fire

Article

Machine Learning Model Reveals Land Use and Climate's Role in Amazon Wildfires: Present and Future Scenarios

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Abstract: Understanding current fire dynamics in the Amazon is vital for designing effective fire management strategies and setting a baseline for climate change projections. This study aimed to analyze recent fire probabilities and project future "fire niches" under global warming scenarios across the Legal Amazon, a scale chosen for its relevance in social and economic planning. Utilizing the maximum entropy method, this study combined a complex set of predictors with fire occurrences detected during 1985–2022. It allowed for the estimation of current fire patterns and projecting changes for the near future (2020–2040) under two contrasting socioeconomic pathways. The results showed strong model performance, with AUC values consistently above 0.85. Key predictors included "Distance to Farming" (53.4%), "Distance to Non-Vegetated Areas" (11.2%), and "Temperature Seasonality" (9.3%), revealing significant influences from human activities alongside climatic predictors. The baseline model indicated that 26.5% of the Amazon has "moderate" to "very high" fire propensity, especially in the southern and southeastern regions, notably the "Arc of Deforestation". Future projections suggest that fire-prone areas may expand, particularly in the southern border regions and near the Amazon riverbanks. The findings underscore the importance of incorporating both ecological and human factors into fire management strategies to effectively address future risks.

Keywords: pyrogeography; fire susceptibility analysis; Maxent; Amazon fire dynamics; climate change; disturbance; fire niche

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1. Introduction

Wildfires are an increasing global environmental concern [1]. This interest is particularly relevant in the Amazon, where changes in historical fire frequencies have been observed over the past few decades [2–5]. These changes have led to environmental degradation, habitat loss, greenhouse gas emissions, and negative impacts on local communities [6–10], threatening both biodiversity and ecosystem services [11–13]. Therefore, understanding and predicting wildfire distribution is essential for formulating effective mitigation and adaptation strategies to minimize negative impacts on the environment and local communities.

Current research in Amazon wildfire dynamics reveals a consensus on the primary drivers of these events, including human and climatic factors [2,3,5,14]. Human activities exert a dominant influence on fire patterns through deforestation fires, pasture and agricultural maintenance, or accidental escapes of intentional fires into degraded forest edges [15–17]. In recent decades, there has been a significant increase in "maintenance fires" in the Amazon [5], with burn patterns varying depending on agricultural and livestock management practices, settlement history, and logistical considerations [18]. Concurrently, climatic changes, such as decreased precipitation and increased temperatures, result in more fire outbreaks during El Niño years [14]. However, even in years considered as La Niña, considered to be of low fire risk, high values of fire outbreaks and burned area have been previously recorded, showing that forests can be vulnerable to fires due to the interaction with other variables [19].

Most studies indicate that the "forest flammability problem" is expected to worsen in the near future due to projected increases in severe fire weather (i.e., favorable meteorological conditions for the start and spread of fire) and ongoing growth at the wildland-farming interface [2,12,15,20–22]. In contrast, other studies suggest that despite the immediate threat of human-induced fires, the long-term trend for the Amazon and other tropical rainforests might be a decrease in fire occurrence due to increasing precipitation brought about by climate change [23]. Thus, understanding and projecting future fire trends is a complex task that depends on various interrelated factors, including climate change, land-use policies, and conservation efforts.

Recently, the application of machine learning models has emerged as a powerful tool for analyzing large volumes of environmental and climatic data, providing a deeper understanding of wildfire dynamics [24]. These models can integrate a wide variety of factors to predict fire occurrence and spread with high accuracy. Furthermore, they enable the simulation of future scenarios considering different land-use trajectories and climate change. Therefore, these computational techniques can help to resolve controversies regarding the future frequency and intensity of fires in the Amazon.

The primary aim of this study was to identify the key drivers of current wildfire occurrences and project different trajectories of fire risk over the coming decades based on future climate scenarios. In addition, the study aimed to develop detailed maps to visualize the spatial distribution of high-risk areas and identify regions that are priorities for preventive interventions and monitoring efforts. These objectives aim to inform public policies, conservation programs, and integrated fire management strategies, supporting the conservation of the Legal Amazon region that is subject to increasing environmental pressures. This research employs advanced machine learning methods to spatially model the distribution of fires in recent periods and predict the probability of future fires. A distinctive aspect of this approach is the integration of a comprehensive temporal dataset of fire scars detected through Landsat imagery and contemporary climate projections, allowing for a more accurate and dynamic understanding of fire probability predictions.

2. Materials and Methods

2.1. Study Area

The Legal Amazon is a geographical region established by the Brazilian government in 1980 (Decree Law No. 1806 on 6 September 1980) for the purposes of environmental management and regional planning. Covering approximately 5 million square kilometers, the region presents multiple environmental, social, and economic challenges, which require coordinated development and conservation efforts. In this study, we adopted a spatial approach using the Legal Amazon as the sampling window (Figure 1A), encompassing nine Brazilian states as well as parts of Tocantins and Maranhão. The region comprehends diverse vegetation types, each representing different fuel conditions (Figure 1B).

The dominant vegetation in the Legal Amazon is Tropical Moist Broadleaf Forests, known in Brazil as the "Amazon Biome", which are generally less fire-prone due to their high biomass and moisture content. In the southern portion of the Legal Amazon, the vegetation shifts to the "Cerrado" and "Pantanal" Biomes, which include Tropical Dry Broadleaf Forests, Tropical Grasslands, Savannas, and Shrublands, all of which are more which are more flammable and fire adapted. Flooded Grasslands, characteristic of the Pantanal, are less likely to burn due to their moisture, though fires can occur and intensify during droughts. Additionally, fire-adapted savanna enclaves exist within the northern Amazon, representing ecosystems with vegetation adapted to fire. It is important to note that these phytogeographic regions have been altered by human activities, and the current land cover configuration is significantly different from the original [26].

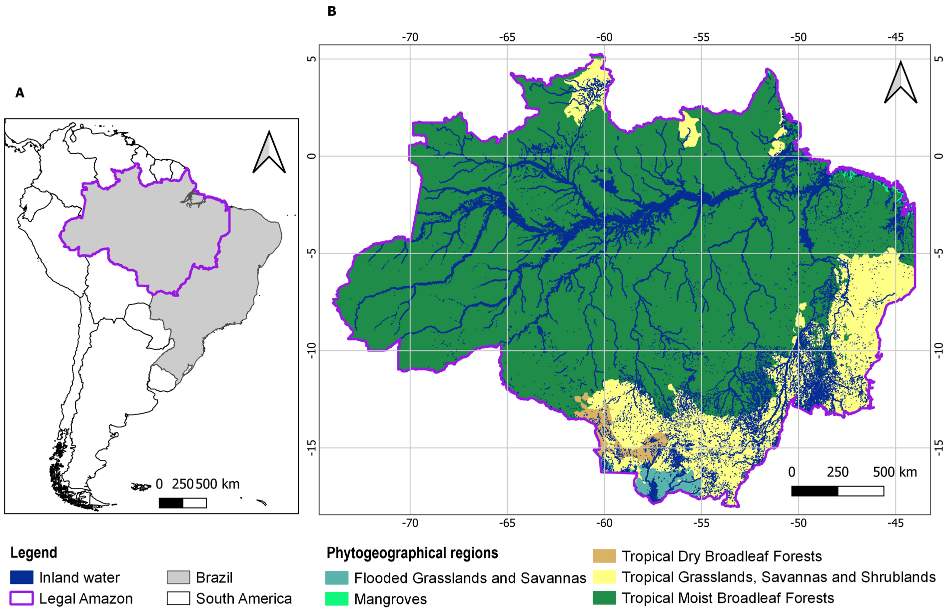

Figure 1. Location and features of the study area. (**A**) The polygon outlined with a purple line indicates the sample window of the study, which encompasses the Legal Amazon region in Brazil and South America. (**B**) The map depicts the phytogeographic regions and major continental water bodies within the Legal Amazon. Data on the limits of the Legal Amazon, water bodies, and political boundaries were sourced from the Brazilian Institute of Geography and Statistics virtual database (https://bdiaweb.ibge.gov.br/). Vegetation data are based on [25], available from the WWF website (https://www.worldwildlife.org/).

The vegetation diversity in the Brazilian Legal Amazon reflects its varied climatic conditions. The region consistently experiences high temperatures, typically ranging from 25 °C to 28 °C, occasionally exceeding 30 °C, with humidity levels often above 80% [27]. Annual rainfall varies between 1500 mm and 3000 mm, with a distinct wet season occurring from December to May [28]. However, seasonal variations in rainfall are more pronounced in the southern Amazon, particularly in the forest–savanna transition regions, and also in the Amazonian savannas.

The fire history of the Amazon biome, which covers the majority of the Legal Amazon, accounts for 41.3% of Brazil's total burned area. Of this biome, 16.4% has been affected by fire at least once, with 1.6% burning annually [4]. Fires are often associated with highly fragmented landscapes; proximity to major roads; and areas dominated by pastures, agriculture, grasslands, and savannas [29]. Regions such as southern Pará, Rondônia, and Mato Grosso, which make up the so-called "agricultural frontier", are among the most affected [11]. Additionally, Amazonian savannas also experience a high concentration of fires, exacerbated by farming practices [30].

2.2. Overview

Firstly, we conducted a fire probability assessment for the recent period (referred to as the "baseline") to replicate the current distribution of fires. After validating the baseline model, we projected future models to estimate changes in fire probabilities for the next decades (2020–2040), considering two contrasting scenarios of climate warming (Figure 2). Specifically, we focused on alterations in climate layers, while assuming that all other predictor variables would remain stable, maintaining conditions akin to those observed presently.

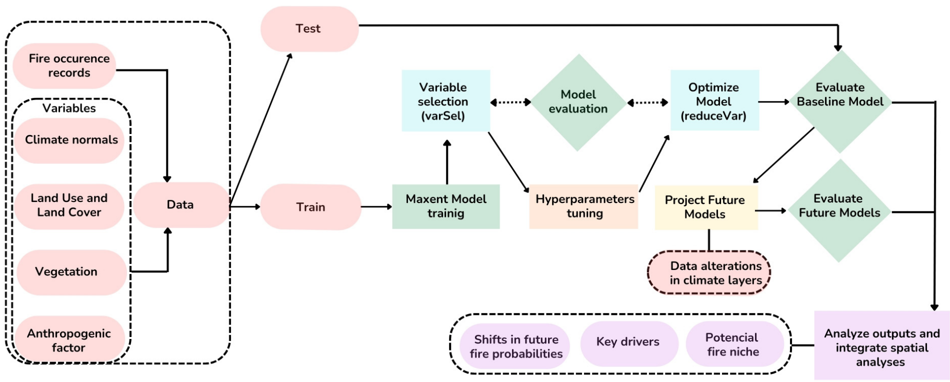

Figure 2. Flow chart of the modeling process.

This approach aligns with previous studies that have identified temperature and precipitation as key factors influencing fire occurrence and behavior [7,20,23]. By isolating climate variables to predict future scenarios, it became possible to assess the direct impact of climate change on fire probabilities, thereby providing valuable insights for future fire management strategies.

2.3. Fire Occurrence Data

Fire occurrences from 1985 to 2022 were extracted from the MapBiomas dataset [31], accessed through the Google Earth Engine (GEE), which utilizes the Landsat product. The MapBiomas dataset provides information on areas with fire scars. Our sampling methodology involved randomly selecting 1000 points from these areas. In this study, we did not filter the samples based on high-frequency values, as more than 95% of all samples had a frequency of less than 15 times.

2.4. Environmental and Human Predictors

We employed land cover and land use data to construct a comprehensive categorical layer essential for evaluating landscape influences on fire patterns. These data weresourced from the MapBiomas dataset [26], comprising categories such as Forest (Forest Formation, Savanna Formation, Mangrove, Floodable Forest, Wooded Sandbank Vegetation), Non-Forest Natural Formation (Wetland, Grassland, Hypersaline Tidal Flat, Rocky Outcrop, and Herbaceous Sandbank Vegetation), Farming (Pasture, Agriculture, and Forest Plantation), Non-Vegetated Areas (Beach, Dune and Sand Spot, Urban Area, and Mining), and Water (River, Lake, Ocean, and Aquaculture).

To refine our analysis and gain deeper insights into the impacts of different land use/cover types on fire patterns, we created separate distance layers using the Euclidean distance calculation. These layers were specifically designed to highlight categories related to human footprint and ignition patterns. The analysis yielded four raster files, with three primarily depicting classes associated with human influence (Farming, Non-Vegetated Area, and Water), while the fourth raster predominantly represented areas of vegetation that have not been significantly impacted by human activity (Native Vegetation).

2.5. Climatic Variables

Bioclimatic variables, encompassing both historical and future data, at a spatial resolution of 30 arc-seconds, are accessible through the WorldClim version 2.1 database (download from http://worldclim.org). The baseline model was based on average climatic data for 1971–2000 [32]. For the future fire models, we utilized the MIROC6 climate model [33], renowned for its robust performance and proven success in other studies focusing on fire modeling in the Amazon region [34]. The future fire models for the early (2021–2040) 21st century were based on two scenarios that combine socioeconomic and technological development (shared socioeconomic pathways—SSPs) [35,36]. These scenarios include an optimistic pathway (SSP1–2.6), representing a low-emission scenario where temperatures are projected to stabilize at approximately 1.3 °C to 1.5 °C above preindustrial levels by the 2030s, and a pessimistic pathway (SSP5–8.5), which assumes an increase in warming to about 1.5 °C to 2.2 °C above preindustrial levels by the same period.

2.6. Variable Selection

First, all layers of environmental and human predictors (Table 1) were resampled to the same pixel size as the climatic data (30 arc-seconds per side, approximately 1 km at the equator) using the nearest neighbor process. This standardization is essential for ensuring consistent analysis across all variables. We then analyzed the variable set to select the most important uncorrelated predictors, aiming to develop parsimonious and interpretable models [37], a critical step in machine learning models for fire prediction. We utilized the functions of "SDMtune" version 1.3.1 [38] to perform an optimized selection of 24 continuous variables. The process began with exploring variable correlation by extracting 10,000 background locations using the "randomPoints" function from the "dismo package" version 1.3-14, processed in the R program version 4.4.0. The algorithm then ranked the variables based on their percent contribution. It checked if the variable ranked as the most important was highly correlated with any other variables, using a Spearman correlation coefficient ($|rs| \leq 0.7$). If correlated variables were found, a leave-one-out Jackknife test was performed among them. The variable that had the least impact on the model's performance, measured by the area under the curve (AUC) of the receiver operating characteristic (ROC), was then discarded. This process was repeated until the remaining variables had a correlation coefficient lower than the provided threshold ($|rs| \leq 0.7$). Additionally, we considered removing variables ranked with very low contribution to reduce model complexity. Using the "reduceVar" function, variables with a permutation importance lower than 2% were removed, but only if their removal did not decrease the model's performance.

Table 1. List of parameters evaluated for assessing Amazon fire propensity, including a brief description of the data, spatial resolution, type of variable, and source (all accessed November 2023).

Class	Variable (Unit)	Description of Data	Resolution	Type [1]	Source
	T_{avg} (°C)	Annual Mean Temperature	30 arc-seconds	Cont	
	$\Delta T_{diurnal}$ (°C)	Annual Mean Diurnal Range (Mean of monthly (max temp − min)) temp))	30 arc-seconds	Cont	
	Isother (%)	Isothermality ($\Delta T_{diurnal}/\Delta T_{annual} \times 100$)	30 arc-seconds	Cont	
	T_{season} (°C)	Temperature Seasonality (Standard Deviation)	30 arc-seconds	Cont	
	T_{max} (°C)	Max Temperature of Warmest Month	30 arc-seconds	Cont	
	T_{min} (°C)	Min Temperature of Coldest Month	30 arc-seconds	Cont	
	ΔT_{annual} (°C)	Annual Temperature Range	30 arc-seconds	Cont	
	T_{wet} (°C)	Mean Temperature of Wettest Quarter	30 arc-seconds	Cont	
	T_{dry} (°C)	Mean Temperature of Driest Quarter	30 arc-seconds	Cont	
	T_{warm} (°C)	Mean Temperature of Warmest Quarter	30 arc-seconds	Cont	
	T_{cold} (°C)	Mean Temperature of Coldest Quarter	30 arc-seconds	Cont	
	PPT (mm)	Annual Precipitation	30 arc-seconds	Cont	
	PPT_{wet} (mm)	Precipitation of Wettest Month (max([PPT_i, ..., PPT_{12}]))	30 arc-seconds	Cont	
	PPT_{dry} (mm)	Precipitation of Driest Month (min([PPT_i, ..., PPT_{12}]))	30 arc-seconds	Cont	
	PPT_{season} (%)	Precipitation Seasonality (coefficient of variation)	30 arc-seconds	Cont	
	PPT_{wet} (mm)	Precipitation of Wettest Quarter	30 arc-seconds	Cont	
	PPT_{dry} (mm)	Precipitation of Driest Quarter	30 arc-seconds	Cont	
	PPT_{war} (mm)	Precipitation of Warmest Quarter	30 arc-seconds	Cont	
	PPT_{cold} (mm)	Precipitation of Coldest Quarter	30 arc-seconds	Cont	
Land use and land cover	LULC (class)	Landsat-based classification of Pan-Amazonian for 2022	30 m resampling for 30 arc-seconds	Cat	[26]

Table 1. *Cont.*

Class	Variable (Unit)	Description of Data	Resolution	Type [1]	Source
Vegetation	Dis_Veget (km)	Euclidean distance calculated from a binary vegetation raster Forest Natural Formation	30 arc-seconds	Cont	[26]
Anthropogenic factor	Dist_Nonveg (km)	Euclidian distance calculated from a binary non vegetated area raster	30 arc-seconds	Cont	[26]
	Dist_water (km)	Euclidian distance calculated from a binary water raster	30 arc-seconds	Cont	[26]
	Dist_urban (km)	Euclidian distance calculated from a binary urban raster	30 arc-seconds	Cont	[26]
	Dist_Farming (km)	Euclidian distance calculated from a binary farming raster	30 arc-seconds	Cont	[26]

[1] Type: continuous (Cont) and categorical (Cat).

2.7. MaxEnt Modeling for Fire Prediction

This study focused on modeling fire occurrences using MaxEnt, a presence-only machine learning algorithm, which iteratively contrasts predictor values at occurrence locations (i.e., ignition points) with those at random locations across the study area [39]. This approach leads to the development of models that can effectively describe complex relationships [40], making it a valuable tool for modeling fire occurrences, particularly in most situations where obtaining precise absence data is challenging.

The model was trained and tested on a dataset split into 70% training data and 30% test data. The model was evaluated using the area under the curve (AUC) metric, which measures the model's ability to distinguish between presence and absence locations. To optimize the model hyperparameters, the authors used the "optimizeModel" function (SDMtune package), which applies a genetic algorithm to expedite the process [38]. This algorithm starts by generating a random initial population of models and evaluates their fitness using the AUC metric on a validation dataset. Fitter models are retained, and a small portion of fewer fit models is kept for diversity. The selected models are then "bred" to create other individuals, with two parent models randomly selected to produce a child model. The child model inherits hyperparameter values from one of the parents through a process called "crossover". Additionally, a "mutation" chance is introduced to further increase variation. This process continues for several generations, with the best-performing model selected as the final optimized model. The optimized model is then used to make predictions on future climatic scenarios. Overall, this approach provides a robust framework for modeling fire occurrences, especially in situations where obtaining precise absence data is challenging [38].

2.8. 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 provides 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 adequacy: 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 cover.

Changes in fire probability in relation to future climate shifts were detected through comparative analyzes between models in relation to the amount of cover occupied by different classes of fire in optimistic and pessimistic scenarios for the 2030s. In addition, we showed potential areas projected for fire invasion (by increasing in locations where current probabilities of fire were low) and retreat (by decreasing in locations where current probabilities of fire were high) in the future scenarios, applying a threshold value of 10%. These results allowed us to identify potential "hotspots of change" for different scenarios. Furthermore, in the Supplementary Materials, we present an analysis of classification agreement (pixel-to-pixel correspondence) calculated using the R package Greenbrown version 2.2 [41], allowing the generation of concordance maps (Supplementary Information).

3. Results

3.1. Performance of the Modelling Approaches

The AUC average test value for the baseline model developed for fire occurrence was 0.864. The AUC values for the 2030s optimistic and 2030s pessimistic models obtained from the validation phase processing exhibited values of 0.866 and 0.857, respectively. These results, as generally recognized by researchers in fire modeling [42], indicate that the MaxEnt models demonstrated excellent predictive performance and goodness of fit with the training datasets.

3.2. Variable Importance

In the analysis, the variables "Distance to Farming", "Distance to Non-Vegetated Areas", and "Temperature Seasonality" emerged as the most influential predictors of fire distribution for the present, as indicated by their substantial permutation importance values (Table 2). Specifically, "Distance to Farming" exhibited a remarkable contribution of 53.4%, underscoring its critical role in determining fire propensity. Similarly, "Distance to Non-Vegetated Areas" accounted for 11.2% of the model's predictive power, followed by "Temperature Seasonality" with a contribution of 9.3%.

Table 2. Permutation importance of variables used for fire modeling in the recent period.

Variable	Permutation Importance (%)
Dist_Farming	53.4
Dist_Nonveg	11.2
T_{season} (°C)	9.3
PPT_{cold} (mm)	9.0
T_{max} (°C)	4.6
PPT (mm)	3.8
PPT_{wet} (mm)	3.3
PPT_{war} (mm)	2.9
Isother (%)	1.9
LULC	0.7

The AUC values calculated by the jack-knife metrics supported this overview and revealed that "Distance to Farming" and "Distance to Non-Vegetated Areas" exhibited substantial individual contributions, evidenced by their impact on AUC when removed (Figure 3). Notably, "LULC" (land use and land cover) and "Annual Precipitation" exhibited high AUC values when considered individually within the model. Despite their lower percent contributions compared to other variables, their strong predictive performance underscores their significant roles in capturing critical environmental gradients relevant to fire occurrence. These findings emphasize the importance of considering comprehensive sets of variables to fully capture the complexities of fire distribution dynamics in ecological studies.

The response curves of the main factors affecting the possibility of fire occurrence highlighted some details regarding the patterns of distribution (Supplementary Figures S2 and S3). Fire occurrence was negatively related to "Distance to Farming" (agriculture, pasture, and forestry), indicating that closer proximity to these land use types enhances the likelihood of fires. Categorical variable analysis (LULC) highlighted farming as the most influential class, affirming its association with fire occurrence. Regarding the relationship between the probability of fire occurrence and the variable "Distance to Non-Vegetated Areas", the response curve suggests that areas in close proximity to roads or urban areas have a higher likelihood of experiencing fires, potentially due to human activities or environmental characteristics.

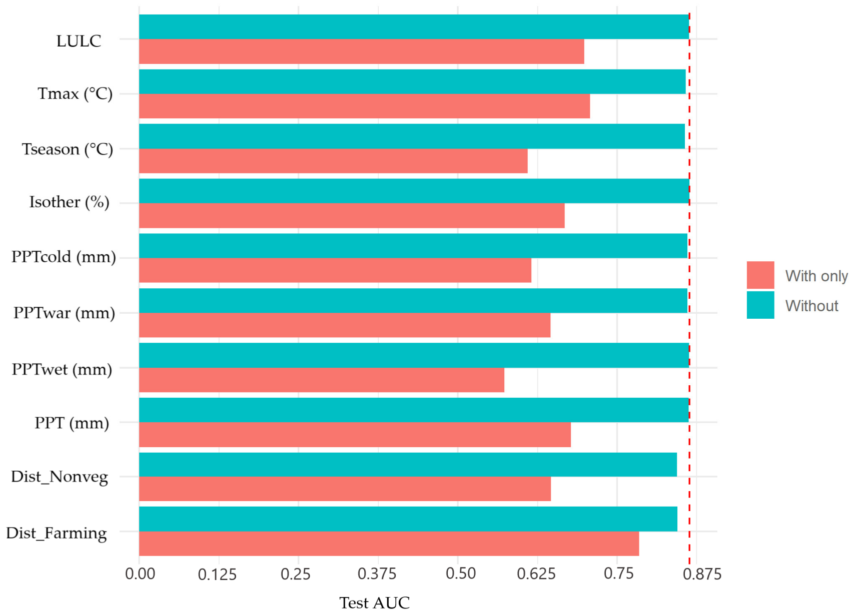

Figure 3. Test AUC values for fire modeling variables, in the recent period, with and without specific features. The red dashed line represents the baseline performance threshold.

Moreover, in relation to variables affecting water availability, our findings revealed that lower annual precipitation levels correlated with increased fire propensity, illustrating a negative relationship between precipitation and fire occurrence. Notably, climate seasonality played a crucial role, as evidenced by "Temperature Seasonality" showing a non-monotonic relationship with fire propensity. This suggests specific ranges of temperature seasonality that increase the likelihood of fires; moderate seasonal temperature variations are typically associated with higher fire incidence, whereas extremely low or high variations may not favor fire-prone conditions. A possible physical explanation for this behavior lies in the relationship between temperature seasonality and the availability of fuel and moisture conditions for fires. Moderate temperature variations throughout the year can create ideal conditions for biomass accumulation, such as dry leaves, branches, and other plant material. These moderate variations are sufficient to sustain plant growth and allow the gradual buildup of flammable material over time. In contrast, more extreme seasonal temperature variations, such as those observed in flooded fields and dry forests of the southern Amazon, can influence fire dynamics in different ways. Extreme temperature fluctuations can potentially create conditions that favor fires by affecting the availability of fuel and moisture. However, in these areas, additional local factors—such as the presence of flooding regimes in wetlands or other environmental influences—can interact with temperature variations to modulate fire propensity.

3.3. Baseline Model of Fire Probability

The baseline model revealed that approximately 26.5% of the Amazon is classified within a "moderate" to "very high" fire propensity class, capturing a complex spatial pattern of fire activity. The spatial pattern of fire probability, as depicted in the provided fire distribution map (Figure 4B), reveals distinct regions within the Amazon basin that are most susceptible to fire occurrences. In general, the central and northern regions of the Amazon Basin exhibit predominantly "Very Low" and "Low" fire suitability (blue areas). On the other side, areas highlighted in red, indicating the highest probability of fire occurrence, are predominantly concentrated along the southern and southeastern edges, in the region known as the "Arc of Deforestation". This region extends from Paragominas (located east of Pará) to Rio Branco (Acre), passing through the states of Mato Grosso and Rondônia. Expanding this corridor, significant areas prone to fires were observed in the states of Maranhão and Tocantins, current areas of expansion of agricultural and livestock activities

(Figure 4A). Other disjunct areas to the north and northeast of the Amazon were also considered fire-prone, corresponding, respectively, to a large part of the state of Roraima and the savanna areas in Amapá. In addition, areas with a high probability of fire were also mapped in areas on the banks of the Amazon River in its lower reaches.

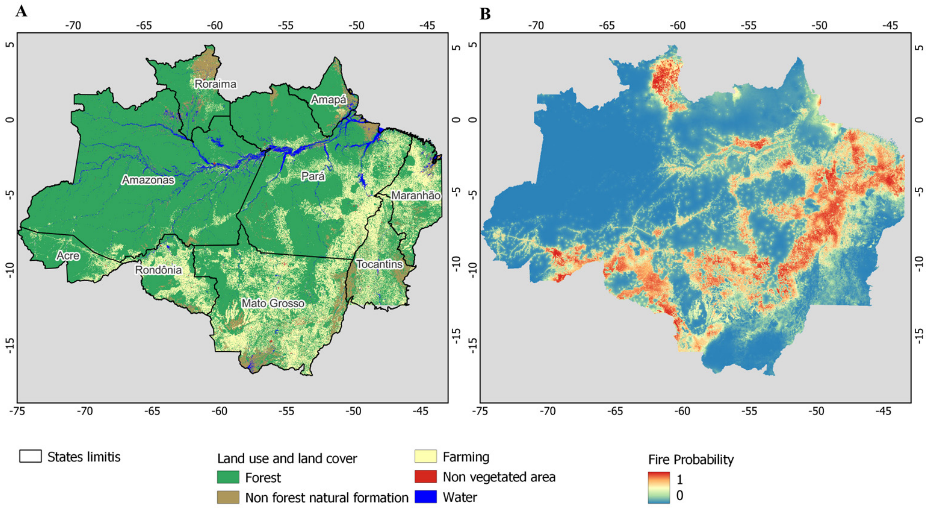

Figure 4. Overview of land use and land cover (LULC) and fire probability in the Legal Amazon: (**A**) LULC showing various categories including forest, non-forest natural formation, farming, non-vegetated areas, and water bodies, along with state boundaries obtained from MapBiomas [26]. (**B**) Fire probability distribution map, with cloglog output values from MaxEnt, indicating regions with varying likelihoods of fire occurrences for the baseline period, with higher probabilities shown in red and lower probabilities in blue.

The proportions of different types of LULC within each fire suitability class vary considerably (Figure 5). In the "Very Low" and "Low" fire suitability classes (probability ≤ 0.3), the representativeness of forest cover is approximately 74% (3.7 million km^2), indicating a lower probability of fire occurrence in areas sensitive to this impact (Figure 5). In contrast, the fire suitability classes "High" and "Very High" (probability ≥ 0.5) show a significant proportion of areas allocated to "Farming" (yellow) use, underlining the strong association between agricultural activities and increased fire risks. Furthermore, "Non-Forest" areas (light brown) show an increasing proportion with increasing fire suitability, particularly notable in the higher classes. These "Non-Forest" areas include savanna enclaves, grasslands, and wetlands, which are more prevalent in regions prone to higher fire incidence.

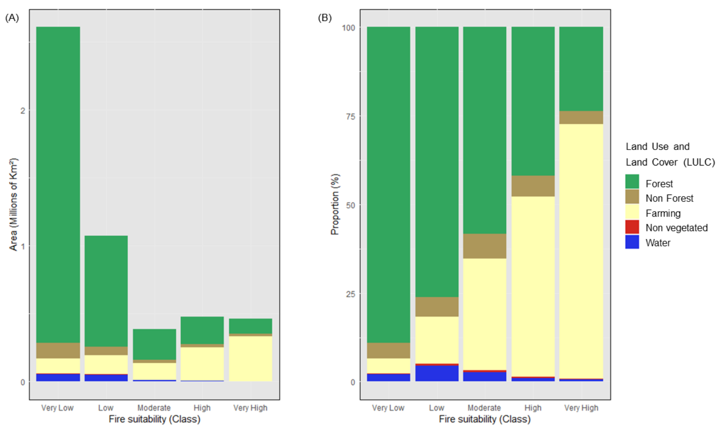

Figure 5. Charts illustrating the relationship between fire suitability classes and land use and land cover (LULC) types in the Amazon basin. The left panel (**A**) displays the area (in millions of km^2) for each fire suitability class (Very Low, Low, Moderate, High, Very High). In the right panel (**B**), the proportion of different LULC types within each fire suitability class is presented.

3.4. Projected Future Fire Probabilities

The future fire distributions projected (Supplementary Figure S1) were transformed into fire suitability maps (Figure 6), showing that large areas of Amazon are expected to experience small near-term changes in fire probabilities. The divergences between the base model and future scenarios are subtle, concentrating transitions from the lowest to the highest fire suitability classes (Figure 6). Among the future scenarios, the trends are similar. However, the pessimistic scenario shows a decrease in the "Very Low" class in relation to the optimistic scenario, and a slight increase in the "Low" class. Therefore, although these changes are not significant individually, they collectively indicate the potential for increased fire risk in the future.

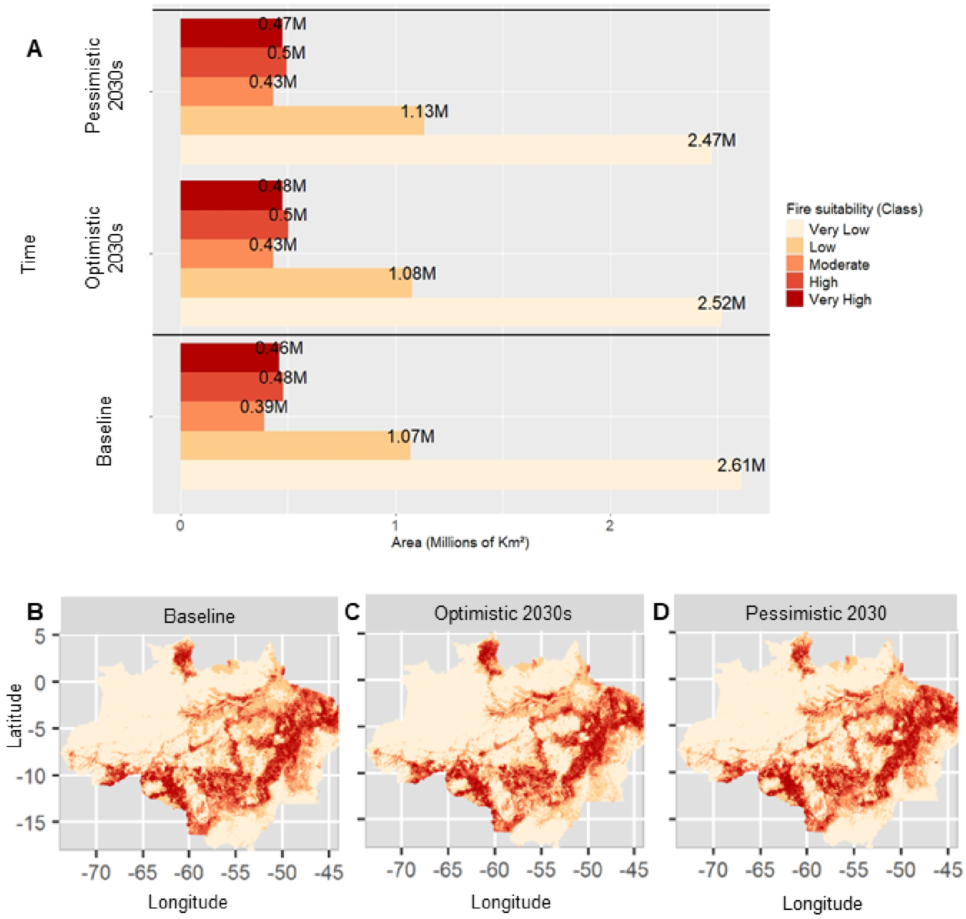

Figure 6. Bar chart with the sum of the areas of the fire suitability levels for each projected fire model (**A**) and predicted fire suitability maps created for the baseline period (**B**) and future climate change scenarios in the 2030s: optimistic (**C**) and pessimistic (**D**). MaxEnt fire probabilities 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 ($0.75 < x \leq 1.00$).

In relation to the spatial distribution of fire suitability (Figure 6), the Kappa concordance results provide valuable insights into the agreement between present conditions and future scenarios, as well as between the future scenarios themselves. Specifically, there is a Kappa concordance of 65.94% between the present and the optimistic 2030 scenario, and a slightly higher Kappa concordance of 67.18% between the present and the pessimistic 2030 scenario. Additionally, there is a Kappa concordance of 78.12% between the future scenarios for 2030. These values suggest a moderate agreement between current conditions and projected future scenarios, with stronger concordance observed between the two future scenarios, reflecting common trends expected in the coming decade. The generated concordance maps are included in the Supplementary Materials (Supplementary Figure S4).

The accompanying figure illustrates these trends spatially, comparing fire suitability changes under optimistic (Figure 7A) and pessimistic (Figure 7B) scenarios for the 2030s. Despite the differences, the overall spatial patterns are similar for future fire niches, supporting the greater Kappa agreement observed between future scenarios. In both scenarios, large areas remain suitable for fires (salmon) while new areas become suitable (red), indicating fire niche expansions. These expansions are mainly concentrated in the southern and southeastern regions of the Amazon, as well as in areas on the margins of the Amazon River in municipalities located close to the border of the states of Amazonas and Pará. Regarding areas of fire niche retraction (blue), the optimistic scenario (Figure 7A) shows a retraction of the fire, especially in areas of non-forest vegetation (campestrian and savannas) located mainly in Roraima. This retraction was observed to a lesser extent in the pessimistic scenario, which even appears to expand the fire niche to areas of savanna enclaves in Amapá and northeast Pará. Therefore, in the coming decades, the fire propensity classes predicted at present appear to remain suitable and expand for both the optimistic and pessimistic scenarios.

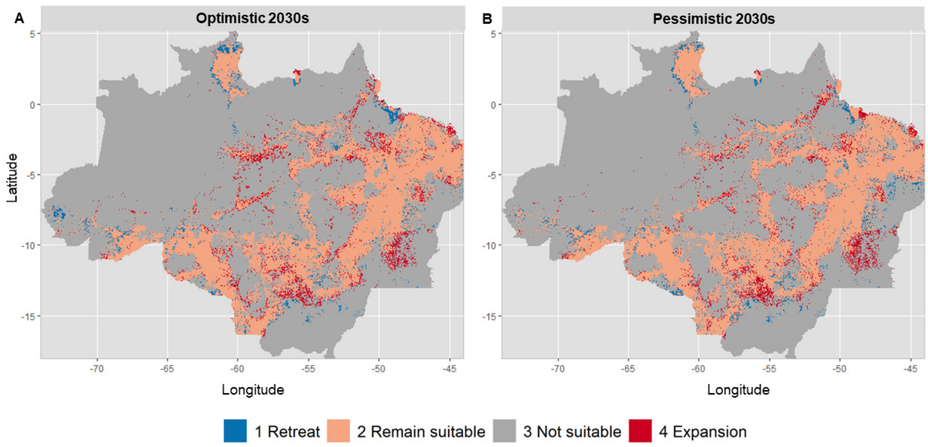

Figure 7. Projected ranges of fire suitability shifts for the (**A**) 2030s optimistic emission scenario; (**B**) 2030s pessimistic emission scenario. Grey regions denote areas where fire is absent or has very low occurrence at present and may remain unsuitable in the future (not suitable), red regions where current fire probabilities are low and may increase in the future (expansion), salmon regions where fire may remain with high probabilities in the future (remain suitable), and blue regions where current fire probabilities are high and may decrease in the future (retreat).

4. Discussion

The performance of our models, indicated by AUC values consistently above 0.85 for both reference and future scenarios, underscores the reliability of our approach. This aligns with established benchmarks in fire modeling [42]. Despite the precision and robustness of our models, it is important to acknowledge certain uncertainties present in the MapBiomas Fire 1.0 dataset. These include potential underreporting of understory forest fires and overreporting of fires in annual crop fields covered with dry material from the harvest [4]. However, our fire niche modeling remains robust and conservative, based on a historical fire dataset from a reliable source, which shows a tendency for more omission than commission errors.

To make future predictions, we maintain a conservative modeling approach, assuming that current land use and land cover patterns remain unchanged, with changes limited to climate factors only. While this conservative stance ensures robustness in the face of uncertainty, it is essential to interpret our results with caution given the intricate interplay between climate and vegetation dynamics [43]. Moreover, the analysis of uncertainty effects between CMIP6 models is outside the scope of this study.

Several other studies have also employed MaxEnt to model fire occurrence in the Amazon, providing valuable comparative insights [44–48]. Their findings corroborate our results, particularly in identifying the "Arc of Deforestation" (southern and southeastern Amazon) as hotspots for fire activity [49]. This distribution is largely influenced by the presence of major highways such as BR-163 (Cuiabá-Santarém), BR-319 (Manaus-Porto Velho), BR-364 in Acre, and BR-230 (Transamazônica Highway), which leads to the inference that there is a strong association of fire with forest clearing and pasture maintenance practices [3]. Nevertheless, the present study contributes to knowledge, spatializing an even larger fire-prone area, which comprises a more extensive zone located in the savanna–forest transition (ecotone zone between the Cerrado and Amazon biomes), covering the states of Maranhão and Tocantins. This region, known as the agricultural frontier, is characterized by historical patterns of agricultural and livestock expansion [2,4]. Another significant contribution of the present study was the mapping of fire-prone areas in the northern and northeastern regions of the Amazon. Although these regions are naturally adapted to fire, they are becoming increasingly susceptible due to fire and anthropogenic pressures [30].

Our spatial fire distribution models highlight the profound interconnection between fire occurrence, climate conditions, and anthropogenic factors. Notably, the significant contribution of "Distance to Agriculture" (53.4%) to the predictive power of the baseline model highlights the strong association between fire propensity and agricultural and livestock activities. This finding is consistent with previous studies that highlight the increased risk of fire in the Amazon due to deforestation fires to remove primary or secondary vegetation, as well as fires used in agricultural or pasture management [2,3,21,29,48–50]. It is worth noting that in recent decades, the management of low-productivity pastures, where fire is used to rejuvenate vegetation and eliminate unwanted weeds, has become the main cause of fires in the Amazon, which contains the largest area of pastures in Brazil [4]. Concerning pasturelands, it has been demonstrated that fire activity can begin years before land use conversion (with deforestation and slash-and-burn practices) and remain elevated for several years after conversion (maintenance fires), especially in forest–pasture transitions [50]. Therefore, we can infer that the most fire-prone areas modeled in the present study are correlated with a combination of factors linked to climate, vegetation cover, and the management of farming areas, especially areas designated for pasture.

Regarding climate variables, "Annual Precipitation" and "Temperature Seasonality" were significant predictors in our fire propensity model in the current decade, especially in regions with little human occupation located in the northwest and central of the Amazon, identified as having a low fire propensity. These fire-free areas rarely experience conditions conducive to biomass burning—such as seasonality, low humidity levels, or windstorms—due to their closed canopy structure, maintaining high humidity even during dry periods [10,20,51]. Conversely, areas of the southern Amazon biome were modeled as having high propensity to fire, demonstrating an association with lower precipitations and greater seasonality. Numerous studies highlight the significance of drought-driven fires in the Amazon, which are closely linked to natural variations in precipitation associated with El Niño events and sea surface temperatures in the North Atlantic [11,13,52–56]. In addition, global observations indicate positive correlations between "Fire Weather Index" and burned areas in tropical moist broadleaf forests, with a notable rise occurring in the southern Amazonia [7,15,57] during the September to November season [58]. Therefore, climatic variables and biomass richness continue to play important roles in the Amazon, especially where human activities have not yet broken the pyrogeographic barriers that regulate fires.

For the next few decades, regardless of land use change projections, our fire models indicate subtle but significant shifts, suggesting a trend towards heightened fire risk across the Amazon. Regarding the emission scenario analyzed, the spatial changes in probability distribution compared to the present indicate that both optimistic and pessimistic scenarios agree on the expansion of the fire niche towards the southern borders of the Amazon. This result corroborates previous studies predicting that increased anthropogenic warming would amplify the potential for high-intensity fires at the Amazon–Cerrado frontier [2,59].

Another important consideration is that if the future follows a pessimistic scenario, regions of the eastern interior near the Amazon River mouth could become areas of concern. These regions, where current fire probabilities are low, had already been mapped as areas of potential fire invasion in the near future (2010–2039) under a medium–high emission scenario [20].

The Kappa concordance results show moderate agreement between current conditions and the optimistic scenario (SSP1–2.6), surpassing the variabilities predicted in the pessimistic scenario (SSP5–8.5). This contradicts the expectation that an optimistic scenario would present fewer changes than a pessimistic one. However, upon careful examination, we note that the main discrepancy arises from the decrease in fire probabilities in savanna enclaves located in the north and northeast of the Amazon. These results can be explained by complex interactions and non-linear responses among climatic variables.

The significant roles of current land use, as well as projected future climate factors in fire risk, highlight the need for integrated management strategies that address both human and environmental dimensions. Our results allow us to infer that it is necessary to adopt policies or actions to mitigate the use of fire in agricultural and pasture areas throughout the Legal Amazon. In relation to spatial arrangement, activities to mitigate present and future fire risks should be intensified in areas along the northeast–southwest arc of the Amazon and on the banks of the Amazon River. On the other hand, in areas of savanna enclaves, mainly located in the north and northeast of the Amazon, integrated fire management is recommended, as long periods without burning can make these areas more flammable. Previous studies have already emphasized the importance of integrated fire management in reducing fire risks and promoting ecosystem resilience [10,60].

Some researchers have demonstrated actions that could be implemented to improve fire suppression, such as preventive measures, control of illegal burnings, and the expansion of fire brigades [2]. We agree with these authors but add that a more holistic and integrated approach can be adopted, including measures that promote sustainable development and social inclusion. In this regard, it is essential to promote policies that incentivize sustainable and technological agricultural practices, reducing the dependence on fire. Training programs and financial subsidies should be expanded to facilitate the transition to land management techniques that do not rely on fire, such as agroforestry and precision agriculture.

A further step in enhancing fire suppression involves establishing rapid response fire brigades within local communities, ensuring that community members themselves are equipped to provide initial responses, thereby increasing combat effectiveness. Socioeconomic activities that rely on slash-and-burn systems also require a tailored approach. It is necessary to develop and implement fire management techniques adapted to these communities, ensuring that these practices are safe and do not pose risks to neighboring forests. Establishing education and awareness programs for small farmers, traditional communities, and indigenous peoples can foster the use of safe and innovative techniques, simultaneously promoting environmental conservation and economic sustainability. These integrated strategies will not only strengthen Brazil's capacity to protect its remaining forests but also promote more resilient and sustainable rural development.

Future research should focus on refining predictive models by incorporating data on fire behavior, as well as projections of land use changes and vegetation dynamics, to more accurately predict fire risks. Additionally, investigating the impact of fire on biodiversity and ecosystem services in the Amazon will provide a deeper understanding of fire dynamics and inform conservation strategies. By integrating these elements, future studies can enhance our ability to predict and manage fire occurrences in the Amazon, ensuring the long-term sustainability of this vital ecosystem.

5. Conclusions

This research significantly advances the understanding of fire dynamics in the Legal Amazon, laying a robust foundation for future studies and policy development aimed at fire risk mitigation. By identifying areas with high fire probability, this study provides critical insights that can enhance strategic decision making. Resources can be more efficiently allocated by prioritizing high-risk zones, ensuring that fire prevention and suppression efforts are concentrated where they are most needed. Furthermore, the spatial mapping and findings from this research can serve as essential tools for technical panels involved in integrated fire management, helping to create tailored strategies that consider the diverse ecosystems of the Legal Amazon. Strengthening the use of these data in management and conservation planning will improve strategic responses and contribute to the long-term preservation of the Legal Amazon's complex and vital ecosystems.

The central role of current land use and projected climate changes in driving fire propensity highlights the urgent need for integrated fire management strategies that address both human and environmental factors. The study's findings emphasize the need to rethink fire use in agriculture and pasture management across the Legal Amazon, as human-driven fires, especially those related to land clearing and pasture maintenance, are major contributors to the region's elevated fire propensity. A transformative shift in fire management practices is required to reduce these risks, including the implementation of sustainable land use practices and improved landscape management, which can help lower the frequency and intensity of fires.

Additionally, this research fills a crucial knowledge gap by identifying areas likely to experience local variations in fire propensity under different climate change scenarios in the coming decades. These insights provide valuable guidance for future planning and adaptation strategies. Future studies can integrate these fire propensity predictions into broader climate adaptation frameworks—such as conservation planning, ecosystem restoration, and sustainable land use policies—thereby enhancing the resilience of both natural ecosystems and human communities against the impacts of fire and climate change.

Finally, the data from this research not only supports fire management but also holds great potential for advancing conservation and restoration efforts. Future studies can incorporate the fire propensity models generated here as input layers into species distribution models to enhance habitat conservation strategies. These models can guide the establishment of buffer zones around vulnerable ecosystems by identifying areas where fire risk is highest and overlaps with critical habitats. This approach will help prioritize regions for reforestation and landscape connectivity efforts. By leveraging these models to target areas where fire dynamics intersect with biodiversity conservation, stakeholders can implement more effective measures to protect habitats and strengthen the long-term resilience of the Legal Amazon's ecosystems.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/fire7100338/s1. Figure S1. Fire probability distribution map, cloglog output values from MaxEnt, indicating regions with varying likelihoods of fire occurrences for: (A) Optimistic 2021–2040 and (B) Future Pessimistic 2021–2040. Higher probabilities are shown in red, while lower probabilities are shown in blue. Figure S2. Univariate response curves showing the relationship between the analyzed variable and the clog-log result for fire probability, presenting the most important predictors: (A) distance to cultivation areas (Dist Farming); and (B) distance to areas without vegetation (Dist Nonveg). Figure S3. Bar chart illustrating the univariate response of the Land Use and Land Cover (LULC) categorical variable on the predicted fire probability. Each bar represents a different LULC category, highlighting its respective influence on fire likelihood. Figure S4. Classification agreement maps in the 2030s for the Legal Amazon, showing the spatial comparison of fire probability between: (A) current conditions and an optimistic scenario (SSP1-2.6). (B) current conditions and a pessimistic scenario (SSP5-8.5). (C) optimistic and pessimistic scenarios for the 2030s. Color shades represent different levels of agreement from very low to very high.

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