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Exploring the Role of Deforestation and Cropland Expansion in Driving a Fire-Transition in the Brazilian Amazon

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Abstract: The Brazilian Amazonian Forest is undergoing significant changes in land use and land cover in the last few decades. This land-use transition, besides climate change, may be responsible for the fire regime transition in this territory. Therefore, we aimed at investigating how the fire-transition occurs over time in the Brazilian Amazonia Forest and identifying the key parameters that can help to predict this change. For this, we collected yearly data on fire occurrence, forest cover, deforestation rates, and cropland areas. We used a 0.45° spatial surface grid, and with these annual values, we produced: (i) generalised linear mixed models of fire occurrence against forest cover, using years and grids as random factors; (ii) annual linear models of fire occurrence against forest cover; (iii) linear models of the apex values against the years; and (iv) generalised linear models of these apex values against deforestation and cropland areas. We found that there is a fire-transition process in the Brazilian Amazon Forest since a quadratic model better predicted the fire occurrence behaviour. Moreover, the fire occurrence apex is transitioning to more forested landscapes, from 50.7% in 2003 to 55% in 2019 (R^2 = 0.3). The deforestation rates and the cropland expansion had important relationships with the fire-transition, the first is related to the fire occurrence in the landscape (R^2 = 0.62), while the second better predicts the transition to more forested areas (R^2 = 0.38). Thus, we found that the fire-transition in the Brazilian Amazon Forest is strongly related to the land-use transition stages in this region.

Keywords: fire-transition; deforestation; cropland expansion; severe droughts

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1. Introduction

Fire dynamics are changing across the world due to climate and land-use changes [1]. Globally, there is a trend of increasing fire season length, due to favourable climate conditions for fire occurrence, such as an overall reduction in air humidity, an increase in surface temperature and the number of rainless days [2]. Yet there has also been a reduction in burned areas between 1988 and 2015, which occurred mainly in regions with low and intermediate levels of tree cover, and was countered by an increase in fire occurrence in closed-canopy forests [3]. Understanding these fire dynamics is particularly important in fire-sensitive regions, such as humid tropical forests; fires have been historically rare or absent in these ecosystems [4,5], and in present day wildfires have a strong negative effect on biodiversity, climate regulation and human wellbeing [6–9].

In humid tropical forests, fires are closely related to land-use changes and the management of agricultural areas. Fire is a fundamental part of the deforestation process, and fire occurrence—as measured by satellites—is linked to the burning of felled trees following the conversion of forests to pasture or cropland [10]. As such, more fires tend to be detected in years with higher deforestation rates [11]. Fires are also crucial for pasture management and subsistence agriculture [12]. In the former, fire is used to periodically clear pastures of trees and weeds that decrease its carrying capacity. In the latter, fire is used for slash-and-burning as part of a farm-fallow cycle. Climate also influences fire occurrence—in the Brazilian Amazon, more fires are detected in years of extreme droughts, which are becoming more common [13–15]. Fires linked to droughts often occur in forests, when reductions in leaf litter humidity allow deforestation and agricultural fires to escape into surrounding forests [12,16,17]. These forest fires are important as they are a major determinant of an Amazonian tipping point [18] and an important driver of biodiversity loss [19] and carbon emissions [20,21].

Although deforestation and agricultural expansion increase fire occurrence in humid tropical forest regions, it has been suggested that this is only temporary. Andela et al. [3] propose a conceptual model in which fire follows a unimodal relationship during land-use transitions across the world. In the humid tropics, Andela et al. [3] predict that fire extent increases in the initial phase of land clearance but then decreases as high capital activities, such as mechanised farming, replace low capital and extensive agriculture [22]. Such a transition is important as it could have an important influence on fire use, and the possibility of ignition events in agricultural land escaping into remaining forests. However, despite some evidence that fire occurrence increases when lands are being cleared, and that there is a reduction of total occurrence of fire across agricultural landscapes [23], we still lack a detailed understanding of how the globally hypothesized fire transition is playing out in the Amazon and how any such transition is being modified by deforestation or changes in agricultural practices.

We address these knowledge gaps by exploring fire activity in the Brazilian Amazon from 2003 to 2019. We used active fire as our measure of fire prevalence at the landscape scale (0.45° by 0.45° grids) and examined it in relation to landscape-scale year-on-year datasets on forest cover, Land-use and Land Cover (LULC) and deforestation. We define a fire transition by the location of the apex of any relation between active fire and forest cover; and define fire prevalence as the height of the apex. Specifically, we ask: (1) is the Brazilian Amazon undergoing a fire-transition, and where is the transition point in relation to forest cover? (2) Has the transition point location and height changed over time? (3) Do annual changes in deforestation or expansion of cropland help predict the changes in the active fire and forest cover relationship peak values?

2. Materials and Methods

2.1. Study Area

The study area focuses on the Brazilian Amazon, a region with distinct climate characteristics and occupation histories. Annual deforestation rates varied substantially during the study period (i.e., 2003–2019). From a peak in 2004, deforestation rates reduced to their lowest level in 2012 and have gradually increased since then, with a severe spike in 2019 (Figure A2b) [24]. A similar pattern occurs when considering deforestation from primary and secondary forests [25], with the lowest level in 2012, but with a greater spike in 2016 (Figure A2a).

2.2. Datasets

We focus our analyses on 2003 to 2019, a period in which the Brazilian Amazon experienced three severe droughts (i.e., 2005, 2010, and 2015–2016) and marked changes in deforestation rates (Appendix A). We set this time range by the availability of the active fire dataset (i.e., MODIS Terra and Aqua satellites data available since mid-2002). We created a 0.45° spatial surface grid, which we used as a base for all our spatial estimates. Subsequently, we removed grid cells with over 20% of savannas or mangroves coverage from the analysis (using 2003 as the base year from the Mapbiomas 5.0 dataset). We have excluded all savanna enclaves from the analyses as fire dynamics and fire outcomes are very different in these fire-dependent ecosystems [26]. In addition, we excluded from the analyses grids that were on the edges of the biome, as they were not fully covered with LULC data (Figure 1). Thus, we investigated 1471 cells in our analysis, wherein we computed all acquired data for each of these cells. We summarise the datasets used, and the methods applied in Figure 2.

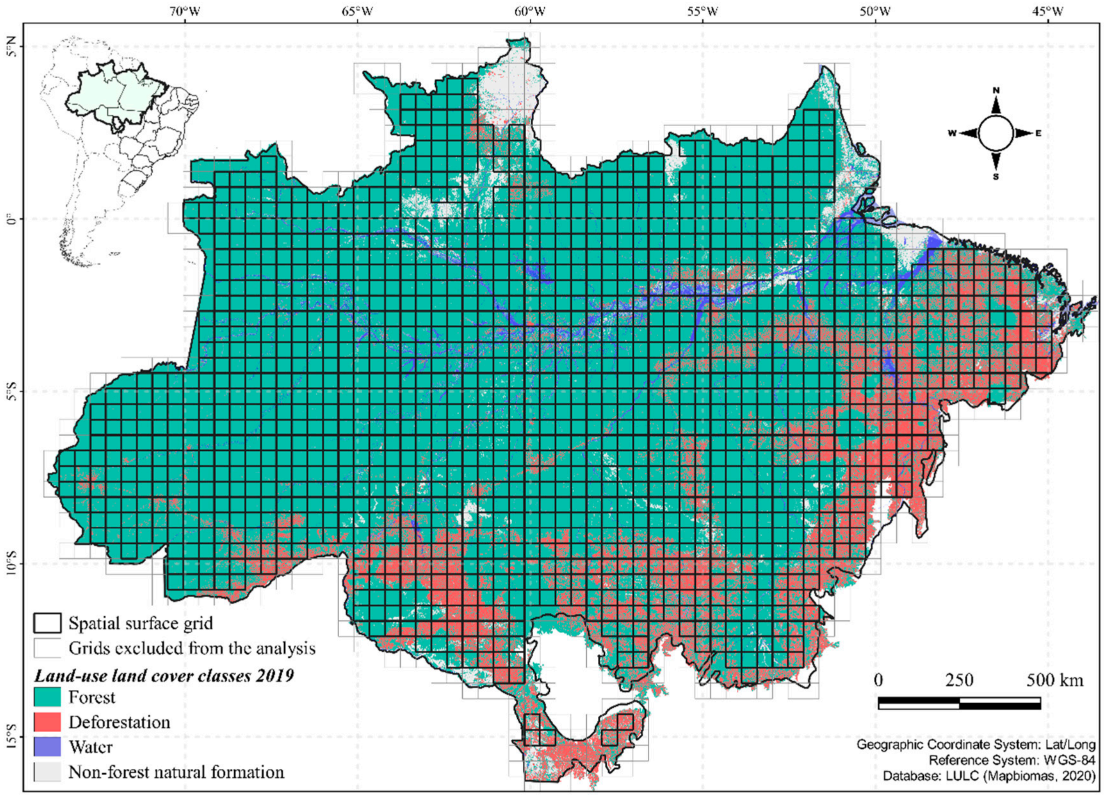

Figure 1. Location of the base spatial surface grids used in our analysis.

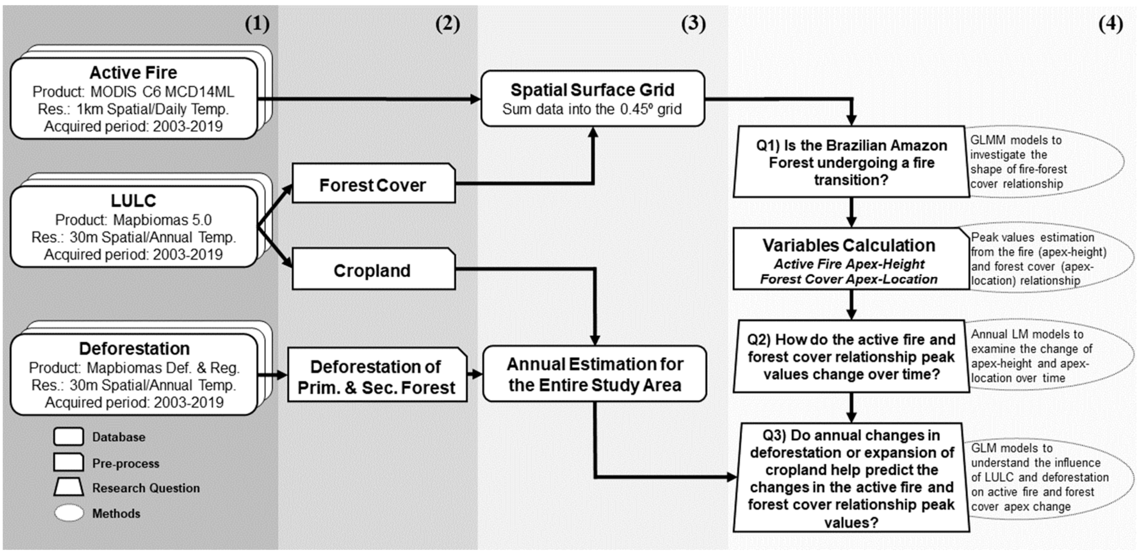

Figure 2. Workflow of the used method, describing: (1) the three main datasets to analyse and interpret the active fire behaviour in relation to forest cover: (i) Active Fire occurrence [27]; (ii) LULC [28,29]; and (iii) Annual Deforestation [25]. (2) The land cover and deforestation metrics derived from these products. (3) The spatial surface grids metrics calculation used for statistical analyses. (4) The key questions.

2.2.1. Active Fire

We used data from MODIS Terra and Aqua satellites, which are produced from MODIS MCD14ML Collection 6, where active fires are detected at a 1 km spatial resolution. The MODIS MCD14ML Collection 6 improved the active fire detection in the Amazon by reducing false positives [27]. This dataset for the Amazon Forest may have low detection rates where canopy cover is particularly dense and is likely to underestimate understory fires. However, our hypotheses are mainly about changes in fire-use in open areas, and we repeat analysis removing dry years to account for the possible influence on forest fires. We collected these datasets in the Fire Information for Resource Management System (FIRMS) platform in a point-vector format. We first acquired data from 1 January 2003 to 31 December 2019 and then aggregated all active fires with confidence levels greater than 30% (nominal and high confidence fires as applied in Chen et al. [30] and Armenteras et al. [31]) within our 0.45° grid cells, counting the annual total for each cell.

2.2.2. Land Use and Land Cover

For this analysis, we used Mapbiomas' collection 5.0 data. The Mapbiomas product estimates forest formation areas, without distinguishing primary from secondary vegetation, so we considered both in our forest cover estimates. In addition, our main hypotheses were focussed on fire use in open lands, which further justifies grouping primary and secondary forests together. Thus, to estimate forest cover values, we calculated the percentage of each grid that is covered by the forest formation class. In addition, we estimated the cropland areas considering only the soybean crops as an intensive stage of land-use transition [22] indicator in the rural areas of the Brazilian Amazon Forest. We considered using other agricultural classes as indicators of cropland areas, but these areas either not present in the landscape or inseparable from small-scale subsistence practices. (However, Table A2 shows that there is no significant difference in the results when temporary crops were also considered). We used the Google Earth Engine platform to process the Mapbiomas dataset and calculate the forest cover percentage for each grid and we also estimated the cropland area per year for the entire study area in our analysis.

2.2.3. Deforestation

We collected the deforestation data from the Mapbiomas Deforestation and Regeneration dataset. This dataset considers 1988 as a base map to analyse the pixel-by-pixel trajectory of deforestation and regeneration up to 2019 [32]. We considered the total deforestation of primary and secondary forests, as both are potential sources of fire ignition [23,33] and the LULC dataset also includes both categories in the forest formation class. To obtain yearly deforestation rates, we processed this dataset in the Google Earth Engine platform to sum the total deforested area within each grid cell. We then estimated yearly deforestation rates for the entire study area.

2.3. Data Analysis

We split the analyses into three stages of data processing: (1) To evaluate whether the Brazilian Amazon is undergoing a fire transition, we examined the shape of the relationship between active fires count and forest cover by comparing three Generalised Linear Mixed Models (GLMM): (i) null, (ii) linear and (iii) quadratic. We produced the GLMMs using each grid cell and each year as random effects variables—a spatial and a temporal variable, respectively. Given the high number of zeros in the fire count dataset, we used a zero-inflation model and set the family as negative binomial, to reduce over-dispersion. We also estimated the R^2-marginal and R^2-conditional for the GLMM produced using the Nakagawa et al. [34] method as it can estimate these values for negative binomial models. To determine the best fit model, we tested and compared the Akaike Information Criterion (AIC) results. (2) Thereafter, to determine whether the transition point of the fire occurrence and forest cover relationship is transitioning over time, we produced yearly quadratic models to extract the vertices values. The use of a quadratic model implies that there is an apex at which we find a maximum number of active fires per year in each grid cell—hereafter, active fire apex-height, and there is also a maximum amount of forest cover for this to happen, the line of symmetry of the equation—hereafter, forest cover apex-location (in Figure 3 there is a visual representation of these variables). Thus, we extracted the apex-height and the apex-location for each year of the active fire and forest cover relationship. We then calculated how these parameters changed over time. The behaviour of the peaks in the active fire-forest cover relationship over time is important; not only is it a direct test of the hypotheses raised by Andela et al. [3], it also allows us to verify in which landscapes (% of forest cover) the fire is more likely to happen. (3) Finally, to examine whether deforestation and cropland expansion can predict changes in the peak values from the active fire and forest cover relationship per year, we produced Generalised Linear Models (GLM) using active fire apex-height and forest cover apex-location as dependent variables, and as independent variables we used: (i) deforestation rates of primary and secondary forests; and (ii) cropland area estimation. In order to find the best-fitting model for active fire apex-height and forest cover apex-location, we used the dredge function analysis, where all possible models are considered, and compared their AIC results. In addition, we produced linear models with the dependent variables and their most significant independent variables. We conducted all statistical analyses in R v. 4.1.0 using glmmTMB [35], MuMIn [36] and stats [37] packages.

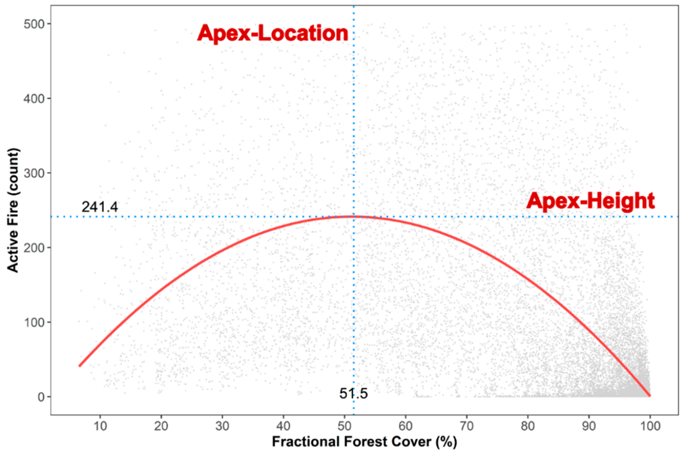

Figure 3. The quadratic relationship between forest cover and active fire counts, as derived from the GLMM analysis. Active fire counts were highest (~241) in grids with 51.5% forest cover. Horizontal blue dotted line represents the active fire apex-height and vertical blue dotted line is the forest cover apex-location. Data points (0.45° grids) are represented in grey.

Our primary objective was to assess whether active fires are being affected by changes in land use, and not climate. We therefore analysed these changes considering two climate scenarios: (i) all years, and (ii) removing years with extreme droughts from the analyses, since in these years the number of active fires is higher than normal because of climate conditions—Appendix B, Table A3, and Figure A4. We also re-analysed the time series separating it into two distinct periods—from 2003 to 2011 and from 2012 to 2019—since the deforestation rates behaviour was very different in the Brazilian Amazon Forest during these two periods—Appendix C. Furthermore, in order to understand the relationship of the results with the anthropogenic dynamics in the region we review the socio-environmental implications of the fire-transition process for the Brazilian Amazon.

3. Results

3.1. Analysing an Amazon Fire-Transition

We found that the distribution between the active fire count and the forest cover percentage, for each grid cell and year, was best described by a quadratic form (dAIC with null model = 767,315.8 and dAIC with linear model = 760.6). The quadratic model is shown in Figure 3. However, the proportion of active fire counts explained by the fixed term alone (percentage of forest cover) was low (R^2 marginal = 0.06), and the variance explained by the entire model was significantly higher (R^2 conditional = 0.59). The markedly higher explanatory power of the entire model suggests a strong influence of the random effects (years and grid cells).

3.2. Key Parameters Defining a Forest Cover-Fire Occurrence Relationship

Both apex-height and apex-location of the forest cover-active fire relationships changed year to year (Figure 4a). The active fire apex-height registered varied from ~127 in 2013 to ~662 in 2005, while the forest cover apex-location varied from 47.03% in 2007 to 56.74% in 2018. This variation was predicted by time, as with active fire apex-height decreasing from ~524 in 2003 to ~139 in 2019 (R^2 = 0.52), and the forest cover apex-location increasing from landscapes with 50.7% of forest cover in 2003 to landscapes with 55.0% of forest cover in 2019 (R^2 = 0.3) (Figure 4b,c).

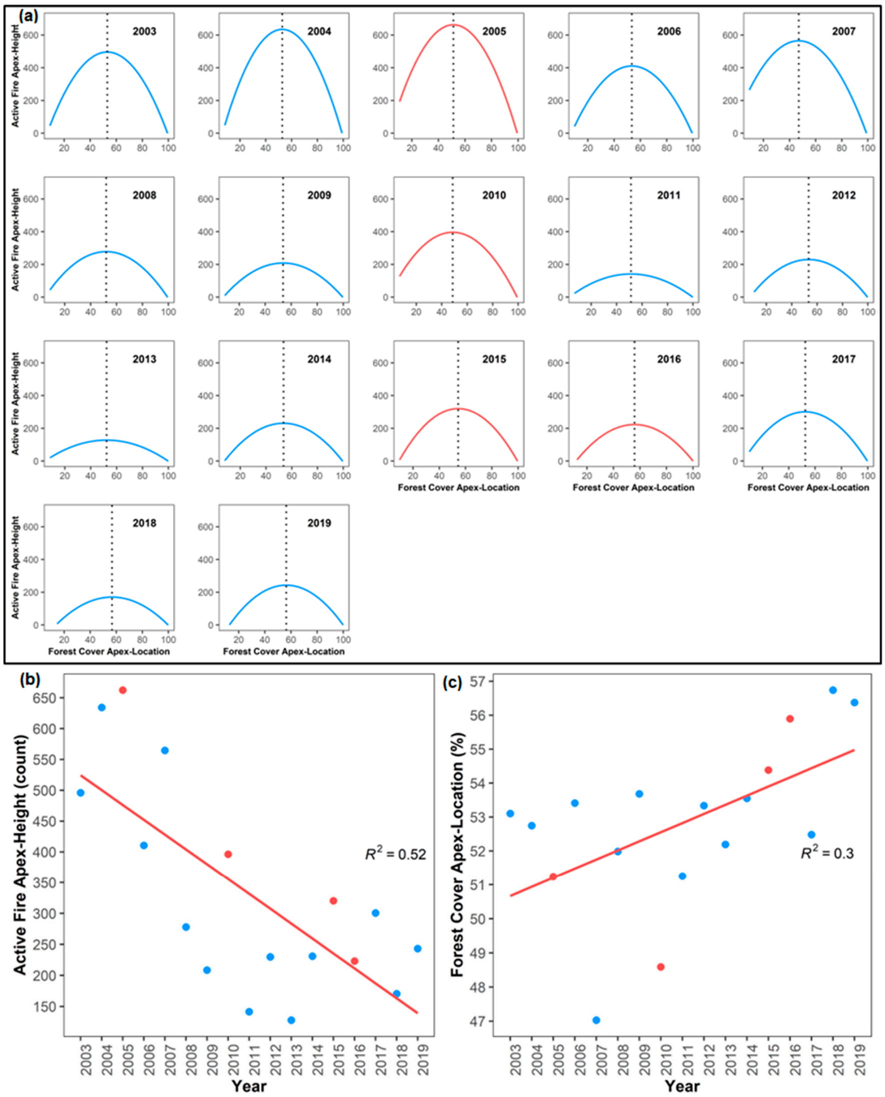

Figure 4. Active fire apex-height and forest cover apex-location behaviour during the analysed years. (**a**) Yearly quadratic models of active fire apex-height and forest cover apex-location relationship. The black dotted lines are the apex of the relationship. Normal climatic years are illustrated with blue plots, and severe dry years are with red plots. (**b**) Active fire apex-height value by year. The red dots are the severe dry years. (**c**) Forest Cover apex-location value by year. The red dots are the severe dry years.

When we investigated these relationships in two different periods (Figure 5): (i) during the 2003–2011 period, the active fire apex-height had an important decreasing trend (R^2 = 0.61) and the forest cover apex-location decreased but with a low significance value (R^2 = 0.11); ii) the opposite happened with the behaviour of these variables during the 2012–2019 period, in which the active fire apex-height slightly increased, with a low significance value (R^2 = 0.038), and the forest cover apex-location significantly increased (R^2 = 0.48). These results therefore indicate an important change in the fire transition during the two different periods, with the first period being most important in determining the decrease in the apex-height, and the second period being more important for determining the increase in the apex-location.

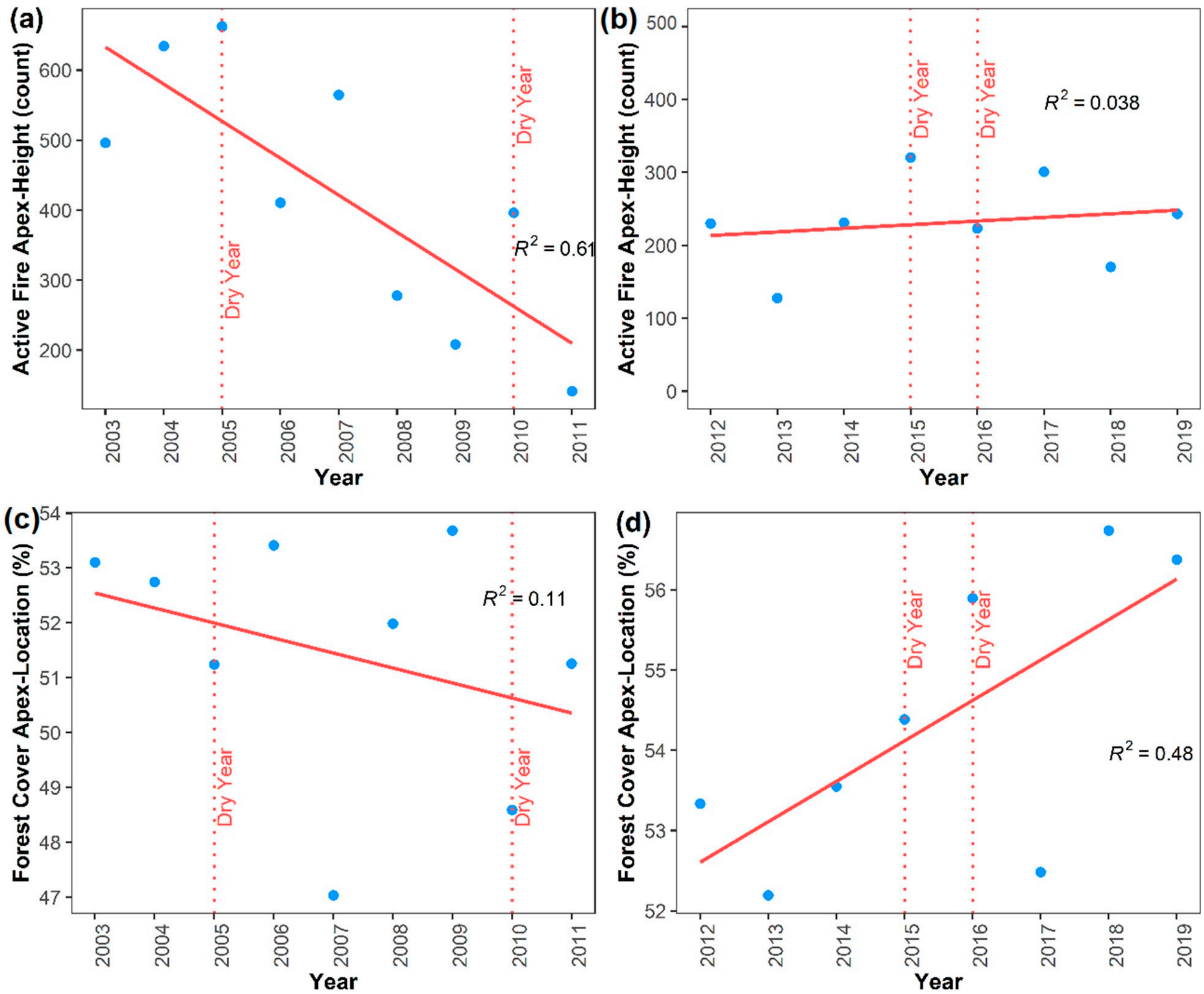

Figure 5. Apex-height and apex-location behaviour in the two analysed periods. (**a**) Active fire apex-height from 2003 to 2011. (**b**) Active fire apex-height from 2012 to 2019. (**c**) Forest cover apex-location from 2003 to 2011. (**d**) Forest cover apex-location from 2012 to 2019.

3.3. The Influence of Deforestation Rates and Cropland Expansion on the Forest Cover-Fire Occurrence Relationship

The dredge analyses (Table A1) showed that two models are more plausible (dAIC < 2) for both active fire apex-height and forest cover apex-location. In these models, we found: (i) the deforestation rates in all best-ranked models for the active fire apex-height (R^2 = 0.59 and *p*-value = 0.0003 in the bivariate analyses—Figure 6a), and (ii) the cropland area is in all best-ranked models for forest cover apex-location (R^2 = 0.38 and *p*-value = 0.009 in the bivariate—Figure 6b). The strength of these relationships improved when we removed the severe dry years from the analyses (lower AIC values—Table A3), and we found better results in the active fire apex-height by deforestation rates model (R^2 = 0.67—Figure A4c). In addition, when we investigated these significant relationships in two different periods (Figure A6), we found that there is a strong relationship between the active fire apex-height and the deforestation rates during the 2003 to 2011 period (R^2 = 0.57 and p-value = 0.02) and an important relationship between forest cover apex-location and cropland area in the 2012 to 2019 period (R^2 = 0.38 and p-value = 0.05). In summary, the key variables are important to describe the active fire apex-height and forest cover apex-location, and the behaviour of each one is better predicted in different periods.

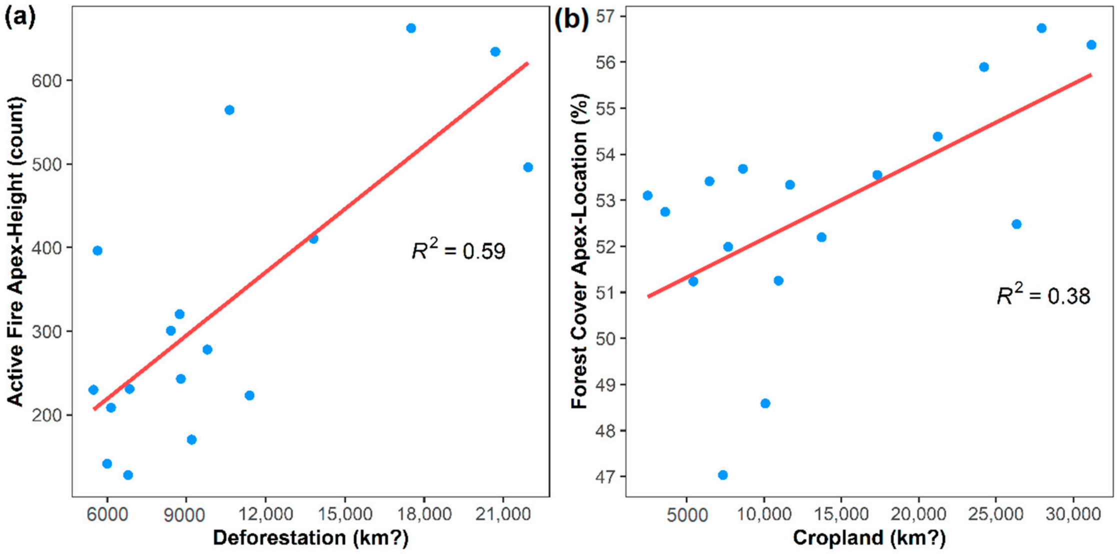

Figure 6. Linear models of the significant variables used to describe active fire apex-height and forest cover apex-location. (**a**) Active fire apex-height by annual deforestation. (**b**) Forest cover apex-location by cropland area.

4. Discussion

4.1. Fire-Transition Patterns in Brazilian Amazon

Our analyses indicated that fire occurrence in Amazonia follows a quadratic relationship with forest cover and spatiotemporal variables. This relationship is not static over time: between 2003–2019, the active fire apex-height decreased while the forest cover apex-location increased. The deforestation rates and the cropland expansion predicted mainly the apex of these relationships within the landscape. Our results show that the reduction in the deforestation rates is crucial to the reduction of fire occurrence, reflecting the fact that many of the detected fires are those detected during the land clearing process. Furthermore, we highlight that the fire occurrence apex is transitioning to more forested landscapes which may be vulnerable to increased deforestation. We also show that the expansion of mechanised agriculture practices is resulting in the peak of fire occurrence shifting towards regions with higher levels of forest cover. Thus, our results broadly support the model of Andela et al. [3]. We found that the fire-transition in the Brazilian Amazonian Forest is related to the stage of land-use transition, increasing during the deforestation process, and further reducing when more advanced agricultural practices are implemented.

The amount of variance explained was higher when we removed the years with severe droughts from the analyses (Table A3 and Figure A4c,d). This is plausible since in these years, the amount of deforestation capture by Mapbiomas (Figure A2a) and the amount of active fire occurrence (Figure A1b) significantly increased, compared to previous years. For instance, Aragão et al. [11] found a 36% increase in fire incidence during the 2015 drought event, and in that year the largest ever ratio between fire and deforestation was registered. On the other hand, the global analysis by Andela et al. [3] indicated that climate is relevant only for the intra-annual fire occurrence behaviour. In the Amazonian forest, intra-annual analyses have indicated that fire occurs mainly during the dry season and there is also a spatial variance in this fire regime [31,38]. These results, in accordance with the scientific literature, indicate that variation in climate has an important role in the fire-transition relationships.

4.2. Spatiotemporal Changes in Fire Occurrence

Our findings suggest that the two key variables responsible for the spatiotemporal variation in the fire-transition process in the Brazilian Amazonian Forest were the annual rates of deforestation and cropland expansion. In addition, our results have shown that in the first analysed period—from 2003 to 2011—higher rates of deforestation led to greater active fire apex-heights, while in the second period—from 2012 to 2019—there is a clearer relationship between the expansion of the cropland areas and the forest cover apex-location. These differences can be explained by changes in the Brazilian Amazon during these periods, as deforestation rates significantly decreased during the first period and constantly increased in the second period [39]; while there was a constant expansion of the cropland reas.

The use of fire is expected during the initial phases of land-use transition (deforestation) since fire is a cheap tool to clear felled vegetation when converting forests to agriculture [22]. The deforestation phase is then followed by consolidation, which often starts with pastures, which may later on be converted into croplands as part of the intensification process [10,40]—although some deforested areas are converted straight to cropland [10]. Fire is a key tool during the initial stages of the clearance process. For instance, Aragão and Shimabukuro [23] found that most of the reported fires occurred in recently deforested areas, indicating that new frontiers of deforestation may increase fire occurrence in the Brazilian Amazon Forest. Morton et al. [10] showed that the cropland expansion trend is linked with the increase in the average size of deforested areas and with the frequency of fire usage for deforestation.

4.3. Socio-Environmental Implications of the Fire-Transition Relationship with Land-Use Variables in the Brazilian Amazon

The fire-transition behaviour and its relationships with deforestation and cropland expansion are key to understanding mechanisms and developing more effective environmental policies. Although agricultural intensification and mechanisation appear to be a solution to fire, this is overly simplistic as they have many important problems associated with them. First, much of the environmental harm associated with deforestation and fire may occur in the initial phase of these relationships, meaning any potential benefits of mechanisation for fire reduction occur when the remaining forests have already been fragmented and degraded. Second, an increase in incentives for cropland expansion may lead to more deforestation [10,40]. Third, high capital activities are responsible for conflicts between land rights of the local populations and the agribusiness sector, since these socioeconomic dynamics only indulge business-as-usual development, excluding people from its process [41,42]. In the Brazilian Amazon, these disputes over territory during the land-use transition are commonly violent [42], causing irreparable social and cultural losses to local communities including the depletion of key ecosystem services provided by the forest [43], which compromises the ways of living of local communities [44]. Moreover, mechanised agriculture is a high-capital intervention that is not affordable for most of the small-scale farmers, who have less access to financial subsidies, besides depending on a supply chain infrastructure to deliver high-income agricultural production limited to peri-urban or easily accessible areas [45]. Finally, cropland expansion invariably involves increased use of agrochemicals, which result in a substantial amount of environmental pollutants entering the soil and being destined to groundwater water and surface water supplies [46] and social conflicts due to the depletion of natural resources [47]. Thus, this land-use transition is unfeasible for sustainable land management.

Taken together, these social and environmental impacts show that intensification should not be seen as a solution to Amazonia's fire problem. Rather, our results highlight the importance of ceasing further deforestation; forest loss is the biggest driver of changes in fire occurrence and marks the start of a transition to more intensive land uses. However, actions taken to reduce deforestation may not on their own be effective at preventing new forest fires, especially given the increases in temperature and reductions in dry season rainfall [48] and increasing levels of forest disturbance [49] that make forests more flammable [12,50]. Tackling forest fires will require a broad range of measures, including greater participatory policy development (e.g., Carmenta et al. [51]), restoration [52], and much greater support for community firefighters and development of coherent fire monitoring and combat plans for protected areas [53].

5. Conclusions

Our study shows that the fire-transition process in the Brazilian Amazonian Forest is mainly related to anthropogenic changes in landscapes and that the fire occurrence apex is transitioning to more forested landscapes. We found deforestation rates as a key determinant of the apex of active fire occurrence, although cropland expansion (presumably in regions with low forest cover) has resulted in the apex of fire occurrence happening in areas with higher forest cover. This transition of the peak of active fire occurrence to areas with more forest cover appears to have accelerated in the last few years (2012–2019 analyses). So, although fire occurrence is lower in the more advanced phases of land-use transition, this fails to resolve fire occurrence at the frontier, where it is associated with deforestation and land speculation, and where it has the potential to affect large areas of previously undisturbed primary forests. Improving our understanding of the relationships underlying fire transition is important for the sustainable planning and management of the Amazon landscape.

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Data Availability Statement: The active fires data (MODIS MCD14ML Collection 6) is freely available in the Fire Information for Resource Management System (FIRMS) platform (https://firms.modaps.eosdis.nasa.gov/active_fire/ (accessed on 1 March 2021)). Both Mapbiomas data used in this paper are freely available on the Mapbiomas platform (https://brasil.mapbiomas.org/en/colecoes-mapbiomas-1?cama_set_language=en (accessed on 1 March 2021)). The deforestation and the precipitation data used in the appendices are freely available, respectively, on the PRODES/INPE platform (http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes (accessed on 1 January 2022)) and on the CHIRPS platform (https://www.chc.ucsb.edu/data/chirps (accessed on 1 January 2022)).

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Conflicts of Interest: The authors declare no conflict of interest.

Appendix A

Most of the active fires occurs in grids with more than 50% of forest cover (Figure A1a), being the peak of hotpots occurrence in landscapes with 80% of forest cover. Over the analysed years, there was an important decrease in the active fires' occurrence (Figure A1b), from peaks of ~300,000 hotspots in the El Niño of 2005 to ~175,000 hotspots in the El Niño of 2015.

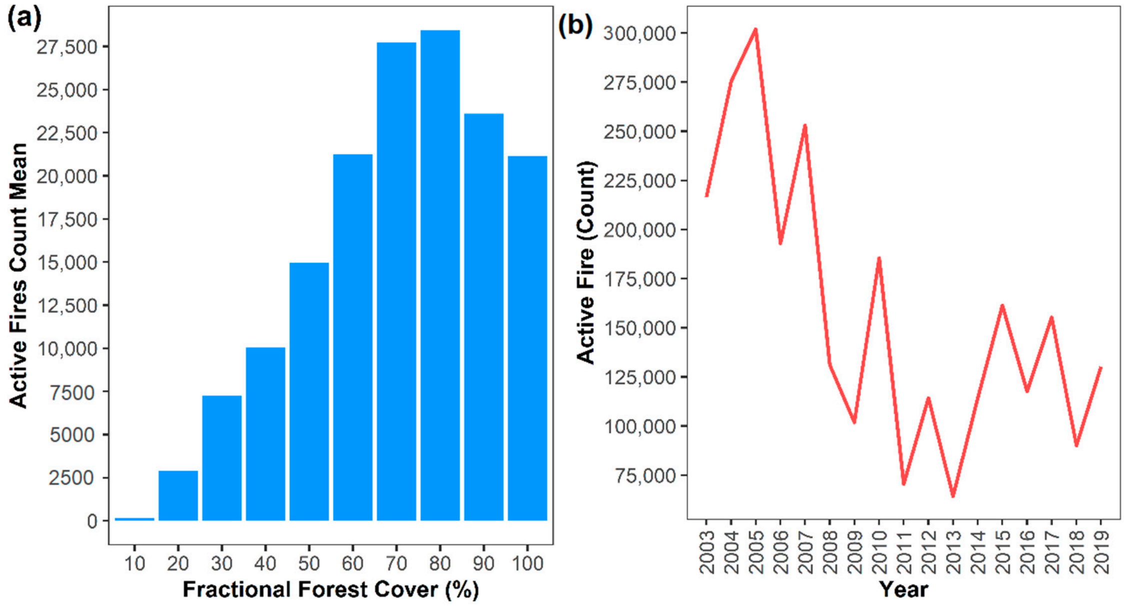

Figure A1. Active fire behaviour plots: (**a**) Mean of active fires per year divided per fractional forest cover of each grid cell. (**b**) Active Fire per year.

We used deforestation data for both primary and secondary forests from the Mapbiomas Deforestation and Regeneration database [25]—Figure A2a. This Mapbiomas database is still new and being improved over time. Its method differs from PRODES/INPE [24] (Figure A2b)—which is the most conventional method to calculate deforestation in the Brazilian Amazon. The Mapbiomas Deforestation and Regeneration database computes deforestation from the first to the last day of the normal year and estimates the deforestation of secondary vegetation. Because of the differences in the deforestations rates patterns at the middle of the time series (decreasing in the first years and then increasing again), we conducted some investigations separating the analyses in two periods (2003–2011 and 2012–2019; Appendix C).

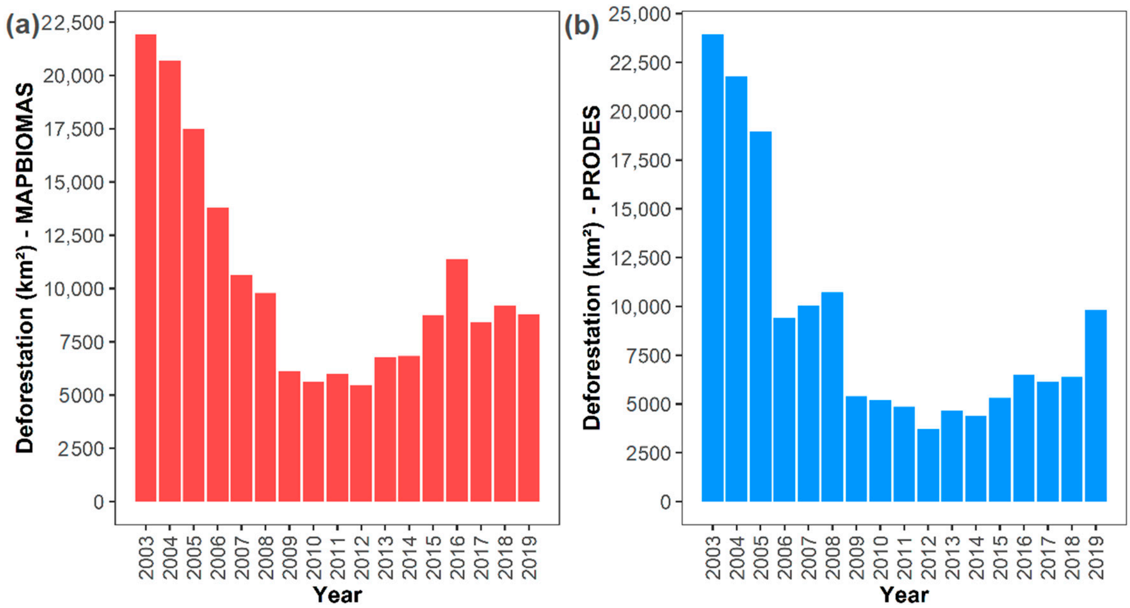

Figure A2. Annual deforestation rates in the study area: (**a**) Mapbiomas Primary and Secondary Vegetation. (**b**) PRODES.

In order to determine the years impacted by severe droughts, we used the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) [54] monthly dataset to calculate the Maximum Cumulative Water Deficit (MCWD) [55,56]. We re-sampled the MCWD data to 0.45° and re-projected it to our grid to compute the pixel-based MCWD anomalies. We calculated these anomalies from the long-term mean from 1981 to 2019 (t) normalised by the standard deviation (σ) [57]. A reclassification was then applied and years with result values smaller than −1.96 were considered as anomalous. Lastly, the number of cells with MCWD anomalies for the entire study area per year was calculated (Figure A3). From these results, we considered 2005, 2010, 2015 and 2016 as dry years, and we made analyses where these years are not modelled to observe their implications in the analyses (Appendix B).

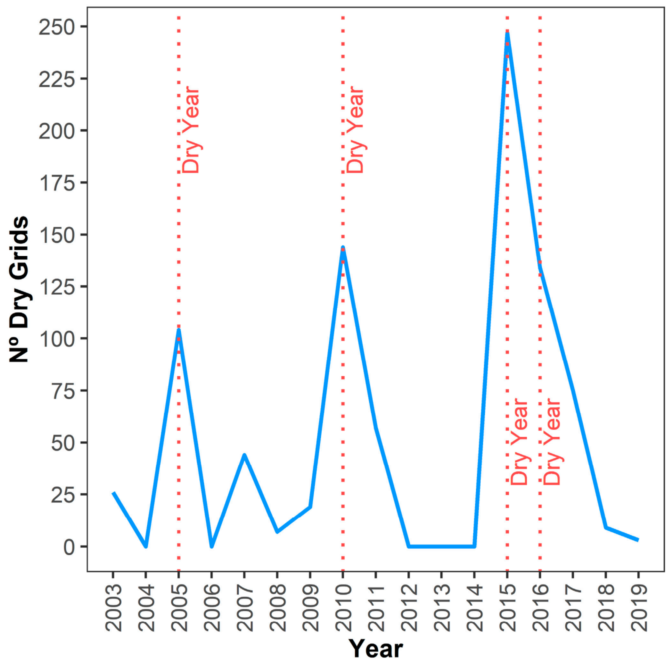

Figure A3. Number of dry grid cells per year. The years that were considered as severe droughts are highlighted in red.

Appendix B

In order to find the best-fitting model for predicting the active fire apex height and the forest cover apex-location, we produced a dredge analysis with the key variables (Table A1). For these models, we considered total deforestation rates of primary and secondary vegetation, and soybean areas as a marker of cropland area. In these analyses, all years were considered. The deforestation rate was the variable that better predicted the active fire apex-location, being in all the best ranked models; and cropland area was the variable most important for predicting the forest cover apex-location. However, both variables were found in the best-fitting models (dAIC < 2) for apex-height and apex-location.

We also analysed the active fire apex-height and forest cover apex-location models, considering soybean and temporary crop as markers of cropland (mechanised production) areas (Table A2). We did not use these models because we could not confirm whether all temporary crops areas were mechanised. However, and for reference only, the results from the models were similar to the ones found when only the soybean areas were considered. Deforestation was the most repeated variable in the active fire apex-height models, and the cropland area was included in a greater number of forest cover apex-location models.

Table A1. Predicted models for the active fire apex-height and forest cover apex-location models. These analyses considered deforestation rates and cropland area as independent variables. The results are ranked by the AIC of each function.

Dependent Variable	Intercept	Cropland Area	Deforestation Area	Deforestation X Cropland	AICc	Delta	Weight
Active Fire Apex-Height 2003–2019	**68.1341**	**NA**	**0.0252**	**NA**	**214.2524**	**0.0000**	**0.5396**
	185.1137	**−0.0053**	**0.0210**	**NA**	**214.8702**	**0.6178**	**0.3962**
	227.6442	−0.0110	0.0176	0.0000	218.8215	4.5690	0.0549
	479.5580	−0.0106	NA	NA	222.6618	8.4093	0.0081
	331.6909	NA	NA	NA	226.4416	12.1892	0.0012
Forest Cover Apex-Location 2003–2019	**50.4838**	**0.0002**	**NA**	**NA**	**78.0671**	**0.0000**	**0.4685**
	47.9510	**0.0002**	**0.0002**	**NA**	**78.2357**	**0.1686**	**0.4306**
	47.7533	0.0002	0.0002	0.0000	82.3456	4.2785	0.0552
	52.8240	NA	NA	NA	83.1258	5.0587	0.0373
	52.7333	NA	0.0000	NA	86.1093	8.0423	0.0084

Table A2. Predicted models for the active fire apex-height and forest cover apex-location models. These analyses considered deforestation rates and cropland area as independent variables. In these models, we considered soybean and temporary crops as cropland area. The results are ranked by the AIC of each function.

Dependent Variable	Intercept	Cropland Area	Deforestation Area	Deforestation X Cropland	AICc	Delta	Weight
Active Fire Apex-Height 2003–2019	**68.1341**	**NA**	**0.0252**	**NA**	**214.2524**	**0.0000**	**0.5024**
	217.5720	**−0.0051**	**0.0203**	**NA**	**214.7015**	**0.4490**	**0.4014**
	339.4363	−0.0152	0.0099	0.0000	217.8758	3.6234	0.0821
	531.5038	−0.0103	NA	NA	221.5704	7.3179	0.0129
	331.6909	NA	NA	NA	226.4416	12.1892	0.0011
Forest Cover Apex-Location 2003–2019	**46.5932**	**0.0002**	**0.0002**	**NA**	**77.1620**	**0.0000**	**0.5438**
	49.8425	**0.0002**	**NA**	**NA**	**78.0471**	**0.8851**	**0.3494**
	45.8719	0.0003	0.0003	0.0000	81.1776	4.0156	0.0730
	52.8240	NA	NA	NA	83.1258	5.9637	0.0276
	52.7333	NA	0.0000	NA	86.1093	8.9473	0.0062

Additionally, we investigated the active fire apex-height and forest cover apex-location without considering dry years (2005, 2010, 2015 and 2016). We found these analyses relevant because in these years, the amount of active fire occurrence tends to be greater than in normal years, which might change the fire-transition patterns during the analysed period (Table A3). In these analyses, we also found the deforestation rates as the key variable for active fire apex-location and cropland area as the main predictor of forest cover apex-location. However, the results of the models performed slightly better without the dry years.

Subsequently, we present the key variables results when compared with the active fire apex-height and forest cover apex-location when the severe dry years (2005, 2010, 2015 and 2016) are not considered in the analyses (Figure A4). In these analyses, the deforestation rates were more significant to describe the active fire apex-height without dry years in the analyses, and the cropland areas were slightly relevant to predict the forest cover apex-location when all years are considered. However, the differences between these models and the ones with all years were not significant.

Table A3. Predicted models for the active fire apex-height and forest cover apex-location models. These analyses considered deforestation rates and cropland area as independent variables. In these models, we removed the years with severe droughts (2005, 2010, 2015 and 2016). The results are ranked by the AIC of each function.

Dependent Variable	Intercept	Cropland Area	Deforestation Area	Deforestation X Cropland	AICc	Delta	Weight
Active Fire Apex-Height No Dry Years	**50.5988**	**NA**	**0.0251**	**NA**	**162.5920**	**0.0000**	**0.8178**
	118.6297	−0.0030	0.0225	NA	165.9493	3.3573	0.1526
	262.6756	−0.0258	0.0104	0.0000	169.8633	7.2713	0.0216
	435.2554	−0.0093	NA	NA	172.8497	10.2576	0.0048
	310.5030	NA	NA	NA	173.7141	11.1221	0.0031
Forest Cover Apex-Location No Dry Years	**51.0259**	**0.0001**	**NA**	**NA**	**61.9643**	**0.0000**	**0.5479**
	52.9153	**NA**	**NA**	**NA**	**63.4096**	**1.4453**	**0.2660**
	49.1293	0.0002	0.0001	NA	64.8540	2.8897	0.1292
	53.0844	NA	0.0000	NA	66.8583	4.8940	0.0474
	47.7071	0.0004	0.0003	0.0000	70.0586	8.0943	0.0096

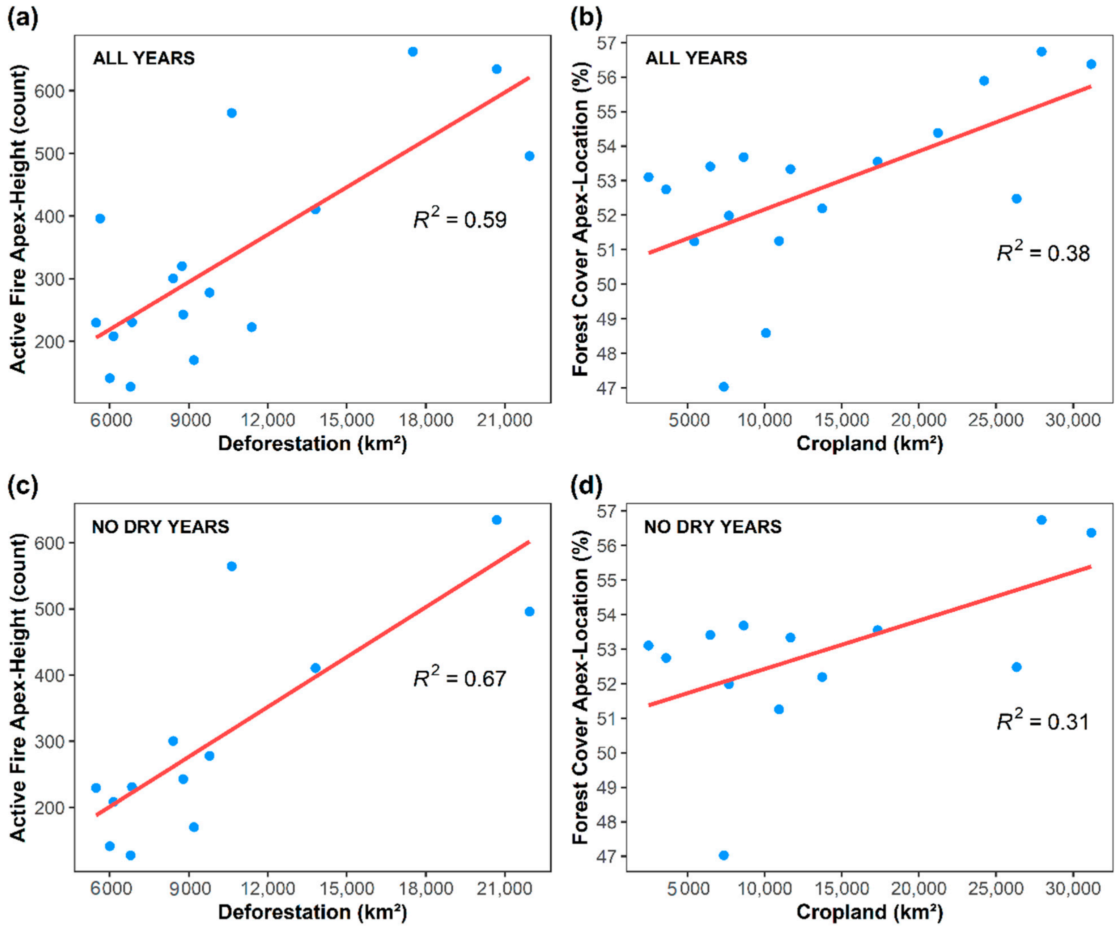

Figure A4. Linear models of the significant variables used to describe active fire apex-height and forest cover apex-location. (**a**) Active fire apex-height by annual deforestation with all years. (**b**) Forest cover apex-location by cropland area over all years. (**c**) Active fire apex-height by annual deforestation without severe drought years. (**d**) Forest cover apex-location by cropland area without severe drought years.

Appendix C

We also analysed the active fire apex-height and forest cover apex-location in two different periods: (i) from 2003 to 2011, period in which the deforestation rates had a significant decrease due to governmental interventions in Amazon to reduce deforestation; and (ii) from 2012 to 2019, during which the deforestation rates first stabilised and then increased again. In addition, there were also differences in the fire behaviour when these two periods are compared. Figure A5 shows the fire behaviour in each grid cell, wherein most of the areas with the oldest occupancy history (northeast and south-southeast) had a reduction in fire occurrence, and the rest had a small increase. Moreover, there are more areas with a significant decrease in fire occurrence than there are areas with a significant increase in fire occurrence.

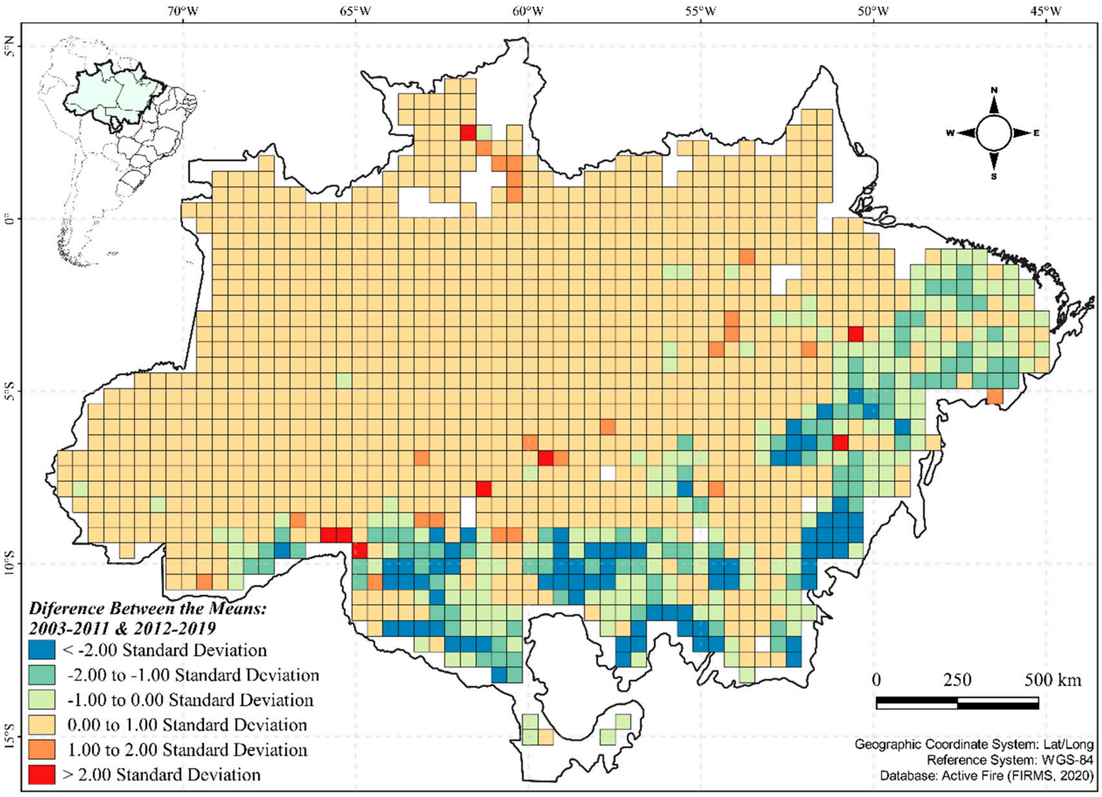

Figure A5. Standard deviation difference between the fire occurrence in the two analysed periods. We made this calculation based on the mean of the second period (2012–2019) minus the mean of the first period (2003–2011).

Additionally, we performed a dredge analysis of the active fire apex-height and forest cover apex-location for each period, to investigate whether deforestation rates or cropland areas can predict their behaviour (Table A4). Our results show that deforestation metrics are good for predicting the apex-height in the 2003–2011 period, while we found the cropland areas in the second best-fitting model for all dependent variables. The apex-location models for the 2012–2019 period had three models with similar AIC, and they also had the smallest AIC values when all analyses are considered.

Table A4. Predicted models for the active fire apex-height and forest cover apex-location models for the two analyses periods: (i) 2003–2011 and (ii) 2012–2019. These analyses considered deforestation rates and cropland area as independent variables. The results are ranked by the AIC of each function.

Dependent Variable	Intercept	Cropland Area	Deforestation Area	Deforestation X Cropland	AICc	Delta	Weight
Active Fire Apex-Height 2003–2011	**147.816**	**NA**	**0.022**	**NA**	**121.706**	**0.000**	**0.523**
	753.998	**−0.048**	**NA**	**NA**	**122.615**	**0.908**	**0.332**
	421.384	NA	NA	NA	124.472	2.766	0.131
	7.281	0.011	0.027	NA	128.872	7.165	0.015
	175.291	-0.023	0.009	0.000	138.938	17.231	0.000
Active Fire Apex-Height 2012–2019	**230.786**	**NA**	**NA**	**NA**	**94.197**	**0.000**	**0.868**
	177.852	0.002	NA	NA	99.182	4.985	0.072
	183.840	NA	0.006	NA	99.572	5.375	0.059
	187.893	0.003	−0.002	NA	108.494	14.297	0.001
	−266.007	0.026	0.061	0.000	126.271	32.074	0.000
Forest Cover Apex-Location 2003–2011	**51.450**	**NA**	**NA**	**NA**	**45.261**	**0.000**	**0.735**
	53.629	−0.0003	NA	NA	48.610	3.348	0.138
	49.862	NA	0.0001	NA	48.836	3.575	0.123
	56.883	−0.0006	−0.0001	NA	55.746	10.485	0.004
	55.904	−0.0004	0.0000	0.0000	67.544	22.283	0.000
Forest Cover Apex-Location 2012–2019	**54.369**	**NA**	**NA**	**NA**	**37.193**	**0.000**	**0.398**
	50.529	**0.0002**	**NA**	**NA**	**37.494**	**0.302**	**0.343**
	49.036	**NA**	**0.0007**	**NA**	**38.094**	**0.901**	**0.254**
	49.194	0.0001	0.0003	NA	45.967	8.774	0.005
	65.328	−0.0007	−0.002	0.0000	61.432	24.239	0.000

We also investigated the individual relationship between the active fire apex-height and the forest cover apex-location per period with each of the key independent variables (Figure A6). Our results shows that the deforestation rates are key to understanding the active fire apex-height in the first period (2003–2011)—Figure A6a, while the increase in the cropland area is strongly related with the increase in the forest cover apex-location in the second period (2012–2019)—Figure A6d. Therefore, to reduce the amount of active fire occurrence per year the deforestation of new areas must be avoided, and investments in mechanized agriculture are not a guarantee that forests will be preserved in the near future, since the increase in its area is related to an increase in the forest cover apex-location investigated in our analyses.

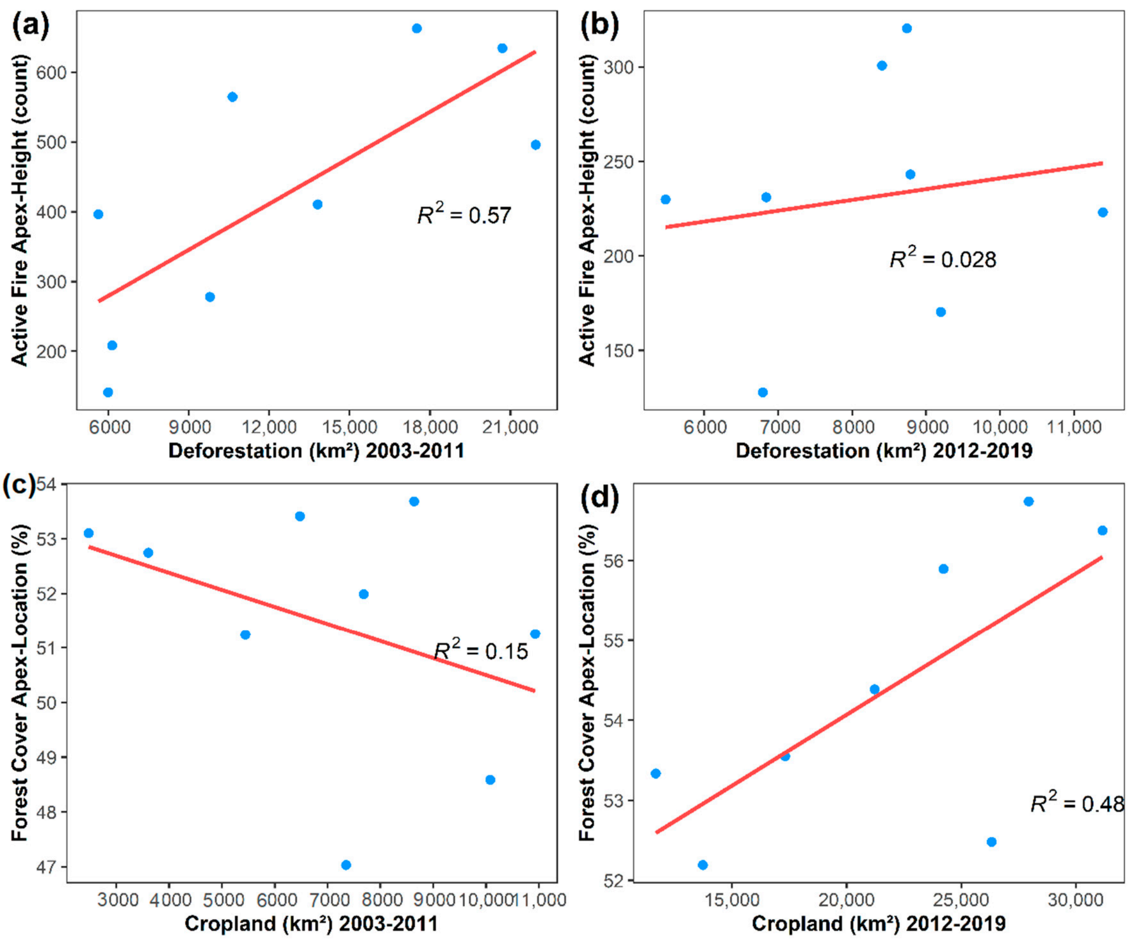

Figure A6. Linear models of the significant variables used to describe active fire apex-height and forest cover apex-location per analysed period. (**a**) Active fire height by annual deforestation from 2003 to 2011. (**b**) Active fire height by annual deforestation from 2012 to 2019. (**c**) Location of the active fire apex in relation to forest cover against cropland area from 2003 to 2011. (**d**) Location of the active fire apex in relation to forest cover against cropland area from 2012 to 2019.

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