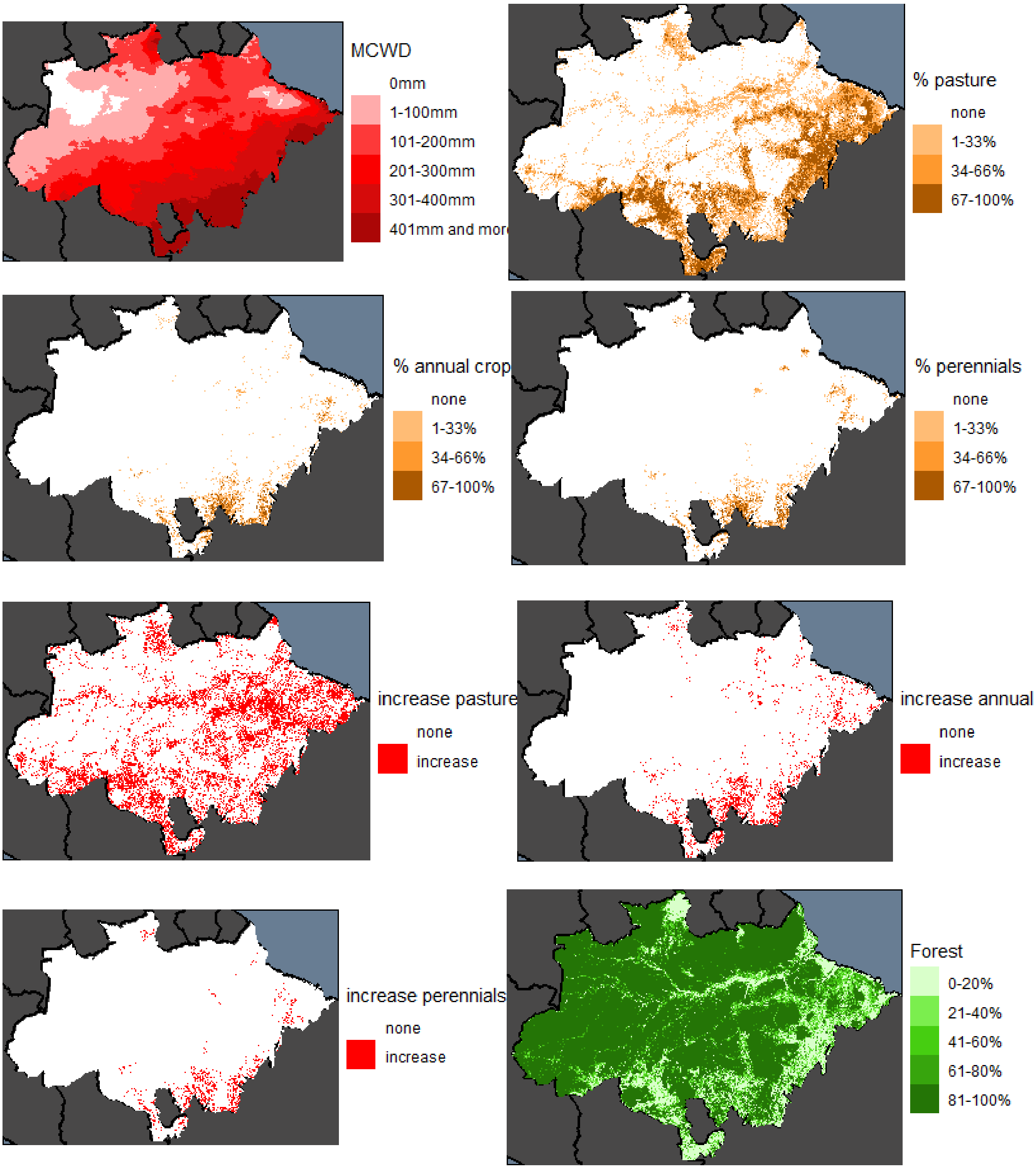
- <u>Sustainable use areas:</u> include forests, environmental protection areas, sustainable development reserves, extractive reserves, areas of relevant ecological interest and natural heritage private reserves
- <u>strictly protected areas:</u> include biological reserves, parks, ecological stations, 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.

Additionally, the database of PADDD events in the Brazilian Amazon was downloaded on padddtracker website (*61*), 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%

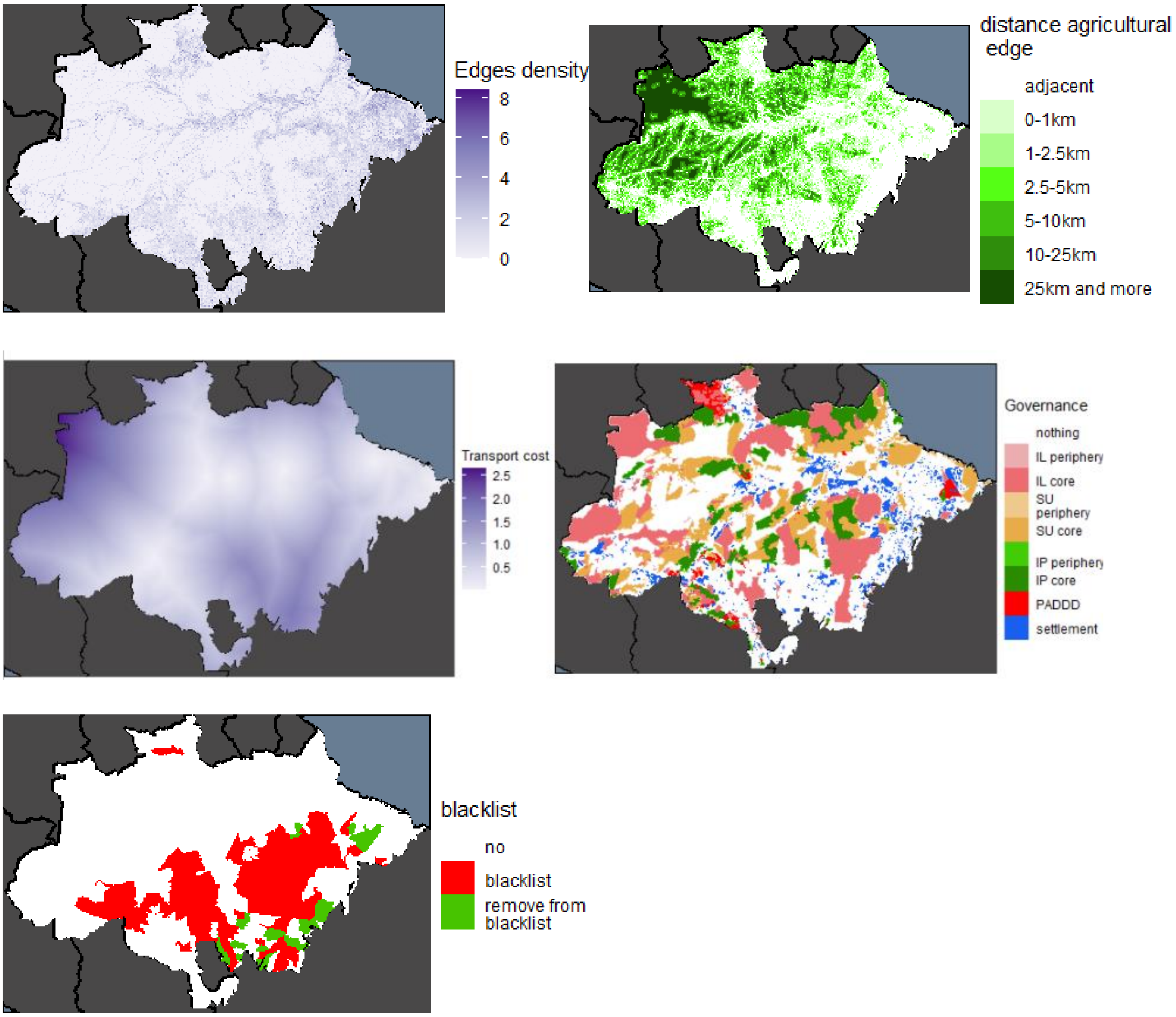


Fig. S4. Map of the processed explanatory variables included in the model for 2020

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" (*62*) 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 (*63*, *64*). 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 ($\sum_{i=1}^{n}$ $cov_{i(st)} * \beta_i + Y_{(st)}$)

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 (*65*).We fitted our LGCP model using inlabru (*3*), 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 (*66*). 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 (*67*), 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.

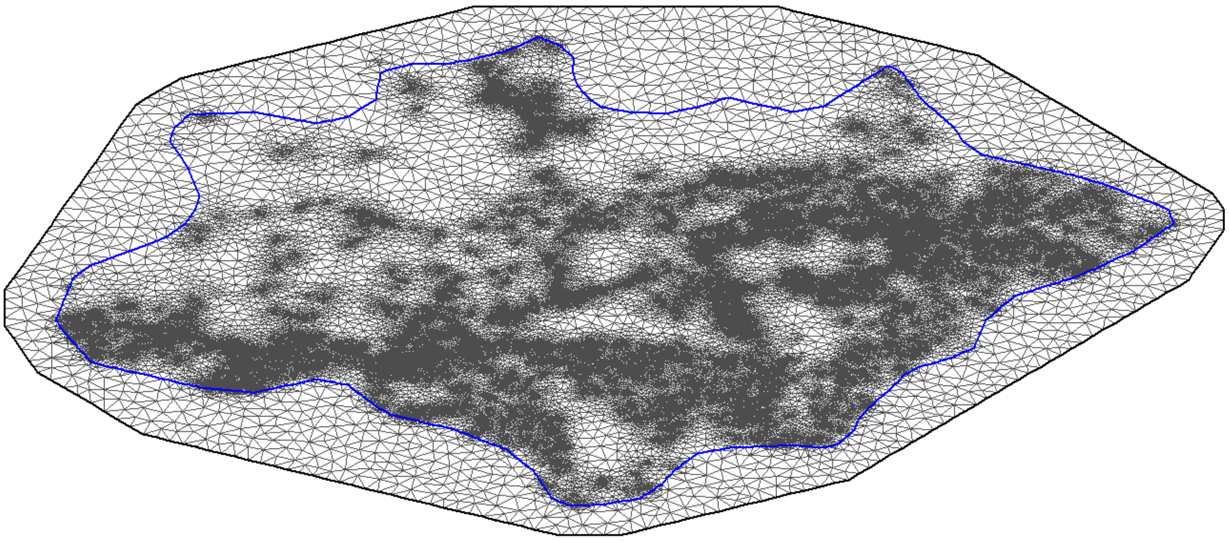


Fig. S5. Mesh created for the 2016-2020 deforestation fires model.

Supporting Information 5: Detailed results for all the models

Model deforestation fires

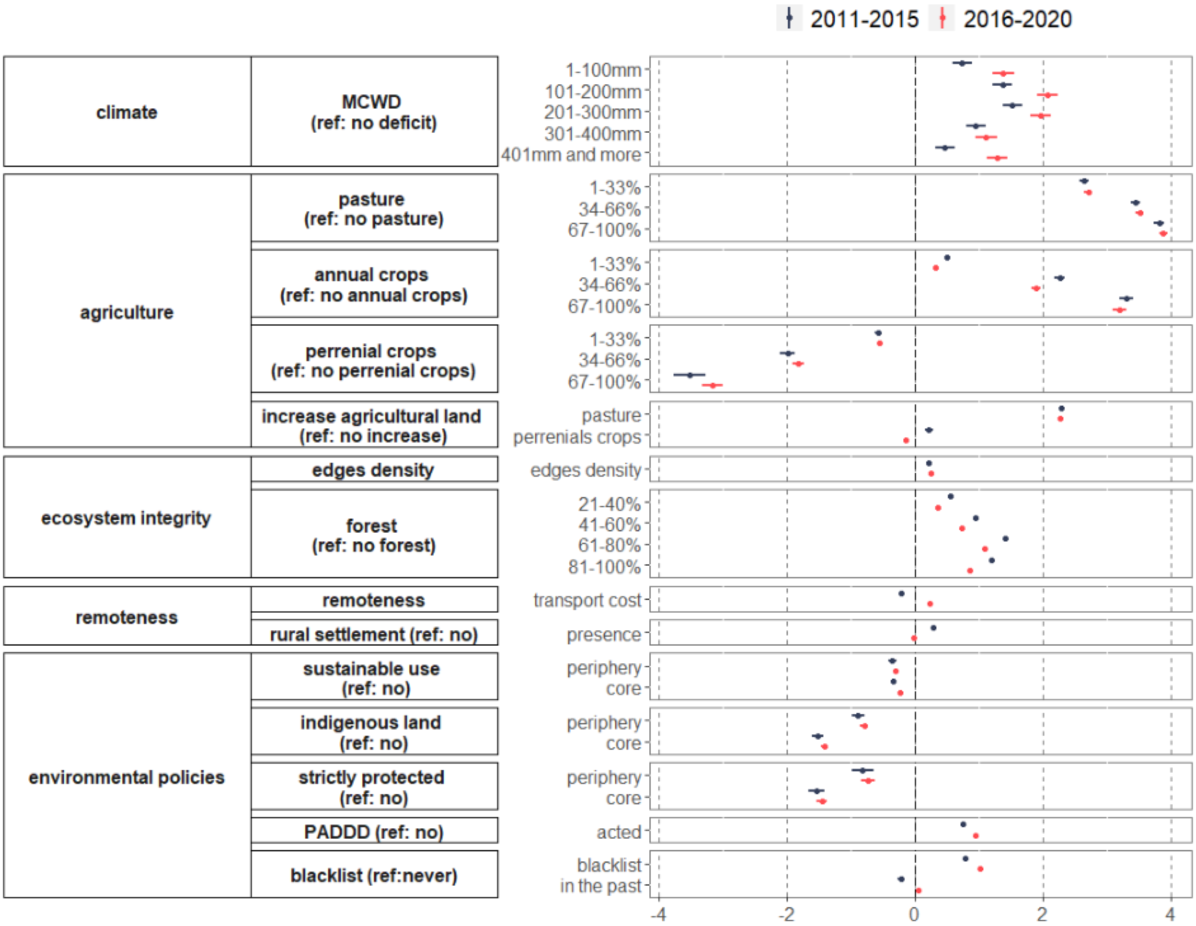


Fig. S6. Posterior means and 95% credible intervals of explanatory variables for deforestation fires in the Brazilian Amazon

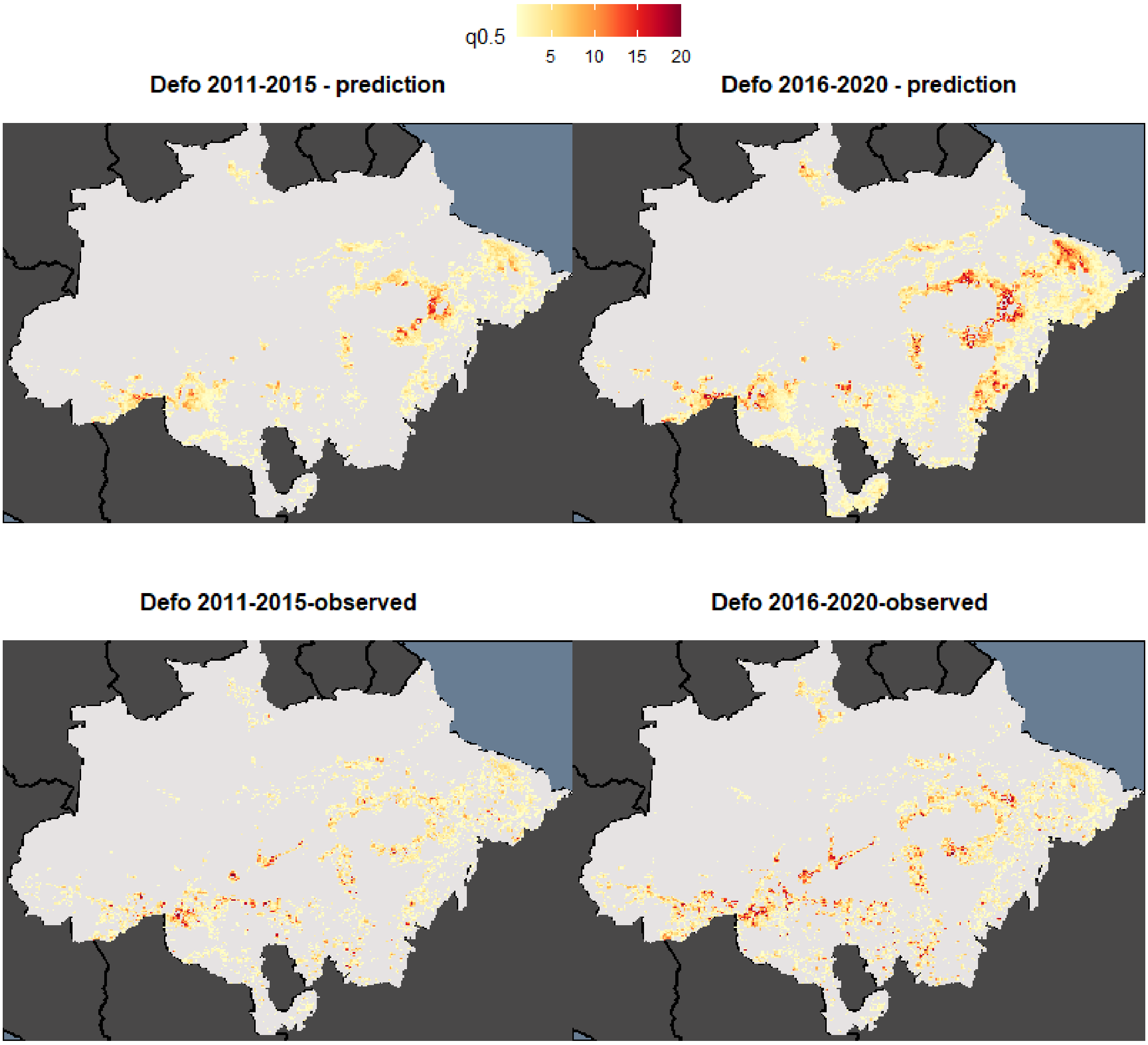


Fig. S7. Map of the number of median numbers of deforestation fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.

Model forest fires

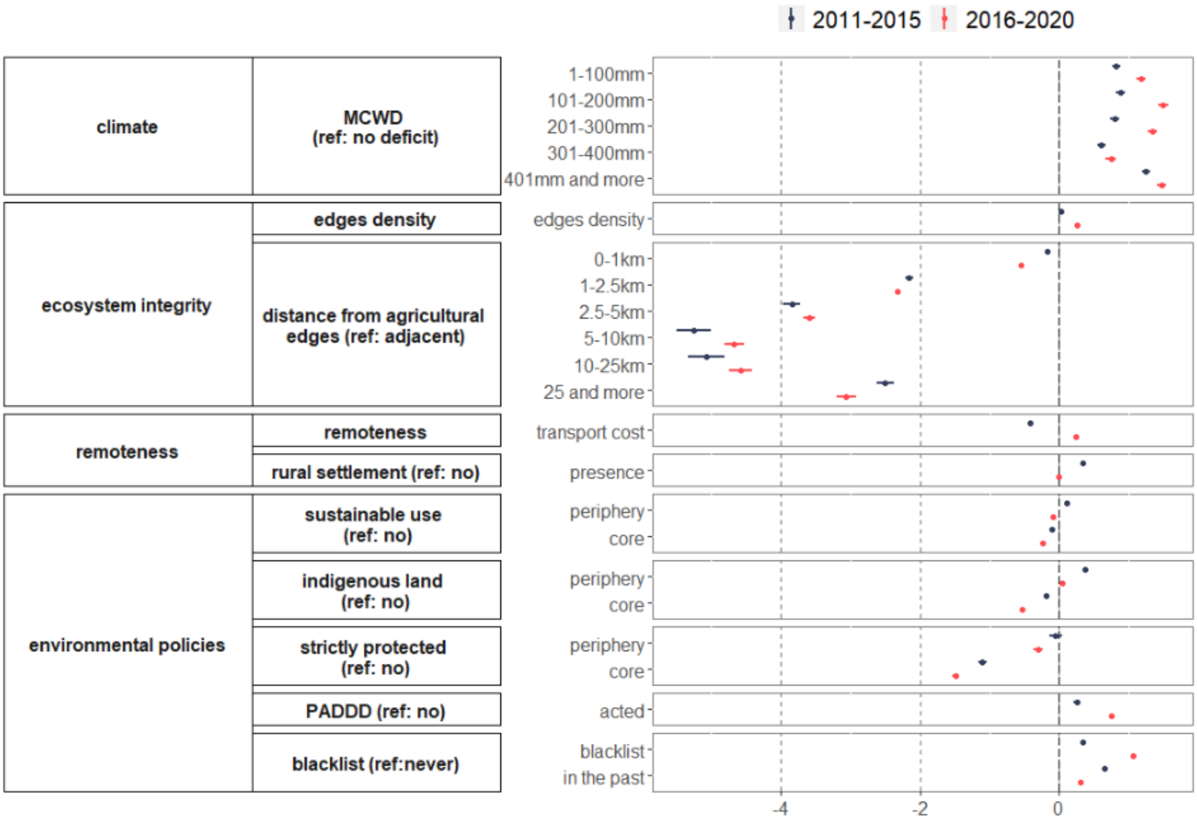


Fig. S8. Posterior means and 95% credible intervals of explanatory variables of explanatory variables for forest fires in the Brazilian Amazon

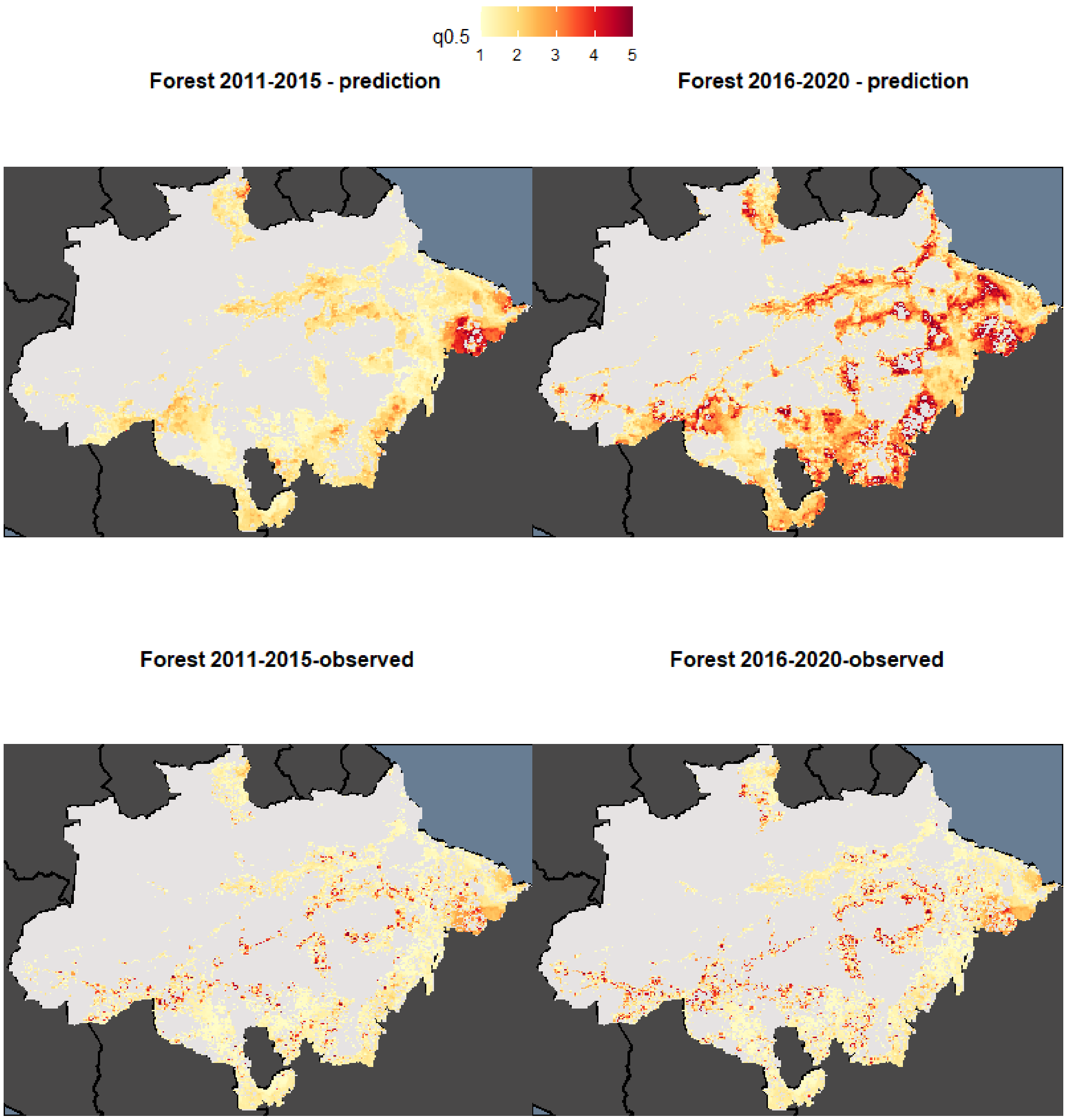


Fig. S9. Map of the number of median numbers of forest fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.

Model agricultural fires

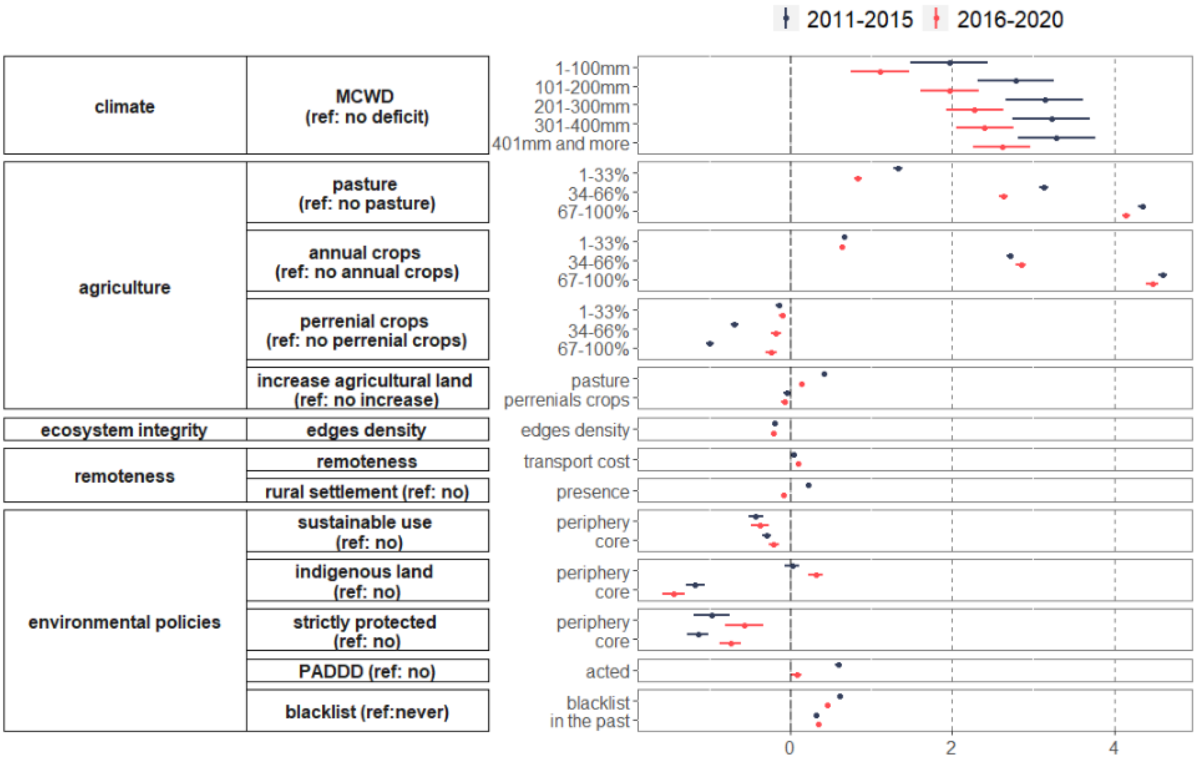


Fig. S10. Posterior means and 95% credible intervals of posterior distribution of explanatory variables for agricultural fires in the Brazilian Amazon

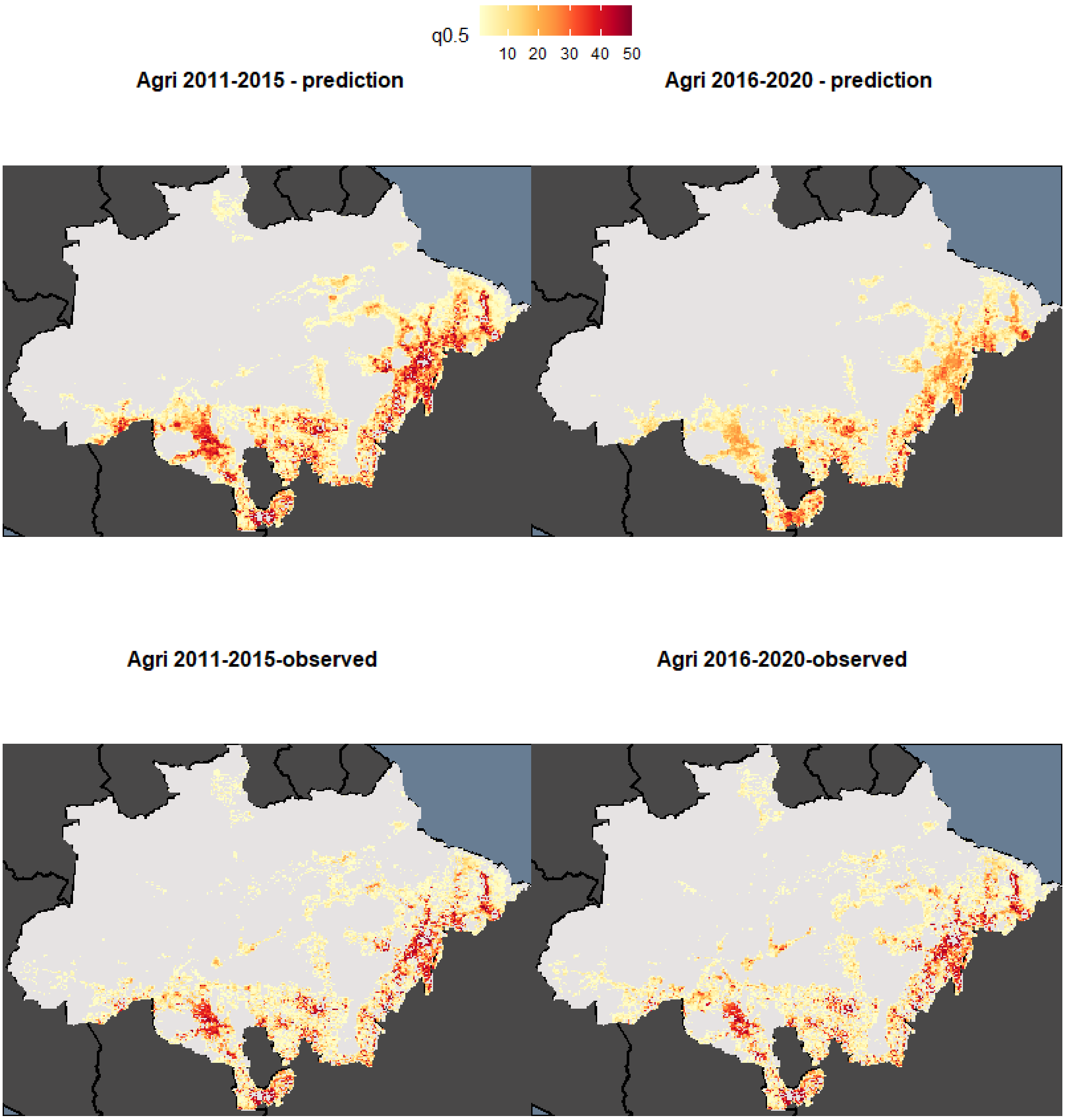


Fig. S11. Map of the number of median numbers of agricultural fires predicted by the models (2000 replicas) and observed in 10km2 pixels for the two periods.

Supporting Information 6: References

1. H. Rue, S. Martino, N. Chopin, Approximate Bayesian inference for latent Gaussian models by using integrated nested Laplace approximations. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*. **71**, 319–392 (2009).
2. F. Lindgren, H. Rue, J. Lindström, 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 (2011).
3. F. E. Bachl, F. Lindgren, D. L. Borchers, J. B. Illian, inlabru: an R package for Bayesian spatial modelling from ecological survey data. *Methods in Ecology and Evolution*. **10**, 760–766 (2019).
4. R Core Team, R: A language and environment for statistical computing (2022), (available at https://www.R-project.org).
5. M. V. F. Silveira, 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, A. L. R. Freitas, A. Z. V. Motta, L. M. E. Carvalho, C. H. L. Silva Junior, L. O. Anderson, L. E. O. C. Aragão, Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land*. **9**, 516 (2020).
6. E. Y. Arima, C. S. Simmons, R. T. Walker, M. A. Cochrane, Fire in the Brazilian Amazon: a Spatially Explicit Model for Policy Impact Analysis. *Journal of Regional Science*. **47**, 541–567 (2007).
7. M. G. Fonseca, L. O. Anderson, E. Arai, Y. E. Shimabukuro, H. A. M. Xaud, M. R. Xaud, N. Madani, F. H. Wagner, L. E. O. C. Aragão, Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications*. **27**, 2514–2527 (2017).
8. B. Soares-Filho, R. Silvestrini, D. Nepstad, P. Brando, H. Rodrigues, A. Alencar, M. Coe, C. Locks, L. Lima, L. Hissa, C. Stickler, Forest fragmentation, climate change and understory fire regimes on the Amazonian landscapes of the Xingu headwaters. *Landscape Ecology*. **27**, 585–598 (2012).
9. L. E. O. C. Aragão, Y. Malhi, R. M. Roman-Cuesta, S. Saatchi, L. O. Anderson, Y. E. Shimabukuro, Spatial patterns and fire response of recent Amazonian droughts. *Geophysical Research Letters*. **34** (2007), doi:10.1029/2006GL028946.
10. M. G. Fonseca, L. E. O. C. Aragão, A. Lima, Y. E. Shimabukuro, E. Arai, L. O. Anderson, Modelling fire probability in the Brazilian Amazon using the maximum entropy method. *International Journal of Wildland Fire*. **25**, 955–969 (2016).
11. L. E. O. C. Aragão, L. O. Anderson, M. G. Fonseca, T. M. Rosan, L. B. Vedovato, F. H. Wagner, C. V. J. Silva, C. H. L. Silva Junior, E. Arai, A. P. Aguiar, J. Barlow, E. Berenguer, M. N. Deeter, L. G. Domingues, L. Gatti, M. Gloor, Y. Malhi, J. A. Marengo, J. B. Miller, O. L. Phillips, S. Saatchi, 21st Century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications*. **9**, 536 (2018).
12. P. M. Brando, J. K. Balch, D. C. Nepstad, D. C. Morton, F. E. Putz, M. T. Coe, D. Silverio, M. N. Macedo, E. A. Davidson, C. C. Nobrega, A. Alencar, B. S. Soares-Filho, Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proceedings of the National Academy of Sciences*. **111**, 6347–6352 (2014).
13. D. C. Nepstad, C. M. Stickler, B. S.- Filho, F. Merry, 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 (2008).
14. D. C. Morton, R. S. Defries, J. T. Randerson, L. Giglio, W. Schroeder, G. R. Van Der Werf, Agricultural intensification increases deforestation fire activity in Amazonia: Deforestation Fires in Amazonia. *Global Change Biology*. **14**, 2262–2275 (2008).
15. A. Cano-Crespo, P. J. C. Oliveira, A. Boit, M. Cardoso, K. Thonicke, Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences*. **120**, 2095–2107 (2015).

16. T. Morello, L. Falcão, 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 (2020).
17. A. Tyukavina, M. C. Hansen, P. V. Potapov, S. V. Stehman, K. Smith-Rodriguez, C. Okpa, R. Aguilar, Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science Advances*. **3** (2017), doi:10.1126/sciadv.1601047.
18. E. N. Broadbent, G. P. Asner, M. Keller, D. E. Knapp, P. J. C. Oliveira, J. N. Silva, Forest fragmentation and edge effects from deforestation and selective logging in the Brazilian Amazon. *Biological Conservation*, 13 (2008).
19. G. P. Asner, D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, J. N. Silva, Selective Logging in the Brazilian Amazon. *Science*. **310**, 480–482 (2005).
20. G. P. Asner, E. N. Broadbent, P. J. C. Oliveira, M. Keller, D. E. Knapp, J. N. M. Silva, Condition and fate of logged forests in the Brazilian Amazon. *Proceedings of the National Academy of Sciences*. **103**, 12947–12950 (2006).
21. J. K. Balch, P. M. Brando, D. C. Nepstad, M. T. Coe, D. Silvério, T. J. Massad, E. A. Davidson, P. Lefebvre, C. Oliveira-Santos, W. Rocha, R. T. S. Cury, A. Parsons, K. S. Carvalho, The Susceptibility of Southeastern Amazon Forests to Fire: Insights from a Large-Scale Burn Experiment. *BioScience*. **65**, 893–905 (2015).
22. J. K. Balch, D. C. Nepstad, L. M. Curran, P. M. Brando, O. Portela, P. Guilherme, J. D. Reuning-Scherer, O. de Carvalho, Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management*. **261**, 68–77 (2011).
23. J. Barlow, C. A. Peres, Fire-mediated dieback and compositional cascade in an Amazonian forest. *Philosophical Transactions of the Royal Society B: Biological Sciences*. **363**, 1787–1794 (2008).
24. C. P. Barber, M. A. Cochrane, C. M. Souza, W. F. Laurance, Roads, deforestation, and the mitigating effect of protected areas in the Amazon. *Biological Conservation*. **177**, 203–209 (2014).
25. M. S. Bowman, G. S. Amacher, F. D. Merry, Fire use and prevention by traditional households in the Brazilian Amazon. *Ecological Economics*. **67**, 117–130 (2008).
26. M. Schneider, C. A. Peres, Environmental Costs of Government-Sponsored Agrarian Settlements in Brazilian Amazonia. *PLoS ONE*. **10** (2015), doi:10.1371/journal.pone.0134016.
27. A. M. Yanai, E. M. Nogueira, P. M. L. de Alencastro Graça, P. M. Fearnside, Deforestation and Carbon Stock Loss in Brazil’s Amazonian Settlements. *Environmental Management*. **59**, 393–409 (2017).
28. A. M. Yanai, P. M. L. de A. Graça, M. I. S. Escada, L. G. Ziccardi, P. M. Fearnside, Deforestation dynamics in Brazil’s Amazonian settlements: Effects of land-tenure concentration. *Journal of Environmental Management*. **268** (2020), doi:10.1016/j.jenvman.2020.110555.
29. G. C. Carrero, P. M. Fearnside, D. R. do Valle, C. de Souza Alves, 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 (2020).
30. T. A. P. West, P. M. Fearnside, Brazil’s conservation reform and the reduction of deforestation in Amazonia. *Land Use Policy*. **100** (2021), doi:10.1016/j.landusepol.2020.105072.
31. R. Carmenta, G. A. Blackburn, G. Davies, C. de Sassi, A. Lima, L. Parry, W. Tych, J. Barlow, Does the Establishment of Sustainable Use Reserves Affect Fire Management in the Humid Tropics? *PLoS ONE*. **11** (2016), doi:10.1371/journal.pone.0149292.
32. C. Nolte, A. Agrawal, K. M. Silvius, B. S. Soares-Filho, 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 (2013).
33. B. Soares-Filho, P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, M. Bowman, L. Hissa, R. Silvestrini, C. Maretti, Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences*. **107**, 10821–10826 (2010).
34. D. Herrera, A. Pfaff, J. Robalino, 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 (2019).

35. J. Assunção, C. Gandour, R. Rocha, Deforestation slowdown in the Brazilian Amazon: prices or policies? *Environment and Development Economics*. **20**, 697–722 (2015).
36. J. Börner, K. Kis-Katos, J. Hargrave, K. König, Post-Crackdown Effectiveness of Field-Based Forest Law Enforcement in the Brazilian Amazon. *PLoS ONE*. **10**, e0121544 (2015).
37. M. Kalamandeen, E. Gloor, E. Mitchard, D. Quincey, G. Ziv, D. Spracklen, B. Spracklen, M. Adami, L. E. O. C. Aragão, D. Galbraith, Pervasive Rise of Small-scale Deforestation in Amazonia. *Scientific Reports*. **8**, 1600 (2018).
38. P. Richards, E. Arima, L. VanWey, A. Cohn, N. Bhattarai, Are Brazil's Deforesters Avoiding Detection? *Conservation Letters*. **10**, 470–476 (2017).
39. I. M. D. Rosa, C. Souza, R. M. Ewers, Changes in Size of Deforested Patches in the Brazilian Amazon: Dynamics of Amazonian Deforestation. *Conservation Biology*. **26**, 932–937 (2012).
40. W. D. Carvalho, K. Mustin, R. R. Hilário, I. M. Vasconcelos, V. Eilers, P. M. Fearnside, 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 (2019).
41. E. J. de Area Leão Pereira, P. J. Silveira Ferreira, L. C. de Santana Ribeiro, T. Sabadini Carvalho, H. B. de Barros Pereira, Policy in Brazil (2016–2019) threaten conservation of the Amazon rainforest. *Environmental Science & Policy*. **100**, 8–12 (2019).
42. L. Ferrante, P. M. Fearnside, Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate. *Environmental Conservation*. **46**, 261–263 (2019).
43. S. M. Pack, M. N. Ferreira, R. Krithivasan, J. Murrow, E. Bernard, M. B. Mascia, Protected area downgrading, downsizing, and degazettement (PADDD) in the Amazon. *Biological Conservation*. **197**, 32–39 (2016).
44. D. Keles, P. Delacote, A. Pfaff, S. Qin, M. B. Mascia, What Drives the Erasure of Protected Areas? Evidence from across the Brazilian Amazon. *Ecological Economics*. **176**, 106733 (2020).
45. J. Assunção, R. Rocha, Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics*. **24**, 115–137 (2019).
46. E. Cisneros, S. L. Zhou, J. Börner, Naming and Shaming for Conservation: Evidence from the Brazilian Amazon. *PLoS ONE*. **10** (2015), doi:10.1371/journal.pone.0136402.
47. C. S. Simmons, R. T. Walker, E. Y. Arima, S. P. Aldrich, M. M. Caldas, The Amazon Land War in the South of Pará. *Annals of the Association of American Geographers*. **97**, 567–592 (2007).
48. C. S. Simmons, The Political Economy of Land Conflict in the Eastern Brazilian Amazon. *Annals of the Association of American Geographers*. **94**, 183–206 (2004).
49. C. S. Simmons, Territorializing land conflict: Space, place, and contentious politics in the Brazilian Amazon. *GeoJournal*. **64**, 307–317 (2005).
50. L. Ferrante, M. Gomes, P. M. Fearnside, Amazonian indigenous peoples are threatened by Brazil's Highway BR-319. *Land Use Policy*. **94** (2020), doi:10.1016/j.landusepol.2020.104548.
51. O. Bolaños, Redefining identities, redefining landscapes: indigenous identity and land rights struggles in the Brazilian Amazon. *Journal of Cultural Geography*. **28**, 45–72 (2011).
52. M. L. Ferreira Barbosa, R. C. Delgado, C. Forsad de Andrade, P. E. Teodoro, C. A. Silva Junior, H. S. Wanderley, G. F. Capristo-Silva, Recent trends in the fire dynamics in Brazilian Legal Amazon: Interaction between the ENSO phenomenon, climate and land use. *Environmental Development*. **39** (2021), doi:10.1016/j.envdev.2021.100648.
53. T. F. Morello, Predicting fires for policy making: Improving accuracy of fire brigade allocation in the Brazilian Amazon. *Ecological Economics*. **169**, 14 (2020).
54. J. M. Adeney, N. L. Christensen, S. L. Pimm, Reserves Protect against Deforestation Fires in the Amazon. *PLoS ONE*. **4** (2009), doi:10.1371/journal.pone.0005014.
55. W. Xu, Y. Liu, S. Veraverbeke, W. Wu, Y. Dong, W. Lu, Active Fire Dynamics in the Amazon: New Perspectives From High-Resolution Satellite Observations. *Geophysical Research Letters*. **48** (2021), doi:10.1029/2021GL093789.
56. L. E. O. C. Aragão, Y. E. Shimabukuro, The Incidence of Fire in Amazonian Forests with Implications for REDD. *Science*. **328**, 1275–1278 (2010).

57. M. J. E. van Marle, R. D. Field, G. R. van der Werf, I. A. Estrada de Wagt, R. A. Houghton, L. V. Rizzo, P. Artaxo, K. Tsigaridis, Fire and deforestation dynamics in Amazonia (1973-2014): Fire Dynamics in Amazonia (1973-2014). *Global Biogeochemical Cycles*. **31**, 24–38 (2017).
58. D. Armenteras, T. M. González, J. Retana, Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests. *Biological Conservation*. **159**, 73–79 (2013).
59. T. Jusys, Changing patterns in deforestation avoidance by different protection types in the Brazilian Amazon. *PLoS ONE*. **13** (2018), doi:10.1371/journal.pone.0195900.
60. D. de C. Victoria, R. F. B. da Silva, J. D. A. Millington, V. Katerinchuk, M. Batistella, Transport cost to port though Brazilian federal roads network: Dataset for years 2000, 2005, 2010 and 2017. *Data in Brief*. **36**, 107070 (2021).
61. PADDtracker, PADDDtracker. *PADDDtracker* (2020), (available at https://www.padddtracker.org).
62. W. R. Tobler, A Computer Movie Simulating Urban Growth in the Detroit Region. *Economic Geography*. **46**, 234 (1970).
63. T. Opitz, F. Bonneu, E. Gabriel, Point-process based Bayesian modeling of space–time structures of forest fire occurrences in Mediterranean France. *Spatial Statistics*. **40** (2020), doi:10.1016/j.spasta.2020.100429.
64. L. Serra, M. Saez, J. Mateu, D. Varga, P. Juan, C. Díaz-Ávalos, H. Rue, Spatio-temporal log-Gaussian Cox processes for modelling wildfire occurrence: the case of Catalonia, 1994–2008. *Environmental and Ecological Statistics*. **21**, 531–563 (2014).
65. R. Carroll, A. B. Lawson, C. Faes, R. S. Kirby, M. Aregay, K. Watjou, Comparing INLA and OpenBUGS for hierarchical Poisson modeling in disease mapping. *Spatial and Spatio-temporal Epidemiology*. **14–15**, 45–54 (2015).
66. P. Juan Verdoy, Enhancing the SPDE modeling of spatial point processes with INLA, applied to wildfires. Choosing the best mesh for each database. *Communications in Statistics - Simulation and Computation*. **50**, 2990–3030 (2021).
67. D. Simpson, H. Rue, A. Riebler, T. G. Martins, S. H. Sørbye, Penalising Model Component Complexity: A Principled, Practical Approach to Constructing Priors. *Statistical Science*. **32** (2017), doi:10.1214/16-STS576.