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Effects of climate and land-use change scenarios on fire probability during the 21st century in the Brazilian Amazon

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Abstract

The joint and relative effects of future land-use and climate change on fire occurrence in the Amazon, as well its seasonal variation, are still poorly understood, despite its recognized importance. Using the maximum entropy method (MaxEnt), we combined regional land-use projections and climatic data from the CMIP5 multimodel ensemble to investigate the monthly probability of fire occurrence in the mid (2041–2070) and late (2071–2100) 21st century in the Brazilian Amazon. We found striking spatial variation in the fire relative probability (FRP) change along the months, with October showing the highest overall change. Considering climate only, the area with FRP ≥ 0.3 (a threshold chosen based on the literature) in October increases 6.9% by 2071–2100 compared to the baseline period under the representative concentration pathway (RCP) 4.5 and 27.7% under the RCP 8.5. The best-case land-use scenario ("Sustainability") alone causes a 10.6% increase in the area with FRP ≥ 0.3, while the worse-case land-use scenario ("Fragmentation") causes a 73.2% increase. The optimistic climate-land-use projection (Sustainability and RCP 4.5) causes a 21.3% increase in the area with FRP ≥ 0.3 in October by 2071–2100 compared to the baseline period. In contrast, the most pessimistic climate-land-use projection (Fragmentation and RCP 8.5) causes a widespread increase in FRP (113.5% increase in the area with FRP ≥ 0.3), and prolongs the fire season, displacing its peak. Combining the Sustainability land-use and RCP 8.5 scenarios causes a 39.1% increase in the area with FRP ≥ 0.3. We conclude that avoiding the regress on land-use governance in the Brazilian Amazon (i.e., decrease in the extension and level of conservation of the protected areas, reduced environmental laws enforcement, extensive road paving, and increased deforestation) would substantially mitigate the effects of climate change on fire probability, even under the most pessimistic RCP 8.5 scenario.

KEYWORDS
fire modeling, forest degradation, hot pixels, maximum entropy, representative concentration pathway, tropical forest

1 | INTRODUCTION

Future changes in fire regimes may have important impacts on a range of natural processes and police issues such as greenhouse gas (GHG) emissions, climate policy, biomes distribution, biodiversity conservation, human safety, public health, and land-use management (Aragão et al., 2018; Barlow et al., 2016; Flannigan, Krawchuk, De Groot, Wotton, & Gowman, 2009). Such changes in the Amazon basin are of special interest given its global importance concerning biodiversity, carbon and water cycles, heat transfer, and its high ethnological diversity (Nobre et al., 2016 and references therein).

Most previous studies on the future fire activity over the Amazon basin project an increase in fire occurrence owing to land-use and/or climate change, although some contrasting results were found. Golding and Betts (2008) and Justino et al. (2011), for example, estimated the impact of the A1B climate change scenario on the environmental susceptibility to fire occurrence based on climatic indices and found a positive trend in fire susceptibility in the Amazon during the 21st century. However, an opposite tendency in fire probability was found by Moritz et al. (2012), using the A2 emission scenario, for some tropical biomes, including the Amazon. Silvestrini et al. (2011), including the effect of land-use change on fire modeling, showed that the combination of the A2 emission scenario with deforestation could cause a 49% increase in fire occurrence out of protected areas over the Amazon until 2050. These studies considered the emissions scenarios of the Intergovernmental Panel on Climate Change (IPCC) Special Report on Emissions Scenarios (SRES; IPCC, 2000), the same ones used in the IPCC Third and Fourth Assessment Reports.

In the IPCC Fifth Assessment Report (IPCC, 2015), the SRES were substituted with the representative concentration pathways (RCPs), a new set of scenarios that include time paths for emissions and concentrations of the full suite of GHGs and aerosols and chemically active gases, as well as land-use/land-cover changes.

Considering all four RCPs and using the outputs of the Earth system model HadGEM2-ES, Betts et al. (2015) found an increase in the meteorologically defined forest fire danger index (FFDI) in the Amazon during the 21st century, with greater increases at higher levels of global warming. The authors warned, however, that the FFDI provides an indication of the effects of simulated changes in weather conditions for the risk of fire, but should not be understood as the fire activity per se since the latter is largely dependent on the susceptibility of the landscape to fire and on the influence of humans on either ignition or fire suppression.

In the Brazilian Amazon, fire is almost entirely human-ignited, given that it usually occurs in the driest period of the year and that lightning in the region is usually accompanied by rain, reducing the chance of igniting a natural fire (Barbosa & Fearnside, 2005). Deforestation and subsequent agricultural activities have increased the anthropogenic ignition sources in the last 40 years, since fire is the main technique used to clear the land and to renew pasture areas (Aragão et al., 2014). Although annual deforestation has sharply decreased from 27,772 km^2 in 2004 to 4,571 km^2 in 2012, it has been fluctuating since then, showing annual variation from −15% up to +29% (INPE, 2017a). Large-scale transportation and energy infrastructure projects, the continuous weakening of environmental and indigenous protection agencies, relaxation of environmental legislation, including reduction of requirements in the environmental licensing process of potentially harmful enterprises, are some of the current threats that raise serious concerns about the future deforestation rates (Aguiar et al., 2016; Fearnside, 2016; Tollefson, 2018). Additionally, secondary vegetation regrowth on previously cleared areas is highly fire-prone given its low and open canopy (Ray, Nepstad, & Moutinho, 2005), mostly in its early regeneration stages and during dry years (Gutiérrez-Velez et al., 2014). Repeated clearing and burning of vegetation regrowth is a widespread practice in the Brazilian Amazon (Neeff, Lucas, Santos, Brondizio, & Freitas, 2006; Zarin et al., 2005), increasing the ignition sources.

The joint and relative effects of land-use change scenarios and RCPs on fire occurrence in the Amazon are still poorly understood, despite their recognized importance. An important contribution to this subject is the recent analysis from Le Page et al. (2017). The authors used future land-use distributions from the land harmonization processing developed for the RCPs (Hurtt et al., 2011) and climatic data from two RCP emission scenarios to simulate fire occurrence by the end of the 21st century with the Human–Earth System FIRE model. Through a factorial experiment, they concluded that climate change is the most important driver of increased Amazon understory fire activity by 2080 (Le Page et al., 2017).

Here, we built on previous studies by using an innovative combination of the land-use projections developed by Aguiar et al. (2016) and the climatic data from the historical simulations and future projections from the CMIP5 multimodel ensemble (Taylor, Stouffer, & Meehl, 2012) to investigate the probability of fire occurrence in the mid (2041–2070) and the end (2071–2100) of the 21st century in the Brazilian Amazon. The land-use projections (Aguiar et al., 2016) included in our fire modeling represent alternative pathways of clear-cut deforestation, secondary vegetation dynamics, and old-growth forest degradation which result from the regional socioeconomic, institutional, and environmental dynamics (i.e., agricultural expansion over forested areas, incentives for secondary forests regeneration and maintenance, extension and level of conservation of the protected areas, environmental laws enforcement, and road paving). These fine-tuned scenarios may provide a more accurate picture of regional processes and the resulting land-use change than the global estimates. The storylines underneath the land-use scenarios are aligned with the IPCC Shared Socioeconomic Pathways (SSPs), and therefore consistent with the new scenario framework in which mitigation, adaptation, and residual climate damage are recently being evaluated (O'Neill et al., 2014; Riahi et al., 2017; van Vuuren et al., 2012). Furthermore, we present a detailed diagnostic of the predictors of fire incidence included in the model and the first assessment of the seasonal variation in the climate change effects on fire probability in each climate-land-use projection. We address the specific questions: (a) What climate or land-use variables contribute the most to the model predictive performance? (b) What is the response of fire relative probability (FRP) to each climate and land-use variable?

(c) What are the separate and joint effects of land-use and climate change on the FRP? and (d) What is the seasonal variation in FRP under an optimistic scenario and under a pessimistic scenario of climate and land-use change combined?

2 | METHODS

2.1 | Study area

The study region encompasses the Brazilian Legal Amazon, an area of approximately 5 million km^2 defined by law including the states of Acre, Amapá, Amazonas, Mato Grosso, Pará, Rondônia, Roraima, Tocantins, and part of Maranhão State located west of 44°W longitude. The most representative forest covers of Legal Amazon are the dense and open tropical rain forests, flooded and non-flooded. They comprise an area equivalent to 30% of the tropical rain forests of the world, considered as the richest ecosystem of the earth in terms of biodiversity (FAO, 2005). Open non-forest vegetation types (such as the savannas and floodplain vegetation) were not considered in this study because information on their land-use change is not available. For that purpose, we used the non-forest map provided by the PRODES monitoring system (60 m spatial resolution) and masked the grid cell if its centroid fell into a non-forest pixel. By 2013, about 762,500 km^2 of the original forested area was deforested, with pasture occupying 63% of that area (INPE/EMBRAPA, 2016).

Rainfall, deforestation, and fire occurrence have a marked annual seasonality over the study area. The dry season (rainfall below 100 m per month) length varies across the region, from 4 months in the south to no water deficit along the year in the central and northwest regions (de Moura et al., 2015). At the present time, on average, the dry season extends from July to September in non-drought years for most of the Brazilian Amazon (Aragão et al., 2008), but occurs mainly between January and March in the northern hemisphere (de Moura et al., 2015). The fire season follows the dry season with the majority of the active fires being detected by satellites from July to September (Anderson et al., 2015; Fonseca et al., 2016). Two peaks of deforestation were described for the study area, one in May, 3 months after the peak of the rainy season, and another coincident with the dry season and fire peak (Aragão et al., 2008). Opposite seasonal patterns are found in the relatively small portion of the Brazilian Amazon that is located in the northern hemisphere, with fire season occurring between December and March (Fonseca et al., 2017).

2.2 | Land-use change data and scenarios

We used agriculture (including both crops and pastures, but predominantly pastures, as described in the *Study area* section; INPE/EMBRAPRA, 2016) and secondary vegetation as land-use predictor variables to model fire occurrence. The baseline values were calculated as the mean between 2005 and 2013, based on the data from the Amazon Deforestation Monitoring Project (PRODES) from the Brazilian National Institute for Space Research (INPE; available at http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes) and from the Mapping land use and land cover in the Brazilian Legal Amazon Program (Terraclass; available at http://www.inpe.br/cra/projetos_pesquisas/dados_terraclass.php).

The approach for building the land-use scenarios combined qualitative and quantitative elements using the Story and Simulation (SAS) approach proposed by Alcamo (2008). The qualitative scenarios were built using a participatory approach (Aguiar et al., 2016; Folhes et al., 2015), and the resulting storylines were aligned with the IPCC SSPs. Storylines were constructed considering two main scenarios. The first, *Sustainability scenario*, was an ideal/desired scenario with equilibrium between socioeconomic achievements and the environment. This scenario was aligned with SSP 1. The second, *Fragmentation scenario*, considers the depletion of natural resources and significant social inequality. This scenario was aligned with SSP 3.

Then, elements from the storylines were selected to be included in quantitative models and to define the adequate model parameters. The selected elements were related to natural resources and land-use dynamics, as shown in Table 1. In the model representing the Sustainability future, the elements are as follows: a decrease in old-growth forest degradation; clear-cut deforestation reaching "zero (non-authorized) deforestation" by 2025; the regeneration of all illegally deforested areas on private properties; and high-value secondary vegetation. The final element will allow areas to become secondary forests by not disrupting regrowth in these areas. The quantification of the opposite scenario considers deforestation rates at levels prior to those in 2004 in response to less environmental protection due to agricultural expansion.

The future land-use covers used in this study result from the combination of the LUCC-ME Modeling Framework and INPE-EM Emission Modeling Framework, as described in Aguiar et al. (2016). The LUCC-ME modeling framework (Aguiar, Carneiro, Andrade, & Assis, 2012) was used to generate annual maps of agricultural cover through 2100, and the INPE-EM modeling framework (Aguiar, Ometto, et al., 2012) was used to generate the secondary vegetation dynamics in deforested areas based on a spatially explicit grid of 25 × 25 km^2. The land-use surfaces for the baseline and for the two projected periods (2041–2070 and 2071–2100) used as input in our fire model are available at https://figshare.com/s/1e2bdefb3b772aa91f5e.

2.3 | Climatic data and emission scenarios

The climatic data were obtained from the CMIP5 multimodel ensemble dataset (Taylor et al., 2012). These are the results of 37 global model runs from several research centers worldwide (https://cmip.llnl.gov/cmip5/availability.html), which are available from the data archives of the Earth System Grid Federation data distribution portal (http://www.earthsystemgrid.org). We considered monthly mean output from historical simulations and future changes in climate variables using the RCP 4.5 and RCP 8.5 scenarios (IPCC, 2013). The RCP nomenclature refers to pathways that reach a specific radiative forcing by

TABLE 1 Socioeconomic, institutional, and environmental dynamics corresponding to the modeled land-use scenarios

	Scenario "Sustainability" (aligned to SSP 1)	Scenario "Fragmentation" (aligned to SSP 3)
Environmental Law Enforcement	Forest Code Restoration (LRs and PPAs) and conservation measures are enforced, incentivized and even surpassed, promoting a Forest Transition process and a "zero" deforestation situation after 2025. Protected areas are fully implemented and respected	Forest Code is not respected and deforestation control measures are discontinued. Protected areas are not fully implemented and protected
Future clear-cut deforestation and old growth forest degradation rates	Deforestation rates follows the current slowdown trend and achieve the deforestation target set to 2020 (3,900 km^2/year), and then a new "Zero" (residual < 1,000 km^2/year) deforestation target after 2025. Degradation rates decrease to 1,000 km^2/year after 2025	Deforestation rates start to rise from 2014 to 2020 and continue uncontrolled until 2,100 (19,500 km^2/year). Degradation rates maintain baseline average (14,700 km^2/year)
Secondary vegetation dynamics	Percentage of secondary vegetation in relation to the deforested area in every cell increase to 35% from 2015 to 2030. Existing areas of secondary vegetation are not disturbed after 2020	Follows the baseline dynamic (less secondary vegetation in more densely occupied areas, ~5 years half-life), including areas of old secondary forests
Changes in road network	On-going paving concluded. No major federal or State roads built after 2017	All paving and planned roads (Federal and State) built, distributed in 2017, 2025, 2030, and 2042
Change in PAs	Maintenance of the 2010 PAs network Fully protected	Decrease in the extension and level of protection of the PAs, gradually returning to the 2002 extension in 2022 (2018 = 2006; 2020 = 2004; 2022 = 2002)

Abbreviation: LR, legal reserve; PA, protected area; PPA, permanent protection areas; SSP, Shared Socioeconomic Pathway (as described in Aguiar et al. (2016)).

the year 2100. For instance, the RCP 4.5 implies a radiative forcing of 4.5 W/m^2 by 2100.

In general, all models agree that temperatures are projected to increase substantially (above 1°C) over the continent of South America. For precipitation, the CMIP5 multimodel ensemble displays some spread in its projections of change. However, during the second half of the century, the majority of the models projects drier conditions in dry season (July–September), particularly in the eastern basin, and with projections for wetter conditions in the western basin (IPCC, 2014).

Based on preliminary jackknife tests (see below), we first tested the contribution of the following monthly climatic variables for the model predictive performance: monthly mean and maximum evaporation, mean and maximum temperature, and mean and minimum precipitation. The variables mean evaporation, maximum temperature, and minimum precipitation showed greater contribution to model performance than their respective averages or extreme values and were therefore kept in the model. The baseline values were calculated for the period between 2003 and 2015. The projections were carried out using the average values for the 2041–2070 and 2071–2100 periods.

2.4 | Modeling future FRP

All climate and land-use variables were resampled to a common 0.25° spatial resolution grid. To calibrate the model, we used the afternoon hot pixel data detected by the MODIS sensor onboard the AQUA satellite, published online by the Fire Monitoring Project from the Centre for Weather Forecast and Climate Studies (CPTEC) of Brazilian INPE (http://www.inpe.br/queimadas, accessed 17 August 2017). Hot pixels consist of the signal detection of the radiance of fire flames, whose emission peak is situated in the 3.7–4.1 μ region of the optical spectrum. MODIS spatial resolution is 1 km, daily temporal resolution. A flaming fire front of at least 30 m × 1 m of extension or larger is detected by the MODIS sensor (http://www.inpe.br/queimadas/faq.php, accessed 10 January 2014). The grid cells which showed 13 or more hot pixels in any September between 2003 and 2015 (1,852 grid cells among a total of 6,024) were considered to have suitable conditions for fire occurrence. From these grid cells, we randomly sampled 500 to be included as fire occurrence points. The "13 or more hot pixels" threshold corresponds to the third quartile of the distribution of the hot pixels number per grid cell in September 2010, as adopted by Fonseca et al. (2016). September was chosen for model calibration because it is currently the peak of the fire season, providing a wide range of environmental conditions driving fire occurrence. Besides the land-use data described above, climatic data from August during the baseline (2003–2015) were used in model calibration, following Fonseca et al. (2016).

The maximum entropy method (MaxEnt) is a general-purpose method for making predictions from incomplete information, with applications in diverse areas (e.g., astronomy, statistical physics, among others). In ecological studies, MaxEnt was introduced by Phillips, Dudík, and Schapire (2004) and Phillips, Anderson, and Schapire (2006) and is successfully applied as a tool for modeling species distribution using presence-only data that is when the absence records are not available (e.g., Couturier et al., 2014; Giovannini, Seglie, & Giacoma, 2014; Pena, Kamino, Rodrigues, Mariano-Neto, & de Siqueira, 2014). Assuming that fire behaves as an organism in the sense that its distribution is influenced by environmental variables, MaxEnt has been used to model fire occurrence at different spatial scales not only in the Brazilian Amazon (Fonseca et al., 2017, 2016), but also, for instance, in the western coast of India (Renard, Pélissier, Ramesh, & Kodandapani, 2012), the United States (Arnold, Brewer, & Dennison, 2014; Bar Massada, Syphard, Stewart, & Radeloff, 2013; Parisien & Moritz, 2009; Parisien et al., 2012; Peters, Iverson, Matthews, & Prasad, 2013), the Patagonian-Andean region (Paritsis, Holz, Veblen, & Kitzberger, 2013), the Bolivian Chiquitania region (Devisscher, Anderson, Aragão, Galván, & Malhi, 2016), and to derive a global analysis of future fire activity (Moritz et al., 2012).

Satellite-based fire records indicate locations that have been burnt, but it is not possible to determine whether other areas were also suitable to burn at that time but did not due to the lack of ignition. Furthermore, fires may not be detected by satellites if it happens on cloudy days, under dense forest cover or between satellite passages. For these reasons, the presence-only approach is appropriate to model fire suitability (Peters et al., 2013).

The analysis was carried out using the MaxEnt software version 3.3.3 (Phillips et al., 2006). This software is a stand-alone Java application freely available at http://biodiversityinformatics.amnh.org/open_source/maxent/ (Phillips, Anderson, Dudík, Schapire, & Blair, 2017) and its source code is now open (https://github.com/mrmaxent/Maxent). The software logistic output was used, which can be interpreted as a normalized suitability surface with values ranging from zero to one, equivalent to a relative (rather than absolute) probability of fire occurrence. MaxEnt uses the values of the predictor variables at the occurrence records and a random sample of their values across the landscape (typically called a background sample) to estimate the target probability distribution of maximum entropy (i.e., most spread out or closest to uniform) subject to a set of constraints (Phillips et al., 2006). The predictor variables and mathematical transformations thereof are called "features," and the constraints are that the expected value of the features should be close to its empirical average at the sample points (here, hot pixels occurrence following the adopted criteria). The transformations can be linear, quadratic, product (equivalent to interaction terms in regression), threshold, or hinge (similar to threshold, except that a linear function is used). We used the bootstrap technique to resample the occurrence points with 50 runs to estimate the outputs mean and standard deviation (Verbyla & Litvaitis, 1989), setting aside 30% of occurrence points for model testing. All parameters used in the model setting can be found in Data S1.

The classifier sensitivity for a particular threshold is the fraction of all occurrence records that are correctly predicted as occurrence instances by the classifier and is also called the true positive rate, representing the absence of omission error. Specificity is the fraction of all absence instances that are correctly predicted as such by the classifier and the quantity 1 − specificity, also known as the false positive rate, represents the commission error (Fielding & Bell, 1997; Phillips et al., 2006). As a threshold-independent measure of model performance, the receiver operating characteristic (ROC) curve is obtained by plotting sensitivity on the *y*-axis and 1-specificity on the *x*-axis for all possible thresholds, and the area under the curve (AUC) value indicates the probability that the model correctly ranks a random presence locality higher than a random background site (Phillips et al., 2006). If the AUC value is 0.5, the model is no better than random, while an area with a value close to 1 indicates an accurate model (Fielding & Bell, 1997). Models with AUC values above 0.75 are considered potentially useful (Elith, 2002). We present the calibration and test AUC values averaged over the 50 replicate runs. Additionally, in order to evaluate the model performance, we used the calibrated model to project the FRP for January and July of the baseline period and compared the resulting surfaces with the actual occurrence of hot pixels in these months using the same occurrence criteria as in the calibration (at least 1 month with 13 or more pixels along the period). This procedure allowed us to assess the model ability to capture the current seasonal variation in fire occurrence and to test whether the occurrence points show higher FRP than the nonoccurrence ones during the baseline. In order to estimate which variables are most important for model predictive performance, we used the jackknife test and assessed test AUC values for models created using each variable individually (Elith et al., 2011).

We projected the effect of climate change only on the future FRP by keeping the baseline values of the land-use variables while projecting for both the mid and end of the century periods and substituting the monthly climate variables by their averages during the respective periods estimated through the global models. As we used in the model calibration predictor data from August and hot pixels from September, 1 month lag was also considered in the projection procedure. For instance, climatic averages for October in the mid-century period were used to estimate the FRP values in November for that period. The analogous procedure was used to estimate the land-use change effect separately (varying land-use data and keeping climate data with their baseline values while projecting future FRP). However, as land use was modeled in an annual time step by Aguiar et al. (2016), we projected the separate future effect of land-use on FRP for October only (using the climatic baseline data from September), which was the month with highest change. An optimistic scenario of both climate and land-use change was built by combining climatic data from the RCP 4.5 for each month and land-use projections from the Sustainability scenario, while the pessimistic scenario was built through the combination of the RCP 8.5 and the Fragmentation land-use data. We also tested the effect of combining RCP 4.5 with the Fragmentation scenario and combining RCP 8.5 with the Sustainability scenario, in order to further access the relative contribution of climate and land use on future fire occurrence.

Fonseca et al. (2016), using the same approach to model FRP in the Brazilian Amazon in 2008 and 2010, reported that the 0.3 threshold would be adequate for binary fire prediction in the region since it allowed for an acceptable false positive error (maximum of 23%) while still resulting in a good sensitivity (i.e., the fraction of all occurrence records that is correctly predicted as occurrence instances by the classifier) in the months of higher fire incidence. Therefore, we analyzed the changes in FRP both as the increase/decrease in its value and as the increase in the proportion of the grid cells with FRP ≥ 0.3.

3 | RESULTS

3.1 | Model performance, variables' contribution, and influence on FRP

Mean training AUC was 0.837 ± 0.007 and mean testing AUC was 0.815 ± 0.012, indicating satisfactory model performance. Validation of the model using the detected hot pixels during the baseline shows that it accurately simulates the seasonal variation in fire occurrence in this period (Figure 1). The simulated FRP surfaces in both January and July follow the regional pattern of fire occurrence and the FRP values in the grid cells that complied with our fire occurrence criteria was significantly higher than in the ones that did not (Figure 1).

Agricultural use is the most effective variable for predicting the distribution of the occurrence data that was set aside for testing, when predictive performance is measured using AUC, followed by minimum precipitation, secondary vegetation cover, and mean evaporation (Figure 2).

The FRP increases with agricultural use up to 20% of the grid cell, then stabilizes and drops after 70% of agricultural use (Figure 3a). The increase in secondary vegetation is related also to an increase in FRP up to ~10% of grid cell cover and maintain high FRP values afterward, although with relatively high variability (Figure 3b). Despite an FRP increase in very low levels of evaporation, FRP decreases when minimum precipitation (Figure 3c) and mean evaporation increase (Figure 3d), as expected. FRP shows a tendency of increase with maximum temperature, although with some unexpected oscillation (Figure 3e).

3.2 | Effects of land-use and climate change on the FRP and its seasonal variation

Considering the projections for October, the month with highest change (see below), climate change alone under the RCP 4.5 scenario

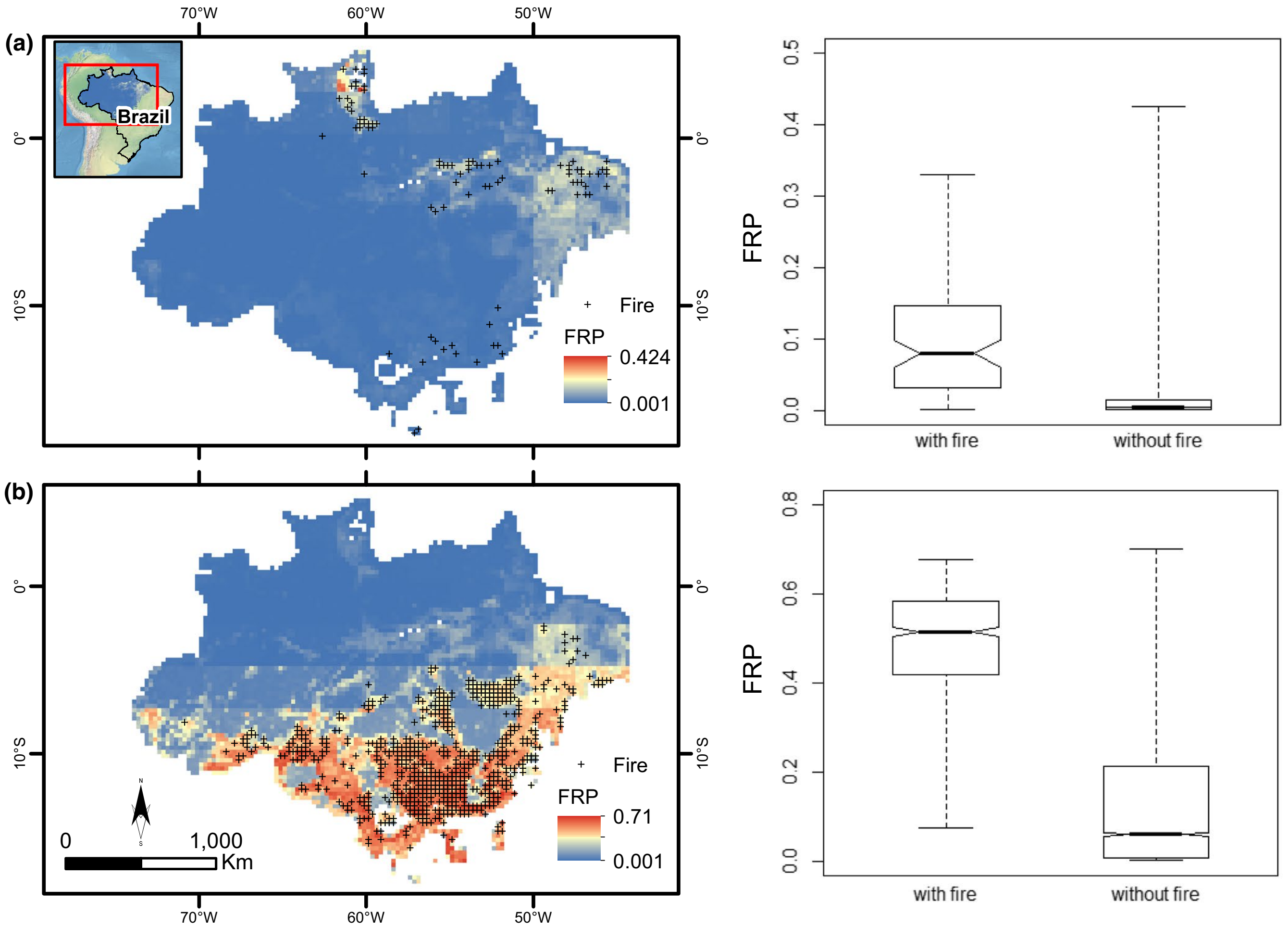

FIGURE 1 Fire relative probability (FRP) surfaces simulated for (a) January and (b) July of the baseline period (from 2003 to 2015). Black crosses (Fire) indicate grid cells where 13 or more MODIS hot pixels were detected in at least 1 month (January or July, respectively) during this period. The box-plots show the distribution of FRP values in grid cells with (with fire) and without (without fire) black crosses. The lower and the upper limits of the box represent the first and third quartiles, respectively, the horizontal line within the box represents the median and the vertical bars represent the data range

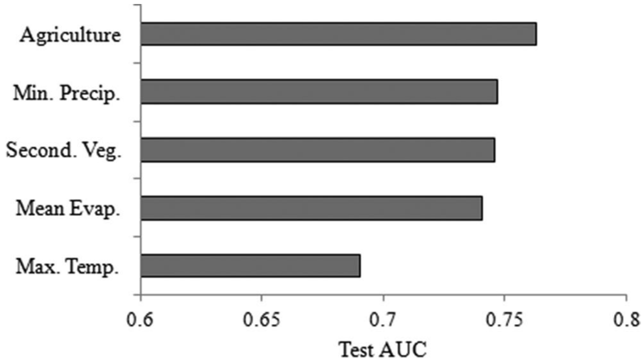

FIGURE 2 Results of the jackknife test for evaluating the isolated effect of each variable on the model performance based on the area under the curve (AUC) metric. Max. Temp., maximum temperature; Mean Evap, mean evaporation; Min. Precip., minimum precipitation; Second Veg., secondary vegetation cover

causes a spatially widespread, but relatively low, increase in FRP in the Brazilian Amazon (Figure 4). The distribution of change in FRP values by the end of the century significantly differs between the RCP 4.5 and RCP 8.5 scenarios (Kolmogorov–Smirnov, $p < 0.01$). Under the RCP 4.5 scenario, by the end of the century 74.1% of the cells shows positive FRP increase up to 0.1 but no cells show more than 0.1 increase in FRP. Considering the RCP 8.5 scenario, we project a positive FRP increase up to 0.1 in 71.0% and an increase between 0.1 and 0.3 in 21.5% of the area, with the remaining 7.5% of the area showing a decrease in FRP up to −0.3. The area with FRP ≥ 0.3 increases by 6.9% by the end of the century compared to the baseline under the RCP 4.5 scenario and by 27.7% under the RCP 8.5 scenario.

The projected changes due to land use only are more intense (Figure 5). Under the Sustainability scenario, 8.0% and 7.6% of the grid cells show an increase ≥0.1 in the mid and the end of the century, respectively. These figures increase to 30.8% and 38.5%, respectively, under the Fragmentation scenario. Changes ≥0.3 by the end of the century are projected in less than 0.1% of the grid cells in the Sustainability scenario, and in 9.5% of the region in the Fragmentation scenario. The number of grid cells with FRP ≥ 0.3 is 10.6% larger by the end of the century under the Sustainability scenario compared to the baseline period, but 73.2% under the Fragmentation scenario. Under the latter scenario, about 54.2% of the grid cells falling within current protected areas or indigenous territories are expected to show an increase in FRP ≥ 0.1 by the end of the century. This represents an area of approximately 1,166,833 km^2, that is twice the size of France territory or five times the size of the United Kingdom.

The change in FRP projected under the optimistic and the pessimistic scenarios of climate-land-use change is shown in Figures 6 and 7, respectively. From January until April, changes are projected mostly for the northern and eastern regions, where most of the fires occur in the present time during these months. However, a low number of grid cells show FRP ≥ 0.3 during these months in either scenarios (Figure 8).

The peak of number of grid cells with FRP ≥ 0.3 is in August–September during the baseline, in the two analyzed periods under the optimistic scenario, and in the 2041–2070 period under the pessimistic scenario. Under the pessimistic scenario, by the end of the century, this number keeps rising until October, when most changes in FRP are projected (Figure 8). Under the optimistic scenario, by the end of the century, a negligible number of grid cells (four) shows change in FRP ≥ 0.3 in October and changes ≥0.1 in

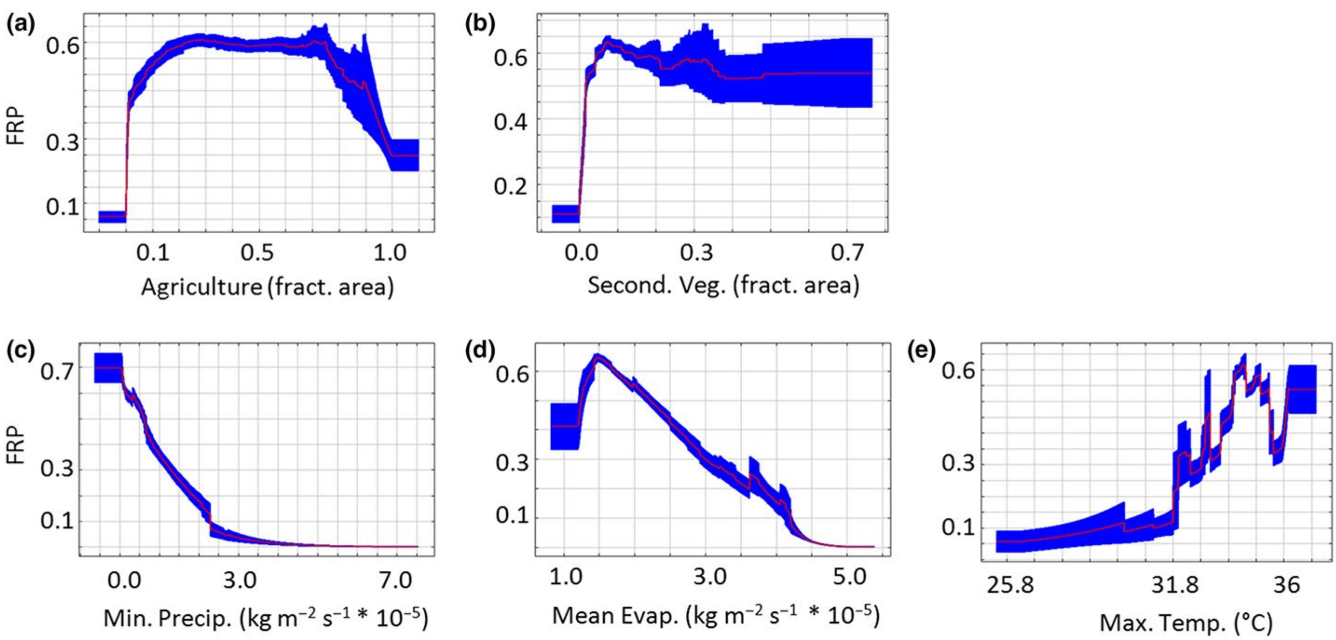

FIGURE 3 Response curves showing how each environmental variable affects the fire relative probability (FRP) predicted by the MaxEnt model. The red line indicates the mean response of 50 MaxEnt runs, and the blue envelope ± 1 *SD*. (a) Agricultural use (fract. Area, fraction of the grid cell area); (b) secondary vegetation cover; (c) minimum precipitation; (d) mean evaporation; (e) maximum temperature

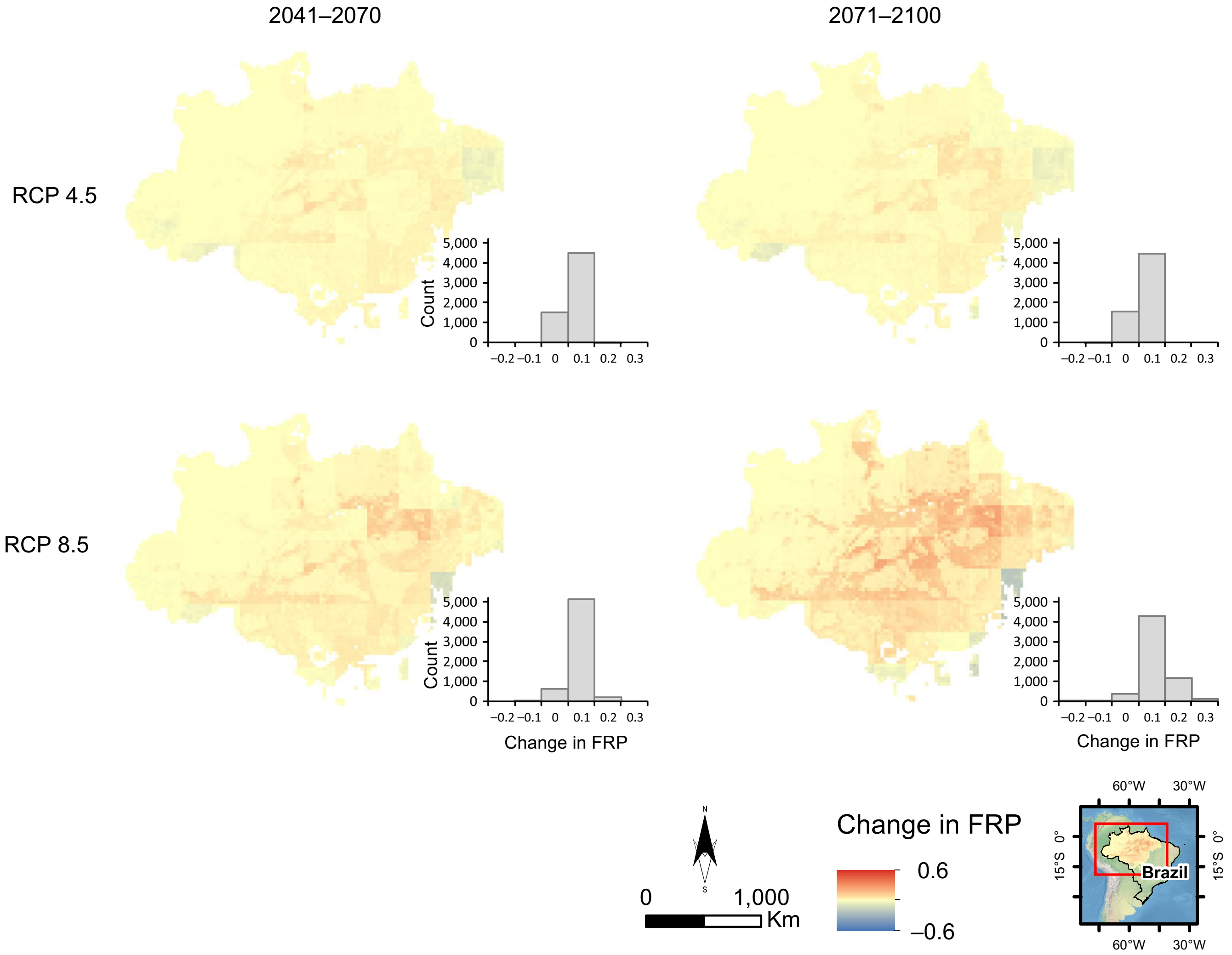

FIGURE 4 Change in fire relative probability (FRP; future minus baseline) projected for October considering the RCP 4.5 and RCP 8.5 emission scenarios

FRP are projected for 13.1% of the study area (Figure 6). The pessimistic scenario, in contrast, causes changes in FRP ≥ 0.3 and ≥0.1 in 20.2% and 53.5% of the study area, respectively, in October by the end of the century (Figure 7). Furthermore, the predicted number of grid cells with FRP ≥ 0.3 is 21.6% and 113.5% higher by the end of the century under the optimistic and under the pessimistic scenarios, respectively, than in the baseline period (Figure 8). Combining the Sustainability land-use and RCP 8.5 scenarios causes a 39.1% increase in the number of grid cells with FRP ≥ 0.3 in October by the end of the century, while the Fragmentation and RCP 4.5 scenarios combined result in 90.9% increase.

4 | DISCUSSION

4.1 | Model performance, variables' contribution, and its influence on FRP

The validation analysis using hot pixels occurrence indicates that the model is able to successfully simulate the spatial pattern of FRP during the baseline period, capturing its seasonal variation. Indeed, fire occurs mostly in the north and northeast regions of the Brazilian Amazon between December and March and from the southwest to the southeast regions from June until November (INPE, 2017b), which was correctly depicted in the FRP surfaces projected for January and July during the baseline period. The AUC values offer additional evidence of the model satisfactory performance.

The high contribution of the agriculture and secondary vegetation variables for the model predictive performance indicates the importance of land-use variables in determining fire occurrence in the study region, as indicated by the jackknife test. Similarly, Devisscher et al. (2016) found that distance to roads, recent deforestation, and human settlements were important variables increasing fire occurrence in the Bolivian Amazon. However, models with only minimum precipitation also presented a quite satisfactory performance, and we expect that the importance of climatic variables is higher in regions with sparse human occupation.

In the literature, the increase in human presence is often associated with a decrease in fire occurrence due to agricultural

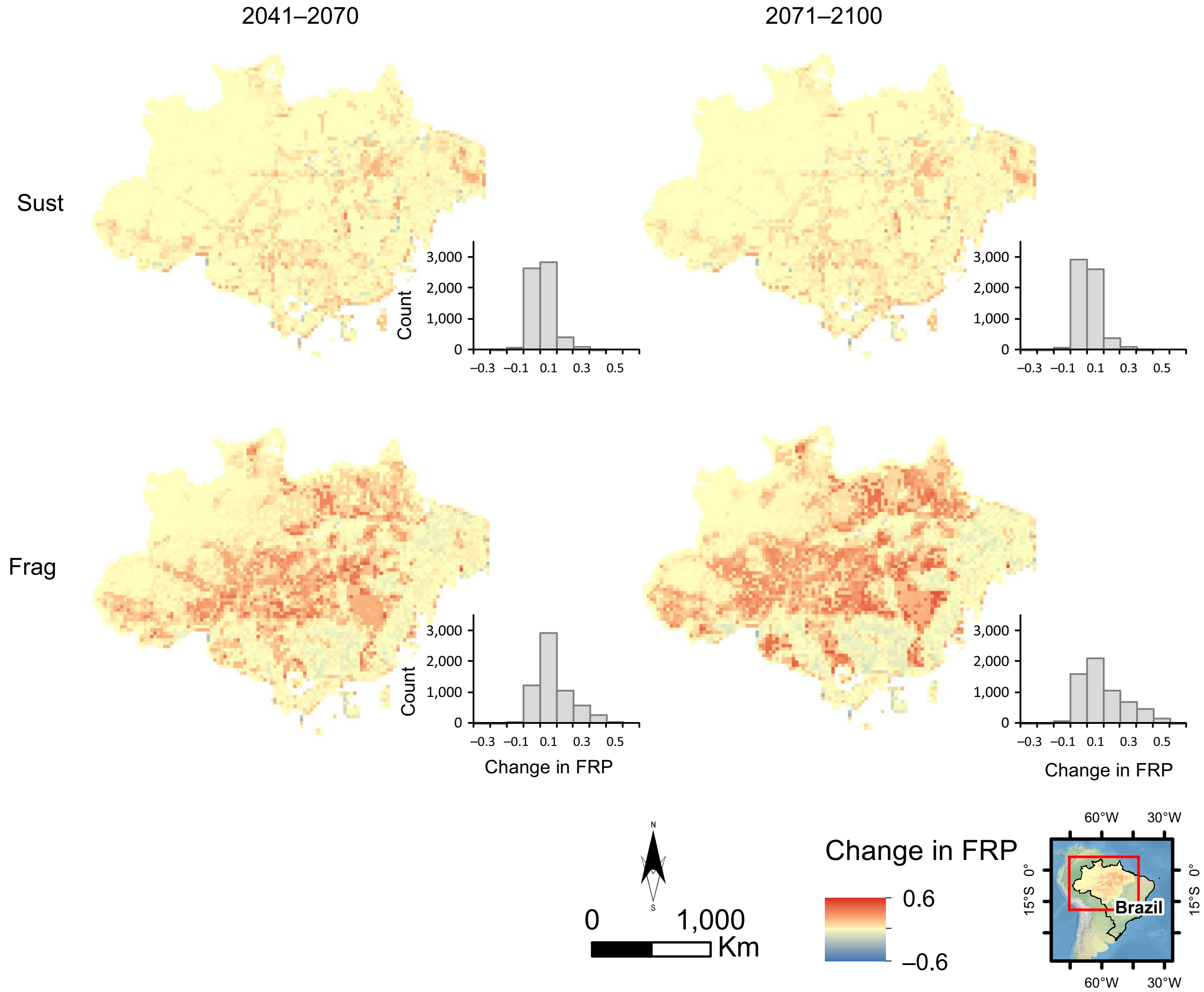

FIGURE 5 Change in fire relative probability (FRP; future minus baseline) projected considering the Sustainability (Sust) and Fragmentation (Frag) land-use change scenarios

expansion and fire suppression, although regional differences are acknowledged (e.g., Andela et al., 2017; Knorr, Jiang, & Arneth, 2016). In the Amazon, given the widespread occurrence of deforestation fires, either for primary or secondary vegetation clearing, and the pervasive use of fire in pasture management, the predominant effect of human presence is an increase in ignition sources (Alencar, Brando, Asner, & Putz, 2015; Devisscher et al., 2016; Fonseca et al., 2016; Silvestrini et al., 2011). However, extremely high levels of deforestation (above 70%) are predicted to decrease the probability of the significant fire events we modeled (i.e., 13 or more hot pixels per 0.25° grid cell), as indicated by the response curve. This may be due to the reduced biomass available to burn in highly deforested landscapes or to the decrease in connectivity among forest patches. Therefore, the observed decline in FRP is consistent with a percolation threshold (Turner et al., 1989) reached when the fractional coverage of a flammable landscape is low enough that it becomes very patchy and discontinuous, resulting in a nonlinear reduction of fire occurrence (Archibald, Staver, & Levin, 2012). An increase in flammability or in ignition frequency may compensate partially the connectivity reduction, but following Archibald et al. (2012), below the percolation threshold, the number of ignitions required to burn the landscape quickly becomes unrealistically high.

The response of FRP to agricultural cover largely depends on the land-use type. Aragão and Shimabukuro (2010) reported a decline in fire incidence in the Brazilian Amazon when intensive mechanized agriculture, mainly annual crops, dominates the landscape beyond the 35% cover threshold. As the area of mechanized annual crops changed from 3% to 6% of the deforested area in the Brazilian Amazon between 2004 and 2014 (INPE/EMBRAPA, 2016), we did not separate this land use from pasture in the model. In case the rate of expansion of intensive agriculture significantly increases during the 21st century, it is possible that it counteracts some of the increase in fire incidence we reported.

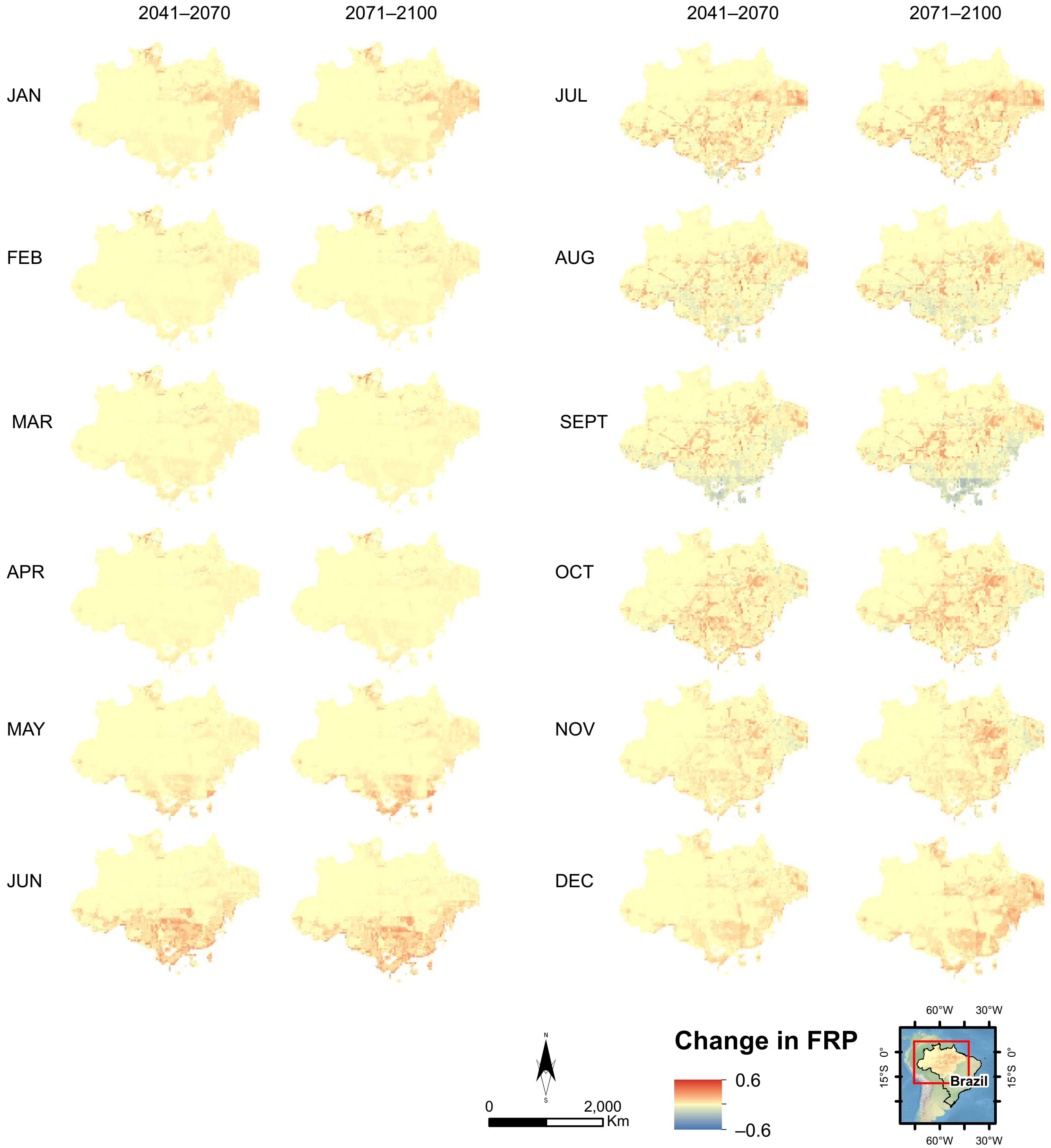

FIGURE 6 Monthly change in fire relative probability (FRP; future minus baseline) in the mid (2041–2070) and the end (2071–2100) of the 21st century projected considering an optimistic scenario (*Sustainability* land-use and RCP 4.5 scenarios)

While the FRP exponentially declines with the minimum precipitation increase, as expected, we found a clear threshold in the increase of FRP as function of maximum temperature from around 32°C onward. The observed oscillation in the FRP response to this variable may be related to the low spatial resolution of the climatic data, causing inadequate sampling of some temperature values. It is interesting to note that this threshold value is well below the average maximum temperature in September (the fire season peak) during the baseline (34.8°C), when 97.3% of the region shows average maximum temperature ≥31.8°C. This may explain why this variable shows such a low contribution for the model predictive performance during the baseline, given that most of the region presents maximum

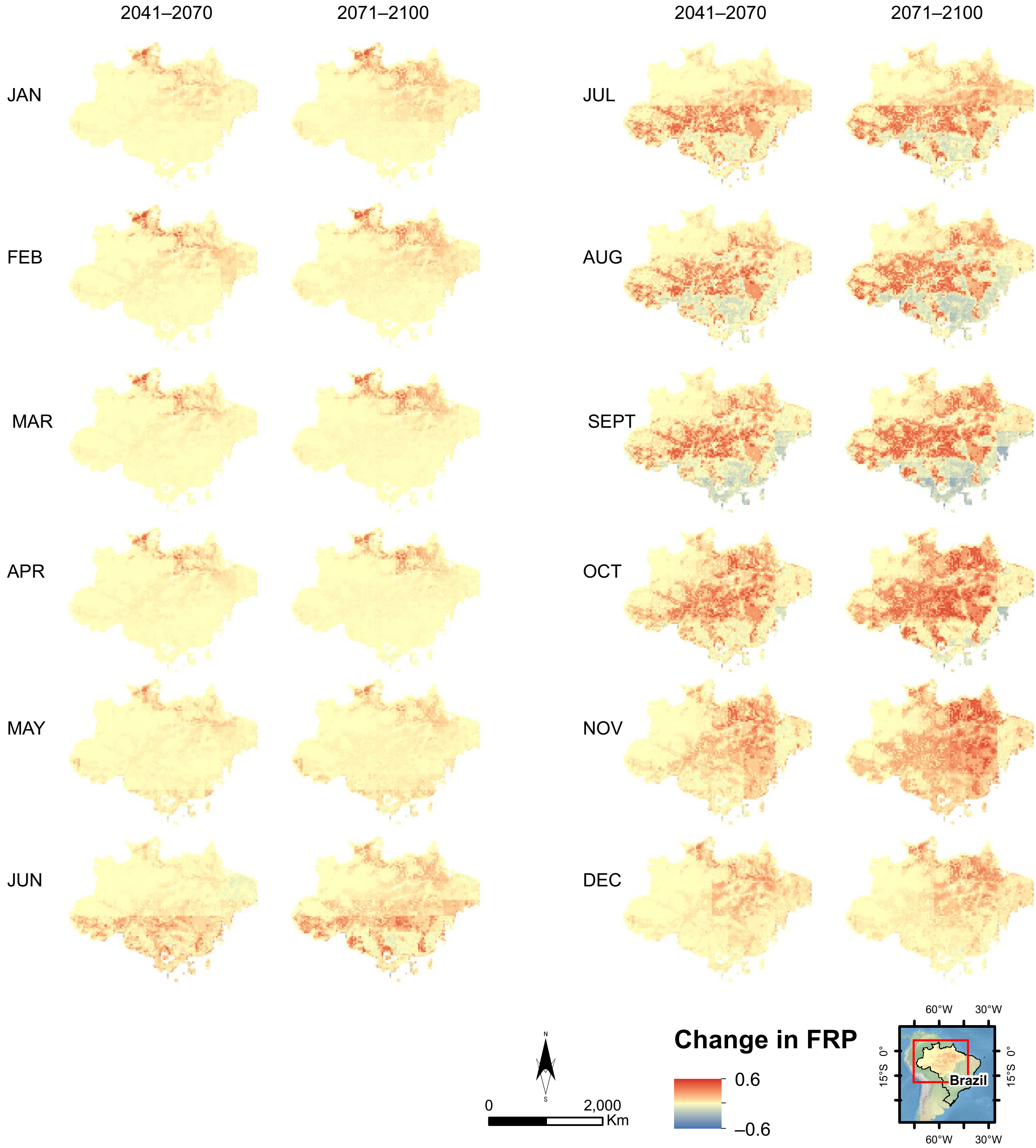

FIGURE 7 Monthly change in fire relative probability (FRP; future minus baseline) in the mid (2041–2070) and the end (2071–2100) of the 21st century projected considering a pessimistic scenario (*Fragmentation* land-use and RCP 8.5 scenarios)

temperature values compatible with high FRP. In other words, the current temperatures are already enough to dry the material and the main drivers of fire are anthropogenic and rainfall. In contrast, in August of the 2071–2100 period under the RCP 8.5 scenario, 88.7% of the study area shows maximum temperature >~36°C, which is the maximum value of maximum temperature in this same month during the baseline. Under the RCP 4.5 scenario, for the same period, this proportion is lower, but still represents over half (54%) of the area. This indicates that, although the response curve suggests a stabilization of the FRP increase after 34.8–36°C, the prevalent maximum temperatures by the end of the century under both analyzed emission scenarios were not adequately sampled, which increases the

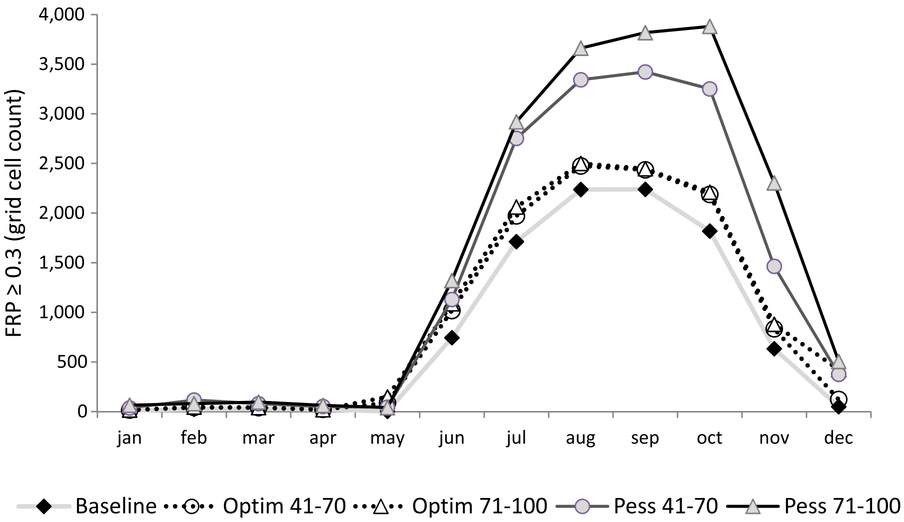

FIGURE 8 Monthly number of grid cells with fire relative probability (FRP) ≥ 0.3 in the surfaces simulated during the baseline (2003–2015), and in the two future periods (2041–2070 and 2071–2100) under the optimistic (Optim) and pessimistic (Pess) land-use and climate change scenarios

uncertainty of model results. Therefore, our projections can be seen as conservative.

4.2 | Effects of land-use and climate changes on the FRP and its seasonal variation

Considering climate change only, the effect of the RCP 4.5 scenario on fire occurrence by the end of the century is quite widespread, reaching most of the region except the northwest, but relatively mild (change in FRP < 0.1). A scenario of higher emissions significantly increases the degree of change in FRP, although still without much effect in the extreme northwest. This is likely related to the relatively low change in precipitation and evaporation (Figure S2) combined with sparse land use and therefore scarcity of ignition sources in this region.

Our results highlight the importance of the effect of land-use change on future fire activity, reported also in other studies (Aragão & Shimabukuro, 2010; Fonseca et al., 2016). The projected effects of land-use change only on fire activity in the Brazilian Amazon surpass the ones due to climate change, both in extent and in intensity. The higher impact of land-use change on FRP compared to climate-change contrasts with the opposite result found by Le Page et al. (2017). This may be partially because our model calibration includes both forest and management fires detected through hot pixels, while Le Page et al. (2017) modeled fire-damaged forests (Morton et al., 2011) only. However, there was a significant correlation between total hot pixels count and forest burn scars between 2007 and 2016 in the Brazilian Amazon (Figure S3). A similar correlation was also reported by Alencar et al. (2015). Therefore, we expect that the higher probability of hot pixels occurrence we found, although not restricted to forest fires, implies, necessarily, in larger fire-damaged forest area too. This is supported by the observation that in the land-use only Fragmentation scenario, the areas with the highest changes in FRP by the end of the century are the currently forested ones, including protected areas and indigenous territories. A more elucidative difference between the two studies may be related to the saturation of the fire response to land-use cell fraction. In Le Page et al. (2017; Figure S3c), ignitions increase up to 0.10 of land-use fraction within the grid cells, while our response curves indicate that FRP saturates at 0.20 of land-use fraction. Furthermore, even the worse-case future land-use distributions from the land harmonization processing developed for the RCP 8.5 scenario (figure 1b in Le Page et al., 2017) is optimistic compared to the future land-use projected by Aguiar et al. (2016; Figure S4). The deforestation rate after 2020 foreseen in the Fragmentation scenario (19,500 km^2/year) is almost three times higher than the one registered in 2017 (6,624 km^2), but it is still much lower than the reported rate in 1995 (29,059 km^2) and the average between 2002 and 2004 (24,939 km^2; INPE, 2017a). Thus, although pessimistic, this scenario is not outside the historical deforestation levels.

The reported increase in FRP due to land-use change is predicted to heavily affect currently protected areas, including the inhabited ones, and indigenous territories, threatening its biodiversity as well as traditional populations and their cultural practices through the depletion of the natural resources they depend upon (Schwartzman et al., 2013). It is quite surprising the coincidence of areas of high change in FRP with the limits of some protected areas. Considering that they are not predicted to be fully deforested even in the Fragmentation scenario (Figure S5), the accentuated increase in FRP within these areas is probably related to the combination of deforestation with the expansion of the more flammable secondary vegetation cover. This highlights also the importance of including secondary vegetation cover in the assessment of land-use effects on fire occurrence.

The two combinations (pessimistic and optimistic) of climate and land-use scenarios differed in the temporal variation of FRP along the century. Under the optimistic scenario, the differences between the FRP in the mid and the end of the century are much less pronounced than in the pessimistic scenario, probably due to the stabilization of GHG emissions in the RCP 4.5. Under the pessimistic scenario, in contrast, the FRP keeps increasing along the century, as expected.

We also found striking spatial variation in the FRP change along the months for both analyzed combinations of climate and land-use scenarios, indicating that the effects of climate change and its interactions with land use vary along the seasons. Under the pessimistic scenario, we found a more widespread increase in FRP from May onwards. Furthermore, that scenario tends to prolong the fire season. A shift in fire peak toward latter months in drought years in the Brazilian Amazon was already reported by Alencar et al. (2015), although with regional variations, and the authors stress the negative impact this may have on fire extent, size, and effects.

Our projections of FRP comprised 30 years averages. However, during years of extreme drought events, the figures can be much worse and pervasive fires may occur even under relatively low deforestation rates. For instance, during the 2015/2016 El Niño event, about 38% of the Roraima state showed fire anomaly ≥1 *SD*, and the two variables with higher contribution to the performance of the fire probability model were the Pacific sea surface warming effect and the road distance (Fonseca et al., 2017). In the same drought event, there was a 36% rise in the number of fires in the Brazilian Amazon compared to the preceding 12 year mean, despite a 76% reduction in the deforestation rate compared to 2003 (Aragão et al., 2018). Based on our current results, in either temporal scale (annual or 30 year average), land-use change would greatly enhance the drought-related fire incidence and resultant carbon emissions in the Brazilian Amazon.

We acknowledge that using a correlative occurrence-based approach, such as MaxEnt, to extrapolate for novel environments is risky, since environmental combinations in future scenarios may not be adequately sampled (Elith, Kearney, & Phillips, 2010). In particular, projections of fire occurrence based on statistical models should be seen as conservative given that these models do not incorporate future self-amplified vegetation–fire–climate feedbacks that could increase ecosystems flammability (Krawchuk, Moritz, Parisien, Van Dorn, & Hayhoe, 2009; Salazar & Nobre, 2010; Zemp, Schleussner, Barbosa, & Rammig, 2017). The effects of CO_2 fertilization on fire regimes (Lapola, Oyama, & Nobre, 2009; Swann, Hoffman, Koven, & Randerson, 2016), which are potentially complex and still largely uncertain, were not modeled as well. Additionally, our approach addresses changes in fire probability, but does not include effects on other aspects of fire regime, such as fire intensity, which may be affected by climate or land-use scenarios in particular ways (e.g., De Faria et al., 2017). The analysis of the effect of the uncertainty among CMIP5 models, mostly concerning future precipitation in the Amazon (IPCC, 2014; Knutti & Sedláček, 2013), is also out of the scope of this study. Despite these limitations, our results provide an important sensitivity analysis, indicating the comparative effect of anthropogenic and climate variables, as well as of different land-use and climate scenarios, and its spatiotemporal variation.

We conclude that limiting global warming through the reduction of GHG emissions is important to avoid pervasive Amazonian ecosystems degradation by fire. However, even under the RCP 4.5 emissions scenario, the socioeconomic, institutional, and environmental dynamics modeled in the Fragmentation land-use scenario (i.e., decrease in the extension and level of conservation of the protected areas, reduced environmental laws enforcement, extensive road paving, and increased deforestation) would cause a decisive increase on fire probability in the region during the 21st century, with consequent negative impacts on biodiversity (Barlow et al., 2016), regional climate (Andreae et al., 2004), human health (do Carmo, Alves, & Hacon, 2013; Smith, Aragão, Sabel, & Nakaya, 2014), forest structure, biomass, and carbon emissions (Alencar, Nepstad, & Diaz, 2006; Anderson et al., 2015; Aragão et al., 2018; Barlow & Peres, 2004; Berenguer et al., 2014; Brando et al., 2014). Conversely, avoiding such regress on land-use governance in the Brazilian Amazon would substantially mitigate the effects of climate change on fire probability, even under the most pessimistic RCP 8.5 scenario.

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REFERENCES

Aguiar, A., Carneiro, T., Andrade, P., & Assis, T. (2012). LuccME-TerraMe: An open-source framework for spatially explicit land use change modelling. *GLP News*, *8*, 21–23.

Aguiar, A. P. D., Ometto, J. P., Nobre, C., Lapola, D. M., Almeida, C., Vieira, I. C., … Castilla-Rubio, J. C. (2012). Modeling the spatial and temporal heterogeneity of deforestation-driven carbon emissions: The INPE-EM framework applied to the Brazilian Amazon. *Global Change Biology*, *18*(11), 3346–3366. https://doi.org/10.1111/j.1365-2486.2012.02782.x

Aguiar, A. P. D., Vieira, I. C. G., Assis, T. O., Dalla-Nora, E. L., Toledo, P. M., Oliveira Santos-Junior, R. A., … Ometto, J. P. H. (2016). Land use change emission scenarios: Anticipating a forest transition process in the Brazilian Amazon. *Global Change Biology*, *22*(5), 1821–1840. https://doi.org/10.1111/gcb.13134

Alcamo, J. (2008). The SAS approach: Combining qualitative and quantitative knowledge in environmental scenarios. In J. Alcamo (Ed.), *Developments in integrated environmental assessment* (Vol. *2*, pp.

123–150). Amsterdam, the Netherlands: Elsevier Inc. https://doi.org/10.1016/S1574-101X(08)00406-7

Alencar, A. A., Brando, P. M., Asner, G. P., & Putz, F. E. (2015). Landscape fragmentation, severe drought, and the new Amazon forest fire regime. *Ecological Applications*, *25*(6), 1493–1505. https://doi.org/10.1890/14-1528.1

Alencar, A., Nepstad, D., & Diaz, M. C. V. (2006). Forest understory fire in the Brazilian Amazon in ENSO and non-ENSO years: Area burned and committed carbon emissions. *Earth Interactions*, *10*(6), 1–17. https://doi.org/10.1175/EI150.1

Andela, N., Morton, D. C., Giglio, L., Chen, Y., van der Werf, G. R., Kasibhatla, P. S., … Randerson, J. T. (2017). A human-driven decline in global burned area. *Science*, *356*(6345), 1356–1362. https://doi.org/10.1126/science.aal4108

Anderson, L. O., Aragão, L. E. O. C., Gloor, M., Arai, E., Adami, M., Saatchi, S. S., … Duarte, V. (2015). Disentangling the contribution of multiple land covers to fire-mediated carbon emissions in Amazonia during the 2010 drought. *Global Biogeochemical Cycles*, *29*(10), 1739–1753. https://doi.org/10.1002/2014GB005008

Andreae, M. O., Rosenfeld, D., Artaxo, P., Costa, A. A., Frank, G. P., Longo, K. M., & Silva-Dias, M. A. F. (2004). Atmospheric science: Smoking rain clouds over the Amazon. *Sciences*, *303*(February), 1337–1341. https://doi.org/10.1126/science.1092779

Aragão, L. E. O. C., Anderson, L. O., Fonseca, M. G., Rosan, T. M., Vedovato, L. B., Wagner, F. H., … Saatchi, S. (2018). 21st Century drought-related fires counteract the decline of Amazon deforestation carbon emissions. *Nature Communications*, *9*(1), 536. https://doi.org/10.1038/s41467-017-02771-y

Aragão, L. E. O. C., Malhi, Y., Barbier, N., Lima, A., Shimabukuro, Y., Anderson, L., & Saatchi, S. (2008). Interactions between rainfall, deforestation and fires during recent years in the Brazilian Amazonia. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *363*(1498), 1779–1785. https://doi.org/10.1098/rstb.2007.0026

Aragão, L. E. O. C., Poulter, B., Barlow, J. B., Anderson, L. O., Malhi, Y., Saatchi, S., … Gloor, E. (2014). Environmental change and the carbon balance of Amazonian forests. *Biological Reviews*, *89*(4), 913–931. https://doi.org/10.1111/brv.12088

Aragão, L. E. O. C., & Shimabukuro, Y. E. (2010). The incidence of fire in Amazonian Forests with implications for REDD. *Science*, *328*(4), 1275–1278. https://doi.org/10.1126/science.1186925

Archibald, S., Staver, A. C., & Levin, S. A. (2012). Evolution of human-driven fire regimes in Africa. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(3), 847–852. https://doi.org/10.1073/pnas.1118648109

Arnold, J. D., Brewer, S. C., & Dennison, P. E. (2014). Modeling climate-fire connections within the great basin and upper Colorado River Basin, Western United States. *Fire Ecology*, *10*(2), 64–75. https://doi.org/10.4996/fireecology.1002064

Bar Massada, A., Syphard, A. D., Stewart, S. I., & Radeloff, V. C. (2013). Wildfire ignition-distribution modelling: A comparative study in the Huron-Manistee National Forest, Michigan, USA. *International Journal of Wildland Fire*, *22*(2), 174–183. https://doi.org/10.1071/WF11178

Barbosa, R. I., & Fearnside, P. M. (2005). Above-ground biomass and the fate of carbon after burning in the savannas of Roraima, Brazilian Amazonia. *Forest Ecology and Management*, *216*(1–3), 295–316. https://doi.org/10.1016/j.foreco.2005.05.042

Barlow, J., Lennox, G. D., Ferreira, J., Berenguer, E., Lees, A. C., Nally, R. M., … Gardner, T. A. (2016). Anthropogenic disturbance in tropical forests can double biodiversity loss from deforestation. *Nature*, *535*(7610), 144–147. https://doi.org/10.1038/nature18326

Barlow, J., & Peres, C. A. (2004). Ecological responses to El Niño-induced surface fires in central Brazilian Amazonia: Management implications for flammable tropical forests. *Philosophical Transactions of the Royal Society B: Biological Sciences*, *359*(1443), 367–380. https://doi.org/10.1098/rstb.2003.1423

Berenguer, E., Ferreira, J., Gardner, T. A., Aragão, L. E. O. C., De Camargo, P. B., Cerri, C. E., … Barlow, J. (2014). A large-scale field assessment of carbon stocks in human-modified tropical forests. *Global Change Biology*, *20*(12), 3713–3726. https://doi.org/10.1111/gcb.12627

Betts, R. A., Golding, N., Gonzalez, P., Gornall, J., Kahana, R., Kay, G., … Wiltshire, A. (2015). Climate and land use change impacts on global terrestrial ecosystems and river flows in the HadGEM2-ES Earth system model using the representative concentration pathways. *Biogeosciences*, *12*(5), 1317–1338. https://doi.org/10.5194/bg-12-1317-2015

Brando, P. M., Balch, J. K., Nepstad, D. C., Morton, D. C., Putz, F. E., Coe, M. T., … Soares-Filho, B. S. (2014). Abrupt increases in Amazonian tree mortality due to drought-fire interactions. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(17), 6347–6352. https://doi.org/10.1073/pnas.1305499111

Couturier, T., Besnard, A., Bertolero, A., Bosc, V., Astruc, G., & Cheylan, M. (2014). Factors determining the abundance and occurrence of Hermann's tortoise *Testudo hermanni* in France and Spain: Fire regime and landscape changes as the main drivers. *Biological Conservation*, *170*, 177–187. https://doi.org/10.1016/j.biocon.2013.12.028

De Faria, B. L., Brando, P. M., Macedo, M. N., Panday, P. K., Soares-Filho, B. S., & Coe, M. T. (2017). Erratum: Current and future patterns of fire-induced forest degradation in Amazonia (2017 Environ. Res. Lett. 9 095005). *Environmental Research Letters*, *12*, 119601. https://doi.org/10.1088/1748-9326/aa9049

de Moura, Y. M., Hilker, T., Lyapustin, A. I., Galvão, L. S., dos Santos, J. R., Anderson, L. O., … Arai, E. (2015). Seasonality and drought effects of Amazonian forests observed from multi-angle satellite data. *Remote Sensing of Environment*, *171*, 278–290. https://doi.org/10.1016/j.rse.2015.10.015

Devisscher, T., Anderson, L. O., Aragão, L. E. O. C., Galván, L., & Malhi, Y. (2016). Increased wildfire risk driven by climate and development interactions in the Bolivian Chiquitania, Southern Amazonia. *PLoS ONE*, *11*(9), 1–29. https://doi.org/10.1371/journal.pone.0161323

do Carmo, C. N., Alves, M. B., & Hacon, S. D. S. (2013). Impact of biomass burning and weather conditions on children's health in a city of Western Amazon region. *Air Quality, Atmosphere and Health*, *6*(2), 517–525. https://doi.org/10.1007/s11869-012-0191-6

Elith, J. (2002). Quantitative methods for modeling species habitat: Comparative performance and an application to Australian plants. In S. Ferson & M. Burgman (Eds.), *Quantitative methods for conservation biology* (pp. 39–58). New York, NY: Springer-Verlag.

Elith, J., Kearney, M., & Phillips, S. (2010). The art of modelling range-shifting species. *Methods in Ecology and Evolution*, *1*(4), 330–342. https://doi.org/10.1111/j.2041-210X.2010.00036.x

Elith, J., Phillips, S. J., Hastie, T., Dudík, M., Chee, Y. E., & Yates, C. J. (2011). A statistical explanation of MaxEnt for ecologists. *Diversity and Distributions*, *17*(1), 43–57. https://doi.org/10.1111/j.1472-4642.2010.00725.x

FAO. (2005). Computerized data gathering and networking as a control and monitoring system for the improvement of and reporting on forest management in the Amazon: The case of Brazil. Retrieved from http://www.fao.org/docrep/009/j5416e/J5416E00.htm#TopOfPage

Fearnside, P. M. (2016). Brazilian politics threaten environmental policies the country's environmental licensing system is threatened. *Science*, *353*(6301), 746–748. https://doi.org/10.1126/science.aag0254

Fielding, A. H., & Bell, J. F. (1997). A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation*, *24*(1), 38–49. https://doi.org/10.1017/S0376892997000088

Flannigan, M. D., Krawchuk, M. A., de Groot, W. J., Wotton, B. M., & Gowman, L. M. (2009). Implications of changing climate for global wildland fire. *International Journal of Wildland Fire*, *18*(5), 483. https://doi.org/10.1071/wf08187

Folhes, R. T., de Aguiar, A. P. D., Stoll, E., Dalla-Nora, E. L., Araújo, R., Coelho, A., … Canto, O. (2015). Multi-scale participatory scenario methods and territorial planning in the Brazilian Amazon. *Futures*, *73*, 86–99. https://doi.org/10.1016/j.futures.2015.08.005

Fonseca, M. G., Anderson, L. O., Arai, E., Shimabukuro, Y. E., Xaud, H. A. M., Xaud, M. R., … Aragão, L. E. O. C. (2017). Climatic and anthropogenic drivers of northern Amazon fires during the 2015–2016 El Niño event. *Ecological Applications*, *27*(8), 2514–2527. https://doi.org/10.1002/eap.1628

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

Giovannini, A., Seglie, D., & Giacoma, C. (2014). Identifying priority areas for conservation of spadefoot toad, *Pelobates fuscus insubricus* using a maximum entropy approach. *Biodiversity and Conservation*, *23*(6), 1427–1439. https://doi.org/10.1007/s10531-014-0674-x

Golding, N., & Betts, R. (2008). Fire risk in Amazonia due to climate change in the HadCM3 climate model: Potential interactions with deforestation. *Global Biogeochemical Cycles*, *22*(4), 1–10. https://doi.org/10.1029/2007GB003166

Gutiérrez-Vélez, V. H., Uriarte, M., DeFries, R., Pinedo-Vásquez, M., Fernandes, K., Ceccato, P., … Padoch, C. (2014). Land cover change interacts with drought severity to change fire regimes in Western Amazonia. *Ecological Applications*, *24*(6), 1323–1340. https://doi.org/10.1890/13-2101.1

Hurtt, G. C., Chini, L. P., Frolking, S., Betts, R. A., Feddema, J., Fischer, G., … Wang, Y. P. (2011). Harmonization of land-use scenarios for the period 1500–2100: 600 Years of global gridded annual land-use transitions, wood harvest, and resulting secondary lands. *Climatic Change*, *109*(1), 117–161. https://doi.org/10.1007/s10584-011-0153-2

INPE. (2017a). Monitoramento da Floresta Amazônica Brasileira por Satélite. Retrieved from http://www.obt.inpe.br/OBT/assuntos/programas/amazonia/prodes

INPE. (2017b). Programa Queimadas. Retrieved from http://www.inpe.br/queimadas/portal

INPE, EMBRAPA. (2016). TerraClass 2004 a 2014: Avaliação da dinâmica do uso e cobertura da terra no período de 10 anos nas áreas desflorestadas da Amazônia legal Brasileira. Retrieved from https://www.embrapa.br/busca-de-publicacoes/-/publicacao/1062992/terraclass-2004-a-2014-avaliacao-da-dinamica-do-uso-e-cobertura-da-terra-no-periodo-de-10-anos-nas-areas-desflorestadas-da-amazonia-legal-brasileira

IPCC. (2000). Emissions scenarios. Retrieved from https://ipcc.ch/pdf/special-reports/spm/sres-en.pdf

IPCC. (2013). Climate change 2013: The physical science basis. In T. F. Stocker, D. Qin, G. K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, & P. M. Midgley (Eds.), *Contribution of Working Group I to the fifth assessment report of the Intergovernmental Panel on Climate Change*. Cambridge, UK and New York, NY: Cambridge University Press.

IPCC. (2014). Central and South America. In V. R. Barros, C. B. Field, D. J. Dokken, M. D. Mastrandrea, & K. J. Mach (Eds.), *Climate change 2014: Impacts, adaptation and vulnerability* (pp. 1499–1566). Cambridge, UK: Cambridge University Press. https://doi.org/10.1017/CBO9781107415386.007

IPCC. (2015). Climate change 2014 synthesis report. In *Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland: IPCC. https://doi.org/10.1017/CBO9781107415324

Justino, F., de Mélo, A. S., Setzer, A., Sismanoglu, R., Sediyama, G. C., Ribeiro, G. A., … Sterl, A. (2011). Greenhouse gas induced changes in the fire risk in Brazil in ECHAM5/MPI-OM coupled climate model. *Climatic Change*, *106*(2), 285–302. https://doi.org/10.1007/s10584-010-9902-x

Knorr, W., Jiang, L., & Arneth, A. (2016). Climate, CO_2 and human population impacts on global wildfire emissions. *Biogeosciences*, *13*(1), 267–282. https://doi.org/10.5194/bg-13-267-2016

Knutti, R., & Sedláček, J. (2013). Robustness and uncertainties in the new CMIP5 climate model projections. *Nature Climate Change*, *3*(4), 369–373. https://doi.org/10.1038/nclimate1716

Krawchuk, M. A., Moritz, M. A., Parisien, M. A., Van Dorn, J., & Hayhoe, K. (2009). Global pyrogeography: The current and future distribution of wildfire. *PLoS ONE*, *4*(4), e5102. https://doi.org/10.1371/journal.pone.0005102

Lapola, D. M., Oyama, M. D., & Nobre, C. A. (2009). Exploring the range of climate biome projections for tropical South America: The role of CO_2 fertilization and seasonality. *Global Biogeochemical Cycles*, *23*(3). https://doi.org/10.1029/2008GB003357

Le Page, Y., Morton, D., Hartin, C., Bond-Lamberty, B., Pereira, J. M. C., Hurtt, G., & Asrar, G. (2017). Synergy between land use and climate change increases future fire risk in Amazon forests. *Earth System Dynamics*, *8*(4), 1237–1246. https://doi.org/10.5194/esd-8-1237-2017

Moritz, M. A., Parisien, M.-A., Batllori, E., Krawchuk, M. A., Van Dorn, J., Ganz, D. J., & Hayhoe, K. (2012). Climate change and disruptions to global fire activity. *Ecosphere*, *3*(6), art49. https://doi.org/10.1890/ES11-00345.1

Morton, D. C., DeFries, R. S., Nagol, J., Souza, C. M., Kasischke, E. S., Hurtt, G. C., & Dubayah, R. (2011). Mapping canopy damage from understory fires in Amazon forests using annual time series of Landsat and MODIS data. *Remote Sensing of Environment*, *115*(7), 1706–1720. https://doi.org/10.1016/j.rse.2011.03.002

Neeff, T., Lucas, R. M., Dos Santos, J. R., Brondizio, E. S., & Freitas, C. C. (2006). Area and age of secondary forests in Brazilian Amazonia 1978–2002: An empirical estimate. *Ecosystems*, *9*(4), 609–623. https://doi.org/10.1007/s10021-006-0001-9

Nobre, C. A., Sampaio, G., Borma, L. S., Castilla-Rubio, J. C., Silva, J. S., & Cardoso, M. (2016). Land-use and climate change risks in the Amazon and the need of a novel sustainable development paradigm. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(39), 10759–10768. https://doi.org/10.1073/pnas.1605516113

O'Neill, B. C., Kriegler, E., Riahi, K., Ebi, K. L., Hallegatte, S., Carter, T. R., … van Vuuren, D. P. (2014). A new scenario framework for climate change research: The concept of shared socioeconomic pathways. *Climatic Change*, *122*(3), 387–400. https://doi.org/10.1007/s10584-013-0905-2

Parisien, M.-A., & Moritz, M. A. (2009). Environmental controls on the distribution of wildfire at multiple spatial scales. *Ecological Monographs*, *79*(1), 127–154. https://doi.org/10.1890/07-1289.1

Parisien, M.-A., Snetsinger, S., Greenberg, J. A., Nelson, C. R., Schoennagel, T., Dobrowski, S. Z., & Moritz, M. A. (2012). Spatial variability in wildfire probability across the western United States. *International Journal of Wildland Fire*, *21*(4), 313. https://doi.org/10.1071/WF11044

Paritsis, J., Holz, A., Veblen, T. T., & Kitzberger, T. (2013). Habitat distribution modeling reveals vegetation flammability and land use as drivers of wildfire in SW Patagonia. *Ecosphere*, *4*(5), 1–20. https://doi.org/10.1890/ES12-00378.1

Pena, J. C. D. C., Kamino, L. H. Y., Rodrigues, M., Mariano-Neto, E., & de Siqueira, M. F. (2014). Assessing the conservation status of species with limited available data and disjunct distribution. *Biological Conservation*, *170*, 130–136. https://doi.org/10.1016/j.biocon.2013.12.015

Peters, M. P., Iverson, L. R., Matthews, S. N., & Prasad, A. M. (2013). Wildfire hazard mapping: Exploring site conditions in eastern US

wildland-urban interfaces. *International Journal of Wildland Fire*, *22*(5), 567–578. https://doi.org/10.1071/WF12177
Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening the black box: An open-source release of Maxent. *Ecography*, *40*(7), 887–893. https://doi.org/10.1111/ecog.03049
Phillips, S. J., Anderson, R. P., & Schapire, R. E. (2006). Maximum entropy modeling of species geographic distributions. *Ecological Modelling*, *190*, 231–259. https://doi.org/10.1016/j.ecolmodel.2005.03.026
Phillips, S. J., Dudík, M., & Schapire, R. E. (2004). A maximum entropy approach to species distribution modeling. Proceedings of the twenty-first international conference on Machine learning. ICML 2004, 655–662. Retrieved from https://www.scopus.com/inward/record.uri?exml:id=2-s2.0-14344261668&partnerID=40&md5=c72ede65bdef69a14c8b6085b1dca1f8
Ray, D., Nepstad, D., & Moutinho, P. (2005). Micrometeorological and canopy controls of fire susceptibility in a forested Amazon landscape. *Ecological Applications*, *15*(5), 1664–1678. https://doi.org/10.1890/05-0404
Renard, Q., Pélissier, R., Ramesh, B. R., & Kodandapani, N. (2012). Environmental susceptibility model for predicting forest fire occurrence in the Western Ghats of India. *International Journal of Wildland Fire*, *21*(4), 368. https://doi.org/10.1071/WF10109
Riahi, K., van Vuuren, D. P., Kriegler, E., Edmonds, J., O'Neill, B. C., Fujimori, S., … Tavoni, M. (2017). The Shared Socioeconomic Pathways and their energy, land use, and greenhouse gas emissions implications: An overview. *Global Environmental Change*, *42*, 153–168. https://doi.org/10.1016/j.gloenvcha.2016.05.009
Salazar, L. F., & Nobre, C. A. (2010). Climate change and thresholds of biome shifts in Amazonia. *Geophysical Research Letters*, *37*(17). https://doi.org/10.1029/2010GL043538
Schwartzman, S., Villas Boas, A., Yukari Ono, K., Gesteira Fonseca, M., Doblas, J., Zimmerman, B., … Torres, M. (2013). The natural and social history of the indigenous lands and protected areas corridor of the Xingu River basin The natural and social history of the indigenous lands and protected areas corridor of the Xingu River basin. *Philosophical Transactions of the Royal Society of London. Series B, Biological Sciences*, *368*, 1–12. https://doi.org/10.1098/rstb.2012.0164
Silvestrini, R. A., Soares-Filho, B. S., Nepstad, D., Coe, M., Rodrigues, H., & Assunção, R. (2011). Simulating fire regimes in the Amazon in response to climate change and deforestation. *Ecological Applications*, *21*(5), 1573–1590. https://doi.org/10.1890/10-0827.1
Smith, L. T., Aragão, L. E. O. C., Sabel, C. E., & Nakaya, T. (2014). Drought impacts on children's respiratory health in the Brazilian Amazon. *Scientific Reports*, *4*, 1–8. https://doi.org/10.1038/srep03726
Swann, A. L. S., Hoffman, F. M., Koven, C. D., & Randerson, J. T. (2016). Plant responses to increasing CO_2 reduce estimates of climate impacts on drought severity. *Proceedings of the National Academy of Sciences of the United States of America*, *113*(36), 10019–10024. https://doi.org/10.1073/pnas.1604581113
Taylor, K. E., Stouffer, R. J., & Meehl, G. A. (2012). An overview of CMIP5 and the experiment design. *Bulletin of the American Meteorological Society*, *93*(4), 485–498. https://doi.org/10.1175/BAMS-D-11-00094.1
Tollefson, J. (2018). Brazil's lawmakers push to weaken environmental rules. *Nature*, *557*, 17. https://doi.org/10.1038/d41586-018-05022-2
Turner, M. G., Gardner, R. H., Dale, V. H., Neill, R. V. O., Turner, M. G., Gardner, R. H., … Predicting, R. V. (1989). Predicting the spread of disturbance across heterogeneous landscapes. *Oikos*, *55*(1), 121–129. https://doi.org/10.2307/3565881
van Vuuren, D. P., Riahi, K., Moss, R., Edmonds, J., Thomson, A., Nakicenovic, N., … Arnell, N. (2012). A proposal for a new scenario framework to support research and assessment in different climate research communities. *Global Environmental Change*, *22*(1), 21–35. https://doi.org/10.1016/j.gloenvcha.2011.08.002
Verbyla, D. L., & Litvaitis, J. A. (1989). Resampling methods for evaluating classification accuracy of wildlife habitat. *Models*, *13*(6), 783–787. https://doi.org/10.1007/BF01868317
Zarin, D. J., Davidson, E. A., Brondizio, E., Vieira, I. C. G., Sá, T., Feldpausch, T., … Denich, M. (2005). Legacy of fire slows carbon accumulation in Amazonian forest regrowth. *Frontiers in Ecology and the Environment*, *3*(7), 365–369. https://doi.org/10.1890/1540-9295(2005) 003[0365:LOFSCA]2.0.CO;2
Zemp, D. C., Schleussner, C. F., Barbosa, H. M. J., & Rammig, A. (2017). Deforestation effects on Amazon forest resilience. *Geophysical Research Letters*, *44*(12), 6182–6190. https://doi.org/10.1002/2017GL072955

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