Comparing the determinants of deforestation, agricultural and forest fires in the Brazilian Amazon between 2009 and 2024

Authors Michel Valette [1,2*], Yiannis Kountouris[1,2], Anna Freni Sterrantino[3,4], Jeremy Woods[1,2] and Morena Mills[1,2]

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

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

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

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

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

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

ABSTRACT

Fires are a major source of carbon emissions and biodiversity loss in the Brazilian Amazon. Climatic and ecological processes affect the flammability of the landscape, while socio-economic processes influence the use of fire. Understanding different types of fires and characterizing how economic, climatic and environmental conditions influence each, is essential for designing effective and targeted land and fire management policies. We investigated the social, economic and environmental determinants of deforestation, agricultural and forest fires between 2009 and 2024 in the Brazilian Amazon. Pastures were associated with the highest number of deforestation and agricultural fires. Protected areas were associated with fewer deforestation and forest fires, and strictly protected areas and Indigenous land experienced more fires close to their borders. Fire occurrence also increased in remote locations between 2009 and 2024. Our results highlight the importance of spatially targeted management practices to curb fires and reduce environmental degradation.

INTRODUCTION

Wildfires are a major driver of tropical forest degradation and carbon emissions globally: 41% of humid tropical forest loss was linked to fire activity between 2003 and 2018 (Van Wees et al. 2021), and tropical forest fires have become an increasingly important carbon source (Jones et al. 2022). Fire disturbances can shift vegetation composition by favouring fire-resistant shrubs and grasses over fire-sensitive trees, reducing biodiversity (Nunes et al. 2022), preventing rainforest regeneration and limiting their resilience to external disturbances (Drüke et al. 2023). Wildfires in tropical landscapes also carry high socio-economic costs, including impact on human health, agricultural assets, infrastructure, and access to forest products (Carmenta et al. 2021). The Brazilian Amazon is particularly affected by increasing fire activity (Jones et al. 2022), which is projected to intensify as climate change drives longer and more intense dry seasons (Abatzoglou et al. 2019) and forests become increasingly fragmented (Ma et al. 2023).

Recurrent wildfire crises in the Brazilian Amazon have historically been attributed to deforestation, with government responses focused on conservation policy and criminalisation of fire use (Sorrensen 2009). While the rapid decline in deforestation after 2004 correlated with a marked decrease in fires, deforestation rates and fire occurrence decoupled, suggesting a growing influence of other drivers (Aragão and Shimabukuro 2010). The failure of criminalisation of fire use can be partly explained by the reliance of local communities on fire for livelihoods (Carmenta et al. 2021; Smith et al. 2025). In the Brazilian Amazon, fire is used for many objectives, such as clearing fields, disposing of crop residues, managing vegetation regrowth and soil fertility or reducing landscape flammability (Pivello 2011). Some of these fires escape their intended confines and turn into forest fires (Cano-Crespo et al. 2015).

In response to failure of criminalisation of fire use (Sorrensen 2009; Machado et al. 2024), Integrated Fire Management has been proposed and was sanctioned by federal law in Brazil in 2024. This approach aims, among other objectives, to understand local fire management, address the root causes of undesirable fires, and align the aspirations of landholders with conservation and fire management objectives (Oliveras Menor et al. 2025). It also emphasis the role of fire control measures, including monitoring, fire breaks, and burning under low-risk meteorological conditions.

Addressing the root causes of undesirable fires requires understanding the relationship between people, land and fires (Mistry and Bizerril 2011). Regional assessments relying on remote-sensing data can support national-level policies, for example through the identification of priority areas for fire brigade deployment (Fonseca Morello et al. 2020). Traditional remote-sensing products and models tend to conflate many fire types, regardless of their management objectives, size, intensity, or impact (Kasoar et al. 2024). Remote-sensing and modelling approaches distinguishing different fire types, each with their respective drivers and impacts on ecosystems and society, can help bridge the gap between policies targeting deforestation, forest degradation, agricultural development (Sorrensen 2009). To date, there are no existing assessments of the drivers associated with different types of fires in the region. Regional analysis of fire drivers focused on either overall fire activity (Fonseca et al. 2017; Silveira et al. 2020), or a single fire type (Armenteras et al. 2013; Silva Junior et al. 2018), despite significant differences in fire size, duration, intensity and rate of spread according to land use burned (Cano-Crespo et al. 2023).

Here, we analyse and compare the processes that drive different fires types, and assess whether they responded similarly to changes in regional environmental governance. Using deforestation and land use datasets, we classify satellite-detected fires into deforestation, agricultural, and forest fires, and apply spatio-temporal statistical models to estimate their relationship with socio-economic and environmental drivers from 2009 to 2024. Deforestation fires burn over small areas, but they are the most intense fires and typically burn over several days, contributing significantly to regional air pollution and carbon emissions (Andela et al. 2022). Agricultural fires are generally short-lived and low intensity but have important impacts on livelihoods, biodiversity and ecosystem services (Morello and Falcão 2020; Andela et al. 2022). Finally, forest fires, which are predominantly caused by escaping deforestation fires and agricultural fires, can burn over extended periods and large areas, driving significant regional forest degradation, associated biodiversity loss and air pollution (Andela et al. 2022; Cano-Crespo et al. 2023).

For each fire type, we fitted models over five time periods, using different phases of the Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAm), a regional program coordinating policies interventions to reduce deforestation. This work contributes to the literature on fire regime drivers in tropical forests (Fonseca et al., 2017; Jones et al., 2022a; Silveira et al., 2020) and the impact of conservation policies on fire regimes in the Brazilian Amazon (Adeney et al., 2009; Libonati et al., 2021; Sorrensen, 2009).

Methods

Outcome variables

The response variables were created using MapBiomas Fogo collection 4 burned areas (30m resolution), MapBiomas land cover collection 10 (30m resolution, Souza et al. 2020), and PRODES deforestation. For each year we stacked the three layers and identified three different types of fires following rules:

- **Deforestation fires:** burned area and deforestation events overlap, represent 3.94 ± 3.66% of the total burned area.
- **Agricultural fires:** burned areas and pastoral/agricultural land cover overlap without deforestation, represent 43.00 ± 4.99% of the total burned area.
- **Forest fires:** burned areas and forest overlap without deforestation, represent 19.91± 9.07% of the total burned areas.

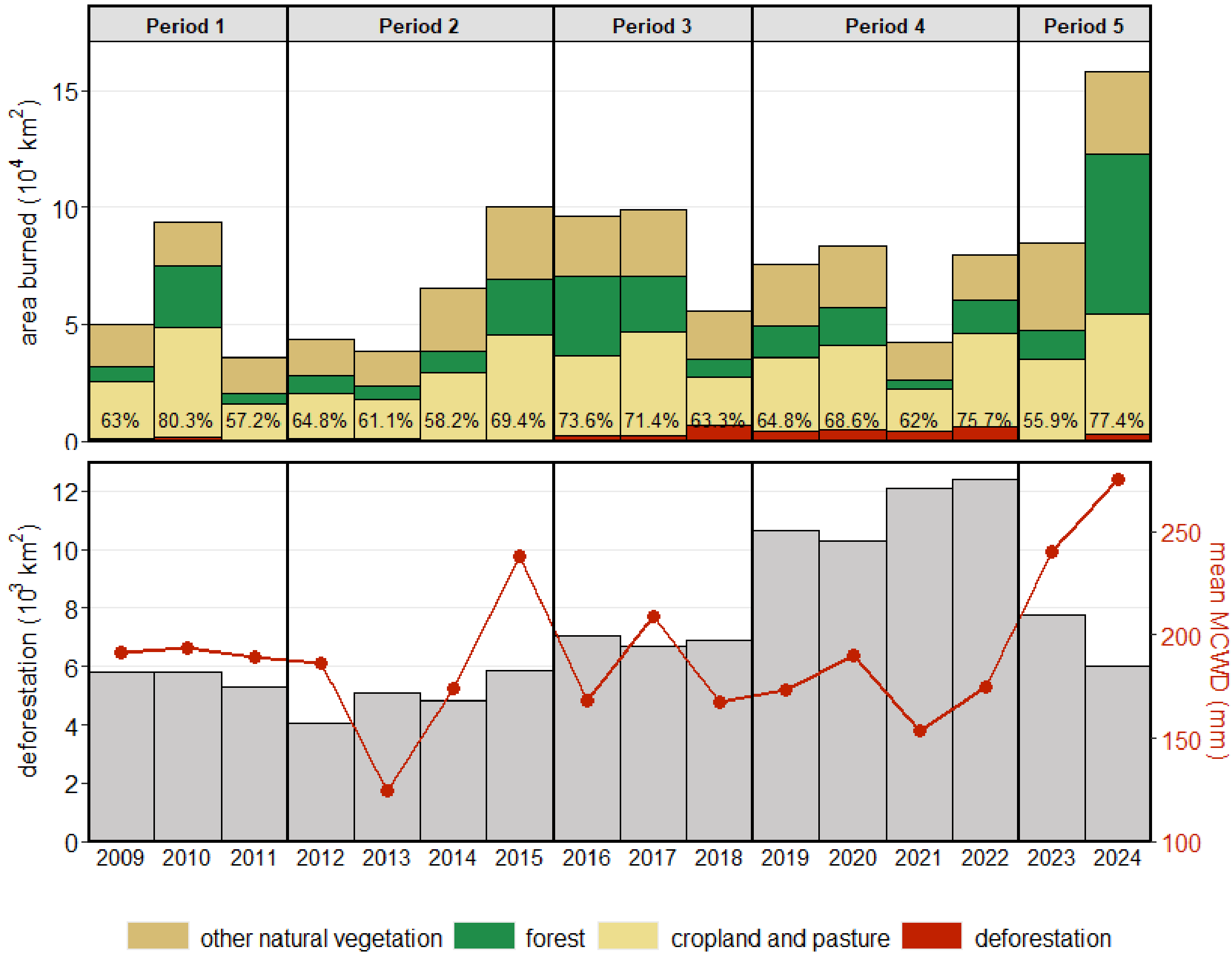

Figure 1. Histogram of the total burned areas for different types of fires (top) and deforestation and drought intensity (bottom). The percentage corresponds to the proportions of the total burned areas represented by the fires modelled each year.

Remaining burned areas are mostly covered by other natural vegetations, which were excluded from modelling given the potential benefits of appropriate fire regimes for biodiversity and wildfire risk reduction in these areas (Bilbao et al. 2010; Ferreira et al. 2022, see Figure 1 for the percentage of fires excluded each year).

Explanatory variables

To identify explanatory variables, we did a non-exhaustive review of the literature and identified 51 relevant papers published between 2004 and 2022, including 24 quantitative analyses of fire drivers and impacts, 17 on deforestation drivers and impacts, 4 on other sources of forest degradation, and 6 providing a broader context on the links between these phenomena (see SI1 for details). This led to the identification of 14 drivers of fire regimes in the Brazilian Amazon, from which 18 variables were initially selected and matched to data sources covering 2009–2024 at the highest available spatial and temporal resolution. After evaluating redundancy and correlation, 12 variables were retained and aggregated into a 1 km grid (Figure 2). To address skewed distributions and improve interpretability, all explanatory variables were categorised (SI2).

Statistical Methods

We modelled fire occurrences on an annual basis, accounting for both spatial and temporal dependence. To handle excess zeros in the data, due to the scarcity of fires pixels compared to unburned pixel, we defined a Zero-Inflated Poisson model for fire events and estimated it within a Bayesian framework (R-INLA). Spatial dependence was captured using the stochastic partial differential equation (SPDE) approach, which provides a computationally efficient, Markovian representation of a Matérn covariance structure (Lindgren et al., 2011). Temporal dependence was incorporated through a first-order autoregressive (AR1) random effect across years.

Drivers	Variable included in the model			Data sources
Response variable	deforestation fires	agricultural fires	forest fires	Mapbiomas Fogo collection 4, Mapbiomas collection 10, PRODES
Drought	maximum cumulated water deficit (mm)			CHIRPS
Forest fragmentation	edge density ($m.ha^{-1}$)		distance from agricultural land (km)	Mapbiomas collection 10
Remoteness	transport cost (RU)			Dataset from de Castro Victoria et al. (2021)
Rural settlement	rural settlement			INCRA (National Institute for Colonization and Agrarian Reform)
Land use	dominant agricultural land use (pasture/annual crops/ perennial crops)			Mapbiomas collection 10
land use change	land use change (pasture/annual crops/ perennial crops)			
Sustainable use areas (IUCN categories IV to VI)	core, periphery (<10km from unprotected areas), outside (unprotected areas <10km from sustainable use area)			World Database on Protected Areas
Indigenous lands	core, periphery (<10km from unprotected areas), outside (unprotected areas <10km from Indigenous land)			
Strictly protected areas (IUCN categories I to III)	core, periphery (<10km from unprotected areas), outside (unprotected areas <10km from strictly protected area)			
PADDD	protected areas that were declassified or downsized			PADDDtracker
Priority list	municipalities that were never on the priority list/ currently on the list/ removed from the list			MMA (Ministry of Environment)

Table 1. Drivers and variables included in the models for different types of fires. The data sources used, and the categorisation of each variable are detailed in further details in SI2.

For each fire type, five models were fitted to investigate changes in the association between variables and fires (see Table 1). Study periods were defined using the phases of the PPDCDAm, a regional program coordinating different policy interventions to reduce deforestation. Each phase was characterized by distinct deforestation dynamics, environmental governance objectives and associated instruments deployed to reach them such as focus on law enforcement or economic incentives to favor sustainable land use practices (West and Fearnside 2021). We removed one year from phase 4 of the PPCDAm to create a period corresponding to Bolsonaro's administration, marked by a weakening of environmental policies and surging deforestation (Menezes and Barbosa 2021).

Period	**2009-2011**	**2012-2015**	**2016-2018**	**2019-2022**	**2023-2024**
Environmental governance	PPCDAm phase 2	PPCDAm phase 3	3 years of PPCDAm phase 4	1 year of PPCDAm phase 4 and temporary suspension	PPCDAm phase 5
Deforestation rate	5 637 ± 295 km^2	4 958 ± 726 km^2	6 864 ± 169 km^2	11 365± 1 040km^2	6 886 ± 1 223 km^2
Average Maximum Cumulated Water Deficit	191 ± 2 mm	181 ± 46 mm	182 ± 24 mm	173 ± 15 mm	258 ± 25 mm
Percentage of burned area classified as deforestation fires	1.84 ± 0.28%	1.21 ± 1.08%	5.91 ± 5.79%	7.27 ± 2.19%	2.00 ± 1.41%
Percentage of burned area classified as agricultural fires	47.25 ± 4.31%	44.52 ± 0.58%	38.91 ± 5.35%	44.29 ± 3.98%	37.10 ± 6.43%
Percentage of burned area classified as forest fires	17.67 ± 9.16%	17.57 ± 4.60%	24.53 ± 10.96%	16.17 ± 4.02%	28.48 ± 20.26%

Table 2. Summary of the deforestation rate, maximum cumulated water deficit, and proportions of the fires classified in each category.

We reported results as log-linear posterior means with 95% credible intervals, referring to posterior probability as probability through the result section for simplicity. To evaluate the accuracy of the models, we determined optimal classification thresholds for each model, derived predicted occurrence of fires and compared them to observed fire presence (SI 4). We also examined different metrics to assess the discriminative ability, precision and recall, probability calibration, distributional fit of residuals and alignment of temporal trends with observed data (SI5). We used the package INLA version 24.10 of the software R 4.4 (R Core Team 2022).

Results

The most important drivers of fire occurrence varied depending on the fire type considered (Figures 3 to 5). Agricultural land use had the strongest positive effect on posterior estimates of deforestation and agricultural fire, with pastoral landscapes showing highest credible rates of fire occurrence. Protected areas had an especially strong inhibitory impact on deforestation and forest fires, while climate and forest degradation had the largest effect on the probability of forest fires. Across the study period, rural settlements were associated with decreasing posterior estimate of all types of fire occurrence, while areas with high transport costs were associated with increasing posterior estimates.

Models performance

Overall, the models reproduce observed fire patterns reasonably well (SI4), with high discriminative ability and good calibration at low fire probability values. However, all models tend to overpredict fire occurrence in the most fire-prone pixels, and predicted probabilities are under-dispersed (SI5). Models for deforestation and agricultural fires consistently outperformed forest fire models, suggesting that the drivers of forest fire occurrence are harder to capture with the selected covariates.

Climatic factors

The probability of forest fire was positively associated with low to medium intensity droughts (1–300 mm MCWD) in all periods except 2019–2022 (Figure 5). The probability of deforestation fire increased during low to medium intensity droughts in 2016–2018, and during moderate drought (101–200 mm MCWD) in 2009–2011 (Figure 3).

Forest degradation

Forest degradation shaped the occurrence of forest fires and, to a lesser extent, deforestation fires. Distance from agricultural land strongly influenced the probability of forest fires, though not consistently across all periods (Figure 5). During 2019–2022, forests without adjacent agricultural land had a lower fire probability than in other periods, regardless of the distance class. By 2023–2024, this effect persisted only within 5 km, with more distant forests reverting to pre-2019 fire probability levels, suggesting a spatial homogenisation of forest fire risk. Forest fragmentation was positively associated with the probability of deforestation fire across all periods (Figure 3).

Infrastructure and development

Transport cost was associated with higher probability of all types of fires across most periods and categories (Figures 3 to 5). High transport costs (>20K RU) displayed the most dynamic relationship with fire presence. High transport costs were associated with a lower probability of forest fire during 2009–2011 but were associated with a higher probability of fire presence for deforestation and forest fires during 2019–2022, and for agricultural fires during 2019–2024. Rural settlements were associated with a decreasing probability of deforestation fire over time (Figure 3), and with a decreasing probability of both agricultural fire until 2018 (Figure 4) and forest fire across all periods, except for 2019–2022 (Figure 5).

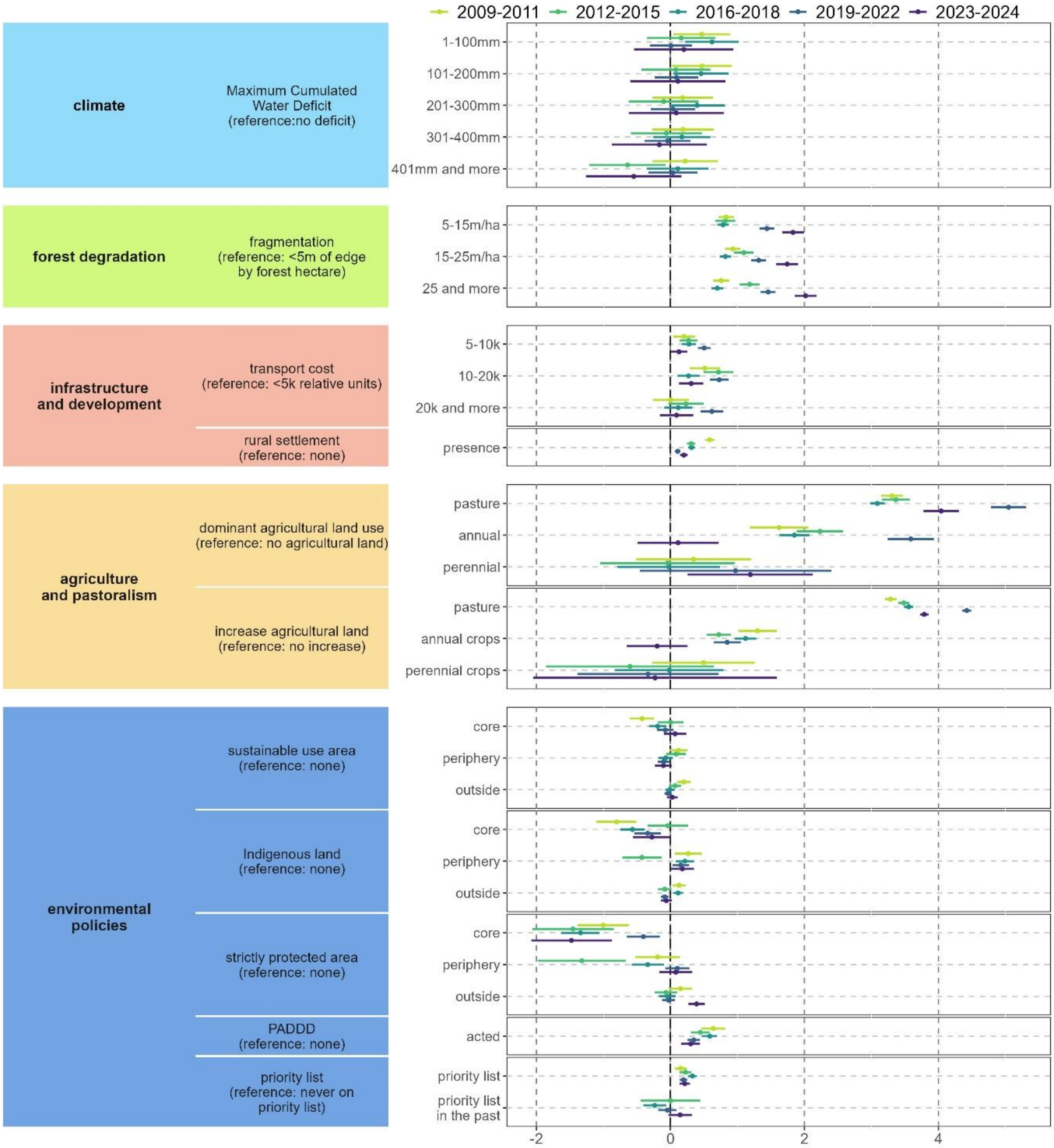

Figure 3. Posterior means and 95% credible intervals for explanatory variables of the models for deforestation fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable negatively associated with probability of deforestation fires occurrence, and intervals higher than 0 indicate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

Agriculture and pastoralism

Land use shaped the probability of fire presence for both deforestation and agricultural fires, with pastures showing a higher probability of fire presence for deforestation fires and, to a lesser extent, agricultural fires (Figures 3 and 4).

The probability of deforestation fires on land with pasture increased from 2019 onwards, and that of agricultural fires during 2023-2024. Annual crops were associated with higher probability of deforestation fire until 2022, though this remained lower than for pastures despite a notable increase in probability during 2019–2022. Perennial crop cover showed a positive association with deforestation fire only during the last period.

Pastures were associated with the highest probability of agricultural fire regardless of the period, while annual crops were associated with higher probabilities of agricultural fires than perennials crop during 2009-2022, and showed a decreasing probability of agricultural fire during 2023-2024.

Increasing pasture cover was associated with the highest probability of fire for both deforestation and agricultural fires, while increasing annual crop cover showed a positive association with deforestation and agricultural fire presence until 2022.

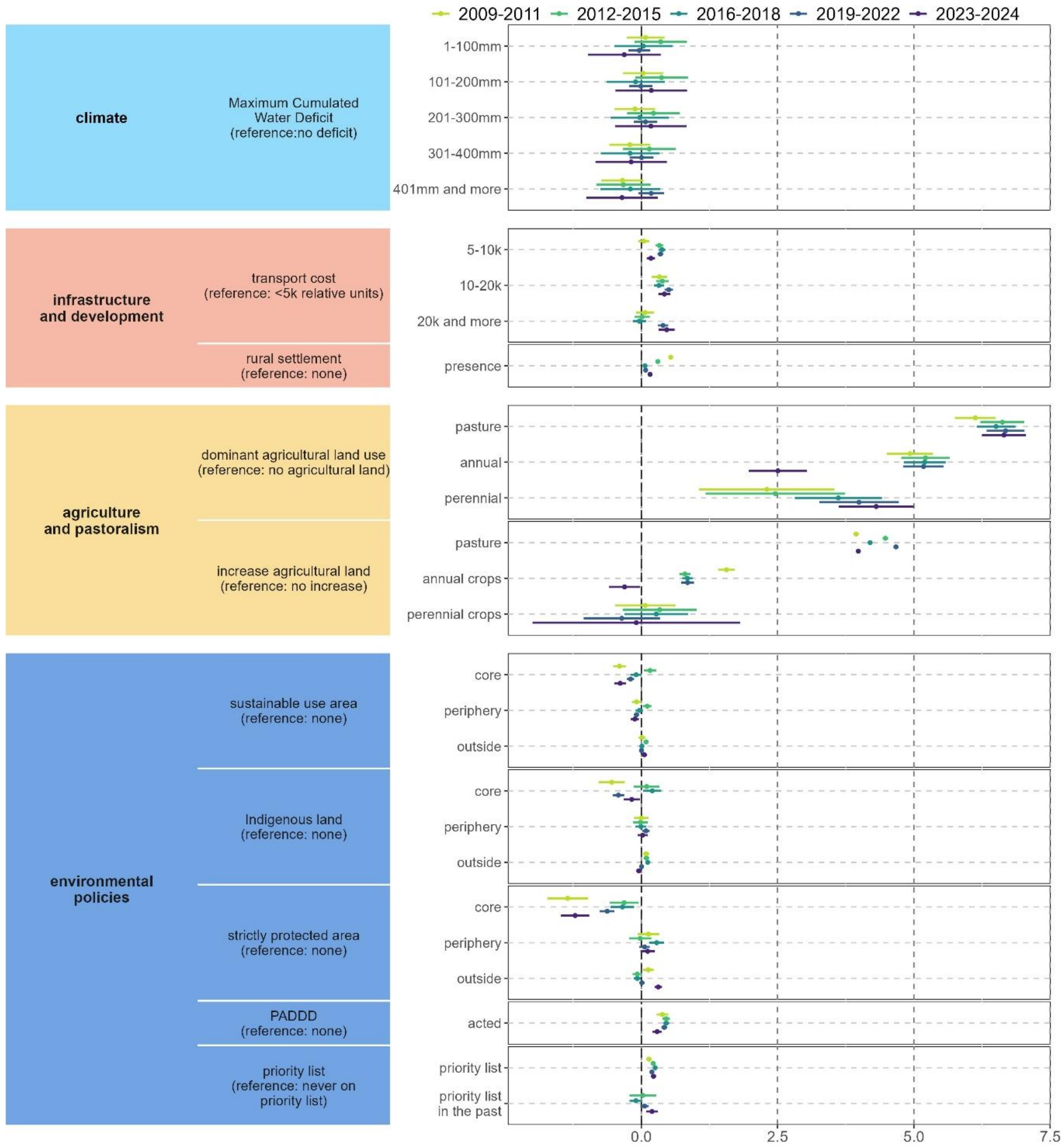

Figure 4. Posterior means and 95% credible intervals for explanatory variables of the models for agricultural fires in the Brazilian Amazon (log scale). Intervals lower than 0 indicate a variable negatively associated with probability of agricultural fires, and intervals higher than 0 indicate variables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

Environmental policies

All types of protected areas were associated with a lower probability of fires, though the strength of this association varied by protection regime, period, and proximity to land outside protected areas. Strictly protected areas, especially their core, provided the most consistent protection across all fire types and periods (Figures 3 to 5). Their core was associated with the lowest probability of deforestation fires during 2012–2015 and 2023–2024. The core of Indigenous lands was also negatively associated with the probability of deforestation fires until 2023, and of forest fires during three out of five periods. The core of sustainable use areas was negatively associated with the probability of deforestation fires until 2018 and of forest fires during the three periods with the lowest deforestation rates.

The probability of fires presence was generally higher in the periphery of all types of protected areas than in their core, though this difference varied across protection regimes. The peripheries of strictly protected areas and Indigenous lands were no longer associated with decreased probability of deforestation fires from 2019 onwards. While the periphery of strictly protected areas was associated with higher probability of forest fire only during the 2019-2022 period, the periphery of Indigenous land was associated with higher probability of forest fires across all periods except the one with the lowest deforestation pressure. Contrastingly, periphery of sustainable use areas were associated with a higher probability of deforestation fires until 2018 and forest fires until 2015. Increased fire probability in the periphery of strictly protected areas coincided with increased probability in their surroundings, and this pattern was unique to a single period

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

Areas that had experienced PADDD were associated with a higher probability of deforestation fires between 2012 and 2018, as well as agricultural fires and forest fires. Municipalities on the priority list were associated with a higher probability of deforestation fires occurring from 2016 onwards, and agricultural fires and forest fires. Municipalities previously removed from the priority list were associated with a lower probability of agricultural fires during 2016–2018 and of forest fires across all periods.

DISCUSSION

Fire regimes in the Brazilian Amazon are shaped by different processes depending on fire type. While past modelling efforts have predominantly treated fire as a single phenomenon, deforestation, agricultural and forest fires are shaped by distinct sets of drivers whose relative importance has shifted over time. We found droughts primarily amplified forest fire risk, while land use and governance drove deforestation and agricultural fires. Fire activity in agricultural landscape persisted beyond initial clearing phase, and all types of fires became increasingly common in areas with high transport cost. Protected areas and Indigenous lands reduced fire probability, but their effectiveness varied by protection regime, proximity to the border, and period of analysis.

Droughts had a limited impact on deforestation and agricultural fires, and primarily influenced probability of forest fires, up until a certain drought intensity. This aligns with studies showing complex and non-linear relationships between weather and fire regimes across the Amazon, where high fire activity can occur during relatively wet years (Fonseca et al. 2019; Libonati et al. 2021). During the period with the lowest drought intensity and highest deforestation pressure, forest fires were more influenced by the landscape configuration than drought intensity, signaling a potential shift in the processes driving their occurrence. The weaker influence of drought on deforestation and agricultural fires suggests these are driven primarily by human decision, consistent with evidence that landholders adjust fire use based on policy interventions and socio-economic factors (Cammelli and Angelsen 2019).

The interiorization of fire regimes

Pastures were associated with a higher probability of both deforestation and agricultural fires, aligning with previous work (Silveira et al. 2020; Nunes et al. 2022; Ribeiro et al. 2024) and highlighting the continued reliance on fires as a land management tool in pastoral landscapes. Fire activity persists beyond initial clearing: pasture and, to a lesser extent, annual crops remain associated with a higher probability of fires over time, consistent with Ribeiro et al. (2024). This persistence of agricultural fires has long-term consequences, including hampering soil carbon accumulation (Stahl et al. 2017), starting wildfires (Cano-Crespo et al. 2015), and preventing the regeneration of secondary forests.

Reduced probability of deforestation and agricultural fires associated with annual and perennial crops and their expansions compared to pastures supports the hypothesis that agricultural intensification can reduce fire activity in tropical landscapes (Andela et al. 2017). However, agricultural intensification is spatially heterogeneous and has indirect effects: accessible areas undergo intensification and associated reduction in fire activity, while deforestation increases in remote areas (Garrett et al. 2018), where limited access to inputs and fire-vulnerable assets makes fire a cost-effective management tool (Carmenta et al. 2019; Cammelli et al. 2020).

The increasing probability of fires in remote, high-transport-cost areas points to the use of fires in new deforestation frontiers opening deeper into the Amazon, likely driven by agricultural intensification and land speculation (Gollnow et al. 2018). During 2019-2022, the period with the highest rates of deforestation, the probability of deforestation fires in pastures and all fire types in high-transport-cost areas increased. The persistence of agricultural fires in remote areas afterwards shows that these pulses of deforestation create lasting impacts and contribute to future forest fires (Mataveli et al. 2024). The Priority List Program appears to extend its effects beyond deforestation (Assunção and Rocha 2019) and influence fire management, which could be useful in controlling post-deforestation fire activity.

The "interiorisation" of fires into regions with high transport costs has profound ecological consequences. These forests, unexposed to fires previously, lack the fire-resistant traits present in seasonally dry Amazonian forests (Balch et al. 2011) and are likely to suffer higher tree mortality and compositional shifts, creating positive feedback loops as altered species composition and increased fuel loads raise future fires probability (Balch et al. 2015; Prestes et al. 2020). This could contribute to the widespread degradation and loss of resilience of forests already observed across the Amazon basin (Boulton et al. 2022), which could partly explain increasing number of fires in forest distant from agricultural land.

Fires and protected areas

The lower probability of fires identified in all types of protected areas extends previous analyses (Adeney et al. 2009; Nolte et al. 2013), showing that they can limit different types of fires. The higher probability of all types of fires after PADDD events underscores the importance of long-term persistence of protected areas to prevent forest degradation. Strictly protected areas were associated with the lowest probability of fires but only outperformed Indigenous lands in limiting deforestation fires during periods with stronger regional enforcement of environmental policies, complementing (Soares-Filho et al. (2010) Indigenous lands were associated with lower probabilities of forest fires, despite frequent fire use in their territories for cultural and livelihood objectives (Pivello 2011). This could be due to the extensive local ecological knowledge mobilised to prevent fires from escaping (Huffman 2013). Increasing probability of forest fires in Indigenous land might reveal emerging threats:

drying climate, changes in vegetation and continuity of the fuel create favorable conditions for large forest fires (Brando et al. 2020; Valette et al. 2026).

Sustainable use areas showed higher fire probabilities than other protected areas, likely because they are inhabited, permit fire-dependent livelihood activities, and receive less funding for fire management than strictly protected areas (Oliveira et al. 2021). Legal requirements regulating fire use in these areas are often unrealistic given the constraints faced by landholders and are frequently disregarded in practice (Carmenta et al. 2013). Loose regulations on land ownership in certain types of sustainable use areas can also lead to extensive deforestation (Jesus and Catojo 2020).

The higher probability of deforestation and forest fires at the periphery of protected areas compared to their cores aligns with previous evidence showing that external fire occurrence and land use partly explain internal fire dynamics (Santos et al. 2021; Walker et al. 2022), and that proximity to highways increases fire prevalence in Indigenous lands (Silva et al. 2022). During 2019-2022, increased deforestation fire probability at these peripheries, but not in adjacent unprotected land or sustainable use areas, suggests heightened land invasion pressure, add influence of broader environmental governance context. Sustainable use areas experienced a different dynamic, with increasingly similar fire probability in their periphery and core overtime, which could indicate an endogenous fire risk. Analysis relying on medium to high-resolution mapping of fires within and close to Indigenous lands and protected areas, as well as ground-based studies, could shed light on the relationship between fires outside and within these areas (Carmenta et al. 2011; Yadav and Thompson 2025).

Conclusion

Climate, forest degradation, infrastructure, agriculture and environmental policies influence agriculture, deforestation and forest fires. Pastures remain the land use associated with highest fire activity. This showcases the need to not only alleviate deforestation but also support better land management strategies on already-deforested land to prevent fires from escaping further degrading the remaining forests.

Since 2009, fire regimes intensified in remote regions of the Brazilian Amazon and, during relatively wet years, landscape configuration became an increasingly important drivers of forest fire. This "interiorization" of fires in the Brazilian Amazon, occurring in the context of a drying climate and a loss of resilience of the forest to external disturbances, raises concerns about potential forest diebacks in the region.

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

Data availability statement

Upon publication, data will be made available in a digital repository, and the analysis code is already accessible https://github.com/michel-va/INLA_SPDE_fire_BA .

References

Abatzoglou, J. T., A. P. Williams, and R. Barbero. 2019. Global Emergence of Anthropogenic Climate Change in Fire Weather Indices. *Geophysical Research Letters* 46: 326–336. doi:10.1029/2018GL080959.

Adeney, J. M., N. L. Christensen, and S. L. Pimm. 2009. Reserves Protect against Deforestation Fires in the Amazon. Edited by Rob P. Freckleton. *PLoS ONE* 4. doi:10.1371/journal.pone.0005014.

Andela, N., D. C. Morton, L. Giglio, Y. Chen, G. R. Van Der Werf, P. S. Kasibhatla, R. S. DeFries, G. J. Collatz, et al. 2017. A human-driven decline in global burned area. *Science* 356: 1356–1362. doi:10.1126/science.aal4108.

Andela, N., D. C. Morton, W. Schroeder, Y. Chen, P. M. Brando, and J. T. Randerson. 2022. Tracking and classifying Amazon fire events in near real time. *Science Advances* 8. doi:10.1126/sciadv.abd2713.

Aragão, L. E. O. C., and Y. E. Shimabukuro. 2010. The Incidence of Fire in Amazonian Forests with Implications for REDD. *Science* 328: 1275–1278. doi:10.1126/science.1186925.

Armenteras, D., T. M. González, and J. Retana. 2013. Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests. *Biological Conservation* 159: 73–79. doi:10.1016/j.biocon.2012.10.026.

Assunção, J., and R. Rocha. 2019. Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics* 24: 115–137. doi:10.1017/S1355770X18000499.

Balch, J. K., D. C. Nepstad, L. M. Curran, P. M. Brando, O. Portela, P. Guilherme, J. D. Reuning-Scherer, and O. de Carvalho. 2011. Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management* 261: 68–77. doi:10.1016/j.foreco.2010.09.029.

Balch, J. K., P. M. Brando, D. C. Nepstad, M. T. Coe, D. Silvério, T. J. Massad, E. A. Davidson, P. Lefebvre, et al. 2015. The Susceptibility of Southeastern Amazon Forests to Fire: Insights from a Large-Scale Burn Experiment. *BioScience* 65: 893–905. doi:10.1093/biosci/biv106.

Bilbao, B. A., A. V. Leal, and C. L. Méndez. 2010. Indigenous Use of Fire and Forest Loss in Canaima National Park, Venezuela. Assessment of and Tools for Alternative Strategies of Fire Management in Pemón Indigenous Lands. *Human Ecology* 38: 663–673. doi:10.1007/s10745-010-9344-0.

Boulton, C. A., T. M. Lenton, and N. Boers. 2022. Pronounced loss of Amazon rainforest resilience since the early 2000s. *Nature Climate Change* 12: 271–278. doi:10.1038/s41558-022-01287-8.

Brando, P. M., B. Soares-Filho, L. Rodrigues, A. Assunção, D. Morton, D. Tuchschneider, E. C. M. Fernandes, M. N. Macedo, et al. 2020. The gathering firestorm in southern Amazonia. *Science Advances* 6. doi:10.1126/sciadv.aay1632.

Cammelli, F., and A. Angelsen. 2019. Amazonian farmers' response to fire policies and climate change. *Ecological Economics* 165. doi:10.1016/j.ecolecon.2019.106359.

Cammelli, F., R. D. Garrett, J. Barlow, and L. Parry. 2020. Fire risk perpetuates poverty and fire use among Amazonian smallholders. *Global Environmental Change* 63. doi:10.1016/j.gloenvcha.2020.102096.

Cano-Crespo, A., P. J. C. Oliveira, A. Boit, M. Cardoso, and K. Thonicke. 2015. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences* 120: 2095–2107. doi:10.1002/2015JG002914.

Cano-Crespo, A., D. Traxl, G. Prat-Ortega, S. Rolinski, and K. Thonicke. 2023. Characterization of land cover-specific fire regimes in the Brazilian Amazon. *Regional Environmental Change* 23: 19. doi:10.1007/s10113-022-02012-z.

Carmenta, R., L. Parry, A. Blackburn, S. Vermeylen, and J. Barlow. 2011. Understanding Human-Fire Interactions in Tropical Forest Regions: a Case for Interdisciplinary Research across the Natural and Social Sciences. *Ecology and Society* 16. doi:10.5751/ES-03950-160153.

Carmenta, R., S. Vermeylen, L. Parry, and J. Barlow. 2013. Shifting Cultivation and Fire Policy: Insights from the Brazilian Amazon. *Human Ecology* 41: 603–614. doi:10.1007/s10745-013-9600-1.

Carmenta, R., E. Coudel, and A. M. Steward. 2019. Forbidden fire: Does criminalising fire hinder conservation efforts in swidden landscapes of the Brazilian Amazon? *The Geographical Journal* 185: 23–37. doi:10.1111/geoj.12255.

Carmenta, R., F. Cammelli, W. Dressler, C. Verbicaro, and J. G. Zaehringer. 2021. Between a rock and a hard place: The burdens of uncontrolled fire for smallholders across the tropics. *World Development* 145. doi:10.1016/j.worlddev.2021.105521.

Drüke, M., B. Sakschewski, W. Von Bloh, M. Billing, W. Lucht, and K. Thonicke. 2023. Fire may prevent future Amazon forest recovery after large-scale deforestation. *Communications Earth & Environment* 4. doi:10.1038/s43247-023-00911-5.

Ferreira, M. J., C. Levis, L. Chaves, C. R. Clement, and G. T. Soldati. 2022. Indigenous and Traditional Management Creates and Maintains the Diversity of Ecosystems of South American Tropical Savannas. *Frontiers in Environmental Science* 10: 809404. doi:10.3389/fenvs.2022.809404.

Fonseca, M. G., L. O. Anderson, E. Arai, Y. E. Shimabukuro, H. A. M. Xaud, M. R. Xaud, N. Madani, F. H. Wagner, et al. 2017. Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications* 27: 2514–2527. doi:10.1002/eap.1628.

Fonseca, M. G., L. M. Alves, A. P. D. Aguiar, E. Arai, L. O. Anderson, T. M. Rosan, Y. E. Shimabukuro, and L. E. O. E. C. De Aragão. 2019. Effects of climate and land-use change scenarios on fire probability during the 21st century in the Brazilian Amazon. *Global Change Biology* 25: 2931–2946. doi:10.1111/gcb.14709.

Fonseca Morello, T., R. Marchetti Ramos, L. O. Anderson, N. Owen, T. M. Rosan, and L. Steil. 2020. Predicting fires for policy making: Improving accuracy of fire brigade allocation in the Brazilian Amazon. *Ecological Economics* 169. doi:10.1016/j.ecolecon.2019.106501.

Garrett, R. D., I. Koh, E. F. Lambin, Y. Le Polain De Waroux, J. H. Kastens, and J. C. Brown. 2018. Intensification in agriculture-forest frontiers: Land use responses to development and conservation policies in Brazil. *Global Environmental Change* 53: 233–243. doi:10.1016/j.gloenvcha.2018.09.011.

Gollnow, F., L. de B. V. Hissa, P. Rufin, and T. Lakes. 2018. Property-level direct and indirect deforestation for soybean production in the Amazon region of Mato Grosso, Brazil. *Land Use Policy* 78: 377–385. doi:10.1016/j.landusepol.2018.07.010.

Huffman, M. R. 2013. The Many Elements of Traditional Fire Knowledge: Synthesis, Classification, and Aids to Cross-cultural Problem Solving in Fire-dependent Systems Around the World. *Ecology and Society* 18. doi:10.5751/ES-05843-180403.

Jesus, S. C. de, and A. M. Z. Catojo. 2020. Deforestation in Conservation Units of the Brazilian Amazon: the case of the Terra do Meio Mosaic. *Ciência e Natura* 42: 1–23. doi:10.5902/2179460X41390.

Jones, M. W., J. T. Abatzoglou, S. Veraverbeke, N. Andela, G. Lasslop, M. Forkel, A. J. P. Smith, C. Burton, et al. 2022. Global and Regional Trends and Drivers of Fire Under Climate Change. *Reviews of Geophysics* 60. doi:10.1029/2020RG000726.

Kasoar, M., O. Perkins, J. D. A. Millington, J. Mistry, and C. Smith. 2024. Model fires, not ignitions: Capturing the human dimension of global fire regimes. *Cell Reports Sustainability* 1: 100128. doi:10.1016/j.crsus.2024.100128.

Libonati, R., J. M. C. Pereira, C. C. Da Camara, L. F. Peres, D. Oom, J. A. Rodrigues, F. L. M. Santos, R. M. Trigo, et al. 2021. Twenty-first century droughts have not increasingly exacerbated fire season severity in the Brazilian Amazon. *Scientific Reports* 11. doi:10.1038/s41598-021-82158-8.

Ma, J., J. Li, W. Wu, and J. Liu. 2023. Global forest fragmentation change from 2000 to 2020. *Nature Communications* 14. doi:10.1038/s41467-023-39221-x.

Machado, M. S., E. Berenguer, P. M. Brando, A. Alencar, I. Oliveras Menor, J. Barlow, and Y. Malhi. 2024. Emergency policies are not enough to resolve Amazonia’s fire crises. *Communications Earth & Environment* 5. doi:10.1038/s43247-024-01344-4.

Mataveli, G., M. W. Jones, R. Carmenta, A. Sanchez, D. J. Dutra, M. Chaves, G. de Oliveira, L. O. Anderson, et al. 2024. Deforestation falls but rise of wildfires continues degrading Brazilian Amazon forests. *Global Change Biology* 30. doi:10.1111/gcb.17202.

Menezes, R. G., and R. Barbosa. 2021. Environmental governance under Bolsonaro: dismantling institutions, curtailing participation, delegitimising opposition. *Zeitschrift für Vergleichende Politikwissenschaft* 15: 229–247. doi:10.1007/s12286-021-00491-8.

Mistry, J., and M. Bizerril. 2011. Why It is Important to Understand the Relationship Between People, Fire and Protected Areas. *Biodiversidade Brasileira - BioBrasil* 2: 40–49.

Morello, T., and L. Falcão. 2020. The Fire Management Dilemma in the Brazilian Amazon: Synthesizing Pathways of Causality across Five Case Studies in the State of Pará. *Human Ecology* 48: 397–409. doi:10.1007/s10745-020-00166-0.

Nolte, C., A. Agrawal, K. M. Silvius, and B. S. Soares-Filho. 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 110: 4956–4961. doi:10.1073/pnas.1214786110.

Nunes, C. A., E. Berenguer, F. França, J. Ferreira, A. C. Lees, J. Louzada, E. J. Sayer, R. Solar, et al. 2022. Linking land-use and land-cover transitions to their ecological impact in the Amazon. *Proceedings of the National Academy of Sciences* 119. doi:10.1073/pnas.2202310119.

Oliveira, A. S., B. S. Soares-Filho, U. Oliveira, R. Van der Hoff, S. M. Carvalho-Ribeiro, A. R. Oliveira, L. C. Scheepers, B. A. Vargas, et al. 2021. Costs and effectiveness of public and private fire management programs in the Brazilian Amazon and Cerrado. *Forest Policy and Economics* 127. doi:10.1016/j.forpol.2021.102447.

Oliveras Menor, I., N. Prat-Guitart, G. L. Spadoni, A. Hsu, P. M. Fernandes, R. Puig-Gironès, D. Ascoli, B. A. Bilbao, et al. 2025. Integrated fire management as an adaptation and mitigation strategy to altered fire regimes. *Communications Earth & Environment* 6. doi:10.1038/s43247-025-02165-9.

Pivello, V. R. 2011. The use of fire in the cerrado and Amazonian rainforests of Brazil: past and present. *Fire Ecology* 7: 16. doi:https://doi.org/10.4996/fireecology.0701024.

Prestes, N. C. C. D. S., K. G. Massi, E. A. Silva, D. S. Nogueira, E. A. De Oliveira, R. Freitag, B. S. Marimon, B. H. Marimon-Junior, et al. 2020. Fire Effects on Understory Forest Regeneration in Southern Amazonia. *Frontiers in Forests and Global Change* 3. doi:10.3389/ffgc.2020.00010.

R Core Team. 2022. R: A language and environment for statistical computing (version V4.1). Vienna, Austria: R Foundation for Statistical Computing.

Ribeiro, A. F. S., L. Santos, J. T. Randerson, M. R. Uribe, A. A. C. Alencar, M. N. Macedo, D. C. Morton, J. Zscheischler, et al. 2024. The time since land-use transition drives changes in fire activity in the Amazon-Cerrado region. *Communications Earth & Environment* 5. doi:10.1038/s43247-024-01248-3.

Santos, A. M. dos, C. F. A. da Silva, A. P. Rudke, and D. de Oliveira Soares. 2021. Dynamics of active fire data and their relationship with fires in the areas of regularized indigenous lands in the Southern Amazon. *Remote Sensing Applications: Society and Environment* 23. doi:10.1016/j.rsase.2021.100570.

Schielein, J., and J. Börner. 2018. Recent transformations of land-use and land-cover dynamics across different deforestation frontiers in the Brazilian Amazon. *Land Use Policy* 76: 81–94. doi:10.1016/j.landusepol.2018.04.052.

Silva, C. F. A., S. T. Alvarado, A. M. Santos, M. O. Andrade, and S. N. Melo. 2022. Highway Network and Fire Occurrence in Amazonian Indigenous Lands. *Sustainability* 14. doi:10.3390/su14159167.

Silva Junior, C., L. Aragão, M. Fonseca, C. Almeida, L. Vedovato, and L. Anderson. 2018. Deforestation-Induced Fragmentation Increases Forest Fire Occurrence in Central Brazilian Amazonia. *Forests* 9. doi:10.3390/f9060305.

Silveira, M. V. F., C. A. Petri, I. S. Broggio, G. O. Chagas, M. S. Macul, C. C. S. S. Leite, E. M. M. Ferrari, C. G. V. Amim, et al. 2020. Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land* 9: 516. doi:10.3390/land9120516.

Smith, C., O. Perkins, J. Mistry, B. A. Bilbao, R. Bliege Bird, A. Cardinal Christianson, K. M. De Freitas, W. Dressler, et al. 2025. A global expert elicitation on present-day human–fire interactions. *Philosophical Transactions of the Royal Society B: Biological Sciences* 380. doi:10.1098/rstb.2023.0463.

Soares-Filho, B., P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, et al. 2010. Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences* 107: 10821–10826. doi:10.1073/pnas.0913048107.

Sorrensen, C. 2009. Potential hazards of land policy: Conservation, rural development and fire use in the Brazilian Amazon. *Land Use Policy* 26: 782–791. doi:10.1016/j.landusepol.2008.10.007.

Souza, C. M., J. Z. Shimbo, M. R. Rosa, L. L. Parente, A. A. Alencar, B. F. T. Rudorff, H. Hasenack, M. Matsumoto, et al. 2020. Reconstructing Three Decades of Land Use and Land Cover Changes in Brazilian Biomes with Landsat Archive and Earth Engine. *Remote Sensing* 12. doi:10.3390/rs12172735.

Stahl, C., S. Fontaine, K. Klumpp, C. Picon-Cochard, M. M. Grise, C. Dezécache, L. Ponchant, V. Freycon, et al. 2017. Continuous soil carbon storage of old permanent pastures in Amazonia. *Global Change Biology* 23: 3382–3392. doi:10.1111/gcb.13573.

Valette, M., R. Metuktire, J. Mistry, K. Metuktire, Y. Juruna, J. Martins, R. Chiaravalloti, J. Bonanomi, et al. 2026. Using Participatory Mapping to Strengthen Indigenous Resilience for Wildfire Risk: Lessons From Capoto/Jarina, Brazil. *Geo: Geography and Environment* 13: e70062. doi:10.1002/geo2.70062.

Van Wees, D., G. R. Van Der Werf, J. T. Randerson, N. Andela, Y. Chen, and D. C. Morton. 2021. The role of fire in global forest loss dynamics. *Global Change Biology* 27: 2377–2391. doi:10.1111/gcb.15591.

Walker, K., A. Flores-Anderson, L. Villa, R. Griffin, M. Finer, and K. Herndon. 2022. An analysis of fire dynamics in and around indigenous territories and protected areas in a Brazilian agricultural frontier. *Environmental Research Letters* 17. doi:10.1088/1748-9326/ac8237.

Yadav, K., and H. Thompson. 2025. Adding Lines Along Pixels: Remote Sensing, Traditional Knowledge and Human–Fire Interactions in Ethiopia and India. *Geo: Geography and Environment* 12: e70050. doi:10.1002/geo2.70050.

Supporting information 1: Framework of potential drivers of fires regimes

At the initial stage of this research, we conducted a non-systematic literature review to investigate the potential theoretical framework of drivers of fire regimes in the region and identify relevant data sources. This non-systematic literature review encompasses 51 publications ranging from 2004 to 2022, focusing on the Brazilian Amazon region. Out of these publications, 24 report results from quantitative analysis of drivers and impacts of fires, 17 report results from quantitative analysis of deforestation drivers and impacts, 4 report results from quantitative analysis looking at forest degradation drivers and impact, as well as 6 additional publications providing broader context on the link between drivers of deforestation, fires and other sources of forest degradation. The following paragraphs describe the main categories of drivers of fire regimes that were identified through the literature review, while table S1 details different links identified between potential variables and fires regimes in the Brazilian Amazon.

Climate

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

Agriculture and pastoralism

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

Forest degradation

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

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

Infrastructure and development

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

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

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

Environmental policies

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

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

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

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

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

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

References

Adeney, J. M., N. L. Christensen, and S. L. Pimm. 2009. Reserves Protect against Deforestation Fires in the Amazon. Edited by Rob P. Freckleton. *PLoS ONE* 4. doi:10.1371/journal.pone.0005014.

Aragão, L. E. O. C., and Y. E. Shimabukuro. 2010. The Incidence of Fire in Amazonian Forests with Implications for REDD. *Science* 328: 1275–1278. doi:10.1126/science.1186925.
Aragão, L. E. O. C., Y. Malhi, R. M. Roman-Cuesta, S. Saatchi, L. O. Anderson, and Y. E. Shimabukuro. 2007. Spatial patterns and fire response of recent Amazonian droughts. *Geophysical Research Letters* 34. doi:10.1029/2006GL028946.
Aragão, L. E. O. C., L. O. Anderson, M. G. Fonseca, T. M. Rosan, L. B. Vedovato, F. H. Wagner, C. V. J. Silva, C. H. L. Silva Junior, et al. 2018. 21st Century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications* 9: 536. doi:10.1038/s41467-017-02771-y.
de Area Leão Pereira, E. J., P. J. Silveira Ferreira, L. C. de Santana Ribeiro, T. Sabadini Carvalho, and H. B. de Barros Pereira. 2019. Policy in Brazil (2016–2019) threaten conservation of the Amazon rainforest. *Environmental Science & Policy* 100: 8–12. doi:10.1016/j.envsci.2019.06.001.
Arima, E. Y., C. S. Simmons, R. T. Walker, and M. A. Cochrane. 2007. Fire in the Brazilian Amazon: a Spatially Explicit Model for Policy Impact Analysis. *Journal of Regional Science* 47: 541–567. doi:10.1111/j.1467-9787.2007.00519.x.
Armenteras, D., T. M. González, and J. Retana. 2013. Forest fragmentation and edge influence on fire occurrence and intensity under different management types in Amazon forests. *Biological Conservation* 159: 73–79. doi:10.1016/j.biocon.2012.10.026.
Asner, G. P., D. E. Knapp, E. N. Broadbent, P. J. C. Oliveira, M. Keller, and J. N. Silva. 2005. Selective Logging in the Brazilian Amazon. *Science* 310: 480–482. doi:10.1126/science.1118051.
Asner, G. P., E. N. Broadbent, P. J. C. Oliveira, M. Keller, D. E. Knapp, and J. N. M. Silva. 2006. Condition and fate of logged forests in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 103: 12947–12950. doi:10.1073/pnas.0604093103.
Assunção, J., and R. Rocha. 2019. Getting greener by going black: the effect of blacklisting municipalities on Amazon deforestation. *Environment and Development Economics* 24: 115–137. doi:10.1017/S1355770X18000499.
Assunção, J., C. Gandour, and R. Rocha. 2015. Deforestation slowdown in the Brazilian Amazon: prices or policies? *Environment and Development Economics* 20: 697–722. doi:10.1017/S1355770X15000078.
Balch, J. K., D. C. Nepstad, L. M. Curran, P. M. Brando, O. Portela, P. Guilherme, J. D. Reuning-Scherer, and O. de Carvalho. 2011. Size, species, and fire behavior predict tree and liana mortality from experimental burns in the Brazilian Amazon. *Forest Ecology and Management* 261: 68–77. doi:10.1016/j.foreco.2010.09.029.
Balch, J. K., P. M. Brando, D. C. Nepstad, M. T. Coe, D. Silvério, T. J. Massad, E. A. Davidson, P. Lefebvre, et al. 2015. The Susceptibility of Southeastern Amazon Forests to Fire: Insights from a Large-Scale Burn Experiment. *BioScience* 65: 893–905. doi:10.1093/biosci/biv106.
Barber, C. P., M. A. Cochrane, C. M. Souza, and W. F. Laurance. 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. *Biological Conservation* 177: 203–209. doi:10.1016/j.biocon.2014.07.004.
Barlow, J., and C. A. Peres. 2008. Fire-mediated dieback and compositional cascade in an Amazonian forest. *Philosophical Transactions of the Royal Society B: Biological Sciences* 363: 1787–1794. doi:10.1098/rstb.2007.0013.
Börner, J., K. Kis-Katos, J. Hargrave, and K. König. 2015. Post-Crackdown Effectiveness of Field-Based Forest Law Enforcement in the Brazilian Amazon. Edited by Ricardo Bomfim Machado. *PLOS ONE* 10: e0121544. doi:10.1371/journal.pone.0121544.

Bowman, M. S., G. S. Amacher, and F. D. Merry. 2008. Fire use and prevention by traditional households in the Brazilian Amazon. *Ecological Economics* 67: 117–130. doi:10.1016/j.ecolecon.2007.12.003.

Brando, P. M., J. K. Balch, D. C. Nepstad, D. C. Morton, F. E. Putz, M. T. Coe, D. Silverio, M. N. Macedo, et al. 2014. Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proceedings of the National Academy of Sciences* 111: 6347–6352. doi:10.1073/pnas.1305499111.

Broadbent, E. N., G. P. Asner, M. Keller, D. E. Knapp, P. J. C. Oliveira, and J. N. Silva. 2008. Forest fragmentation and edge effects from deforestation and selective logging in the Brazilian Amazon. *Biological Conservation*: 13.

Cano-Crespo, A., P. J. C. Oliveira, A. Boit, M. Cardoso, and K. Thonicke. 2015. Forest edge burning in the Brazilian Amazon promoted by escaping fires from managed pastures. *Journal of Geophysical Research: Biogeosciences* 120: 2095–2107. doi:10.1002/2015JG002914.

Carmenta, R., G. A. Blackburn, G. Davies, C. de Sassi, A. Lima, L. Parry, W. Tych, and J. Barlow. 2016. Does the Establishment of Sustainable Use Reserves Affect Fire Management in the Humid Tropics? Edited by Clinton N. Jenkins. *PLOS ONE* 11. doi:10.1371/journal.pone.0149292.

Carrero, G. C., P. M. Fearnside, D. R. do Valle, and C. de Souza Alves. 2020. Deforestation Trajectories on a Development Frontier in the Brazilian Amazon: 35 Years of Settlement Colonization, Policy and Economic Shifts, and Land Accumulation. *Environmental Management* 66: 966–984. doi:10.1007/s00267-020-01354-w.

Carvalho, W. D., K. Mustin, R. R. Hilário, I. M. Vasconcelos, V. Eilers, and P. M. Fearnside. 2019. Deforestation control in the Brazilian Amazon: A conservation struggle being lost as agreements and regulations are subverted and bypassed. *Perspectives in Ecology and Conservation* 17: 122–130. doi:10.1016/j.pecon.2019.06.002.

Cisneros, E., S. L. Zhou, and J. Börner. 2015. Naming and Shaming for Conservation: Evidence from the Brazilian Amazon. Edited by Edward Webb. *PLOS ONE* 10. doi:10.1371/journal.pone.0136402.

Ferrante, L., and P. M. Fearnside. 2019. Brazil's new president and 'ruralists' threaten Amazonia's environment, traditional peoples and the global climate. *Environmental Conservation* 46: 261–263. doi:10.1017/S0376892919000213.

Ferreira Barbosa, M. L., R. C. Delgado, C. Forsad de Andrade, P. E. Teodoro, C. A. Silva Junior, H. S. Wanderley, and G. F. Capristo-Silva. 2021. Recent trends in the fire dynamics in Brazilian Legal Amazon: Interaction between the ENSO phenomenon, climate and land use. *Environmental Development* 39. doi:10.1016/j.envdev.2021.100648.

Fonseca, M. G., L. E. O. C. Aragão, A. Lima, Y. E. Shimabukuro, E. Arai, and L. O. Anderson. 2016. Modelling fire probability in the Brazilian Amazon using the maximum entropy method. *International Journal of Wildland Fire* 25: 955–969. doi:10.1071/WF15216.

Fonseca, M. G., L. O. Anderson, E. Arai, Y. E. Shimabukuro, H. A. M. Xaud, M. R. Xaud, N. Madani, F. H. Wagner, et al. 2017. Climatic and anthropogenic drivers of northern Amazon fires during the 2015-2016 El Niño event. *Ecological Applications* 27: 2514–2527. doi:10.1002/eap.1628.

Herrera, D., A. Pfaff, and J. Robalino. 2019. Impacts of protected areas vary with the level of government: Comparing avoided deforestation across agencies in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 116: 14916–14925. doi:10.1073/pnas.1802877116.

Kalamandeen, M., E. Gloor, E. Mitchard, D. Quincey, G. Ziv, D. Spracklen, B. Spracklen, M. Adami, et al. 2018. Pervasive Rise of Small-scale Deforestation in Amazonia. *Scientific Reports* 8: 1600. doi:10.1038/s41598-018-19358-2.

Keles, D., P. Delacote, A. Pfaff, S. Qin, and M. B. Mascia. 2020. What Drives the Erasure of Protected Areas? Evidence from across the Brazilian Amazon. *Ecological Economics* 176: 106733. doi:10.1016/j.ecolecon.2020.106733.

Morello, T., and L. Falcão. 2020. The Fire Management Dilemma in the Brazilian Amazon: Synthesizing Pathways of Causality across Five Case Studies in the State of Pará. *Human Ecology* 48: 397–409. doi:10.1007/s10745-020-00166-0.

Morello, T. F. 2020. Predicting fires for policy making: Improving accuracy of fire brigade allocation in the Brazilian Amazon. *Ecological Economics* 169: 14.

Morton, D. C., R. S. Defries, J. T. Randerson, L. Giglio, W. Schroeder, and G. R. Van Der Werf. 2008. Agricultural intensification increases deforestation fire activity in Amazonia: Deforestation Fires in Amazonia. *Global Change Biology* 14: 2262–2275. doi:10.1111/j.1365-2486.2008.01652.x.

Nepstad, D., S. Schwartzman, B. Bamberger, M. Santilli, D. Ray, P. Schlesinger, P. Lefebvre, A. Alencar, et al. 2006. Inhibition of Amazon Deforestation and Fire by Parks and Indigenous Lands: Inhibition of Amazon Deforestation and Fire. *Conservation Biology* 20: 65–73. doi:10.1111/j.1523-1739.2006.00351.x.

Nepstad, D. C., C. M. Stickler, B. S.- Filho, and F. Merry. 2008. Interactions among Amazon land use, forests and climate: prospects for a near-term forest tipping point. *Philosophical Transactions of the Royal Society B: Biological Sciences* 363: 1737–1746. doi:10.1098/rstb.2007.0036.

Nolte, C., A. Agrawal, K. M. Silvius, and B. S. Soares-Filho. 2013. Governance regime and location influence avoided deforestation success of protected areas in the Brazilian Amazon. *Proceedings of the National Academy of Sciences* 110: 4956–4961. doi:10.1073/pnas.1214786110.

Pack, S. M., M. N. Ferreira, R. Krithivasan, J. Murrow, E. Bernard, and M. B. Mascia. 2016. Protected area downgrading, downsizing, and degazettement (PADDD) in the Amazon. *Biological Conservation* 197: 32–39. doi:10.1016/j.biocon.2016.02.004.

Richards, P., E. Arima, L. VanWey, A. Cohn, and N. Bhattarai. 2017. Are Brazil's Deforesters Avoiding Detection? *Conservation Letters* 10: 470–476. doi:10.1111/conl.12310.

Rosa, I. M. D., C. Souza, and R. M. Ewers. 2012. Changes in Size of Deforested Patches in the Brazilian Amazon: Dynamics of Amazonian Deforestation. *Conservation Biology* 26: 932–937. doi:10.1111/j.1523-1739.2012.01901.x.

Santos, A. M. dos, C. F. A. da Silva, A. P. Rudke, and D. de Oliveira Soares. 2021. Dynamics of active fire data and their relationship with fires in the areas of regularized indigenous lands in the Southern Amazon. *Remote Sensing Applications: Society and Environment* 23. doi:10.1016/j.rsase.2021.100570.

Schneider, M., and C. A. Peres. 2015. Environmental Costs of Government-Sponsored Agrarian Settlements in Brazilian Amazonia. Edited by RunGuo Zang. *PLOS ONE* 10. doi:10.1371/journal.pone.0134016.

Silveira, M. V. F., C. A. Petri, I. S. Broggio, G. O. Chagas, M. S. Macul, C. C. S. S. Leite, E. M. M. Ferrari, C. G. V. Amim, et al. 2020. Drivers of Fire Anomalies in the Brazilian Amazon: Lessons Learned from the 2019 Fire Crisis. *Land* 9: 516. doi:10.3390/land9120516.

Soares-Filho, B., P. Moutinho, D. Nepstad, A. Anderson, H. Rodrigues, R. Garcia, L. Dietzsch, F. Merry, et al. 2010. Role of Brazilian Amazon protected areas in climate change mitigation. *Proceedings of the National Academy of Sciences* 107: 10821–10826. doi:10.1073/pnas.0913048107.

Soares-Filho, B., R. Silvestrini, D. Nepstad, P. Brando, H. Rodrigues, A. Alencar, M. Coe, C. Locks, et al. 2012. Forest fragmentation, climate change and understory fire regimes on the Amazonian landscapes of the Xingu headwaters. *Landscape Ecology* 27: 585–598. doi:10.1007/s10980-012-9723-6.

Tyukavina, A., M. C. Hansen, P. V. Potapov, S. V. Stehman, K. Smith-Rodriguez, C. Okpa, and R. Aguilar. 2017. Types and rates of forest disturbance in Brazilian Legal Amazon, 2000–2013. *Science Advances* 3. doi:10.1126/sciadv.1601047.

Walker, K., A. Flores-Anderson, L. Villa, R. Griffin, M. Finer, and K. Herndon. 2022. An analysis of fire dynamics in and around indigenous territories and protected areas in a Brazilian agricultural frontier. *Environmental Research Letters* 17: 084030. doi:10.1088/1748-9326/ac8237.

West, T. A. P., and P. M. Fearnside. 2021. Brazil's conservation reform and the reduction of deforestation in Amazonia. *Land Use Policy* 100. doi:10.1016/j.landusepol.2020.105072.

Xu, W., Y. Liu, S. Veraverbeke, W. Wu, Y. Dong, and W. Lu. 2021. Active Fire Dynamics in the Amazon: New Perspectives From High-Resolution Satellite Observations. *Geophysical Research Letters* 48. doi:10.1029/2021GL093789.

Yanai, A. M., E. M. Nogueira, P. M. L. de Alencastro Graça, and P. M. Fearnside. 2017. Deforestation and Carbon Stock Loss in Brazil's Amazonian Settlements. *Environmental Management* 59: 393–409. doi:10.1007/s00267-016-0783-2.

Yanai, A. M., P. M. L. de A. Graça, M. I. S. Escada, L. G. Ziccardi, and P. M. Fearnside. 2020. Deforestation dynamics in Brazil's Amazonian settlements: Effects of land-tenure concentration. *Journal of Environmental Management* 268. doi:10.1016/j.jenvman.2020.110555.

Supporting information 2: Explanatory variables selection and preprocessing

Explanatory variables selection

Running large-scale models with many variables and interpretation of their results can prove challenging, especially if some of the variables are derived from poor-resolution data. Thus, after the identification of potential drivers of fire regimes and data sources that could be used to derive variables, we excluded variables for the following reasons:

- **Datasets quality:** collected in ways that compromise their interpretability
- **Redundancy among variables:** several variables could be proxies for the same underlying drivers of fire regimes or are highly correlated with other variables
- **Data distribution:** some variable's distributions are skewed over few values and would contribute little information in the large-scale models

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

- **Temperature and precipitation:** these two climatic factors affect the flammability of the ecosystems by determining the balance between water inputs from precipitation and water losses through evaporation and evapotranspiration. We used the Maximum Cumulated Water Deficit, a drought index that accounts for both phenomena (see next section for more details) and quantifying the degree of water stress that vegetation experiences over the course of a year.

- **Past fires:** while initially considered as a proxy for past forest degradation, the interpretation of this variable could be quite challenging as fire tend to recur at the same pixels and past fires could be a proxy for other phenomena driving fire occurrences.

- **Law enforcement efforts:** A list of embargos issued by the IBAMA for environmental infractions was available, but the data were aggregated at a municipality level. Moreover, the distribution of the data was highly skewed, affecting mainly a few municipalities and was highly correlated to municipalities on the priority list.

- **Population:** the available data consisted of projections from the IBGE aggregated at a municipality level. Population serves as a proxy for human pressure, 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, concentrating large shares of the total population, corresponding to major urban centres.

Explanatory variables Preprocessing

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

$$\text{if } CWD_{n-1} - 100 + precipitation_n < 0,$$

$$\text{then } CWD_n = CWD_{n-1} - 100 + precipitation_n ,$$

$$\text{else } CWD_n = 0$$

The 100mm corresponds to an average evapotranspiration rate. Then, for each pixel the lowest CWD value for each year was retained, representing the intensity of water stress intensity over a year. A raster stack was created with the Maximum cumulated water deficit for each year of the study period, before being divided into 6 categories. Precipitation data were from CHIRPS dataset (Funk et al. 2015).

Maximum Cumulated Water Deficit	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
0 mm	9.5%	11%	8.0%	13%	3.9%
1-100mm	23%	24%	23%	26%	14%
101-200mm	20%	19%	29%	23%	17%
201-300mm	24%	25%	22%	17%	26%
301-400mm	15%	17%	13%	14%	20%
401mm and more	8.2%	3.8%	5.9%	7.6%	19%

Table S2. Summary of the percentage of pixels in each category over the 5 periods of analysis.

Agricultural land use Mapbiomas collection 10 was used to characterize land uses (Souza et al. 2020). 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> soybean, sugarcane, rice, cotton and other annual crops (ID 39+20+40+41+62)
- <u>Perennial crops:</u> Forest plantations, coffee, citrus and other perennial crops (ID 9+35+46+47+48)

The coverage of each agricultural land was calculated for each 1km pixel and incorporated into raster stacks, before assigning the dominant agricultural land use.

Agricultural land use	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
pasture					
<1%	74%	74%	73%	72%	70%
1-50%	16%	16%	16%	17%	17%
51-100%	11%	11%	11%	12%	13%
annual crop					
<1%	97%	96%	94%	94%	94%
1-50%	2.4%	3.1%	4.4%	4.8%	5.0%
51-100%	0.6%	0.9%	1.1%	1.3%	1.4%
perennial crop					
<1%	100%	99%	99%	99%	99%
1-50%	0.4%	0.5%	0.6%	0.6%	0.6%
51-100%	<0.1%	<0.1%	<0.1%	<0.1%	<0.1%
dominant agricultural land use					
no agricultural land	68%	68%	66%	64%	63%
pasture	30%	29%	30%	31%	33%
annual crop	1.9%	2.6%	3.4%	3.7%	3.7%
perennial crop	0.5%	0.5%	0.5%	0.5%	0.5%

Table S3. Summary of the percentage of pixels in each category over the 5 periods of analysis

Agricultural land use increases Mapbiomas collection 10 was used to look at the expansions of pastures, annual crops and perennial crops. The percentage of each agricultural land category was compared to the previous year, and pixels with a >1% increase in the identified land category were classified as having increasing cover.

Agricultural land use increase	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
no increase	93%	92%	92%	91%	92%
increase pasture	5.9%	6.1%	6.7%	8.1%	7.8%
increase annual crop	0.7%	1.5%	1.4%	0.8%	0.6%
increase perennial crop	<0.1%	0.1%	0.1%	<0.1%	<0.1%

Table S4. Summary of the percentage of pixels in each category over the 5 periods of analysis

Forest fragmentation Edge density was calculated using the forest category of Mapbiomas 10 (ID 3+6) and the landscapemetrics package in R at a 1km resolution, then a raster stack was created with the edge density values and was categorized.

Fragmentation	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
edges density					
<5m/ha	67%	66%	65%	64%	63%
5-15m/ha	14%	14%	14%	14%	15%
15-25m/ha	13%	13%	13%	14%	14%
>25m/ha	7.0%	7.2%	7.6%	8.2%	8.0%

Table S5. Summary of the percentage of pixels in each category over the 5 periods of analysis

Distance from agricultural edges Mapbiomas collection 10 was used to identify pixels which contain any type of agricultural land use, before calculating the distance between the centroid of these pixels and the nearest pixels without any agricultural land. Then, the resulting raster stack was categorized.

Distance from agricultural land	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
Adjacent	22%	22%	23%	25%	26%
0-1km	8.4%	8.4%	8.4%	8.9%	9.1%
1-3km	9.4%	9.3%	9.2%	10%	11%
3-5km	5.9%	5.9%	5.8%	6.7%	7.2%
5-10km	11%	11%	11%	13%	14%
10-25km	20%	20%	19%	22%	22%
25km and more	24%	24%	23%	16%	11%

Table S6. Summary of the percentage of pixels in each category over the 5 periods of analysis

Remoteness The transport cost to port dataset developed by de Castro Victoria et al. (2021) was used, as it accounts for the evolution of the road network in the region, but also the presence of ports to export agricultural commodities. Since transport cost information was only available for 2005, 2010 and 2017, the transport cost of 2005 was used for 2009, the transport cost of 2010 was used for the 2011-2016 period and the transport cost of 2017 was used for the 2017-2020 period. Then, the resulting raster stack was categorized.

Transport cost	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
>5K RU	7.4%	7.9%	7.9%	7.9%	7.9%
5-10K RU	17%	18%	18%	18%	18%
10-20K RU	39%	39%	39%	39%	39%
20K RU and more	36%	35%	35%	35%	35%

Table S7. Summary of the percentage of pixels in each category over the 5 period of analysis

Rural Settlements

The shapefile of rural settlement available on the INCRA website (INCRA) was selected for delimiting the different rural settlements, filtering out any sustainable use and quilombola territories that were classified as sustainable use areas, according to the Brazilian national protected areas system.

Land governance	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
rural settlement	4.8%	4.9%	4.9%	4.9%	4.9%
other type of land governance	95%	95%	95%	95%	95%

Table S8. Summary of the percentage of pixels in each category over the 5 period of analysis

Governance protected areas data were obtained from the WDPA which includes both the spatial delimitation of protected areas, their classification according to the Brazilian 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 (IUCN categories IV to VI)
- Strictly protected areas: include biological reserves, parks, ecological stations, wildlife refuges, and natural monuments (IUCN categories I to III).
- Indigenous lands: including only indigenous land that has completed the delimitation process

These protected areas have been divided between periphery areas, corresponding to the first ten kilometers between the protected areas and unprotected areas (excluding internal buffer between two different protected areas), and core areas, more than ten kilometers from the protected areas or indigenous land border with unprotected areas. An outside area was also delimited in undesignated land located within 10km of a protected area.

Additionally, the database of PADDD events in the Brazilian Amazon was downloaded on padddtracker website (PADDtracker 2020), and the downgrading of protected areas was excluded as they might not necessarily represent a weaker protection effort in the region. A raster stack was created recording the pixels covered by PADDD events at or before each year of the period of study.

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

Land governance	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
no protection	38%	38%	37%	36%	35%
indigenous land periphery	6.6%	6.6%	6.6%	6.5%	6.5%
indigenous land core	16%	16%	16%	16%	16%
indigenous land outside	6.0%	5.9%	5.8%	5.8%	5.8%
sustainable use periphery	5.9%	5.8%	6.0%	6.2%	6.3%
sustainable use core	10%	10%	11%	11%	11%
sustainable use outside	5.4%	5.3%	5.5%	5.6%	5.6%
strictly protected periphery	2.4%	2.5%	2.6%	2.6%	2.5%
strictly protected core	6.0%	6.2%	6.5%	6.6%	6.6%
strictly protected outside	1.8%	1.9%	1.9%	2.0%	1.9%
protected area downsizing and degazettement	1.5%	1.7%	1.8%	1.8%	1.8%

Table S9. Summary of the percentage of pixels in each category over the 5 period of analysis. This table summarises all of the variables related to land governance, including the existence of rural settlement, sustainable use areas, Indigenous land, integral protection areas and PADDD events.

Priority list

The list of priority municipalities published by the ministry of the environment was 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 both decreasing deforestation pressure and the fulfilment of certain conditions, such as registration in the rural land registry.

Municipalities on priority list	period 1 (2009-2011)	period 2 (2012-2015)	period 3 (2016-2018)	period 4 (2019-2022)	period 5 (2023-2024)
never on priority list	82%	80%	76%	72%	69%
priority list	18%	19%	22%	25%	27%
removed from priority list	0%	0.5%	1.5%	2.9%	3.3%

Table S10. Summary of the percentage of pixels in each category over the 5 period of analysis

Collinearity testing

Following the preprocessing of all covariates, Cramér's V was computed for each pair of categorical variables to assess the degree of association among them (Fig. S1). Most pairwise values were below or equal to 0.4, suggesting no strong association between covariates. The only value exceeding 0.4 was between distance from agricultural land and agricultural land use change (V = 0.43); however, these variables were not included in the same models simultaneously. We therefore considered multicollinearity among covariates to be acceptable.

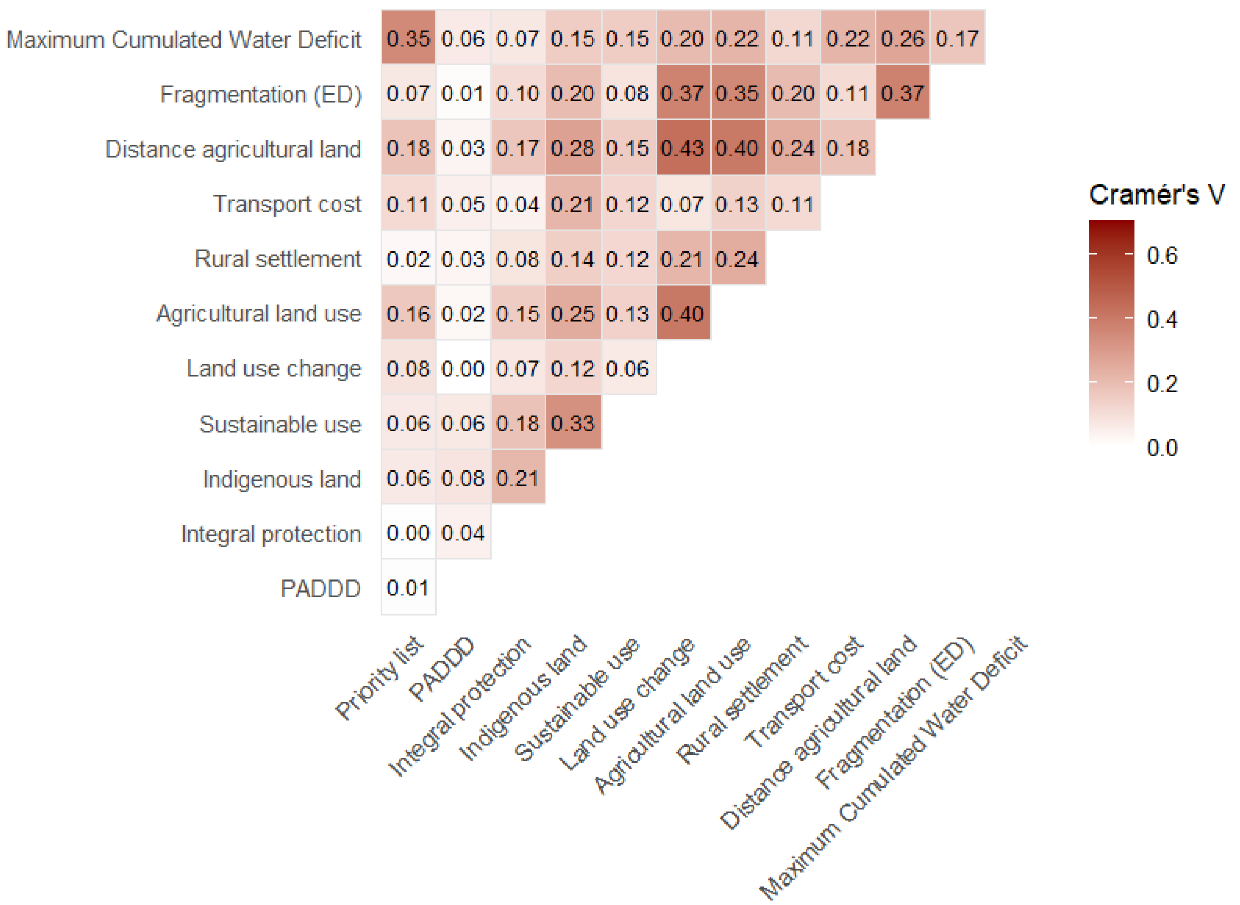

Figure S1. Pairwise association between categorical covariates, measured using Cramér's V. Values range from 0 (no association) to 1 (perfect association).

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

Compared to previous work for understanding the drivers of fire regimes in the Brazilian Amazon, one major difference in our analysis was the inclusion of a spatio-temporal component. A careful design of the models attempts to include most of the important drivers of the fire regimes, but some drivers can hardly be captured by numerical variables (e.g. fine-scale governance process), while for other drivers no data sources could be identified (e.g. logging and forest degradation). According to Tobler's first law, "everything is related to everything else, but near things are more related than distant things" (Tobler 1970) 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 (Serra et al. 2014; Opitz et al. 2020). 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.

$$\text{Number Active Fires}_{(st)} \sim \text{Poisson}\,(\text{Intensity process}_{(st)})$$

$$\text{Intensity process}_{(st)} = \exp\,(\textstyle\sum i{=}1n \;\; cov_{i(st)} * \beta_i + Y_{(st)})$$

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.

Zero-Inflated Binomial Model

The Zero-Inflated Binomial (ZIB) model is a class of models suited to binary or count response variables that contain more zeros than would be expected under a standard binomial distribution. In our case, the response variable is the presence or absence of at least one active fire detection within a pixel in a given year. Because fires are rare events at the scale of a 1 km pixel, the large majority of pixel-year observations record no fire, generating an excess of zeros that a standard logistic model would inadequately capture.

The model treats the observed data as arising from a mixture of two processes. With probability π, an observation is drawn from a point mass at zero, reflecting pixel-years where fire was absent solely due to the rarity of the event at this spatial and temporal scale. With probability $(1 - \pi)$, an observation is drawn from a Bernoulli distribution governed by the covariates and the spatiotemporal dependence structure, such that:

$$P(Y(s,t) = 1) = (1 - \pi) \cdot p(s,t)$$

where *Y(s,t)* is the observed fire presence or absence at location *s* and year *t*, *π* is the zero-inflation parameter estimated from the data, and *p(s,t)* is the probability of fire occurrence modelled as a function of the explanatory variables and the residual spatiotemporal process. The model was fitted within the INLA/inlabru framework described below, retaining the SPDE approach to represent the spatiotemporal dependence structure.

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 (Carroll et al. 2015).We fitted our LGCP model using inlabru (Bachl et al. 2019), 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 (Juan Verdoy 2021). Briefly, the spatial process can be represented by the basic function:

$$U_{(s)} = \sum_{k=1}^{m} \psi_k(s) w_k$$

where ψ_k are basis function, W_k 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 (Simpson et al. 2017), 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.

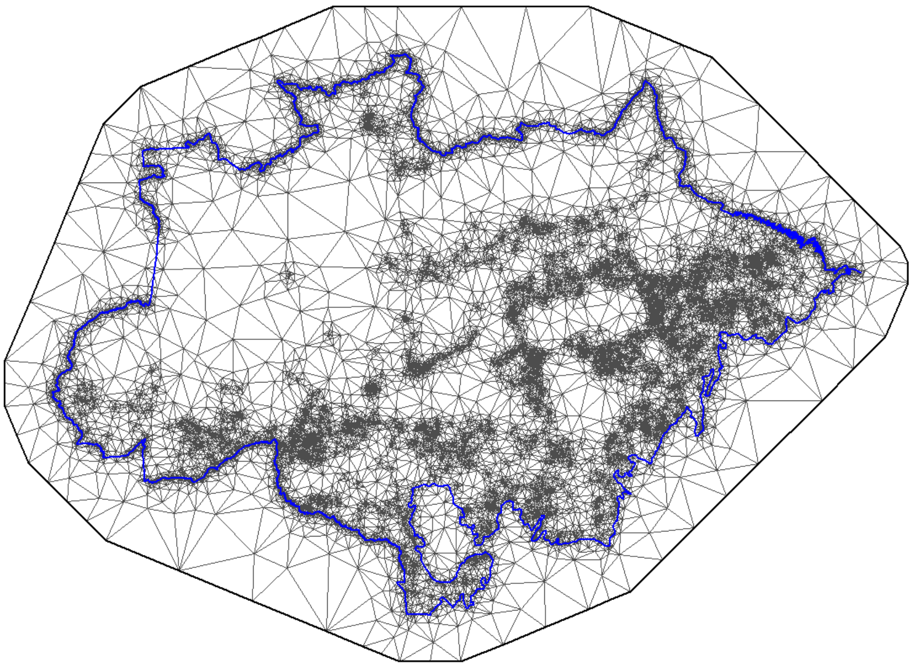

Figure S2. Mesh created for the 2009-2011 deforestation fires model.

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

For each of the models, we determined an optimal threshold by computing the Precision-Recall curve and selecting the threshold value with the best harmonic means of precision and recall F1.

F1= 2 . (Precision · Recall) / (Precision + Recall)

This approach ensures that the threshold balances the trade-off between over- and under-predicting fire occurrence, The resulting binary predictions were then compared to observed fire presence maps to derive the predicted versus observed fire counts.

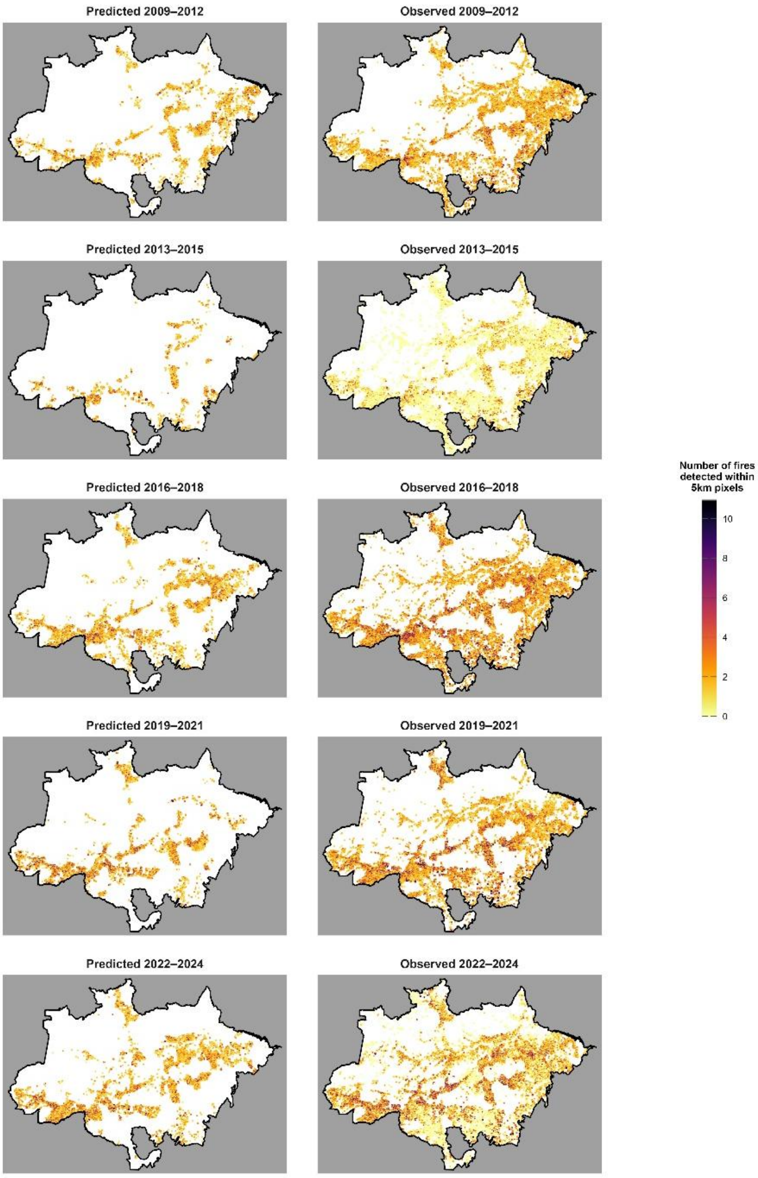

Figure S3. Maps of the median numbers of deforestation fires predicted by the models (left column) and observed by Mapbiomas fogo (right column) in $10km^2$ pixels for the five periods.

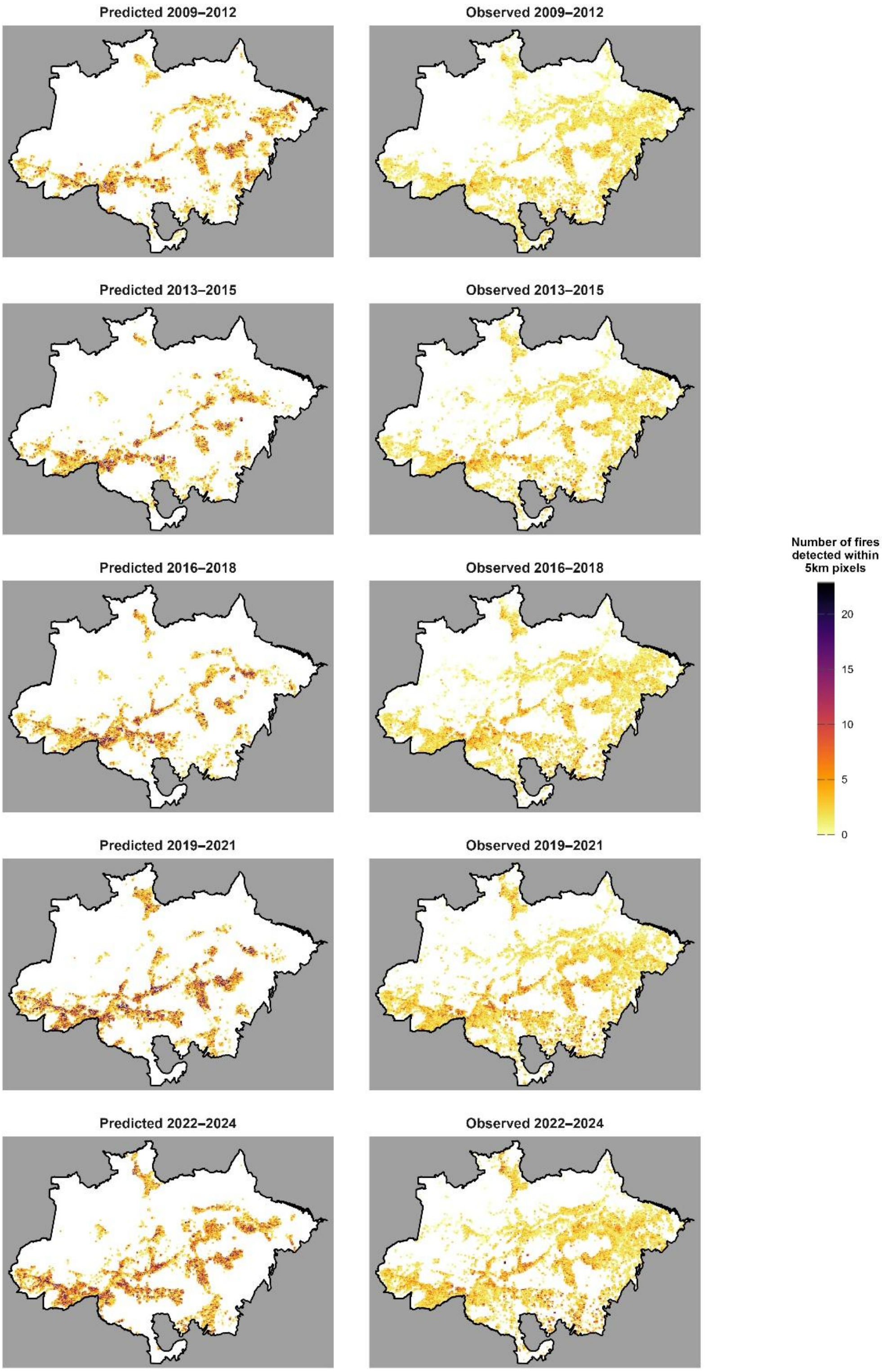

Figure S4. Maps of the median numbers of agricultural fires predicted by the models (left column) and observed by Mapbiomas fogo (right column) in 10km^2 pixels for the five periods.

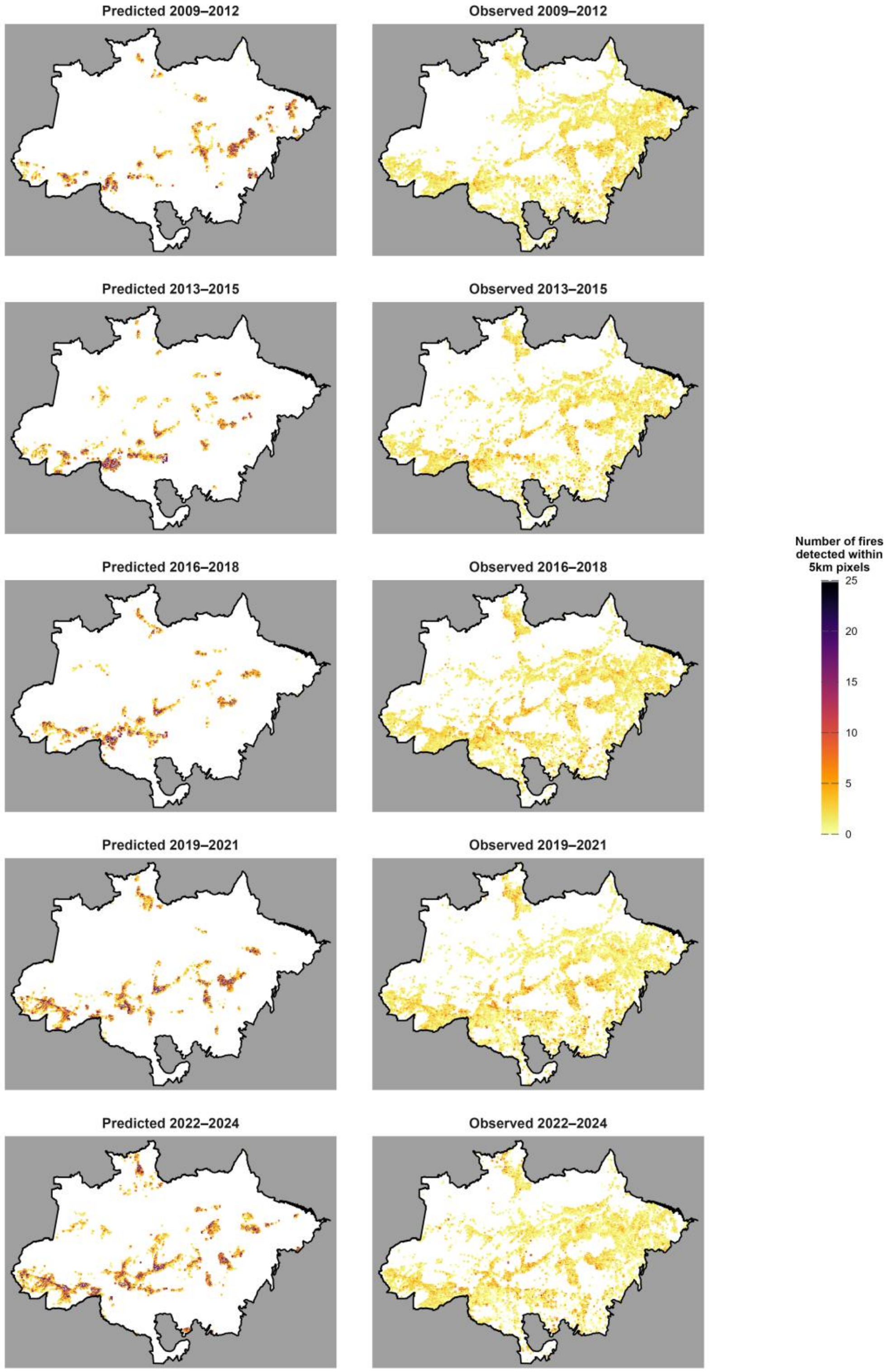

Figure S5. Maps of the median numbers of forest fires predicted by the models (left column) and observed by Mapbiomas fogo (right column) in 10km^2 pixels for the five periods.

Supporting Information 5: Models performamce diagnostics

We evaluated the models across six complementary dimensions of our model: discriminative ability, precision at varying recall levels, probability calibration, distributional fit of residuals, uniformity of probability integral transforms, and alignment of temporal trends with observed data.

ROC curve and AUC were used to assess discriminative ability, while Precision-Recall curves provided a complementary metric better suited to the strong class imbalance in the data. Calibration plots assessed whether predicted fire probabilities are consistent with observed fire frequencies. Dunn-Smyth randomised quantile residual QQ plots evaluated the distributional assumptions of the model. PIT histograms were examined to detect over-dispersion or under-dispersion. Finally, estimated temporal random effects were compared to observed interannual variability to assess whether the model adequately captures temporal trends.

We choose different test that could compare predictions with observed data, potential issues with model design, and the representation of temporal effects. The results from the model diagnostics indicate several different things:

- **ROC curve:** AUC values were consistently high across all fire type models, indicating that all models reliably distinguish pixels where fire occurred from those where it did not. Agricultural fire models tended to achieve the highest AUC values, while forest fire models showed the lowest.

- **Precision-recall curve:** All models showed high initial precision that declined progressively with increasing recall. Peak precision was substantially higher for agricultural fire models (up to ~0.80) and deforestation fire models (up to ~0.75) than for forest fire models (up to ~0.25), indicating that agricultural and deforestation fire pixels are more reliably identified than forest fires.

- **Calibration plot:** predicted probabilities aligned well with observed fire frequencies at low probability values, but some models displayed an outlying point at high predicted probability values where observed frequency was markedly lower than predicted, indicating overprediction of fire occurrence in the most fire-prone pixels. This pattern was most pronounced in the deforestation models and during the two first period of the agricultural fires and forest fires models
- **QQ plot Dunn-Smyth Residuals**: QQ plots were well-aligned with the theoretical normal quantiles across most of the distribution for all models and periods, suggesting that the main drivers of fire occurrence are adequately captured by the covariates.

- **PIT histograms**: All models displayed an almost identical PIT pattern, with values concentrated almost entirely at 1.0 and a small residual spike at 0.0. This pattern indicates strong under-dispersion: the models assign predicted probabilities that are either very close to 0 or very close to 1, with little uncertainty in between. This overconfidence is a known limitation of ZIB models applied to highly imbalanced binary data and likely reflects residual spatial heterogeneity not fully captured by the covariate structure.

- **Temporal validation**: across all models, the temporal random effects correctly reproduced the direction of interannual variability but predicted fire probabilities were consistently higher than observed values, typically by a factor of 1.5 to 3

<u>**Model deforestation fires period 1 (2009-2011)**</u>

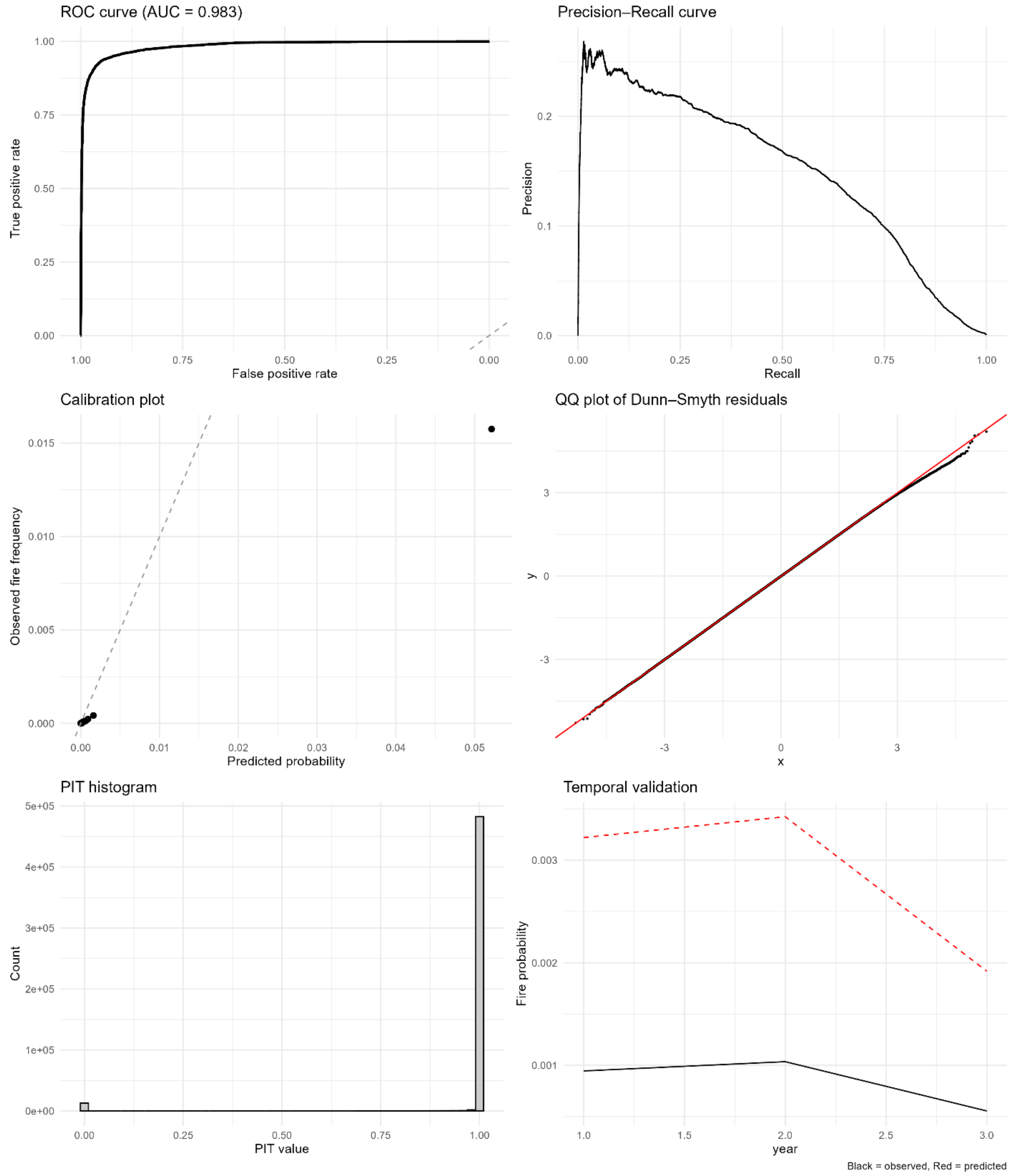

Figure S6. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model deforestation fires period 2 (2012-2015)

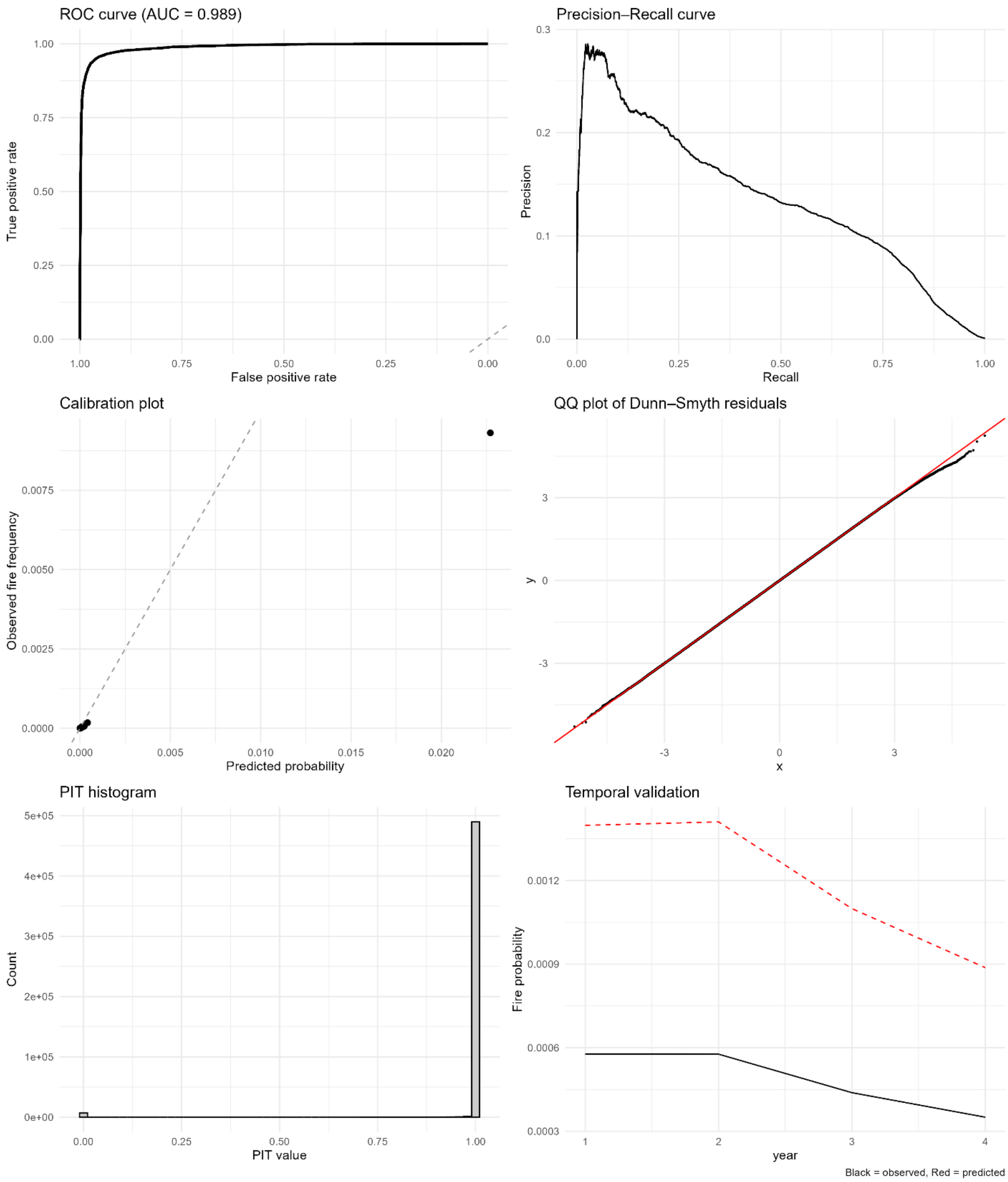

Figure S7. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model deforestation fires period 3 (2016-2018)

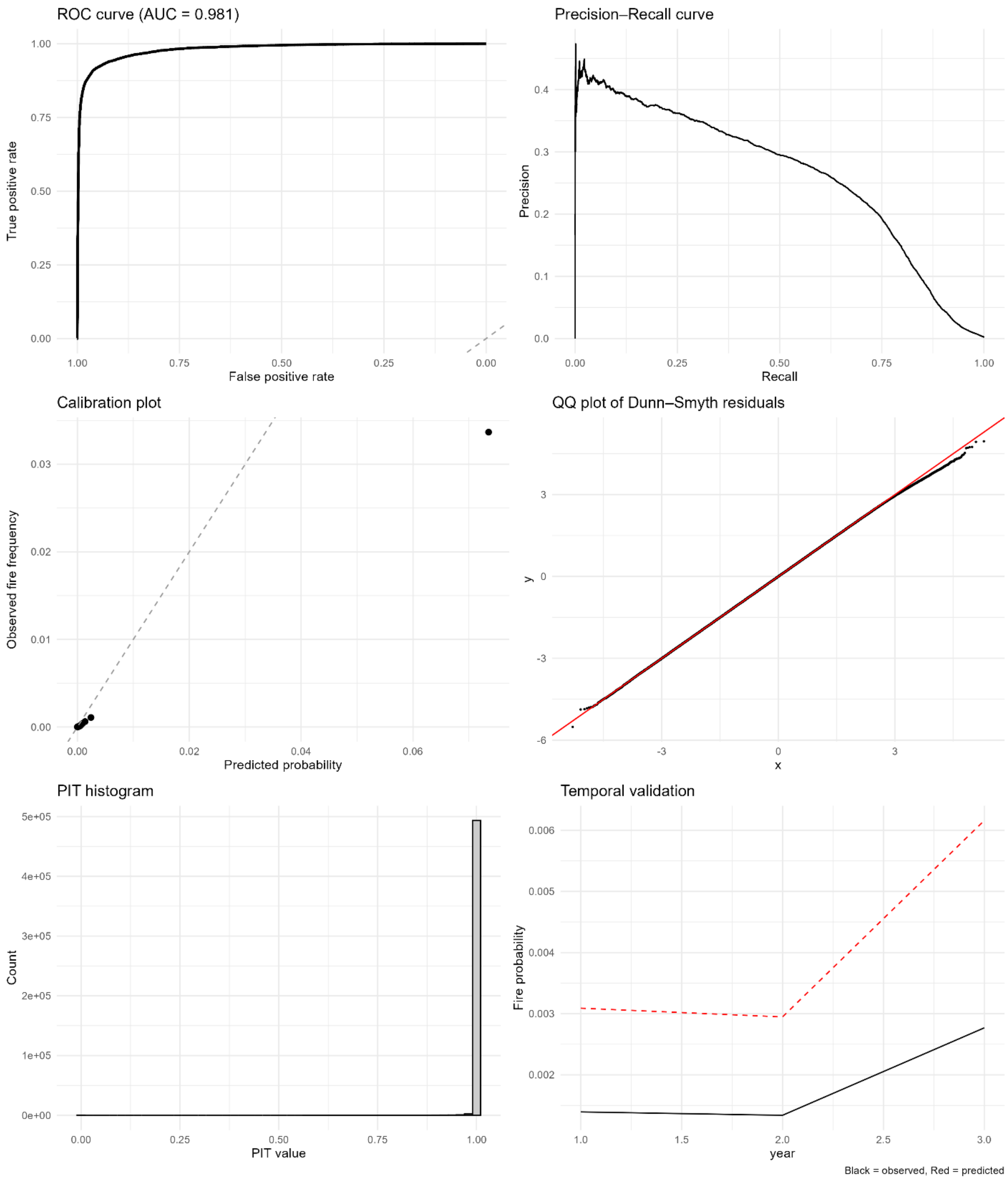

Figure S8. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model deforestation fires period 4 (2019-2022)

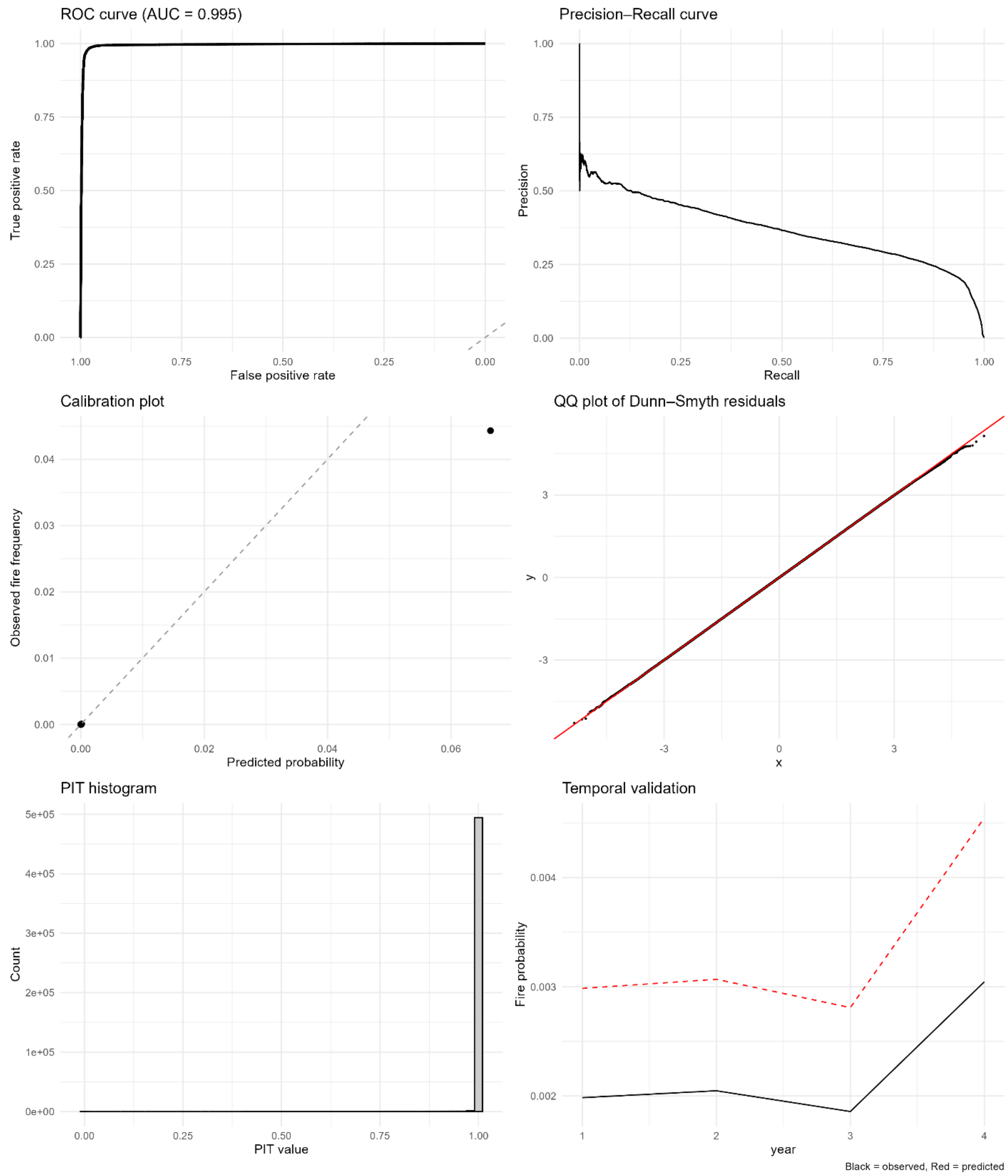

Figure S9. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model deforestation fires period 5 (2023-2024)

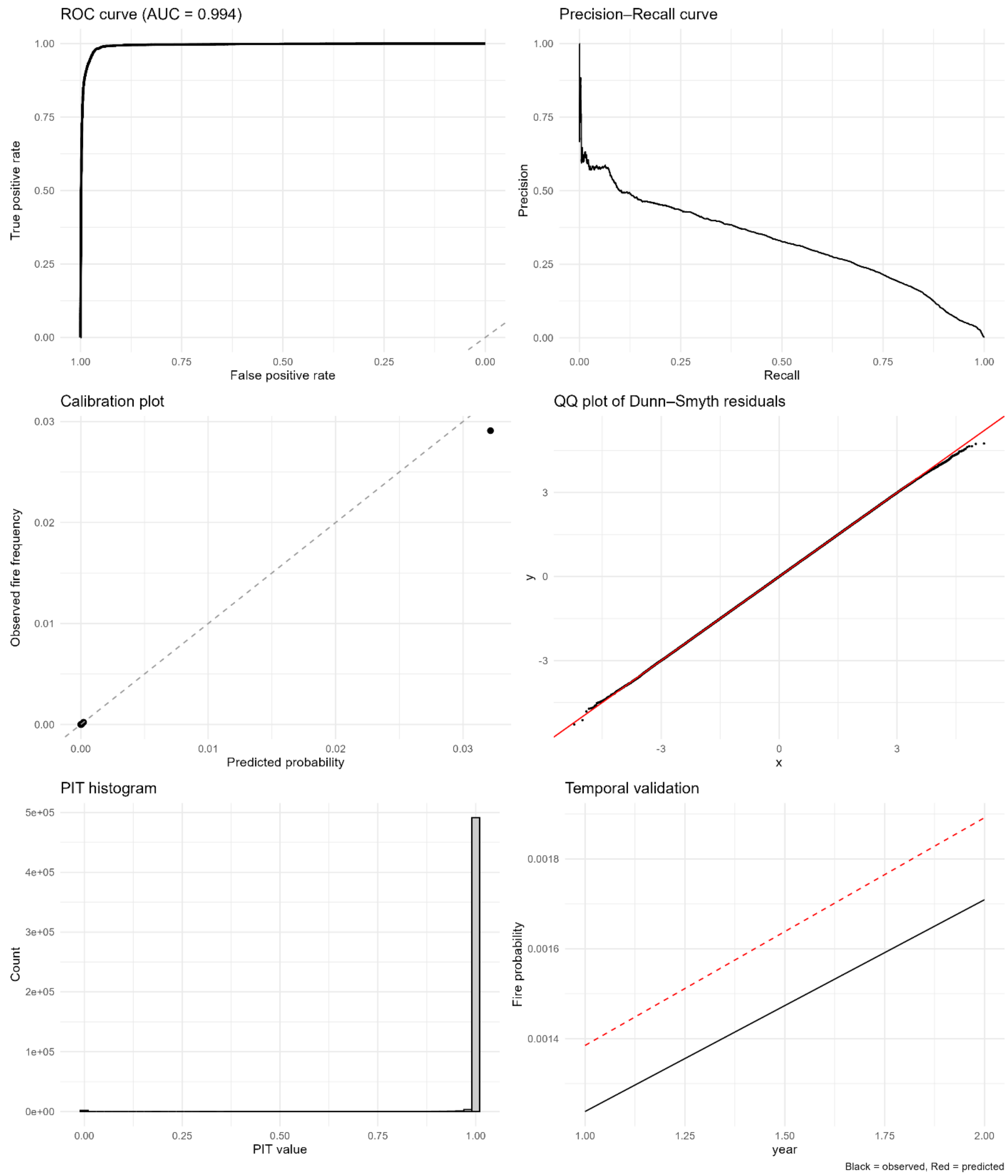

Figure S10. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation.

Model agricultural fires period 1 (2009-2011)

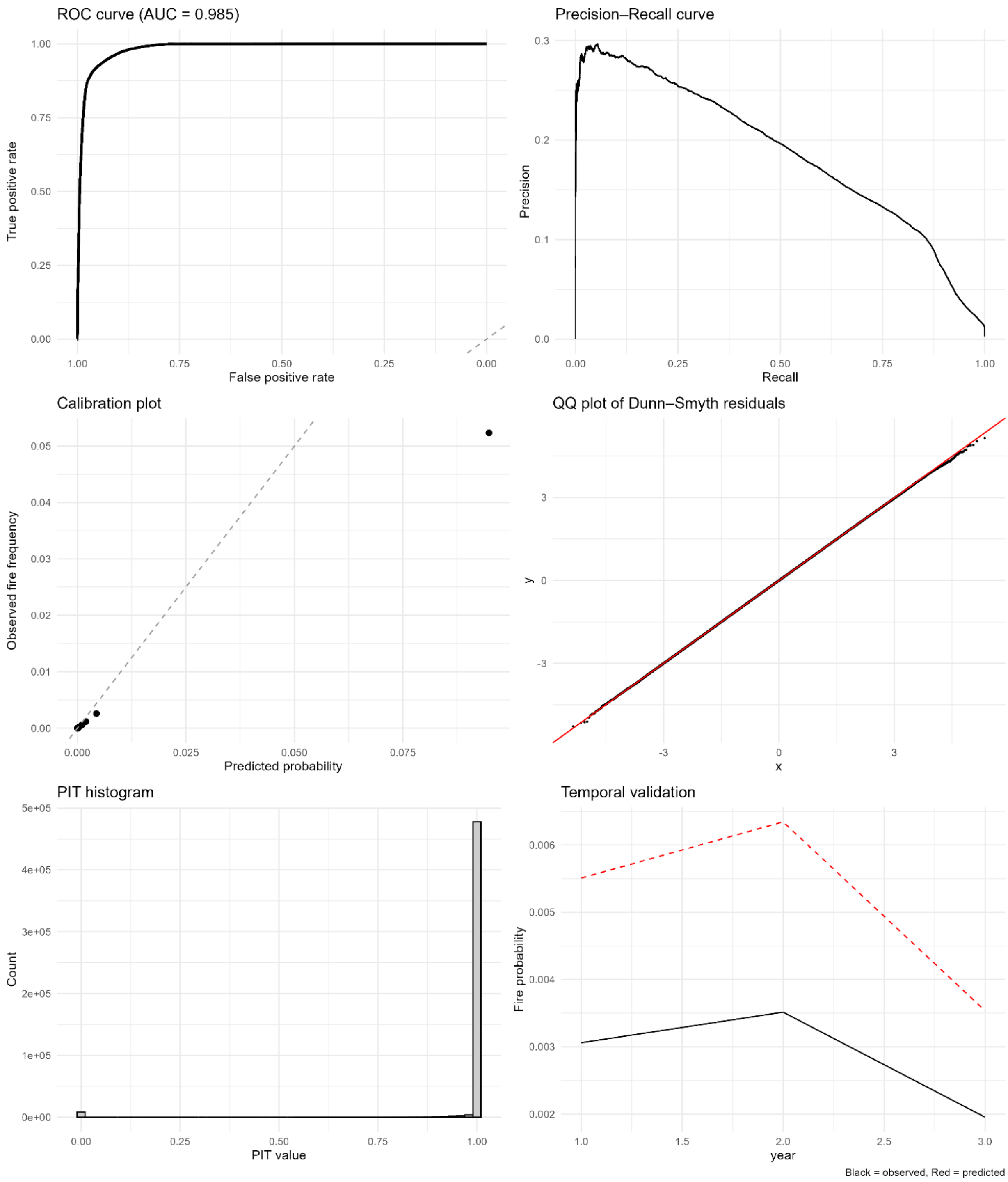

Figure S11. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model agricultural fires period 2 (2012-2015)

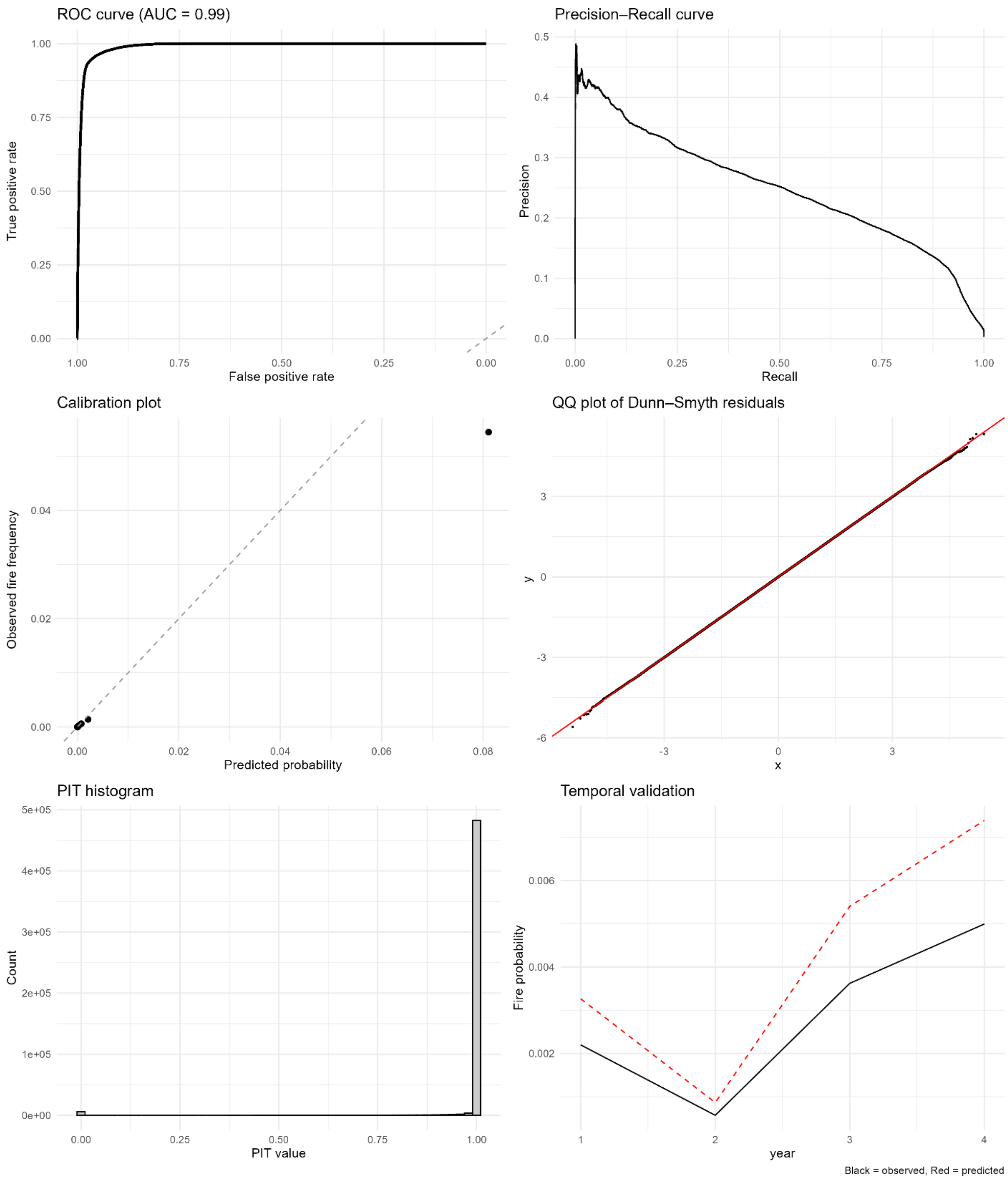

Figure S12. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model agricultural fires period 3 (2016-2018)

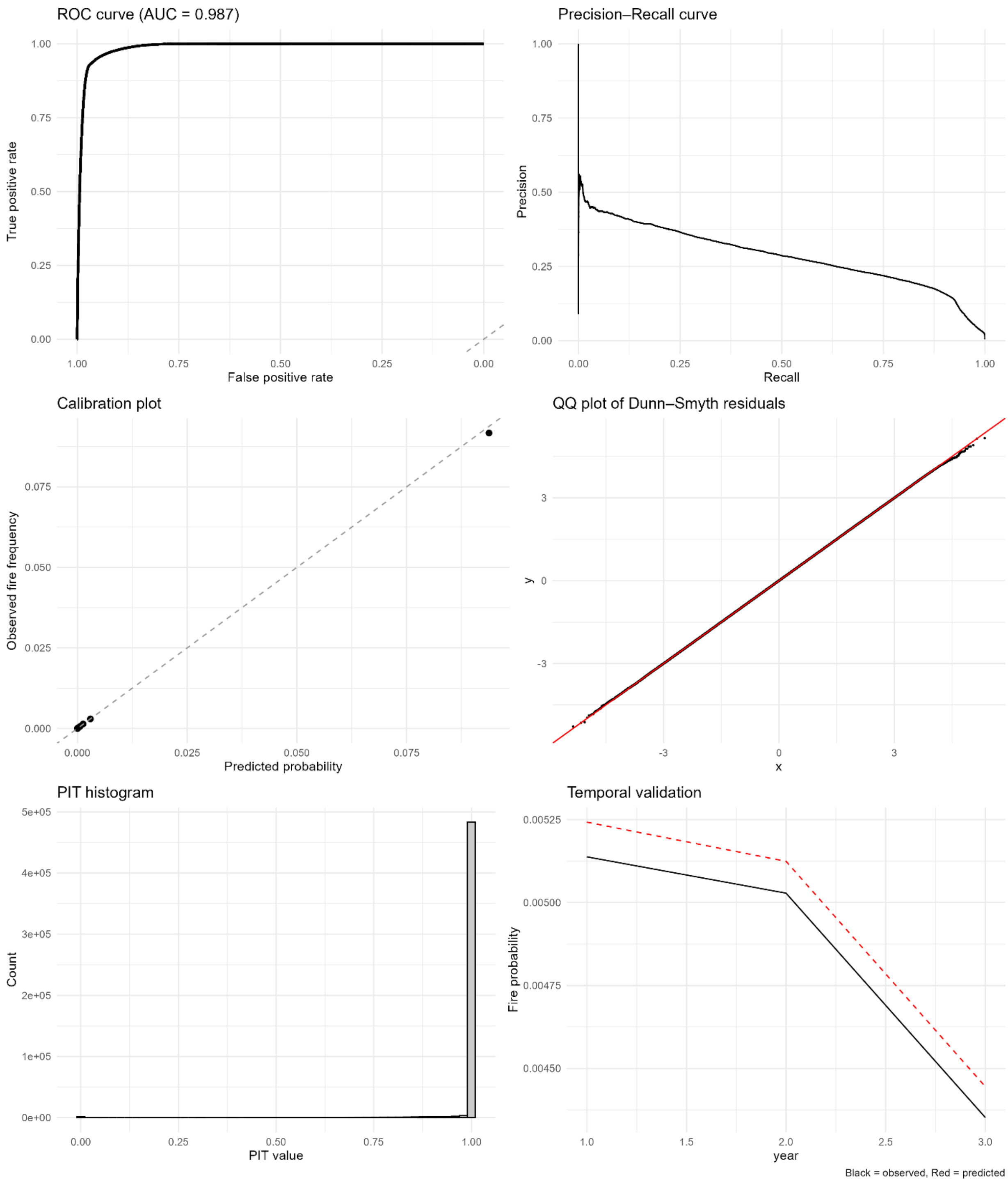

Figure S13. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model agricultural fires period 4 (2019-2022)

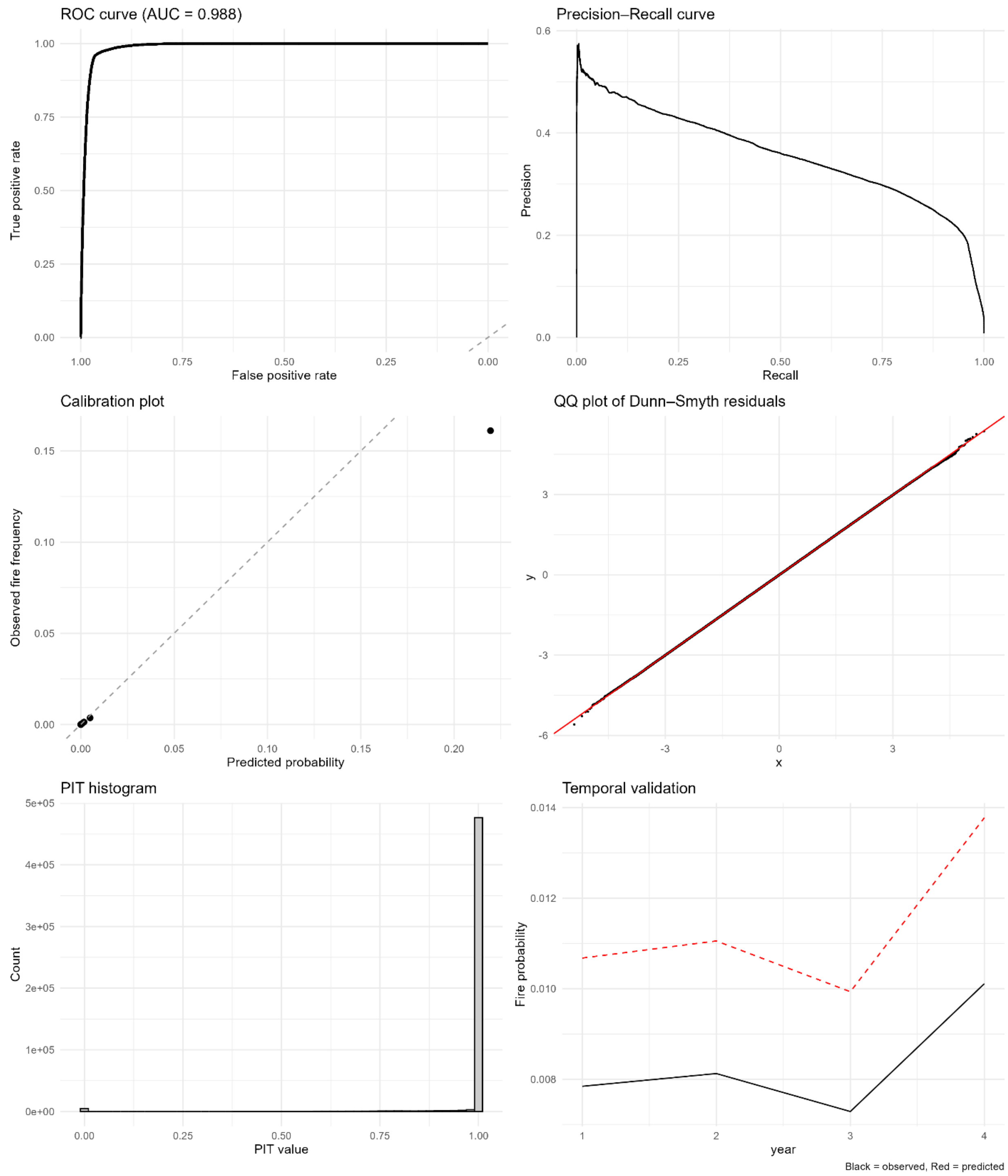

Figure S14. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model agricultural fires period 5 (2022-2024)

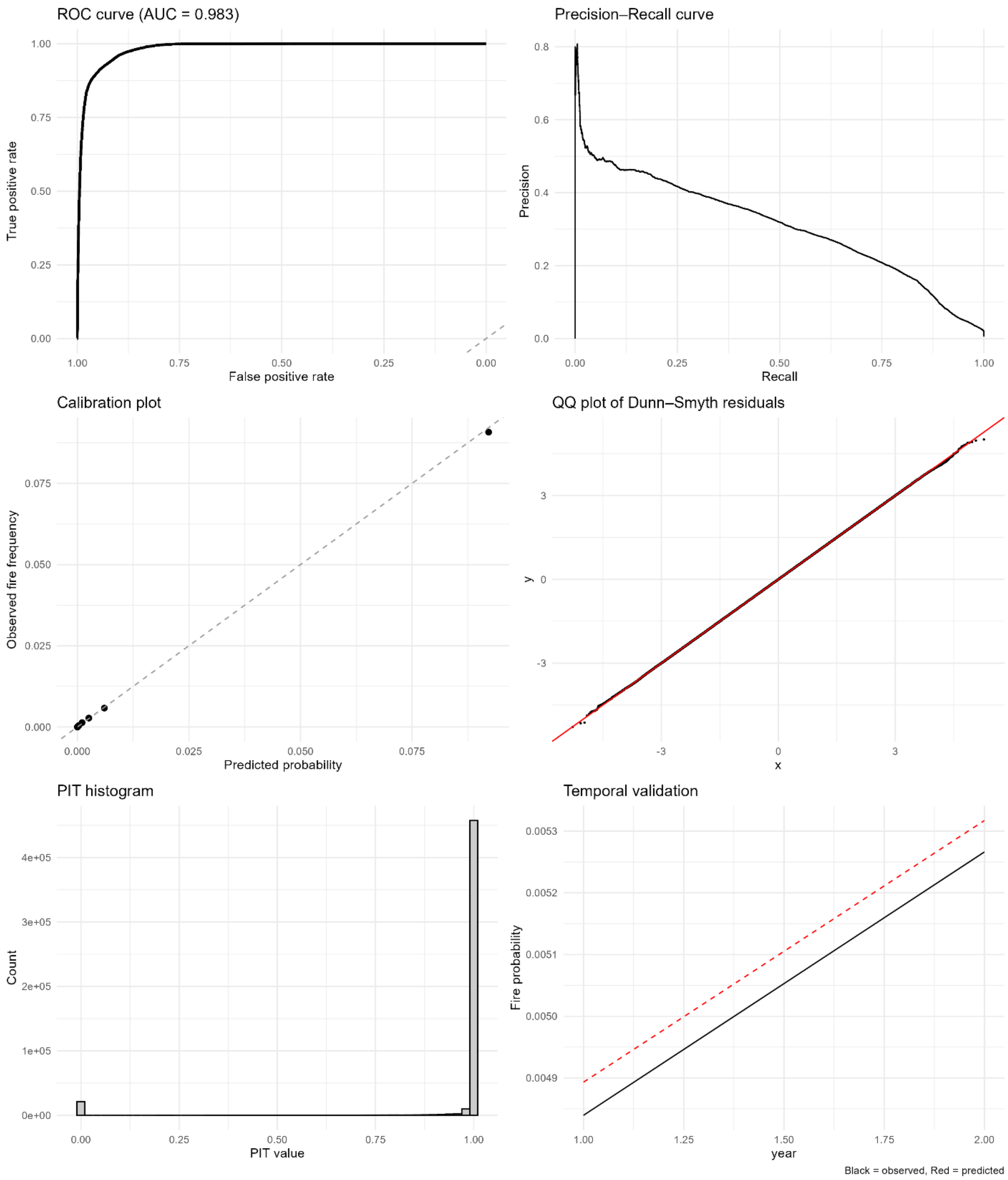

Figure S15. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model forest fires period 1 (2009-2011)

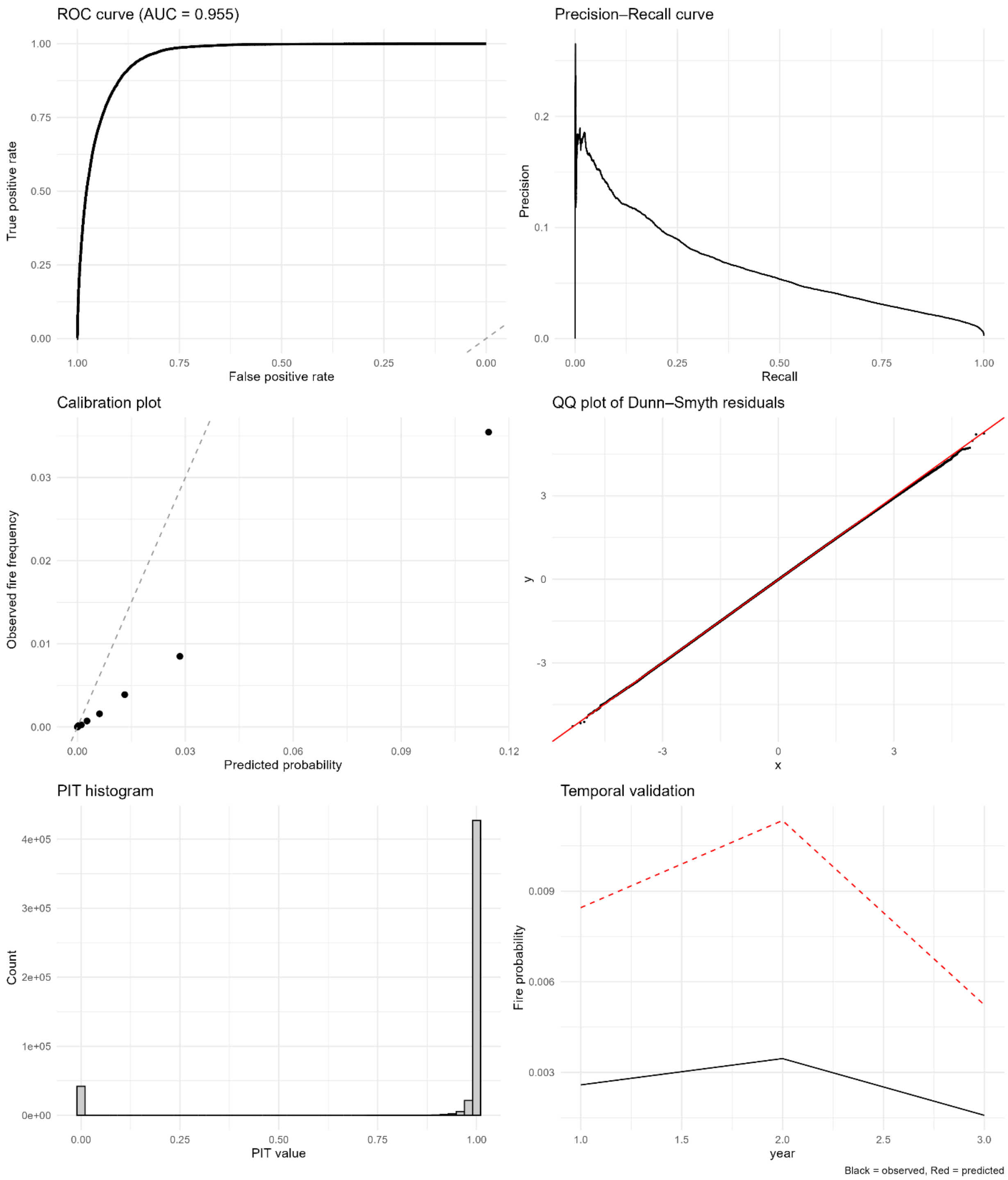

Figure S16. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model forest fires period 2 (2012-2015)

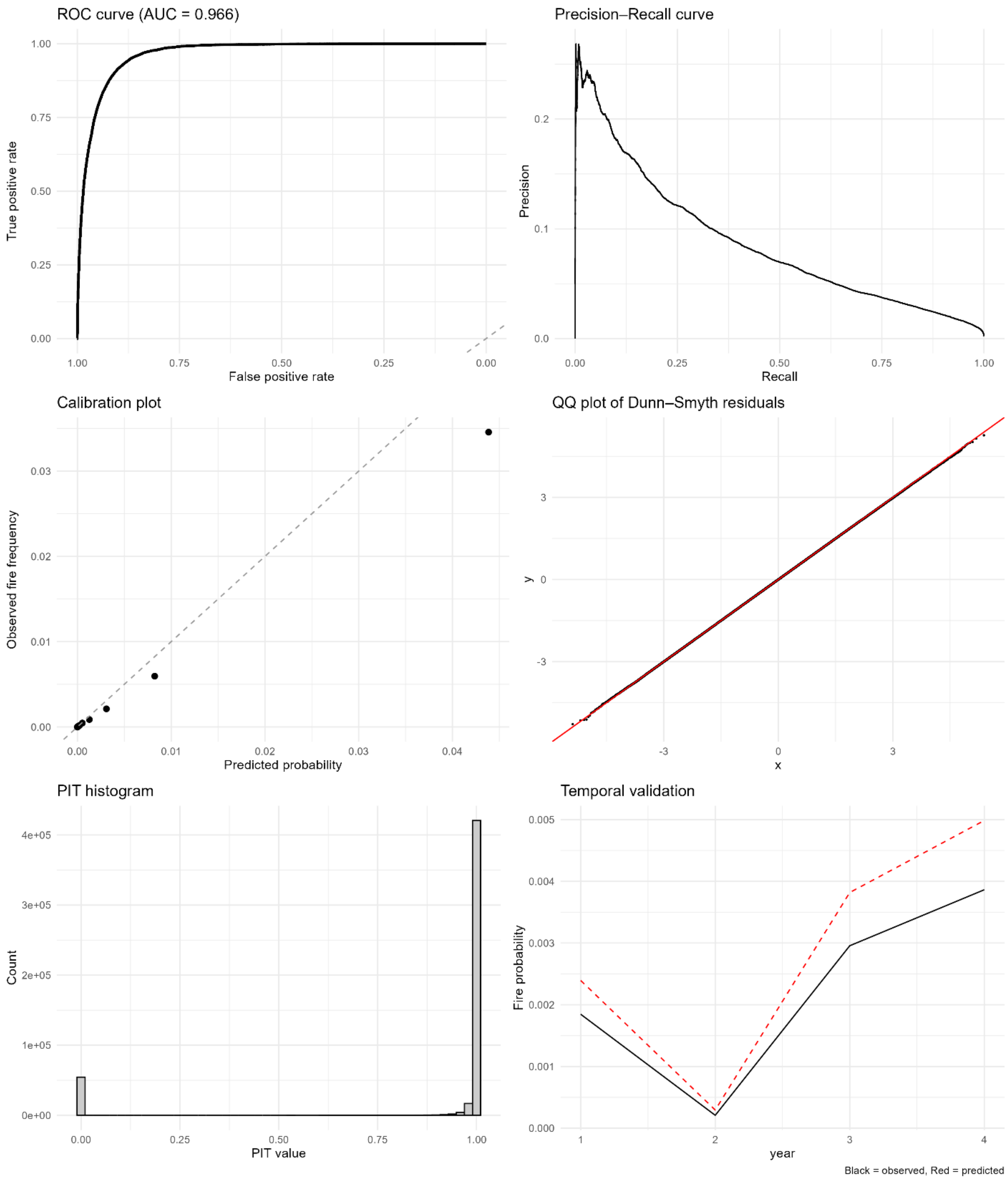

Figure S17. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model forest fires period 2 (2016-2018)

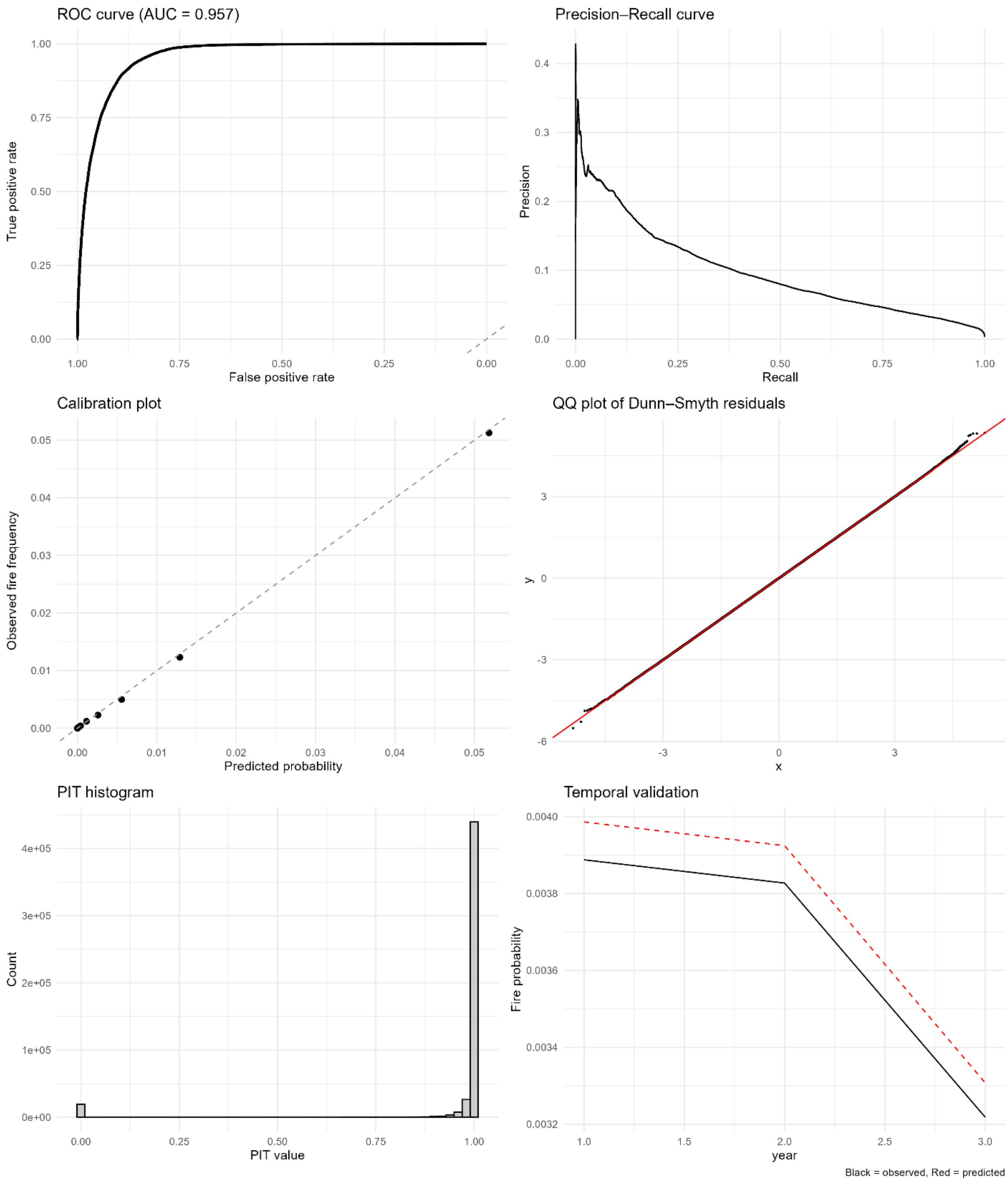

Figure S18. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model forest fires period 4 (2019-2022)

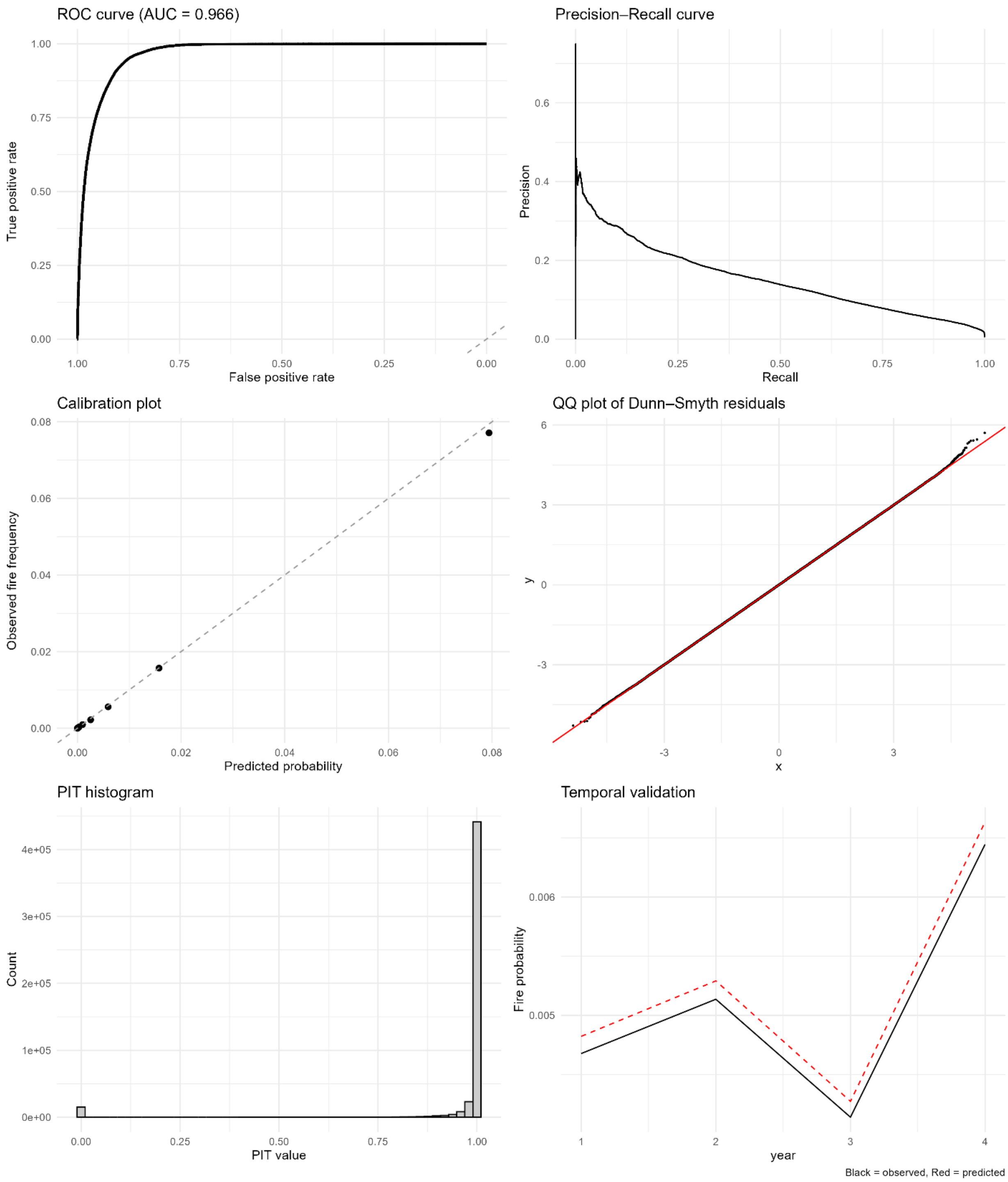

Figure S19. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation

Model forest fires period 5 (2022-2024)

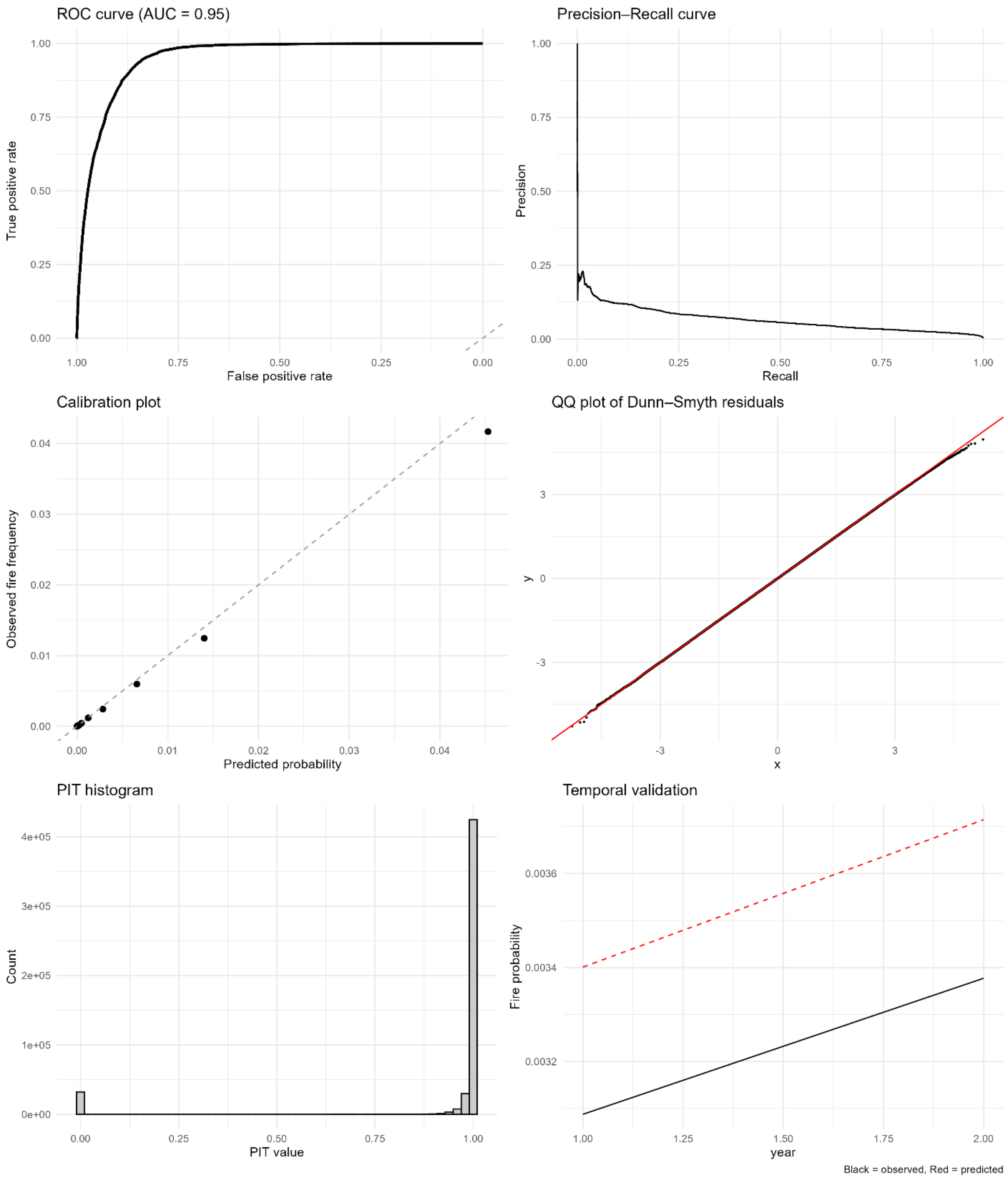

Figure S20. Diagnostics of the models including the ROC, Precision-Recall curve, classification plot, qqplot of Dunn-Smyth residuals, PIT histogram and temporal validation