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Fire propensity in Amazon savannas and rainforest and effects under future climate change

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ABSTRACT

Background. Fire dynamics in the Amazon, while not fully understood, are central to designing fire management strategies and providing a baseline for projecting the effects of climate change. **Aims.** The study investigates the recent fire probabilities in the northeastern Amazon and project future 'fire niches' under global warming scenarios, allowing the evaluation of drivers and areas of greatest susceptibility. **Methods.** Using the maximum entropy method, we combined a complex set of predictors with fire occurrences detected during 2000–2020. We estimated changes in fire patterns in the near (2020–2040) and distant (2080–2100) future, under two contrasting scenarios of shared socioeconomic pathways. **Key results.** Based on current conditions, the spatial fire pattern is affected by farming activities and fire is more common in savannas than in forests. Over long time scales, changes toward a warmer and drier climate, independent of land cover change, are expected to create conditions more conducive to burning. **Conclusion and implications.** Our study helps in understanding the multiple ecological and human interactions that result in different fire regimes in the Amazon. Future efforts can improve outcomes through more complex models that couple predictions of land use and land cover changes, shifts in vegetation resulting from climate change and fires, and fuel dynamics.

Keywords: Amazon, climate change, disturbance, fire niche, fire risk, fire susceptibility, MaxEnt, modelling, remote sensing, wildfires.

Introduction

The Amazon is recognised for extensive dense rainforest, where natural fire disturbance is rare and has occurred in isolated small patches throughout its evolutionary history, owing mainly to climatic conditions and low combustibility (Fearnside 1990; Uhl and Kauffman 1990; Pivello 2011). Embedded in this forest matrix are also disjointed areas of savanna vegetation (Pires and Prance 1985; Prance 1996; de Carvalho and Mustin 2017), with fragments of varying sizes located in the northeastern region. The persistence of Amazon savannas is dependent on disturbances to prevent canopy closure, with fire playing an important role through complex interactions involving climate, resources and species traits (Hoffmann *et al.* 2012).

Despite the widespread recognition that changes in natural historic fire regimes can greatly affect the sustainability of fire-sensitive and fire-prone ecosystems (Hardesty *et al.* 2005; Pausas and Keeley 2009; Pivello 2011), evidence reveals that human-induced ignitions and anthropogenic-driven climate changes are already increasing fire activity in the Brazilian Amazon (Nobre *et al.* 1991; Cox *et al.* 2004; Malhi *et al.* 2008; Marengo *et al.* 2008; Zhao *et al.* 2017; Jimenez *et al.* 2018). Several studies have focused on the region along the 'deforestation arc' between the eastern and southern edges, supporting the synergistic influences of fire and logging, fragmentation and years of severe droughts (Uhl and Buschbacher 1985; Nepstad *et al.* 2004; Aragão *et al.* 2007, 2008; Morton *et al.* 2008; Righi *et al.* 2009; Lima *et al.* 2012; Morton *et al.* 2013; Fanin and van der Werf 2015; Barbosa *et al.* 2019; Dong *et al.* 2021; Libonati *et al.* 2021). However, for the northeastern Amazon, there is a lack of literature on integrative assessments to estimate the spatial susceptibility to fire considering climatic, environmental and anthropogenic factors simultaneously.

Regarding the potential effects of global warming on changing fire regimes in the Amazon, the majority of the published literature suggests that forest flammability will intensify in some locations in the near future, especially if deforestation rates increase, but also if they decline (Alencar *et al.* 2015; Le Page *et al.* 2017; Brando *et al.* 2020). Simulated fire regimes indicated an acceleration of fire activity across the southeastern Brazilian Amazon in the coming decades (Brando *et al.* 2020). Even regions of the eastern interior (near the Amazon River mouth), where current fire probabilities are low, have been predicted as areas of fire invasion in the near future (2010–2039) under a medium–high emission scenario (Krawchuk *et al.* 2009). By the end of the century, the projections show more frequent fires, particularly under scenarios with higher degrees of warming (temperature increase greater than 3°C), demonstrating an expansion of fire to regions in the north (near the equatorial line), south and east (Scholze *et al.* 2006). On the other hand, a minority group of authors has reported the existence of a trajectory of decrease in fire activity in the tropics (including the Amazon) that would be strengthened until the end of the 21st century under a mid–high emission scenario (Moritz *et al.* 2012). Therefore, the direction (increase or decrease) and magnitude of projected changes in fire activity at a regional scale in the Amazon are still topics under debate.

In this research, multiple environmental and human factors were included in an analysis to predict and investigate the spatial distribution of fire probability in the northeastern Amazon and to model future 'fire niches' under scenarios of global warming during the 21st century using climate normals projected by the global climate model CNRM-CM6-1 (Voldoire *et al.* 2019). Our objectives were: fill the gaps in knowledge about the recent distribution of fire probabilities and the most important drivers in the northeastern Amazon; examine the differences between the recent fire environment and future scenarios of climate change; and analyse whether projected surfaces of suitability for fire occurrence will represent future threats to forest and savanna formations. We hypothesise that pessimistic high emission scenarios will increase the environmental propensity for the occurrence of fire, expanding the current geographic distribution of fire in tropical forest areas.

Material and methods

Study area

Our study considers a spatial approach of geopolitical boundaries (Amapá state) because this is the level of decision making for management of the territory. Amapá state is limited to the south and north by wide rivers (Amazonas and Oyapock rivers), to the east by an estuarine and oceanic coastal area (Amazonas estuary and the Atlantic Ocean) and to the west by pristine rainforest. The Amapá area extends over 142 470 km^2, of which approximately 73% was destined for the maintenance of traditional people and conservation, including five indigenous territories and thirteen protected areas (PA), managed by the government (from different jurisdictions) and established under different categories (Brazilian legislation, Law 9985/2000) (Fig. 1).

Overview, assumptions and sources of uncertainty

First, we predicted fire probability in the recent period (hereafter 'baseline') aiming to reproduce present-day fire distributions. The sample window extended beyond the Amapá boundary, encompassing regions of the lower part and the mouth (estuary) of the Amazon River, which are influenced by flooding and urban centres (e.g. Belém and Santarém, located in Pará state), and including French Guiana and most of Suriname. Accounting for the validity of the baseline model, we projected future models to estimate changes in fire probabilities in the next decades (2020–2040) and at the end of this century (2080–2100), considering two contrasting scenarios of climate warming. The future fire models were fitted altering only the climate layers, assuming that all other predictor variables would remain stable, maintaining conditions similar to those found at the current time. This was a deliberate choice, as temperature and precipitation variables consistently surface as major controls of fire (Krawchuk *et al.* 2009). However, our simplifying assumption is deliberately biased, underestimating fire propensity, as we do not consider future changes in variables related to fuel dynamics, vegetation shifts and ignition rates. We emphasise that we do not incorporate dynamic vegetation and fuel models into our fire models, as it is still not well understood how vegetation systems will respond to climate change (McDowell *et al.* 2013; Williams and Abatzoglou 2016).

Fire occurrence data

Fire occurrences were obtained for the period between 2000 and 2020 from the Fire Information for Resource Management System (FIRMS) dataset gathered from Google Earth Engine (GEE), which uses the standard MODIS (Moderate Resolution Imaging Spectroradiometer) MOD14/MYD14 Fire and Thermal Anomalies product (MODIS 2021). These data were filtered to select only the MODIS hotspots with median values for confidence levels equal to 100% because it would not be desirable to have false positives. Using this criterion, we identified a total of

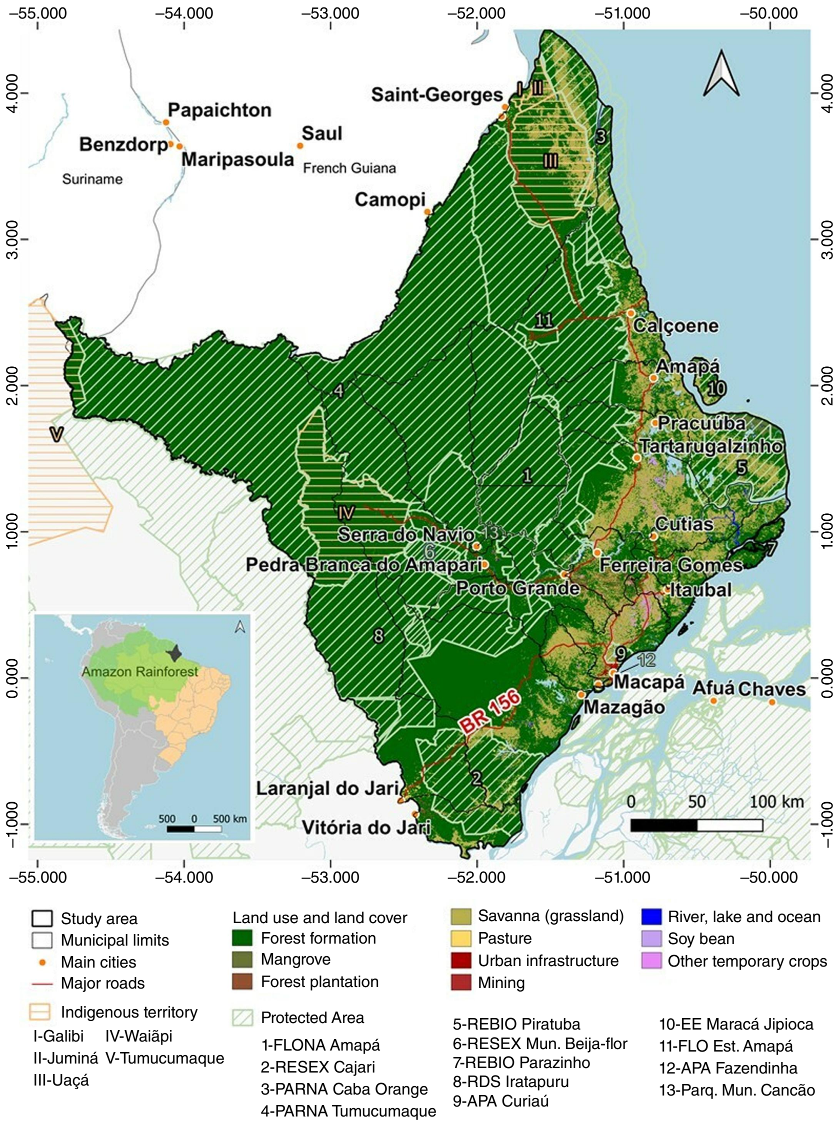

Fig. 1. Land use and land cover in the Amapá state in 2019 according to MapBiomas (Collection 5) (Souza *et al.* 2020), also including the vector layers: political boundaries, indigenous lands, protected areas, highways and main cities. In the legend, each protected area is identified by the name of the reserve preceded by the abbreviation of the national category to which it belongs, including the restricted protection units (ecological station, EE; national park, PARNA; city park, Mun. Parq.; and biological reserve, REBIO) and sustainable use (environmental protection area, APA; national forest, FLONA; state forest, FLO Est; extractive reserve, RESEX; and sustainable development reserve, RDS).

2253 fire occurrences, of which 236 were registered in the state of Amapá.

Environmental and human predictors

Land-use and land cover

Land use and land cover information (Fig. 1) is a key variable that can provide an assessment of landscape fire patterns. These data were used as a categorical layer and gave rise to continuous layers using the Euclidean distance to represent the influences of distinct floristically structured vegetation and human activities.

The vegetation was characterised considering three aspects: flammability, assessed through the Normalized Difference Vegetation Index (NDVI) to measure the live fuel moisture content (Chuvieco 2003); fire probability, linked to the amount of fuel (Krawchuk *et al.* 2009) and represented as biomass density; and fuel type, through information on two vegetation cover classes (forest and savanna).

Human influence

Aiming to assess the human footprint related to ignition patterns, we retrieved information on the spatial distribution of available road infrastructure (Ministério dos Transportes 2019), protected areas (Ministério do Meio Ambiente 2020), land use types and waterways (Project MapBiomas 2019). These factors are frequently associated with human ignitions (Flannigan *et al.* 2009; Bowman *et al.* 2011; Archibald *et al.* 2013; Chuvieco *et al.* 2014). The data collected gave rise to five raster files of human influence sources, in which each cell represented a distance value (Euclidean method) from the closest road, water, farming activity, urban land use and protected areas.

Elevation and climatic variables

Bioclimatic variables (historical and future climate) and elevation data (Shuttle Radar Topography Mission (SRTM)) are available in the WorldClim version 2.1 database

Table 1. List of parameters evaluated for assessing fire propensity in the northeastern Amazon, including a brief description of the data, spatial resolution, type of variable and source (all accessed March–April 2021).

Class	Variable (unit)	Description of data	Resolution	Type	Source
Climate normals	T_{avg} (°C)	Annual mean temperature	2.5 arc-min	Cont	Fick and Hijmans (2017) for the period 1971–2000 and Voldoire et al. (2019) for future fire models
	$\Delta T_{diurnal}$ (°C)	Annual mean diurnal range (mean of monthly (max temp − min temp))	2.5 arc-min	Cont	
	Isother (%)	Isothermality ($\Delta T_{diurnal}/\Delta T_{annual} \times 100$)	2.5 arc-min	Cont	
	T_{season} (°C)	Temperature seasonality (standard deviation)	2.5 arc-min	Cont	
	T_{max} (°C)	Max. temperature of warmest month	2.5 arc-min	Cont	
	T_{min} (°C)	Min. temperature of coldest month	2.5 arc-min	Cont	
	ΔT_{annual} (°C)	Annual temperature range	2.5 arc-min	Cont	
	T_{wet} (°C)	Mean temperature of wettest quarter	2.5 arc-min	Cont	
	T_{dry} (°C)	Mean temperature of driest quarter	2.5 arc-min	Cont	
	T_{warm} (°C)	Mean temperature of warmest quarter	2.5 arc-min	Cont	
	T_{cold} (°C)	Mean temperature of coldest quarter	2.5 arc-min	Cont	
	PPT (mm)	Annual precipitation	2.5 arc-min	Cont	
	PPT_{wet} (mm)	Precipitation of wettest month ($\max([PPT_i, \ldots, PPT_{12}])$)	2.5 arc-min	Cont	
	PPT_{dry} (mm)	Precipitation of driest month ($\min([PPT_i, \ldots, PPT_{12}])$)	2.5 arc-min	Cont	
	PPT_{season} (%)	Precipitation seasonality (coefficient of variation)	2.5 arc-min	Cont	
	PPT_{wet} (mm)	Precipitation of wettest quarter	2.5 arc-min	Cont	
	PPT_{dry} (mm)	Precipitation of driest quarter	2.5 arc-min	Cont	
	PPT_{war} (mm)	Precipitation of warmest quarter	2.5 arc-min	Cont	
	PPT_{cold} (mm)	Precipitation of coldest quarter	2.5 arc-min	Cont	
Topography	Elevation (m)	SRTM elevation data	2.5 arc-min	Cont	Fick and Hijmans (2017)
Land use and land cover	LULC (class)	Landsat-based classification of Pan-Amazonia for 2019	30 m resampling for 2.5 arc-min	Cat	Project MapBiomas (2019), Souza et al. (2020)
Vegetation	NDVI (dimensionless)	Annual median NDVI between 2001 and 2020	500 m resampling for 2.5 arc-min	Cont	Didan (2015)
	Biomass (Mg/ha)	Woody biomass density	500 m resampling for 2.5 arc-min	Cont	Baccini et al. (2012)
	Dis_forest (km)	Euclidean distance calculated from a binary forest raster	2.5 arc-min	Cont	Project MapBiomas (2019)
	Dist_savanna (km)	Euclidian distance calculated from a binary savanna raster	2.5 arc-min	Cont	Project MapBiomas (2019)
Anthropogenic factors	Dist_road (km)	Euclidian distance to paved roads calculated from a vector file	2.5 arc-min	Cont	Ministério dos Transportes (2019)
	Dist_water (km)	Euclidian distance calculated from a binary water raster	2.5 arc-min	Cont	Project MapBiomas (2019)
	Dist_urban (km)	Euclidian distance calculated from a binary urban raster	2.5 arc-min	Cont	Project MapBiomas (2019)
	Dist_Farming (km)	Euclidian distance calculated from a binary farming raster	2.5 arc-min	Cont	Project MapBiomas (2019)
	Dist_PA (km)	Euclidian distance to protected areas from a vector file	2.5 arc-min	Cont	Ministério do Meio Ambiente (2020)

Type: Continuous, CONT; categorical, CAT.

(downloaded from http://worldclim.org). The baseline model was based on average climatic data for 1971–2000 (Fick and Hijmans 2017). The future fire models were based on average climatic data projected from CNRM-CM6-1, the fully coupled atmosphere–ocean general circulation model (GCM) of the sixth generation jointly developed by Centre National de Recherches Météorologiques (CNRM) and Cerfacs for the sixth phase of the Coupled Model Intercomparison Project 6 (CMIP6) (Voldoire *et al.* 2019). In the present work, we considered the CNRM-CM6-1 model because it performs reasonably well in humid regions (Parsons 2020; Yazdandoost *et al.* 2021). The future fire models for the early (2021–2040) and end of (2071–2100) the 21st century were based on two scenarios that combine socioeconomic and technological development (shared socioeconomic pathways, SSPs) (O'Neill *et al.* 2013; Gidden *et al.* 2019), an optimistic scenario (SSP 1-2.6, a low emission scenarios, where temperatures will stabilise at approximately 1.8°C, relative to 1850–1900, by the end of the century) and a pessimistic scenario (SSP 5-8.5, which assumes an increase in warming of nearly 4.4°C by 2100 over preindustrial levels and crossing a 2°C increase in 2050).

Variable selection

First, all layers of environmental and human predictors (Table 1) were resampled to the same pixel size as the climatic data (2.5 arc min a side or approximately 5 km at the equator) using the nearest-neighbour process. Then, we analysed the variable set for the baseline model to select the most important uncorrelated predictors and lead parsimonious and interpretable models (Merow *et al.* 2013). Two procedures were used to reduce multicollinearity between variables, as per Mohammadi *et al.* (2021). We started with an implementation of an optimised selection of 29 variables (continuous variables), processed in the R program (R Core Team 2020), based on the sample size corrected for the highest area under the curve (AUC) of the receiver operating characteristic (ROC) and the lowest Akaike information criterion (AIC). Variables were removed by setting a contribution threshold of 1%, regularisation multiplier of 1–5 with increments of 0.5 and Pearson's correlation coefficient $> |0.7|$. Then, to overcome multicollinearity between the selected variables, we calculated the variance inflation factor (VIF) using the R package usdm (Naimi *et al.* 2014) and excluded variables with VIF > 5.

Overall, seven variables were selected, of which two were associated with human factors ('Distance to roads' and 'Distance to farming') and one was associated with topography ('Elevation'); there were four climatic layers for 1970–2000 (one for temperature and three for precipitation): temperature annual range, annual precipitation, precipitation seasonality and precipitation of the warmest quarter. Additionally, we included the categorical variable related to land use land cover (LULC) types, resulting in a final dataset that converged to a total of eight variables considered in the construction of the 'baseline' and 'future' fire probability models.

MaxEnt modelling of fire occurrences

We assessed the fire potential in different regions by treating fire as an entity analogous to an ecological species and applying ecological niche theory, specifically ecological niche modelling, via the maximum entropy (MaxEnt) method. We chose the MaxEnt method because it is a presence-only machine learning algorithm that iteratively contrasts multiple predictor values at occurrence locations (i.e. ignition points) with those of random locations across the study area (Elith *et al.* 2010), resulting in models that are able to describe complex relationships (Parisien *et al.* 2012). The conceptual approach and MaxEnt method have been recommended for fire studies carried out in different parts of the world, with different objectives (Parisien *et al.* 2012; Renard *et al.* 2012; Bar Massada *et al.* 2013; Arpaci *et al.* 2014; De Angelis *et al.* 2015; Duane *et al.* 2015; Davis *et al.* 2017; Li *et al.* 2017; Adab *et al.* 2018; Fonseca *et al.* 2019; Molina *et al.* 2019; Xiong *et al.* 2020; Arenas-Castro and Sillero 2021). Here, the analyses were performed using the open-source 'MaxEnt' software version 3.4.4. (Phillips *et al.* 2020).

The algorithm was run with default settings (more details can be found in Phillips *et al.* 2006, 2017; Phillips and Dudík 2008), except that the 'Maximum iterations' value was set to 5000, the number of replications was set to 1000 and the 'Random seed' option was selected. We fitted baseline and future climatic models to our data using the subsample replicate run type, with 70% of the fire occurrence cells used as training data and 30% as test data. Therefore, 30% of the test data and a set of 10 000 random background cells were used to validate the model.

Model evaluation and variables' contributions

Model performances were evaluated with the widely used AUC statistic (Fielding and Bell 1997), which measures the ability of the model prediction to discriminate fire presence from background points. Although AUC has been criticised (Lobo *et al.* 2008), it is the standard method to assess prediction accuracy because of its threshold independence (Phillips *et al.* 2006; Franklin and Miller 2009) and the simplicity of interpreting its results (Bar Massada *et al.* 2013).

The relative importance of the predictor variables in the model was tested using two approaches provided by MaxEnt: percentage contribution and jack-knife metrics (leave-one-out cross-validation). The percentage contribution is determined by a heuristic approach in which values represent the cumulative gain (fit) to the model provided by the corresponding variable (Phillips 2017). The jack-knife approach was used to measure how much unique information each variable provides in explaining the fire distribution as each variable is excluded one at a time when running the model with the remaining variables (Baldwin 2009).

Spatial fire distribution of the baseline model and change analysis

The output probability of fire was given by the complementary log-log transformation (cloglog format), which gives an estimated value between 0 and 1, with higher values demonstrating more fire-prone conditions. To carry out zonal analyses, we classified the pixels of the models into five levels of suitability: very low ($0.00 < x \leq 0.10 \rightarrow 1$), low ($0.10 < x \leq 0.30 \rightarrow 2$), moderate ($0.30 < x \leq 0.50 \rightarrow 3$), high ($0.50 < x \leq 0.75 \rightarrow 4$) and very high ($0.75 < x \leq 1.00 \rightarrow 5$). For the baseline model, we quantified the area occupied by each habitat suitability class for fire occurrence in relation to its land use and land cover.

Changes in fire probability in relation to future climate shifts were detected through two distinct methods. The first recognised the differences between the modelled predictions after their conversions into binary maps, applying the 10th percentile training presence logistic threshold to define suitable and unsuitable raster cells. Overlay analysis was conducted between the baseline and each predicted future model, resulting in four expected change maps, where projected decreases in fire propensity were indicated as retreats and increases as invasions. These results allowed us to identify potential 'hotspots of change' for different scenarios and temporal scales. The second method comprised comparative analyses between the models in relation to the coverage by different fire classes in different scenarios and a classification agreement (pixel-by-pixel correspondence) analysis computed using the R packages Greenbrown (Forkel and Wutzler 2015) and DiffeR (Pontius and Santacruz 2015), allowing the generation of shift maps (Supplementary information). Additionally, concerns about how fire probabilities would change in areas currently occupied by forests and savannas under different emission scenarios were analysed using summary statistics in the form of percentage loss or gain in different fire suitability classes.

Results

Performance of the modelling approaches

The AUC average test value for the baseline model developed for fire occurrence was 0.817 ± 0.008 (Fig. 2). The AUC values for the 2030s optimistic, 2030s pessimistic, 2090s optimistic and 2090s pessimistic models obtained from the validation phase processing exhibited respective values of 0.803, 0.816, 0.817 and 0.803. These results, according to the thresholds proposed by Vilar *et al.* (2016) in research on fire modelling, indicate that the predictive performance of the MaxEnt models was excellent in terms of goodness-of-fit with the training datasets.

Variable importance

Regarding the relative contributions of the environmental variables, 'Distance to Farming', 'Precipitation Seasonality' and 'Elevation' were the strongest predictors of fire distribution, with contributions of 55.4, 16.8 and 10.4%, respectively (Supplementary Table S1). The AUC values calculated by the jack-knife metrics supported this overview and revealed that the individual importance of these three variables was high (Fig. 2).

The response curves of the main factors affecting the possibility of fire occurrence highlighted some details regarding the patterns of distribution (Supplementary Fig. S1). Fire occurrence was negatively related to 'Distance to Farming', demonstrating that fires are more likely to occur closer to agriculture, pasture and silviculture. Water availability, especially precipitation seasonality, emerged as the main climatic driver of fire probability. The probability of fire occurrence displayed a complex relationship with elevation, with fire occurrence exhibiting a peak at approximately 100 m and then increasing again from approximately 400 m above sea level. This result demonstrates that the occurrence of fire is more frequent in the Amazon lowlands and plain regions, but our sample window also captured fire occurrences in Guyana's Shield region.

Baseline model of fire probability

The baseline model captured a complex spatial pattern of fire activity (Fig. 3). In general, areas where fire was not observed in the fire dataset had 'very low' and 'low' predicted fire probabilities (probability ≤ 0.3). These classes occupied approximately 80.6% (114 925 km^2) of the territory of the state of Amapá, and the current coverage of these areas is represented, almost entirely, by forest vegetation (81.3%) (Fig. 4). In relation to areas of high fire probability (≥ 0.5 probability), we observed a strong coincidence with the distribution of savanna vegetation and with forests located close to areas currently used for agriculture and pasture.

Spatially, we observed that the region classified as 'very low' suitability was located in western Amapá state, a relatively isolated region with a higher relief, including the pristine rainforest ranges of Tumucumaque National Park, the largest protected area of tropical forest in the world. The model predicted 'low' fire probabilities in forests in the most central region of the state, in wetlands, floodplain forests and mangroves. The class of 'moderate' fire suitability was found mainly in areas occupied by savannas, savanna–forest transition areas and along the highway that connects the state of Amapá from north to south (Highway BR156).

The highest probability classes (8528 km^2) were concentrated in two regions, one in the central eastern part of Amapá state and the other located close to the French Guiana border. In the most central area, 'very high' probabilities (≥ 0.75 probability) were linked mainly to agricultural activities, including forestry for the national and international

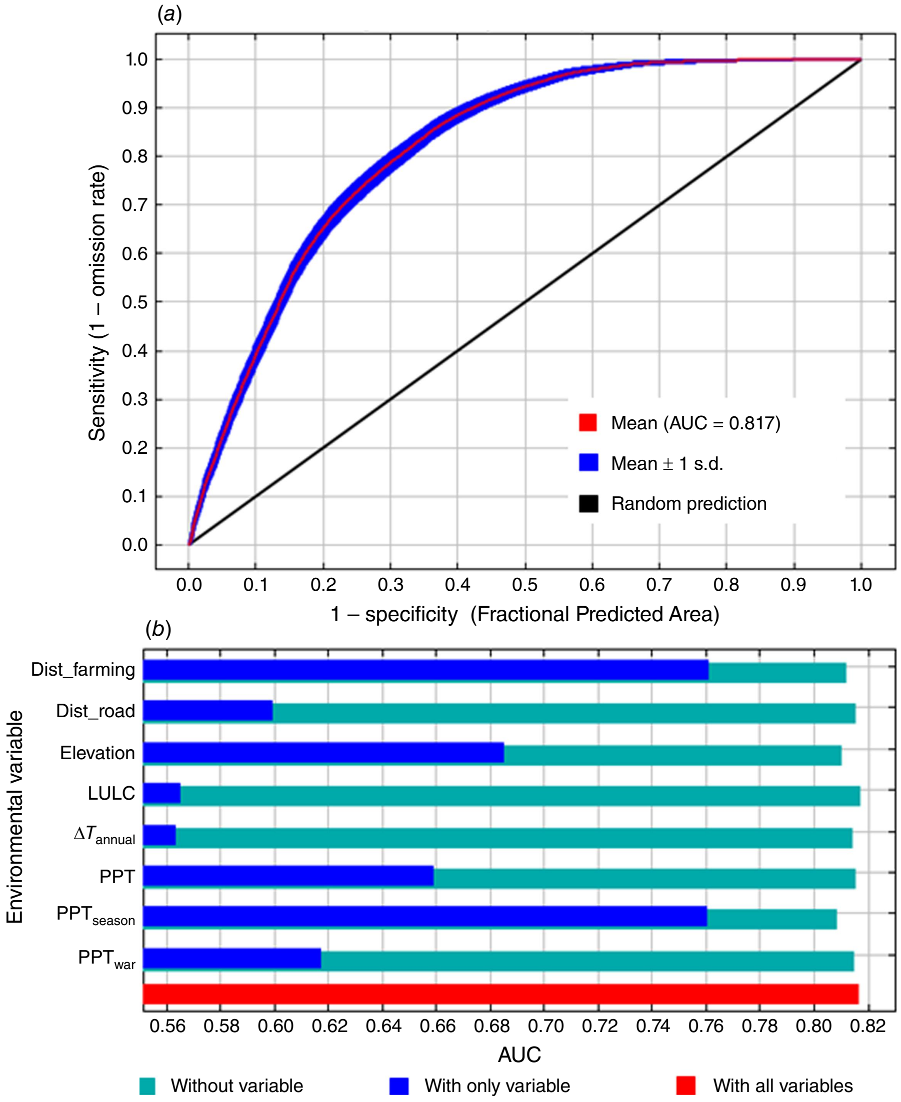

Fig. 2. Baseline MaxEnt model evaluation: (*a*) receiver operating characteristic (ROC) curve for the predicted distribution averaged over the 1000 replicate runs; (*b*) estimations of variable importance using jack-knife test, with coloured bars showing average AUC gains for each variable. The green, blue and red bars represent results of the model created excluding one particular variable, with only one variable and with all variables, respectively.

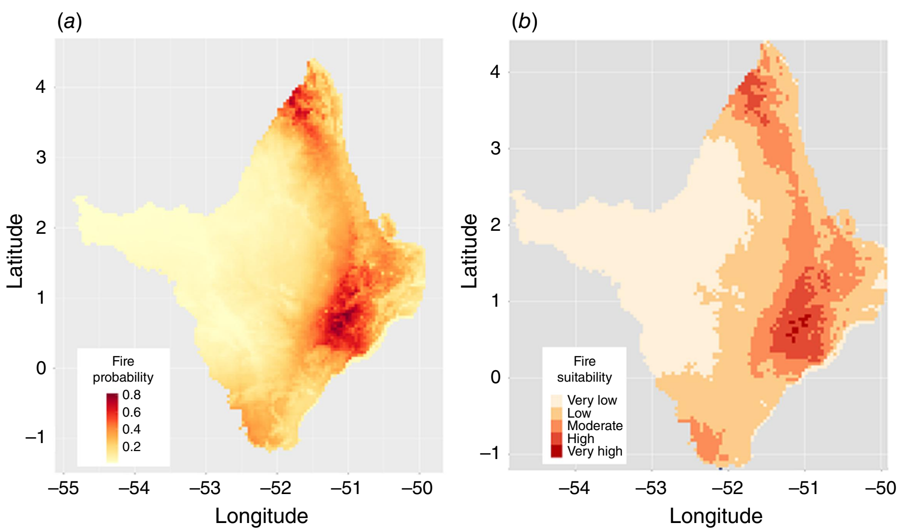

Fig. 3. The modelled distribution of fire occurrence under current conditions (baseline model) showing: (*a*) cloglog output values from MaxEnt with fire probabilities represented by a colour gradient scale, from yellow (low) through red (high); (*b*) MaxEnt fire probabilities classified into five suitability categories (levels of suitability for ignition occurrence): very low ($0.00 < x \leq 0.10$), low ($0.10 < x \leq 0.30$), moderate ($0.30 < x \leq 0.50$), high ($0.50 < x \leq 0.75$) and very high ($0.75 < x \leq 1.00$).

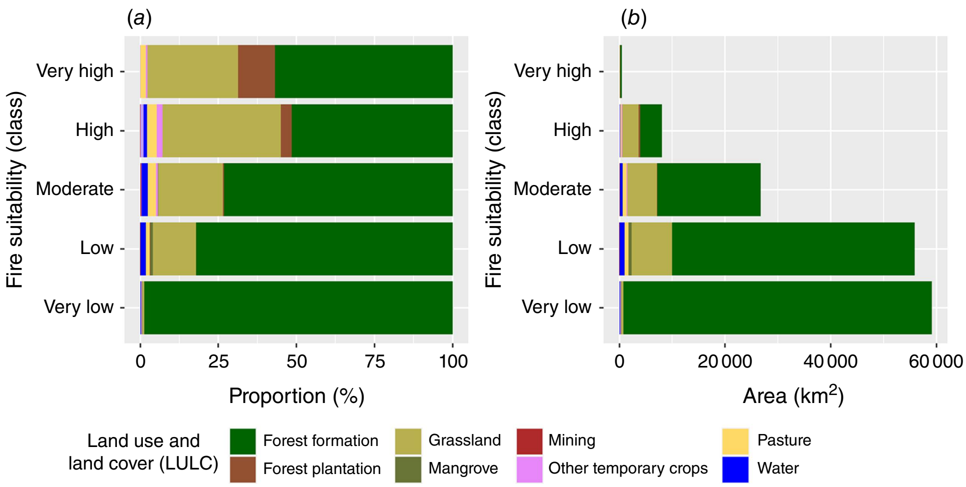

Fig. 4. Area of land use and land cover (LULC) within each fire suitability category (class) estimated for the current period (baseline MaxEnt model) and represented by absolute (*a*) and relative values (*b*). The LULC data were obtained from MapBiomas (Collection 5) for 2019 (Project MapBiomas).

markets. Relative to the region located north of Amapá, extensive cattle raising seemed to be a major driver of fire occurrence, but influences from subsistence or small-scale agriculture practiced by indigenous communities also existed.

Projected future fire probabilities

The future fire distributions projected (Supplementary Fig. S2) showed that large areas of Amapá state are expected to experience small near-term changes in fire probabilities. Then, in the coming decades, the fire propensity classes predicted in the present seem to hold for both the optimistic and pessimistic scenarios. These results are demonstrated by areas where fire propensity remained unchanged in the shift maps (Fig. 5) and also by high agreement between the baseline and the 2030s models (Supplementary Fig. S3). However, predicted changes deviated significantly more from current conditions over time and under a higher emission scenario.

We observed high similarity between the optimistic and pessimistic emission scenarios projected for the near future (91% agreement). However, it is important to note that under a high emission scenario (pessimistic 2030s), some areas in northern Amapá state showed projections of decreasing fire probability (Fig. 5). This seems to be related to conditions of lower seasonal precipitation, because the average annual temperature was predicted with values higher than the optimistic scenario and there was a forecast reduction in annual precipitation (5.5% less than current conditions).

Toward the end of the 21st century, the model for the low emission scenario showed relative similarity to the baseline (87% agreement) and high dissimilarity with respect to the pessimistic scenario (49.2% agreement). The pessimistic model, in turn, showed high dissimilarity to the baseline model (53%), mainly due to the increase in area occupied by moderate and high suitability classes for fire occurrence (Fig. 6).

Changing disturbance regimes in forest areas and savannas

In the near future, an optimistic low emission scenario would result in little change to fire probabilities in areas currently occupied by savannas, but some forest areas would become more susceptible to fire. In spatial terms, expansion of fires in forest areas would occur in the central part of the state in both pessimistic and optimistic scenarios (Fig. 5). On the other hand, if the pessimistic scenario prevails in the coming decades, forest and savanna vegetation located in the north of the state of Amapá will be less threatened by fire risk.

Toward the end of the 21st century, the pessimistic scenario for high emissions indicates the expansion of areas of greater suitability for fire occurrence in forest or savanna areas compared with the baseline. This finding is evidenced by the increase in the proportion of moderate and high classes and decrease in the proportion of classes with lower fire probability for both types of vegetation (Fig. 7).

Comparing the optimistic and pessimistic scenarios projected for 2090s, we found that the pessimistic scenario showed increases in high suitability fire classes of ~9.6% for forests and 15.8% for savannas.

Discussion

Fire distribution under current conditions

Our spatial fire distribution modelling emphasised that fire, climate conditions and farming are inextricably linked. Regarding climate constraints that influence fire distribution,

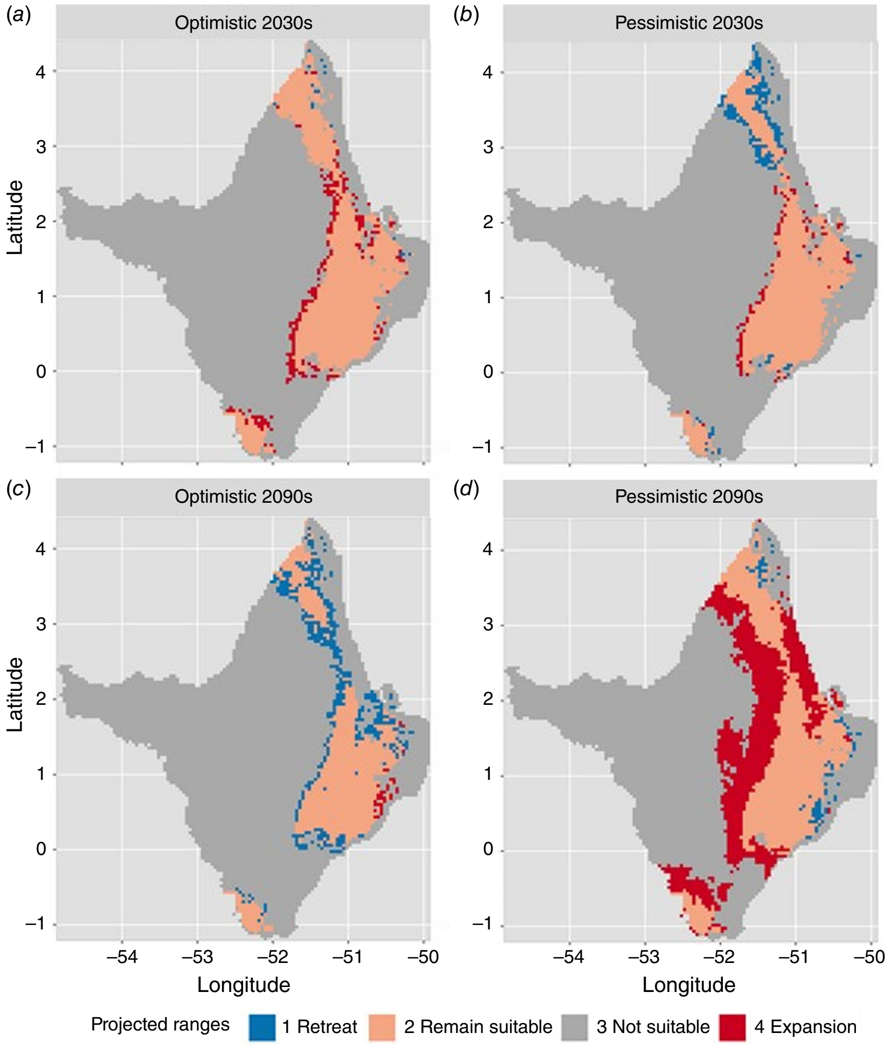

Fig. 5. Projected ranges of fire suitability shifts for the: (*a*) 2030s optimistic emission scenario; (*b*) 2030s pessimistic emission scenario; (*c*) 2090s optimistic emission scenario; (*d*) 2090s pessimistic emission scenario. Grey regions denote areas where fire is absent or has very low occurence at present and may remain unsuitable in the future (not suitable), red where current fire probabilities are low and may increase in the future (expansion), salmon where fire may remain with high probabilities in the future (remain suitable) and blue where current fire probabilities are high and may decrease in the future (retreat).

we identified three dominant variables: precipitation seasonality, annual precipitation and annual temperature range. These variables are associated with biomass drying and climatic seasonality, processes that characterise the occurrence of savannas and result in their greater propensity for fire. However, a significant proportion of the areas occupied by Amazon savannas had low fire probability, which suggests that in these areas, flooded soils represent the main restrictive factor for the occurrence of ignition, as well as for the growth of trees. Flooding processes occur in Amapá (Santos 2016; Anthony *et al.* 2021) due to: the overflow of water in a river or lake onto neighbouring lands (fluvial flood); the accumulation of rainwater (pluvial flood); and the inundation of land along the coast by seawater (coastal flood).

We also found evidence that human-induced fire events are the main driver of ignition in the northeastern Amazon region, highlighting a strong relationship between fires and agricultural systems, which can be intensified by the presence of roads. This result is similar to that reported by Archibald *et al.* (2013), whose research on global pyrome identification resulted in the classification of much of the state of Amapá into a region where human activities, particularly deforestation and agriculture, are a major force that disrupts the fire system. The use of fire for land management is 'embedded in the culture and economic logic of millions of rural Amazonians', as this primary technique approach facilitates land clearing, improves soil fertilisation in slash-and-burn agriculture and favours cattle pasture (extensive system), either in implementation or during maintenance (Nepstad *et al.* 2001).

Our fire model captured the spatial concentrations of very highly fire-prone areas, which are related to altered fire regimes, mainly in landscapes originally covered by savanna vegetation. There are some reasons for crop, livestock and forestry activities occurring in preference in savannas rather than in forests in the northeastern Amazon: lower economic costs, fewer environmental restrictions and greater access to road networks. These results reinforce the finding that in Amapá, savannas are highly threatened ecosystems that have received very little attention, with gaps in scientific

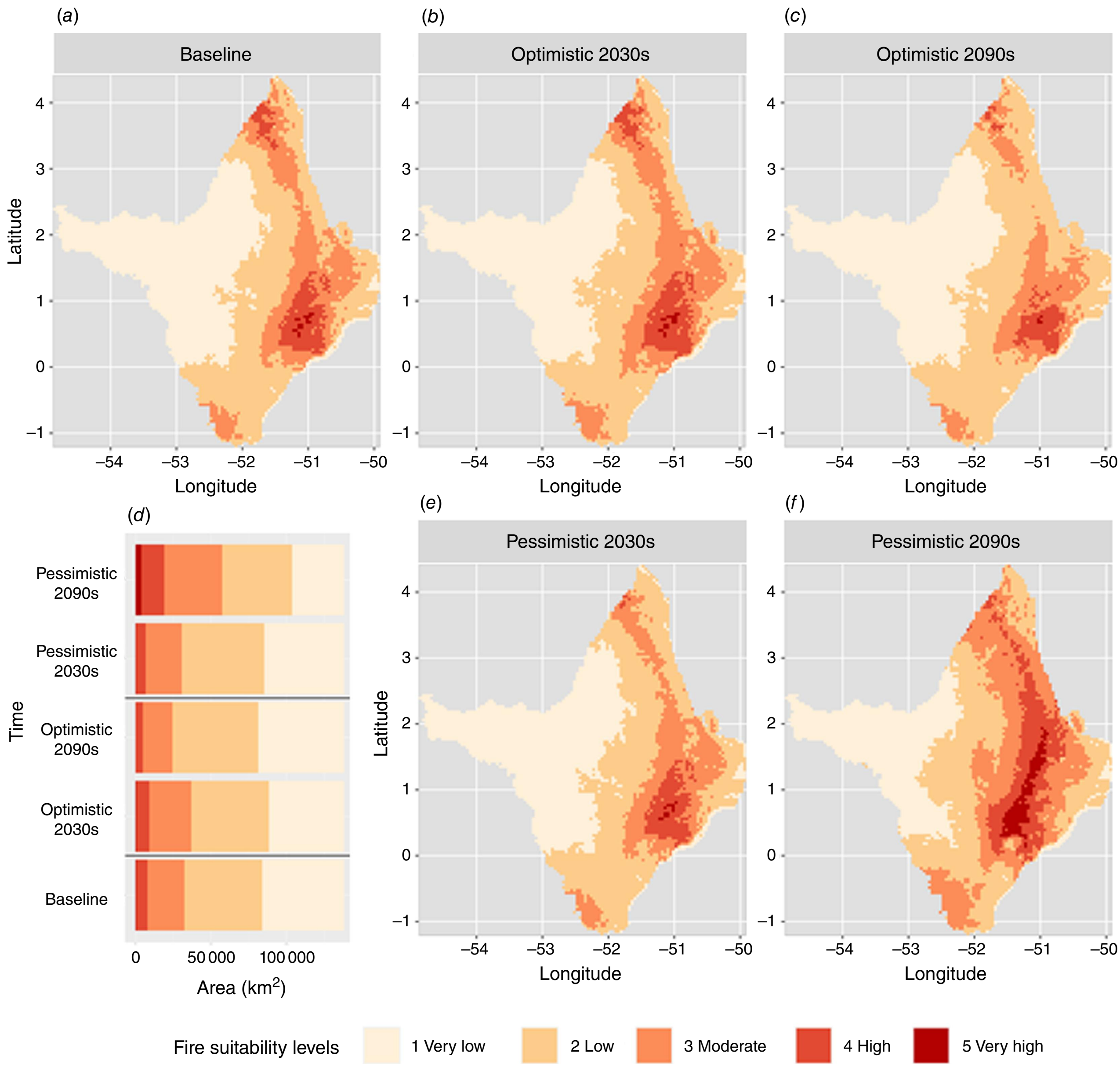

Fig. 6. Predicted fire suitability maps created for different time periods and future climate change scenarios: (*a*) current period; (*b*) 2030s under optimistic emission scenario; (*c*) 2090s under optimistic emission scenario; (*e*) 2030s under pessimistic emission scenario; and (*f*) 2090s under pessimistic emission scenario. In addition, we present a bar chart (*d*) with the sum of the areas of the fire suitability levels for each projected fire model.

knowledge and almost no protection, compared with the forested parts of the state (Mustin *et al.* 2017).

For savanna areas, the sustainable use of fire for managing cattle ranching and protected areas is recommended, but the regimes must be fitted to local specific features (Pivello 2011; Borges *et al.* 2016; Mustin *et al.* 2017; Pivello *et al.* 2021). In addition, environmental, economic and social benefits can be generated if aspects of fire susceptibility are considered in the analyses to define zoning regulations by legal instruments, ordering the suitable use of the land and fire regime prescriptions. Furthermore, considering the influence of farming on fire occurrence outbreaks, strategies to adjust agricultural practices should be considered, such as training farmers to improve the use of fire and increase safety measures (Adab *et al.* 2018).

Regarding fire ignitions influenced by road networks, we observed a greater vulnerability of roadside vegetation, especially in areas covered by forest along the BR156 highway. According to Pivello (2011), roads facilitate logging activities, and the extraction of large trees opens the forest canopy, decreases the local moisture, and strongly increases forest susceptibility to wildfires. For regions near the BR156

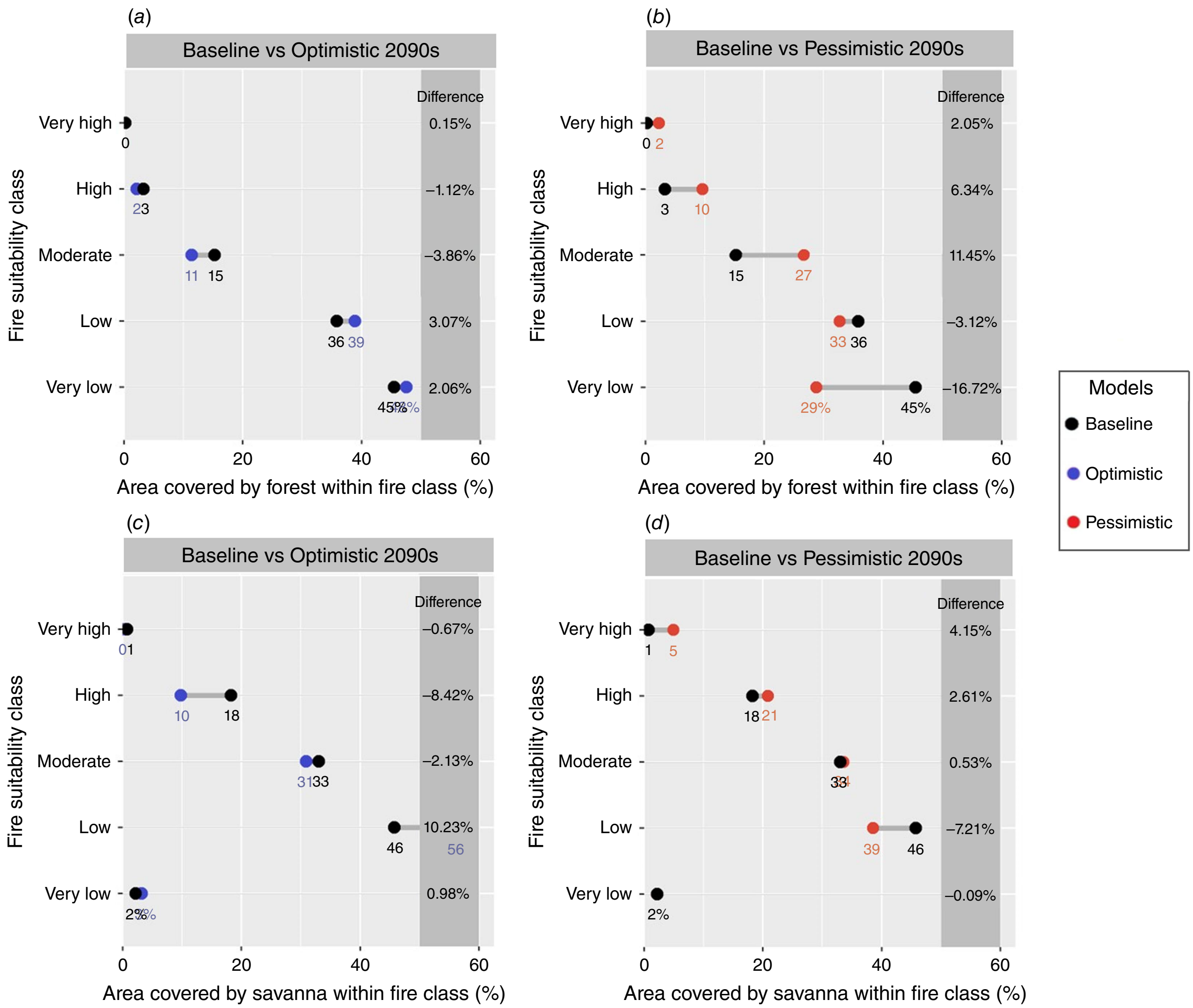

Fig. 7. Comparison of baseline fire model for Amapá state and future projections for 2090s (2071–2100) analysed through gains and losses (Difference) in flammability classes within forest and savanna vegetation types, considering: (*a*, *c*) optimistic emission scenario (SSP 1-2.6); and (*b*, *d*) pessimistic emission scenario (SSP 5-8.5). The fire models are represented by circles with colours, black for the baseline model, blue for the optimistic 2090s model and red for the pessimistic 2090s model.

highway, we suggest fire prevention and mitigation strategies, prioritising the allocation of public resources and support systems to combat illegal burning. We also note the strategies suggested by Pivello (2011), which include the development of policies to stimulate fire-free practices and small-scale agricultural projects. We recognise the importance of creating mechanisms that support and favour the continued development of markets and incentives for small-scale producers for sustainable development (Mustin *et al.* 2017).

Fire patterns and climate-related changes

For the next few decades, our modelled potential fire distributions were very similar to those for the present time, regardless of the emission scenario analysed. In line with these results, Krawchuk *et al.* (2009), in a previous study on global pyrogeography, demonstrated that for a medium–high emission scenario, no invasions or fire retreats were found for the same region. However, this would only be achieved under sustainable land use projections. According to Fonseca *et al.* (2019), when land conversion predictions (fragmented landscapes) are coupled with intermediate emission scenarios, the changes can be significant, with an increase in the probability of fire occurrence in the intermediate future (2041–2070).

Regarding changes in fire niches in the late 21st century, the patterns of expansion and contraction demonstrate more pronouncedly divergent situations when comparing the optimistic and pessimistic scenarios (Fig. 5). In this sense, our results confirm our hypothesis, as the large expansion of fire-prone areas was projected to occur under a scenario of higher emissions independently of land cover change. Consequently, continued emissions of greenhouse gases would increase biodiversity loss, put the water cycle at risk and negatively affect the ecosystem services provided to local people.

These threats may be even greater than projected in this study and fire propensity may expand to an even larger area than projected here, beause we do not associate predictions of land use and land cover changes. Regarding human influence, although the state of Amapá has extensive areas with restrictions for land use conversion, it is likely that fast changes in land cover around protected areas could lead to an increase in the potential for future fires. The increase in the occurrence of fires can also lead to conversions in vegetation types, as observed by Brando *et al.* (2014) in southeastern Amazonia, where the synergistic effect between fire and recent severe droughts has led to the conversion of forest species to flammable grass species near forest edges. Therefore, the magnitude of fire disturbances may be amplified by positive feedback loops between fires and increases in forest flammability (Cochrane and Schulze 1999; Cochrane *et al.* 1999; Nepstad *et al.* 2001; Hoffmann 2003; Balch *et al.* 2015). Grass–fire cycles, for example, are important for many forest frontiers where fires interact positively with exotic grass invasion (D'Antonio and Vitousek 1992; Veldman and Putz 2011; Silvério *et al.* 2013), with potentially disastrous consequences considering synergies between deforestation and climate change (Malhi *et al.* 2009; Silvestrini *et al.* 2011; Le Page *et al.* 2017; Xu *et al.* 2020).

Maintaining or increasing current patterns of fire occurrences in the northeast region of the Amazon could change the role of the world's largest rainforest in balancing the global carbon budget. According to evidence found by Gatti *et al.* (2021), the eastern region of the Amazon can already be considered as a source of carbon emissions. Therefore, in this study, we provide information that can help decision makers to outline fire prevention, management and suppression strategies, minimising the risks of degradation of Amazonian ecosystems.

Limitations

Our projections are biased in terms of the algorithm selected for the modelling itself and the set of future climate data obtained from a single GCM. Therefore, without a doubt, there are limitations in our results that mainly stem from the lack of accuracy or precision in the climate data restricted by the predictions of the CNRM-CM6-1. Furthermore, our results should be interpreted with caution for the late 21st century, because we do not associate predictions of land use and land cover changes, shifts in vegetation resulting from climate change and fires, and fuel dynamics. Therefore, our simulations should be interpreted as a motivation for future efforts, which can advance contributions through more complex models.

Conclusion

In recent years, the synergy between socioeconomic and environmental factors has resulted in a greater spatial concentration of regions with a high probability of fire occurrence in the northeast Amazon. Farming activities were identified as the main driver for the occurrence of ignitions and the highest fire activity was observed in Amazonian savannas and savanna–forest transition. As savannas are fire-dependent, sustainable use of fire is recommended, but forest fires are likely to be a cause for concern in the face of climate change impacts. For the coming decades, our models suggest that wildfire potential is projected to expand into some currently pristine and highly humid forests, regardless of the emission scenario analysed. Regarding long-term scales, the conditions predicted under the high emission scenario (SSP 5-8.5) show a significant increase in fire propensity in areas previously unaffected by fire. Consequently, this scenario would negatively affect people, biodiversity and ecosystems on a local scale, as well as resulting in global ecological threats. Conversely, the optimistic emissions scenario (SSP 1-2.6) shows the importance of limiting global warming to 1.8°C by the end of the century to minimise the environmental and social costs associated with wildfires in the Amazon. Our predictions of future trends in fire activity are inherently uncertain and can be considered conservative, because our model does not incorporate feedbacks between vegetation and climate, or land use and land cover changes. However, our results represent a major contribution to addressing regional and global challenges posed to human well-being and biodiversity. Therefore, the present research can allow stakeholders to identify where propensity for future fires might (or not) increase in order to apply efficient short and long-term action planning.

Supplementary material

Supplementary material is available online.

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