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**Environment**

# Modeling and prediction of fire occurrence in the southwest of the Amazon using the Maximum Entropy method

## Modelagem e predição da ocorrência de fogo no sudoeste da Amazônia utilizando o método da Máxima Entropia

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## ABSTRACT

This study aims to estimate the probability of fire occurrence in the southern region of the state of Amazonas using the maximum entropy method. Data on climatic variables (precipitation, water deficit and temperature), protected areas, and land-use changes were selected and submitted to a principal component analysis to determine which would be the predictor variables included in the model. The modeling was performed using the MaxEnt 3.3.3. Calibration was performed from fires in August 2018 and the model was applied to simulate the distribution of the probability of occurrence of these events in August 2019. The model fit was evaluated using the area under the curve - AUC (independent evaluation of the threshold), sensitivity and specificity (threshold dependent assessment), and a jackknife test was applied to assess the isolated contribution of predictor variables. The results indicated that both the threshold-independent (AUC = 0.9439 ± 0.0007) and the threshold-dependent assessment show a satisfactory performance of the model. The most susceptible areas were concentrated mainly in the municipalities of Lábrea and Boca do Acre, which have the highest deforestation rates and pasture areas in the region. The most effective variables in the predictive performance of the model were the distance of roads and the Normalized Difference Vegetation Index – NDVI. The maximum entropy method proved to be an important tool to guide decisions on actions to prevent and fight fires in southern Amazonas.

**Keywords**: Amazon forest; Use and occupation; Environmental modeling

## RESUMO

O presente estudo tem como objetivo em estimar a probabilidade de ocorrência de incêndios na região sul do estado do Amazonas a partir do método da máxima entropia. Dados de variáveis climáticas, áreas protegidas e mudanças de uso do solo foram selecionados e submetidos a uma análise de componentes principais para determinar quais seriam as variáveis preditoras incluídas no modelo. A modelagem foi efetuada utilizando o programa computacional MaxEnt 3.3.3. A calibração foi realizada a partir de incêndios de agosto de 2018 e o modelo foi aplicado para simular a distribuição da probabilidade de ocorrência destes eventos em agosto de 2019. O ajuste do modelo foi avaliado utilizando a área abaixo da curva – AUC (avaliação independente do limiar), sensibilidade e especificidade (avaliação dependente do limiar) e um teste jackknife foi aplicado para avaliar a contribuição isolada das variáveis preditoras. Os resultados indicaram que tanto a avaliação independente do limiar (AUC = 0,9439 ± 0,0007) quanto a dependente do limiar apontam um desempenho satisfatório do modelo. As áreas mais suscetíveis concentraram-se principalmente nos municípios de Lábrea e Boca do Acre, que possuem as taxas de desmatamento e áreas de pastagem mais elevadas da região. As variáveis mais efetivas no desempenho preditivo do modelo foram a distância de estradas e o Índice de Vegetação por Diferença Normalizada – NDVI. O método da máxima entropia mostrou-se uma importante ferramenta para orientar decisões sobre ações de prevenção e combate a incêndios no sul do Amazonas.

**Palavras-chave**: Floresta amazônica; Uso e ocupação; Modelagem ambiental

## 1 INTRODUCTON

The Amazon Basin has an estimated area of 6.3 million square kilometers, which contains the largest portion of contiguous rainforest and an estimated 15% of the planet's biodiversity, in addition to enormous ethnic and cultural diversity (Borma and Nobre, 2013). Most of this region is located in Brazilian territory, in the so-called Legal Amazon, which comprises the states of Pará, Amazonas, Rondônia, Roraima, Acre, Amapá, and also part of Tocantins, Mato Grosso, and Maranhão, with an area of 5,217.423 km² (Instituto Brasileiro de Geografia e Statística - IBGE, 2014).

Historically, economic development strategies based on the discourse of occupation of the Amazon and the predatory exploitation of natural resources have promoted the suppression of vegetation and increased pressure on native forests (Nogueira et al., 2019). This suppression occurred mainly along a strip called "Arc of Deforestation", which extends across the south of the region, from Maranhão to Rondônia (Cohen et al., 2007).

Inserted in the arc of deforestation, the southern mesoregion of Amazonas occupies an area of 474,021.81 km², equivalent to approximately 30% of the state's territory, and comprises the municipalities of Boca do Acre, Pauini, Humaitá, Manicoré, Novo Aripuanã, Borba, Apuí, Lábrea, Canutama and Tapauá (IBGE, 2014). Many of these municipalities have logging and large-scale cattle raising as their main economic activity, especially along the BR 230 – Transamazônica (Santos et al., 2023).

As fire is the main practice used to clear land during the deforestation process, remove secondary vegetation, and renew pastures, the expansion of occupation frontiers has greatly increased ignition sources and, consequently, the occurrence of fires (Fonseca et al., 2017). In the year 2019, the ten municipalities in the Brazilian Amazon that had the highest deforestation between January and July were the same ones that had the highest number of fires throughout the year (Lemos et al., 2025). Among these municipalities, three belonged to the southern mesoregion of Amazonas (Silva Junior et al., 2018).

Fires cause several environmental impacts, such as the destruction of vegetation cover and humus, death of microorganisms and wildlife, loss of soil nutrients, and acceleration of the erosion process, in addition to the potential climate effects caused by the emission of aerosol particles, such as the impairment in the development of rainfall and changes in the radiation balance (Santos et al., 2017). The synergy between deforestation, logging, land management practices associated with fire, along with an increasingly drier climate, tend to increase the occurrence of fires in the Amazon, leading the remaining forests into impoverishment (Nepstad et al. 2001).

Thus, the development of new fire management practices and combat strategies becomes increasingly important to help reduce the degradation of Amazonian ecosystems (Fonseca et al., 2016). In this context, modeling the occurrence of fires can be a fundamental approach as it allows us to evaluate the effects of the interaction between climate and land use in these events and thus, mitigate their possible impacts (Silvestrini et al., 2011).

Studies carried out in different parts of the globe have tried to develop fire prediction models based on artificial neural network methods, classification and regression trees, Maximum Entropy (MaxEnt), among others (Bisquert et al., 2012; Oliveira et al., 2012). Among these, the MaxEnt method, introduced in ecological studies by Phillips et al. (2006), was successfully applied to model the occurrence of fires in the Brazilian Amazon (Fonseca et al., 2016; Fonseca et al. (2017); Lemos et al., 2025).

According to Marcos Júnior and Siqueira (2009), MaxEnt can be defined as a *machine learning* technique that estimates the probability distribution closest to the uniform distribution, under the restriction that the expected values for each environmental variable are following the empirical values observed at the points of occurrence. When applied to fire prediction, fire susceptibility maps are obtained, which can help identify specific locations for the allocation of human and financial resources aimed at prevention and combat actions (Arpaci et al., 2014).

Therefore, given the socio-environmental problem of fire occurrences in southern Amazonas, this work had the following hypotheses: i) the Maximum Entropy method has the potential to assist in modeling fire prediction in the Amazon and ii) climate variations, protected areas and changes in land use can interact in predicting fire behavior. Thus, the present paper aimed to model and predict the occurrence of fires in the southwest of the Amazon using the Maximum Entropy method.

## 2 MATERIALS AND METHODS

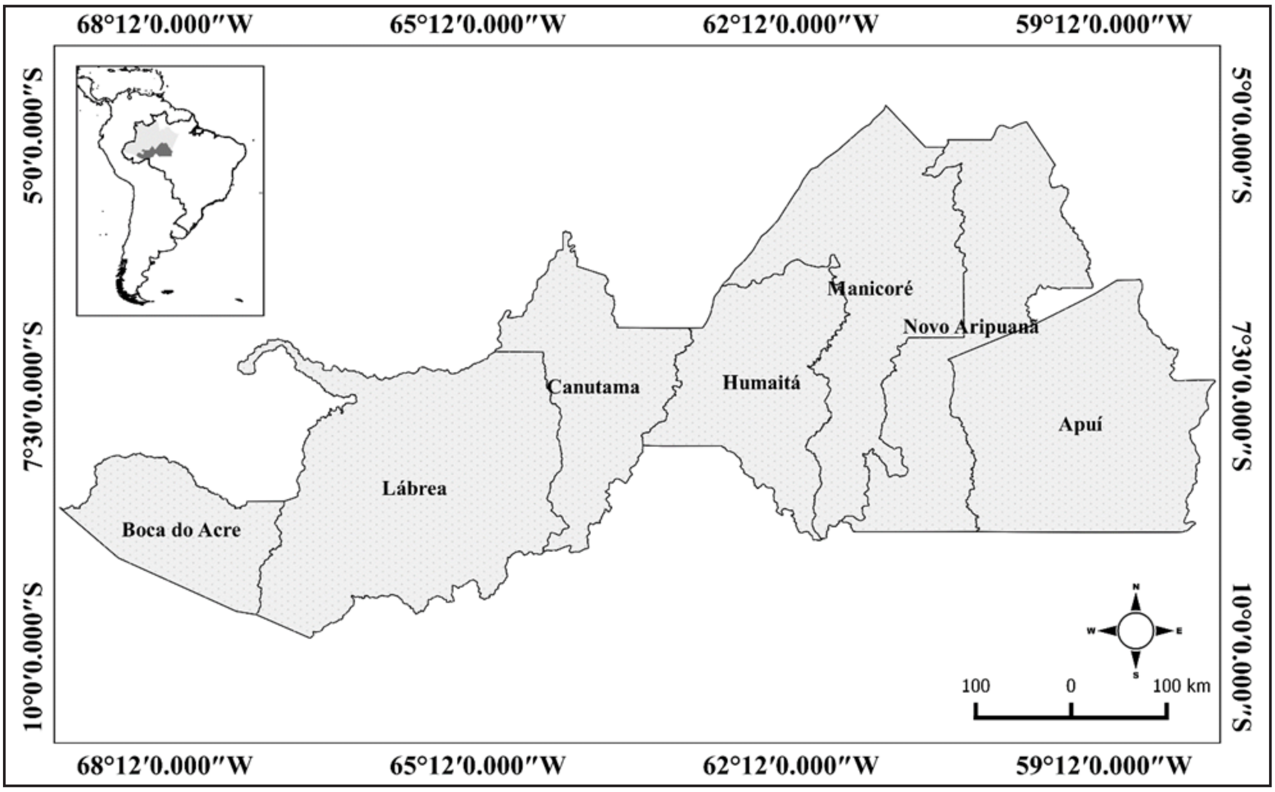
### 2.1. Study area

The study was developed for a catchment area in the southern state of Amazonas, southwest of the Brazilian Amazon, comprising the municipalities of Apuí (07º 11’ S, 59º 53’ W, 135 m), Boca do Acre (08º 45’ S, 67º 23’ W, 116 m), Canutama (06° 32’ S, 64° 22’ W, 55 m), Humaitá (07º 30’ S, 63º 01’ W, 58 m), Labrea (07º 15’ S, 64º 47’ W, 75 m), Manicoré (05° 48’ S, 61° 18’W, 45 m) and Novo Aripuanã (05° 07’S, 60° 22’ W, 20 m)

(Figure 1), from an area of 296,500 km², corresponding to 20% of the total area of the state (Vasconcelos et al., 2015). In this area, accumulated deforestation in 2019 reached 12,960 square kilometers, and, on average, about 55% of all hot spots recorded in the state of Amazonas are detected there each year (White, 2018).

The predominant vegetation types are Dense Ombrophilous Forest, Open Ombrophilous Forest, and Savannah (IBGE, 2004). From the climatic point of view, the climate in the study area is of the Am type-tropical monsoon, according to the Köppen classification, and has average temperatures ranging between 25 and 27 °C and the average rainfall in the order of 2401 to 3200 mm (Alvares et al., 2013). The seasonal periods are well defined, with a prolonged rainy season (October to April), a short-term dry period (June to August), and the months of May and September as the transition between them (Pedreira Junior et al., 2018).

Figure 1 – Location of the study area of the Southern State of Amazonas




Source: Authors (2023)

## 2.2 Database

Initially, a filtering of the data from the hot pots detected by the *Moderate Resolution Imaging Spectroradiometer* - MODIS sensor, on board the AQUA satellite, for August 2018, were obtained from the National Institute for Space Research - INPE Fire Monitoring Project (http://www.inpe.br/queimadas/bdqueimadas/), being used in the research from 35%. Hotspots consist of satellite detections of the radiance emitted by burning materials, which emit energy mainly in the average thermal range of 3.7 μmto 4.1 μm of the optical spectrum (Anderson et al., 2017). The MODIS sensor has a spatial resolution of 1 km and produces daily data, being able to detect a fire front of at least 30 m in length (INPE, 2016).

Data were obtained from ten environmental and socio-economic variables that, based on recent studies (Fonseca et al., 2016; Silvestrini et al., 2011; White, 2018), exert a direct or indirect influence on the occurrence of fire outbreaks, which were manipulated using the QGIS 3.4 software, being converted and/or resampled to the matrix format with a spatial resolution of 0.001°. These being: Precipitation (monthly - GPM/NASA), Accumulated Water Deficit (monthly - Present study), Surface Temperature (monthly - MODIS/USGS), Altimetry - SRTM/INPE), Normalized Difference Vegetation Index (NDVI) (16 days - MODIS/EMBRAPA), Distance from Highways (Present study), Pasture Area (annual - MAPBIOMAS/LAPIG), Deforested Area (annual - PRODES/INPE), Conservation Units (ICMBio) and Indigenous Lands (FUNAI).

## 2.3 Choice of predictor variables

To define which predictor variables would be included in the model, a Principal Component Analysis – PCA was applied to the set of ten variables, using the ESRI ArcMap 10.5 computer program. Hongyu et al. (2015) defined PCA as a statistical technique of multivariate analysis that linearly transforms an original set of variables, initially correlated with each other, into a substantially smaller set of uncorrelated variables that contain most of the information in the original set.

From the PCA, a correlation matrix and a group of *n* components were obtained that explain the variance of the data set in a decreasing scale of importance. The Dalapicolla (2016) methodology was used as a selection criterion, which suggests the inclusion of the two main variables of each generated component (those that presented the greatest contribution to the component) and the exclusion of those that presented a correlation greater than 70% with some of the variables included.

### 2.4 Calibration

At first, the modeling of significant fire events (large or long-term areas) was carried out based on the methodology adopted by Fonseca et al. (2016). To this end, the study area was divided into a 0.1 resolution grid, so that a fire event was considered only when 7 or more heat spots were detected in a given grid cell during the calibration month, which corresponds to the third quartile of the distribution of the number of heat sources per grid cell.

Subsequently, the model was calibrated based on the August 2018 fire events, which corresponds to the first month of the burning season in the state of Amazonas (White, 2018), in addition to predictor variables of monthly burned areas for July 2018 and annual areas for 2017. The analysis was performed using Maxent software (version 3.3.3) for modeling species habitats (Phillips et al., 2006), with 70% of fire records used for training and 30% for testing. The software produces different results from one run to the next, using the same input. Therefore, a *bootstrap* resampling technique with 20 runs was used so that the program makes an average and generates a final model. This technique involves randomly partitioning data with replacement into multiple training and testing sets (Giannini et al., 2012).

We chose to use the software's logistic output, which can be understood as a normalized adequacy surface with values from zero to one, and, therefore, equivalent to a relative (and not absolute) probability of fire occurrence (Fonseca et al., 2016).

The Maxent estimates a target probability distribution by finding the distribution of maximum entropy (ie, the most widespread and closer to uniform), subject to a set of constraints that represent our incomplete information about the target distribution (Phillips et al., 2006). More detailed explanations of the technical aspects of Maxent can be found in Phillips et al. (2006) and Phillips et al. (2017).

## 2.5 Simulation

From the Maxent model calibrated for August 2018, the simulation for August 2019 was carried out aiming to estimate the spatial distribution of the probability of occurrence of fires for this period. As a result of that, annual predictor variables for 2018 and monthly for July 2019 were used.

## 2.6 Assessment

The predictive capacity of the model was evaluated as a function of its Operating Characteristic Curve - ROC, which is obtained by plotting the sensitivity (also known as the true positive rate, representing no omission error) on the y-axis and the value 1 - specificity (also known as the false positive rate, representing overprediction error) on the x-axis. This step can be understood as the internal validation of the model and the Area Under the Curve - AUC is calculated based on the validation test data of Maxent itself, representing an index independent of a cutoff limit (Phillips et al., 2006). The AUC values range from 0 to 1, with a value of 0.5 indicating that the model is not superior compared to a random one, and a value close to 1 indicating a satisfactory model performance.

The external validation took place by applying seven cutoff thresholds to the product of the simulation carried out in August 2019, namely: the minimum cutoff threshold (generated by MaxEnt), which represents the lowest predicted value different from zero among the locations of training (Phillips et al., 2006); and thresholds 0.05, 01, 0.2, 0.3, 0.4, and 0.5. This method results in a binomial spatial distribution different from the susceptible area for each applied file. Thus, the sensitivity (absence of omission error) and specificity (absence of overprediction error) of the model were calculated from the generation of a confusion matrix, with presence and absence points defined as a function of the cells of significant fire events identified in August 2019.

The generated binomial susceptibility maps were also used to calculate the percentages of the susceptible area by cutoff threshold and by the municipality in the study area. The dependence of the susceptibility predicted by the model concerning each variable used in the forecast was evaluated through the creation of response curves, based on the generation of different individual models for each corresponding variable. Finally, a *jackknife* test was applied to assess the isolated effect of all variables on model performance based on the AUC measure.

## 3 RESULTS

### 3.1 Choice of predictor variables

As shown in Table 1, there was a correlation greater than 0.7 between the variable monthly rainfall and DHA (0.729); monthly precipitation and LST (-0.874); and deforested area and pasture area (0.717).

DHA was the second variable that contributed the most to PC2 while precipitation was the second most important contribuitor to PC3. Deforested area and pasture area were, respectively, the first and second variables that most contributed to PC7 (Table 1). Therefore, monthly rainfall and pasture area were not included in the model.

Table 1 – Variables evaluated through correlation analysis and principal component analysis

| | | | | | Correlation Analisys | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **Alt** | **DHA** | **AD** | **DE** | **LST** | **NDVI** | **AP** | **Ppt** | **TI** | **UC** |
| Alt | 1 | - | - | - | - | - | - | - | - | - |
| DHA | -0.113 | 1 | - | - | - | - | - | - | - | - |
| AD | 0.088 | -0.001 | 1 | - | - | - | - | - | - | - |
| DE | 0.153 | 0.140 | -0.223 | 1 | - | - | - | - | - | - |
| LST | -0.413 | -0.361 | -0.180 | -0.554 | 1 | - | - | - | - | - |
| NDVI | 0.051 | 0.083 | -0.345 | 0.142 | -0.223 | 1 | - | - | - | - |
| AP | 0.102 | -0.019 | 0.717* | -0.208 | 0.211 | -0.353 | 1 | - | - | - |
| Ppt | -0.376 | 0.729* | -0.012 | -0.061 | -0.874* | -0.026 | -0.042 | 1 | - | - |
| TI | -0.118 | -0.141 | -0.087 | 0.063 | 0.074 | 0.012 | -0.072 | -0.040 | 1 | - |
| UC | 0.084 | -0.255 | -0.149 | 0.139 | 0.644 | 0.106 | -0.107 | -0.183 | -0.173 | 1 |
| | | | | | **Principal Component Analisys** | | | | | |
| | **PC1** | **PC2** | **PC3** | **PC4** | **PC5** | **PC6** | **PC7** | **PC8** | **PC9** | **PC10** |
| Alt | 0.031* | 0.945** | -0.316 | -0.072 | 0.005 | 0.002 | 0.000 | 0.001 | 0.000 | 0.030 |
| DHA | 0.021 | -0.287* | -0.920** | 0.263** | -0.004 | 0.001 | 0.000 | -0.001 | 0.000 | -0.047 |
| AD | 0.000 | 0.000 | 0.000 | 0.000 | -0.092 | -0.126 | 0.751* | -0.640** | 0.021 | 0.028 |
| DE | 0.999* | -0.023 | 0.029 | -0.006 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.004 |
| LST | -0.004 | -0.007 | 0.020 | 0.239 | 0.159 | 0.043 | 0.005 | 0.016 | 0.006 | 0.956* |
| NDVI | 0.000 | 0.000 | 0.000 | 0.001 | 0.000 | 0.009 | -0.137 | -0.195 | -0.971* | 0.010 |
| AP | 0.000 | 0.000 | 0.000 | 0.001 | -0.014 | -0.055 | 0.627** | 0.740** | -0.237** | -0.009 |
| Ppt | -0.003 | -0.155 | -0.230* | -0.932** | 0.037 | 0.008 | 0.001 | 0.004 | 0.001 | 0.230** |
| TI | 0.000 | -0.001 | 0.002 | -0.003 | -0.162* | 0.979** | 0.118 | -0.032 | -0.001 | -0.016 |
| UC | 0.000 | 0.001 | 0.003 | -0.003 | 0.969* | 0.143** | 0.099 | -0.058 | -0.003 | -0.167 |

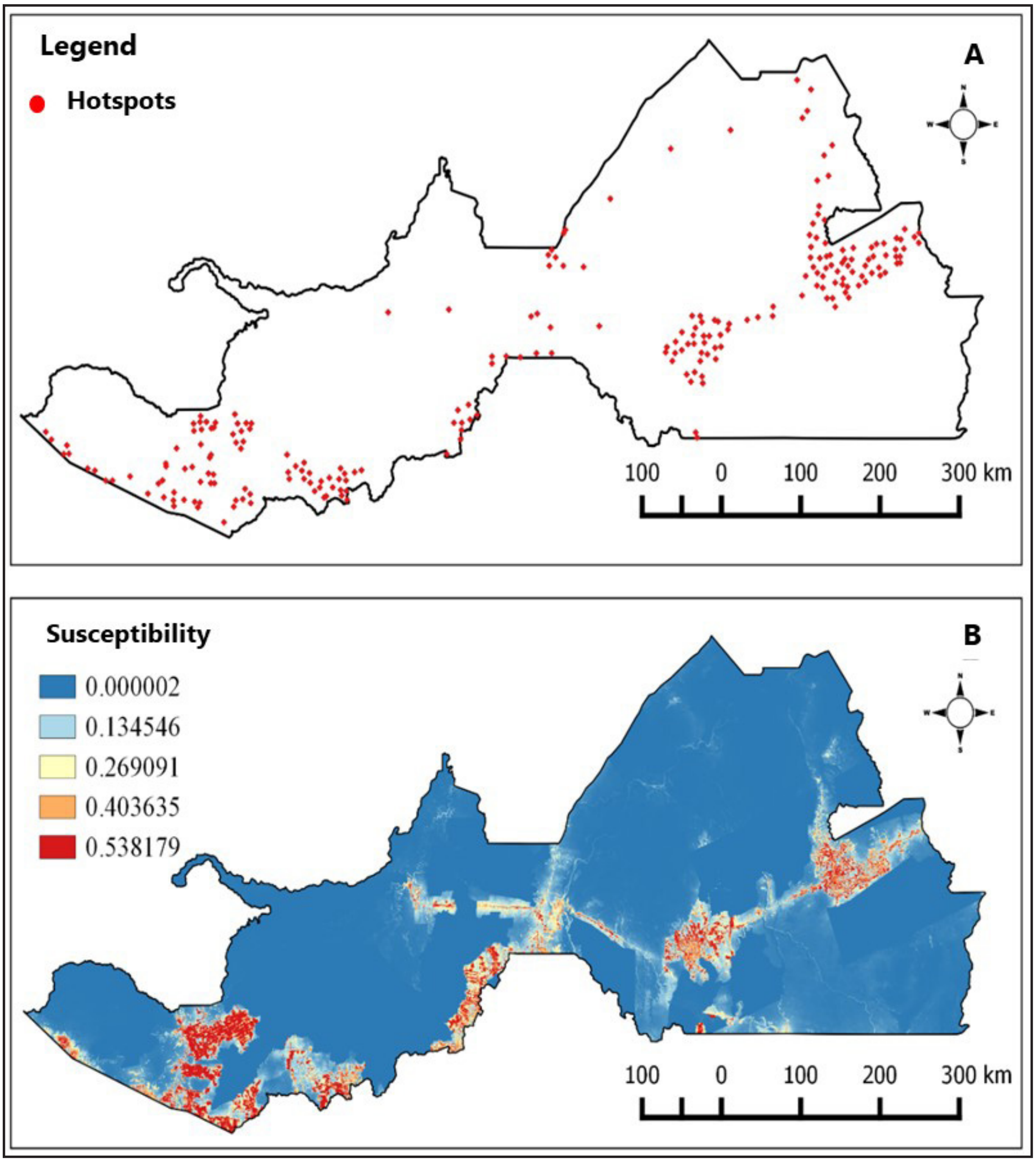
Source: Author (2023)

Alt: ALtimetry; DHA: Accumulated Monthly Water Deficit; AD: Deforested Area; DE: Distance from Roads; LST: Surface Temperature; NDVI: Normalized Difference Vegetation Index; AP: Pasture Area; Ppt: Monthly Precipitation; TI: Earth Indian; UC: Units Conservation; * variable included in the model; ** variable repeated or correlated

### 3.2 Fire occurrence modeling

98 occurrences of significant fire events were identified for August 2018, of which 69 were used for training and 29 for testing. The generated model presented values of AUC 0.956 ± 0.007 for training data and 0.9439 ± 0.0128 for test data.

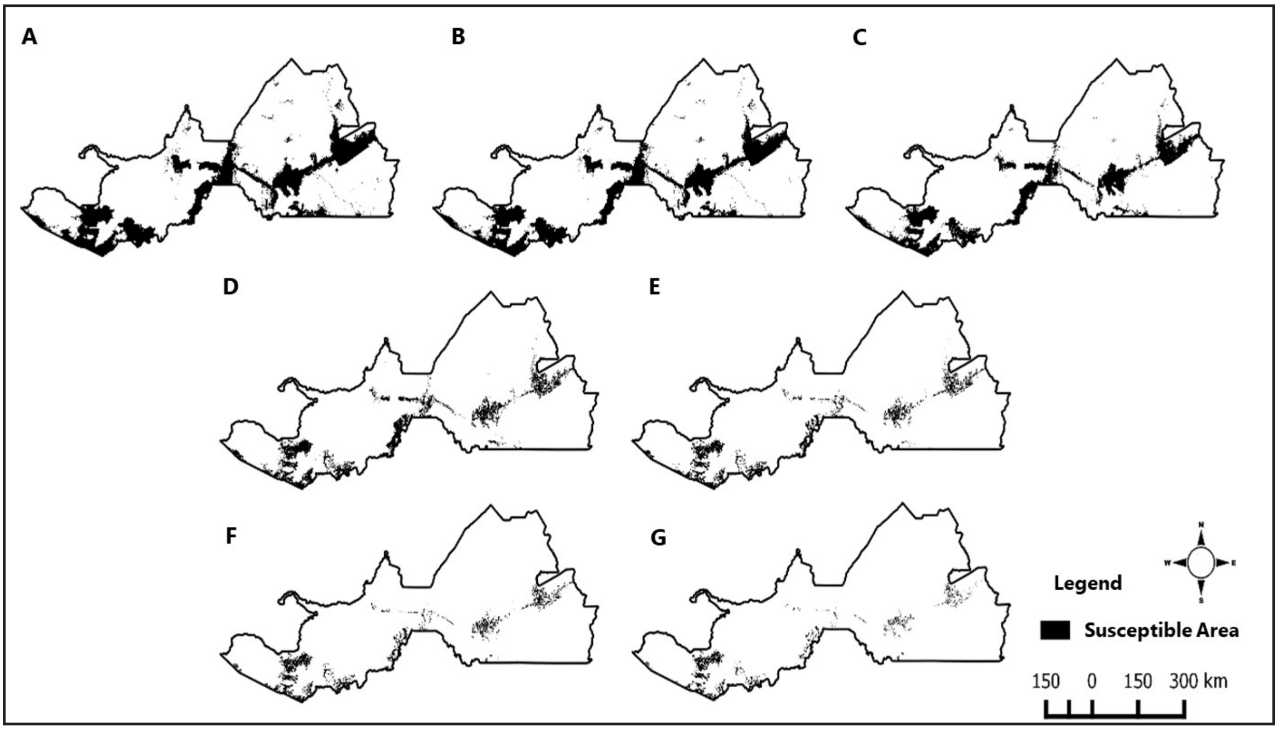
Figure 2 – Fire occurrences in August 2019 (A); distribution of the probability of fire occurrence in August 2019




Source: Authors (2023)

For August 2019, the number of fire occurrences was 229 (Figure 2A), substantially higher compared to the same period of the previous year. Simulation results for August 2019 indicated output values between 0.000002 for less susceptible areas and 0.538 for more susceptible areas and are displayed in Figure 2B.

Figure 3 – Special distribution of the susceptible area obtained from the application of the minimum cut-off thresholds (A), 0.05 (B), 0.1 (C), 0.2 (D), 0.3 (E), 0.4 (F) and 0.5 (G)




Source: Authors (2023)

The minimum cutoff threshold obtained was 0.035. From its application, about 19.44% of the study area (57,695.78 km²) was identified as a susceptible area. In this threshold, it was also verified that of the 229 cells with fire occurrences, 215 coincided with susceptible area pixels, and 16 with non-susceptible areas. Of the 2223 cells identified as points of absence (without the occurrence of significant fires), 1943 were located in a non-susceptible area and 280 in a susceptible area. These results indicate a sensitivity of 0.931 and a specificity of 0.874. The cutoff threshold of 0.05, in turn, indicated a susceptible area equivalent to 17.51% of the study area (51,967.75 km²) and obtained a sensitivity of 0.9177 and a specificity of 0.891.

For cutoff thresholds from 0.1 to 0.5, the susceptible area is equivalent to 13.19% (41,213.5 km²), 8.29% (24,579.85 km²), 5.8% (17,197 km²), 4.25% (12,601.25 km²) and 2.64% (7,827.6 km²) of the study area; the absence of omission error was 0.861, 0.675, 0.545, 0.433 and 0.294; and the absence of error overpredict was 0.929, 0.964, 0.977, 0.982 and 0.987; respectively.

The spatial distribution of the susceptible area from the applied cutoff thresholds can be seen in Figure 3.

The highest percentages of susceptible area for the minimum cutoff threshold among the municipalities in the southern region were presented by Boca do Acre (29.5%), Humaitá (22.1%), and Canutama (21.1%), respectively. For the 0.05 and 0.1 thresholds, the highest values were also from Boca do Acre (26.5% and 20%, respectively), followed by Canutama (20.1% and 17.8%) and Lábrea (19 .4% and 15.7%).

At a threshold of 0.2, Canutama had the highest percentage of the susceptible area (14.3%), followed by Boca do Acre (13.7%) and Lábrea (8.2%). In the subsequent thresholds, the highest percentages were once more presented by Boca do Acre (10.7%, 8.1%, and 5.6%, respectively), followed by Lábrea (8.2%, 6.9%, and 5.4 %) and Canutama (7.4%, 4.9,% and 2.7%) (Table 2).

Table 2 – Percentage of susceptible area by cutoff threshold per municipality in the southern region of Amazonas

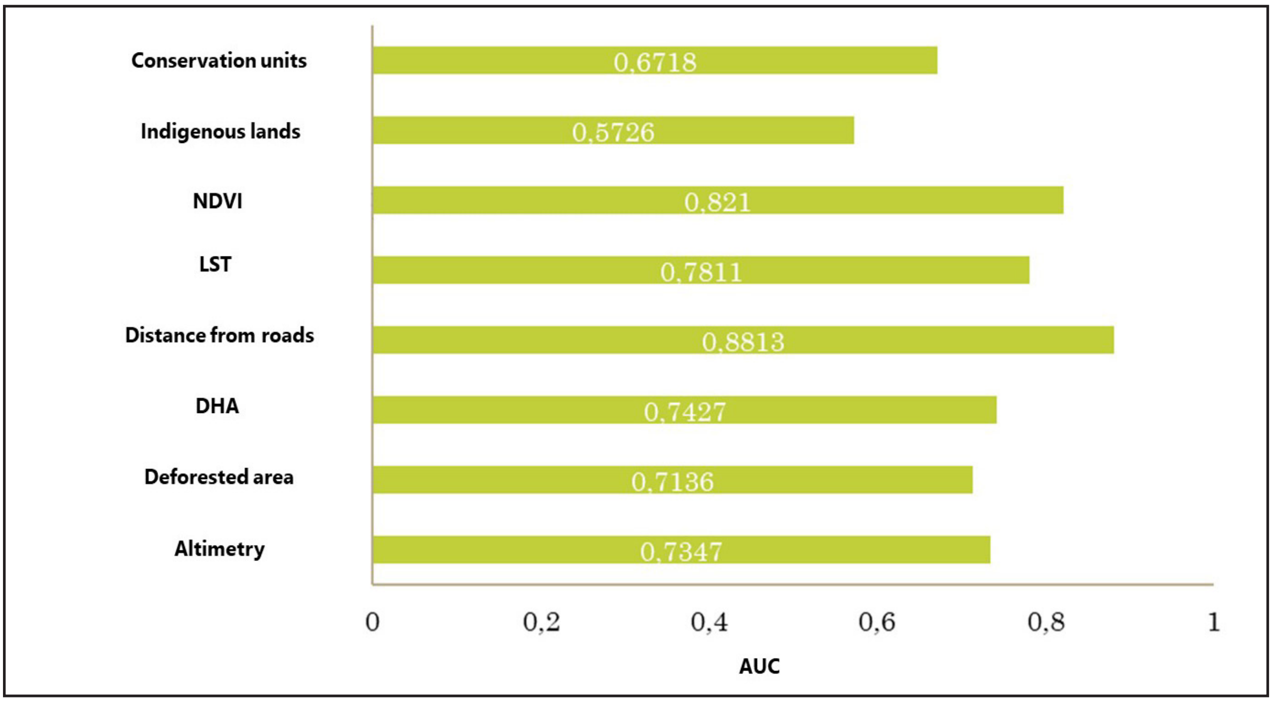
| | **Area susceptible by cutoff threshold (%)** | | | | | | |
|---|---|---|---|---|---|---|---|
| | **0,035** | **0,05** | **0,1** | **0,2** | **0,3** | **0,4** | **0,5** |
| Apuí | 19,4 | 16,9 | 11,9 | 6,6 | 5,0 | 3,7 | 1,7 |
| Boca do Acre | 29,5 | 26,5 | 20,0 | 13,7 | 10,7 | 8,1 | 5,6 |
| Canutama | 21,1 | 20,1 | 17,8 | 14,3 | 7,4 | 4,9 | 2,7 |
| Humaitá | 22,1 | 19,0 | 11,6 | 5,6 | 2,6 | 1,4 | 0,5 |
| Lábrea | 20,6 | 19,4 | 15,7 | 10,3 | 8,2 | 6,9 | 5,4 |
| Manicoré | 12,1 | 10,7 | 7,8 | 4,0 | 3,0 | 2,3 | 1,1 |
| Novo Aripuanã | 17,6 | 15,5 | 10,3 | 5,3 | 2,8 | 1,8 | 1,1 |

Source: Authors (2023)

### 3.3 Contributions of environmental variables

Distance from roads (AUC = 0.8813) and NDVI (0.821) were the variables that most influenced the performance of the model, followed by LST (AUC = 0.7811), DHA (AUC = 0.7427), altimetry (AUC = 0.7347), deforested area (AUC = 0.7136), conservation units (AUC = 0.6718) and indigenous lands (AUC = 0.5716), as shown in Figure 4.

Figure 4 – Jackknife test results to assess the isolated effect of all variables on model performance based on the Area Below the Curve measure - AUC




Source: Authors (2023)

The distance of roads showed an inverse relationship with the probability of fire, especially in the first 10 km. The NDVI, in turn, showed a significant negative relationship for values above 0.8, approximately. The response curves of the LST, DH and altimetry variables showed similar behavior. Conservation units and indigenous lands had a negative relationship with the probability of fire occurrence, while the deforested area had a positive relationship with them.

The two municipalities that presented the highest percentages of the susceptible area in the three highest cutoff thresholds used have agricultural activities as a strong characteristic. The first, Boca do Acre, has the largest cattle herd in the south of the state of Amazonas, with over 350.000 heads, and a pasture area equivalent to 9% of the total area of the municipality. In addition, the municipality has a deforested area of 11.6% of the total region. Lábrea, with the second largest susceptible area, also has strong livestock production (especially in BR-230), in addition to increasing land grabbing, deforestation and illegal logging activities in its southern and western portions, the deforested area, which is equivalent to 6.9% of its total area.

## 4 DISCUSSION

PCA proved to be effective for removing redundant variables, as it has already been verified in other studies (Houngyu et al., 2015; Sabino et al., 2014). The correlation between the deforested area and the pasture area was expected since cattle raising is the main responsible for deforestation in the Brazilian Amazon (Ribeiro et al., 2009). The accumulated water deficit and precipitation, in turn, were correlated, as one was calculated in function of the other, thus creating dependence between the variables (Lemos et al, 2025).

The AUC values generated by the model, both for training and for testing, indicated an adequate performance for the standards presented in similar studies (Fonseca et al., 2016; Massada et al., 2013). In the cutoff threshold, it was found that the errors of omission significantly increased at the highest cutoff thresholds. Some of these errors may result from the occurrence of fires in areas with little human interference, such as conservation units and indigenous lands, due to the subsistence activities of traditional people (Brazilian culturally-specific groups). The use of fire by indigenous people in agricultural management activities, for example, is reported in several studies (Mistry and Bizerril, 2011).

However, forecast errors were significantly reduced at higher court thresholds. In some cases, these errors may be related to limitations in ignition sources — most of which are of anthropogenic origin — resulting in areas suitable for fire occurrence remaining unburned (Fonseca et al., 2016).

The human and financial resources for firefighting actions are limited. Forecast errors are considered more serious than errors of omission, as they can result in the misdirection of these resources. Therefore, to define priority areas, the application of higher cut-off limits, such as 0.3, 0.4 and 0.5, is more appropriate.

Nevertheless, the high AUC values resulting from the *jackknife* test for the variable distance from roads were expected, but they were higher than those obtained by Fonseca et al. (2017) and Madassa et al. (2013). This can be considered to indicate that anthropogenic influence is the main responsible for the occurrence of fires in southern region.

The negative relationship of road distance with the probability of fire occurrence, especially in the first 10 km, was also verified in other studies (Silvestrini et al., 2011). For Fearnside et al. (2012), the availability and quality of roads are related to the cost of transport and, therefore, directly affect deforestation rates. Nevertheless, Silvestrini et al. (2011) found that hotspots closely follow the main roads in the Amazon region and attributed this to a strong association of fire with forest clearing and pasture maintenance practices.

The significant influence of NDVI on fire prediction was verified in some recent studies (Goldarag et al., 2016), which can be attributed to its ability to distinguish certain aspects of land use and occupation, such as bodies of water, areas of dense forest and undergrowth (Coutinho et al., 2016). NDVI values above 0.8 indicate the presence of forest areas at a high stage of development, aged over 70 years (Mallmann et al., 2015). Therefore, the tendency is for these areas to present high levels of moisture and little or no human influence, which justify the inverse relationship with the probability of fire occurrence.

The significant contribution of surface temperature to fire susceptibility is corroborated by Bisquert et al. (2012), who obtained an accuracy of 76% using it as the only fire predictor. Silva Júnior et al. (2018), in turn, state that the spatial distribution of the LST generally has maximum peaks in urban areas and minimum peaks in forest areas and that fires, however, occur mainly in agricultural, pasture, or undergrowth areas which are at different temperature ranges from the two extremes mentioned. This premise is aligned with the behavior of the response curve obtained for the variable, which has lower output values at both extremes.

The effect of accumulated water deficit in the prediction indicates that natural factors can also influence fire occurrence. This variable is related to the degree of moisture in the system, which may or not enable the formation of dry combustible material (Fernandes et al., 2011). According to Fonseca et al. (2016), accumulated water deficit data up to three months before the simulated month significantly affect the performance of the Maxent model in predicting fires. Furthermore, in the southern municipalities, the accumulated water deficit tends to be intensified and attenuated, respectively, in El Niño and La Niña years, due to precipitation anomalies resulting from these events (Lemos et al., 2025).

The water deficit response curve indicated that the positive relationship with the probability of fire occurrence was limited to deficits of up to 150 mm/month, becoming negative from this value onwards. This behavior occurs because, although the variable directly influences the amount of moisture in the combustible material, the spatial distribution of fires depends on the occurrence of ignition sources, most of which are of anthropic origin (Fonseca et al., 2016; Fonseca et al., 2017)

This aspect can also be considered when interpreting the altimetry response curve, a variable that does not have a well-defined relationship with the fire occurrence. However, the low probability of fires at lower altitudes corroborates with Silvestrini et al. (2011), who identified this negative relationship for altitudes up to 70 m and attributed to this fact the existence of floodplains and wetlands.

The smallest contributions to the predictive performance of the model were the land-use variables inserted in binary format (indigenous lands, conservation units, and deforested areas, respectively), an aspect that may have hampered the model's calibration and underestimated the importance of these variables. On the other hand, the behavior of the response curves was similar to that seen in other studies: a positive relationship between the probability of fires and the deforested area and a negative relationship with conservation units and indigenous lands (Anderson et al., 2017; Fonseca et al., 2016; Silvestrini et al., 2011; White, 2018).

## 5 FINAL REMARKS

The MaxEnt model presented satisfactory performance and proved to be a potentially useful tool in preventing and fighting fires in southern Amazonas. The variables that presented the greatest contribution to the model were Distances from Roads, Vegetation Index by Normalized Difference, and Surface Temperature.

The use of remote sensing data allows for periodic updating of predictor variables, resulting in different spatial distributions of fire susceptibility over time. Its application would make it possible to assess the susceptibility to fire in the surroundings of native forest areas, guiding the application of preventive actions, especially in the driest periods of the year. The model can also be used to assess impacts arising from the opening of new roads and the suppression and recovery of vegetation.

In new studies, it is suggested to combine the MaxEnt method with estimates of deforestation rates and different scenarios of potential climate change to model the spatial-temporal dynamics of the probability of fire occurrence over the next decades.

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