RESEARCH PAPER

FUZZY INFERENCE SYSTEM FOR MAPPING FOREST FIRE SUSCEPTIBILITY IN NORTHERN RONDÔNIA, BRAZIL

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ABSTRACT. Forest fires are global phenomena that pose an accelerating threat to ecosystems, affect the population life quality and contribute to climate change. The mapping of fire susceptibility provides proper direction for mitigating measures for these events. However, predicting their occurrence and scope is complicated since many of their causes are related to human practices and climatological variations. To predict fire occurrences, this study applies a fuzzy inference system methodology implemented in R software and using triangular and trapezoidal functions that comprise four input parameters (temperature, rainfall, distance from highways, and land use and occupation) obtained from remote sensing data and processed through GIS environment. The fuzzy system classified 63.27% of the study area as having high and very high fire susceptibility. The high density of fire occurrences in these classes shows the high precision of the proposed model, which was confirmed by the area under the curve (AUC) value of 0.879. The application of the fuzzy system using two extreme climate events (rainy summer and dry summer) showed that the model is highly responsive to temperature and rainfall variations, which was verified by the sensitivity analysis. The results obtained with the system can assist in decision-making for appropriate firefighting actions in the region.

KEYWORDS: Fuzzy logic; GIS; forest fires; Amazon; fire control

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INTRODUCTION

Forest fires cause immeasurable environmental impacts. On top of economic damage and public health-related problems, which are commonly observed immediately after fires, later events such as climatic and environmental changes caused by large amounts of CO_2 emitted into the atmosphere lead to the increasing greenhouse effect, thus resulting in major ecological disturbances (Machado and Lopes 2014; Aragão et al. 2018; Venkatesh et al. 2020).

In the past, the occurrence of forest fires was naturally related to climatic fluctuations, such as changes in temperature and rainfall; however, in recent decades, anthropogenic activities have caused major alterations in the fire regime (Chuvieco et al. 2019) since changes in land use associated with climate change can increase the frequency and severity of these events (Aquilué et al. 2020). Thus, understanding their spatial and temporal distribution is not trivial (Machado and Lopes, 2014) since it includes a set of dynamic factors driven by the interaction of biotic and abiotic processes that depend on the geographic scale (Aragão et al. 2018; Mota et al. 2019; Pourghasemi et al. 2020; Ribeiro et al. 2020).

Data from the Fire Information for Resource Management System (FIRMS) indicates that between 2000 and 2018 there were about 7.27 million outbreaks of fire in South America (NASA, 2020). In Brazil, the occurrence fire outbreaks has significantly increased in recent years due to several factors, such as deforestation, agropastoral activities, and uncontrolled burning (Caúla et al. 2015; Barlow et al. 2019). Although the entire national territory suffers from these events, historical data shows that 80.66% of fires occur in the Amazon and Cerrado biomes, with an average of 170,000 fire outbreaks per year, predominantly between July and October (INPE, 2020).

The effective management of these events requires centralized planning, which includes identifying the locations with the greatest fire susceptibility. This identification can enable the management of critical areas and serve as a basis for developing more accurate fire warning systems and a consistent institutional program (Adab et al. 2013; Eugenio, 2016; White et al. 2016; Barlow et al. 2019). The methods usually employed in planning include integrating remote-sensing techniques, statistical methods, and GIS (Jaiswal et al. 2002; Adab et al. 2013; Mota et al. 2019; Pourghasem et al. 2020; Gizatullin and Alekseenko, 2022), which are employed through probabilistic, stochastic models, or a mixture of both.

Despite proving high effectiveness in studies at local scale, at regional scale the GIS and statistical methods have limitations due to multiple complex interactions related to the degree of subjectivity these events have, spatial distribution of the events, and uncertainties caused by spatial and temporal resolution of the ignition data. This makes it difficult to eliminate uncertainties regarding the inaccuracy of the data and, as a result, these models present difficulties when associating products with data inaccuracies in the GIS environment, thus resulting in errors in the final products (Bui et al. 2017; Moayedi et al. 2020; Sahiner et al. 2022). Therefore, it is necessary to develop new models that make it possible to deal with uncertainties and inaccuracies, while also improving the ability to predict these events.

As an alternative methodology, the fuzzy theory introduced by Zadeh (1965) provides a logical approach that is capable of dealing with complex systems, such as those observed in forest fire events that have spatial and temporal variability, as well as subjectivity, and providing an adequate mathematical treatment (Zadeh 1965; Araya-Muñoz et al. 2017; Bressane et al. 2020; Fernandes et al. 2023). Recent environmental applications that use the fuzzy approach integrated with GIS have shown advantages over traditional techniques in evaluating several phenomena, such as susceptibility to flooding (Sahana and Patel, 2019), landslides (Nwazelibe et al. 2023), drought (Nikolova et al. 2021), and soil erosion (Souza et al. 2019), and anthropic impact on watersheds (Lopes et al. 2021).

Considering that the fuzzy theory is used to analyze the causality of uncertain events (Román-Flores et al. 2020; Sahiner et al. 2022), including the causes of forest fires (Pourghasemi et al. 2020; Ribeiro et al. 2020), and that the fuzzy method can work with uncertainties related to the spatial and temporal data resolution (Lopes et al. 2021; Sahiner et al. 2022), this study presents a fuzzy inference system that considers climatic and anthropic variables as input variables for mapping fire susceptibility, with the study area of the northern region of the Rondônia state, Brazil, due to the high number of fires registered there in recent years.

MATERIALS AND METHODS

Study Area

The study was conducted in the north of the Rondônia state. It is an area of around 89,900 km^2 (Figure 1) that covers 14 municipalities and has a population density of 8.0 inhabitants/km^2. This region is mostly occupied by agricultural and cattle-ranching lands due to administrative and financial support from governmental colonization programs in the Brazilian Amazon that have taken place from the 1970s onwards (Alves et al. 2021). These programs are characterized by the implementation of colonization settlements, which are preceded by high deforestation rates due to the expansion of agricultural lands and cattle-ranching (Alves et al. 2021; Duarte et al. 2021), thus making the region a part of the "Arc of Deforestation" in the Brazilian Amazon.

In this region, fire is commonly used for clearing the land after deforestation and for pasture renewal (Caúla et al. 2015; Barlow et al. 2019). Consequently, around 70% of the fire outbreaks in Rondônia have occurred in its northern part, with 90% of them being registered between August and October during the dry season (SEDAM, 2020).

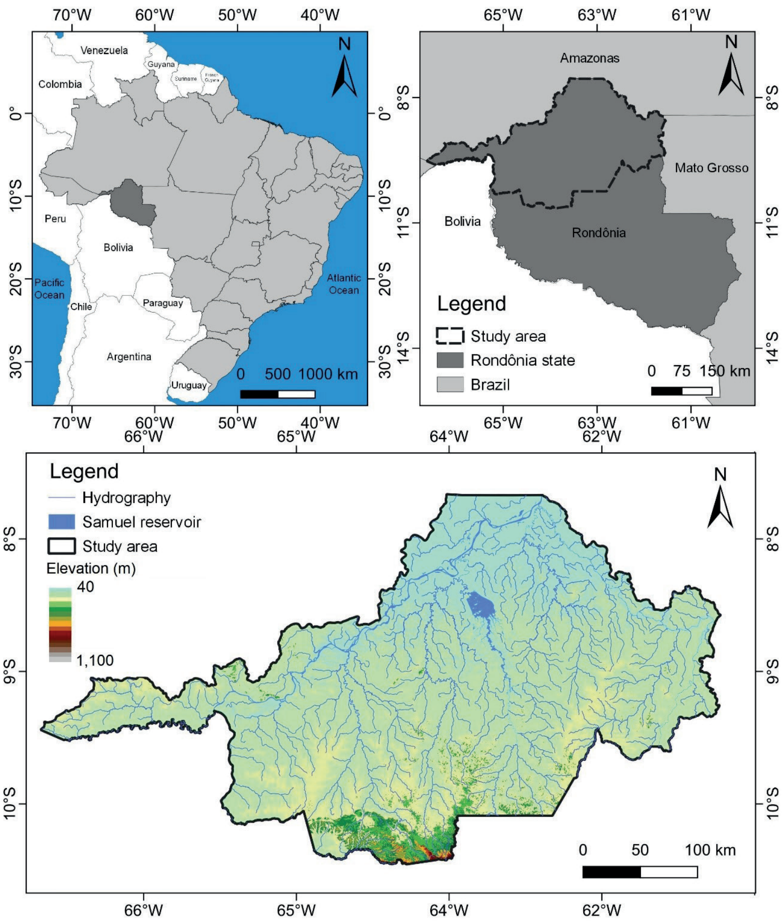

Fig. 1. Study area in northern Rondônia

According to the Köppen classification (Alvares et al. 2013), the region's climate is of the Aw type (Rainy Tropical Climate), with average annual precipitation of 2,250 mm. It has a well-defined dry period from June to August, with monthly precipitation below 50 mm, and a rainy period from November to April, with monthly precipitation above 220 mm. The average annual temperature in the region is 25.5 °C, with a maximum of 34.4 °C in August and a minimum of 19.2 °C in July (Silva et al. 2018).

The indigenous vegetation presents diverse characteristics, comprising open ombrophylous forests, dense ombrophylous forests, savannas, pioneer formations, and contact or transition forests. Additionally, there are areas of anthropogenic activity that are primarily occupied by pastures and family farming (SEMA, 2012; Schlindwein et al. 2012). In this region, deforestation occurs predominantly in areas that consist of open ombrophylous forests and dense ombrophylous forests, predominantly due to livestock farming.

Fuzzy System Proposal

Several previous studies propose the association of factors to indicate the spatial predisposition of forest fire occurrence (Jaiswal et al. 2002; Bonazountas et al. 2005; Parente and Pereira, 2016; Mota et al. 2019; Pourghasemi et al. 2020). However, methodological association of several factors is quite complicated, in addition to being impractical and possessing regional degrees of subjectivity (Carmo et al. 2011; Gralewicz et al. 2012). Furthermore, large-scale data are not always available, especially in remote areas like Brazilian Amazon.

This study gathered a set of factors mentioned in previous research that can be obtained from remote sensing data to compose a fuzzy inference model. This model is characterized by a Max-Min inference system proposed by Mamdani and Assilian (1975). This system is one of the most commonly used in geosciences since, besides being abstractly defined, it employs linguistic variables, which facilitates their application (Acaroglu et al. 2008).

The four main components of the fuzzy inference system are input fuzzification, fuzzy rule base, fuzzy inference method, and defuzzification. To "fuzzify" the input variables into a common range [0,1], each variable is transformed into linguistic variables (low, moderate, and high values) that can be calculated by Equations 1, 2 and 3, and represented by a triangular (Equation 4) and a trapezoidal (Equation 5) membership functions, which overlap and form fuzzy regions, thus allowing data to belong to more than one set (Cocconello et al. 2014; Román-Flores et al. 2020).

$$\mu_x(L) = f\left(x, a_{xL}, b_{xL}, c_{xL}, d_{xL}\right) \quad (1)$$

$$\mu_x(M) = f\left(x, a_{M}, b_{xM}, c_{xM}, d_{xM}\right) \quad (2)$$

$$\mu_x(H) = f\left(x, a_{xH}, b_{xH}, c_{xH}, d_{xH}\right) \quad (3)$$

where the function *f(x;a,b,c,d)* is given by Equations 4 or 5, x refers to the input variables, and the subscripts (*xL, xM, xH*) refer to the variables' membership function parameters for the low, medium, and high classes.

$$\mu(x;a,b,c) = max\left\{min\left\{\frac{x-a}{b-a}, \frac{c-x}{c-b}\right\}, 0\right\} \quad (4)$$

$$such\ that \backslash a, b, c \in R$$

$$\mu(x;a,b,c,d) = max\left\{min\left\{\frac{x-a}{b-a}, 1, \frac{d-x}{d-c}\right\}, 0\right\} \quad (5)$$

$$such\ that \backslash a, b, c, d \in R$$

where μ corresponds to the membership function, and the variables *a, b, c,* and d correspond to the parameters that represent the shape of the triangular and trapezoidal function. In this study, we chose functions of mixed relevance, employing trapezoidal functions for exact extensions and triangular functions for abrupt transitions.

The rule base comprises a set of IF … THEN rules that associate the inputs forming the fuzzy system outputs. These rules are based on the relationships between the variables, for instance: *IF temperature is low AND precipitation is low AND distance from highways is low AND land use and occupation is low, THEN fire hazard is very low*

The output variable comprising fire susceptibility was characterized by the following language terms: very low, low, moderate, high, and very high. Triangular membership functions represented these variables. Finally, the centroid method was used to transform the fuzzy output variable into a crisp numerical value (defuzzification). This method calculates the average of the areas representing the degrees of the fuzzy subset pertinence (Román-Flores et al. 2020).

Determining the Input Variables

The input variables selected for the fuzzy system referred to precipitation, temperature, distance from highways, and land use, and were obtained from open remote sensing products.

Land surface temperature for the study area (in Kelvin) was estimated from thermal images taken by the MODIS (Moderate Resolution Imaging Spectroradiometer) sensor, product MOD11 (Land Surface Temperature - LST) from Terra and Aqua satellites, at ~1 km spatial resolution. The data are available at the United States Geological Survey website (USGS, 2020). Data from the USGS were chosen for the calculations as their estimates were observed in situ for the Amazon region by Gomis-Cebolla et al. (2018). Monthly data were obtained between August and October 2018 at 1 km spatial resolution in GeoTIFF format using the Google Earth Engine platform. Then, the conversion from Kelvin to Celsius degrees was performed through the GIS environment.

Monthly precipitation (in mm) was obtained from the Global Precipitation Measurement (GPM), IMERG Version 6, with ~1 km spatial resolution, which was provided by the Japan Aerospace Exploration Agency (JAXA, 2020). These data are similar to the values observed by surface rainfall stations in the region (Santos et al. 2019). The monthly average data for August-October 2018 were obtained in GeoTIFF format using the Google Earth Engine platform and processed at a 1 km spatial scale.

Data on highways and minor roads in the region were obtained by joining the database of the National Department of Transport Infrastructure (DNIT, 2020) and crowdsource mapping data from OpenStreetMap (OSM Foundation, 2020). These data were pieced together, and the Euclidean distance of the vicinities was calculated, being spatialized with a spatial resolution of 1 km.

Land use data for the region were obtained from the database of the Annual Mapping of Land Cover and Land Use in Brazil (MapBiomas) project for 2018. These data were produced from the pixel-by-pixel classification of images from the Landsat satellite sensor series using machine-learning algorithms via the Google Earth Engine platform. They are available in GeoTIFF format for the entire country (MapBiomas, 2020). These data were processed with GIS with a spatial resolution of 1 km.

All data were treated and manipulated using ArcGIS 10.5 software (ESRI, 2016), adopting the Universal Transverse Mercator-UTM coordinate projection system, SIRGAS 2000 Datum, zone 20 south.

Fuzzy System

The variables were categorized according to the intervals defined in previous research. Thus, the temperature was categorized according to Melo et al. (2012), Mohammadi et al. (2014), and Assis et al. (2014). For precipitation, the studies by Oliveira et al. (2017), Silva and Pontes Jr. (2011), and Assis et al. (2014) were used. Land use was categorized following Venturi and Antunes (2007), Ribeiro et al. (2012), and Assis et al. (2013), while distance from minor roads was categorized according to intervals defined by Adab et al. (2013), White et al. (2016), and Gholamnia et al. (2020).

However, there is no consensus on the class interval definition for the assessed variables. As an example of subjectivity in class intervals, for temperature, Melo et al. (2012) defined the low class as <13 °C, moderate as between 13 °C and 24 °C, and high as >24 °C. Meanwhile, Mohammadi et al. (2014) defined them as <16 °C, between 16 °C and 30 °C, and >30 °C, respectively, whereas Assis et al. (2014) defined them as <23.4 °C, between 23.40 °C and 24.15 °C and >24.54 °C. Considering this subjectivity of the classes, fuzzy sets were built for each variable, and Table 1 presents the parameters compiled based on expert knowledge of the model's fuzzy association (μ(x;a,b,c,d)). It should be noted that this system's application in other climatic regions requires rule set adaptation since the model's response is intrinsically related to the variation of local environmental conditions.

According to the association functions presented in Table 1, each attribute has specific contributions that can imply increased or reduced susceptibility to fire. Temperature, for example, is important because, apart from influencing soil moisture, it is directly linked to the combustion of vegetation, so the higher the temperature, the greater the susceptibility to fire (Pourghasemi et al. 2020). On the other hand, high precipitation rates increase soil moisture content, decrease water stress, and hence reduce susceptibility to fire (Vadrevu et al. 2006; Venkatesh et al. 2020).

Highways and minor roads also contribute to fires since they help to clear up new areas for agriculture, cattle-ranching, and logging, thus facilitating fire outbreaks. The greater the proximity of highways and minor roads, the greater the susceptibility to fire (Ribeiro et al. 2012). The landscape's structure and the way land use patterns are organized strongly influence the fire occurrence because these dynamics are associated with the spatial distribution of the fuel load constituted by the type of vegetation and available biomass (Aquilué et al. 2020).

Model Sensitivity Analysis

Model validation is a crucial step as it tests the effectiveness and accuracy of the methodology used. In this case, we evaluated the ability of the model to map the areas with fire susceptibility. For this purpose, the data on fire outbreaks were obtained from the Fire Database of the National Institute for Space Research (INPE, 2010), and classified according to the number of observations per km^2. Fire occurrence was classified as very low (0 to 0.3), low (0.3 to 0.7), moderate (0.7 to 1), high (1 to 1.3), and very high (>1.3), as proposed by Nascimento et al. (2017).

Then, partitioning was performed through joint training (80%) and testing (20%) for the implementation of the fuzzy system, and the analysis of the ROC (receiver operating characteristic) and AUC (area under the curve) was performed to determine the accuracy of the proposed model. The ROC curve plots the true positive rate on the Y-axis and the false positive rate on the X-axis, with area under the curve (AUC) values ranging from 0.5 to 1.0, whereby the forecast accuracy can be classified as excellent (0.9-1.0), very good (0.8-0.9), good (0.7-0.8), average (0.6-0.7), or poor (0.5-0.6), as described by Chen et al. (2018).

To evaluate the efficiency of the fuzzy system, the model was tested considering the mapped fire susceptibility classes and the inventory of fire outbreaks in the region. This evaluation was carried out for the base year (2018) and two extreme climatic events, with a rainy summer period of 2001 and a dry summer period of 2007, according to the classification of extreme events described by Tejas et al. (2012) and França (2015).

Since fire susceptibility is highly dependent on the association of the input variables, evaluating the impact of the input association functions on the final result was of the utmost importance and was performed by Monte Carlo simulations

Table 1. Fuzzy membership function parameters compiled from specialized literature

Susceptibility Classes		Temperature (°C)	Precipitation (mm)	Distance from highways (m)	Land use Classes
Low	a	0	80	6,000	0
	b	0	80	6,000	0
	c	13	22	3,000	8
	d	24	10	2,000	12
Moderate	a	13	22	3,000	8
	b	24	10	2,000	12
	c	24	20	2,000	12
	d	30	2	1,000	20
High	a	24	10	2,000	12
	b	30	2	1,000	20
	c	50	0	0	30
	d	50	0	0	30

*Land-use classes defined by recategorization based on the number of «CAPTION CODES - COLLECTION 5» from the MapBiomas project.

(1,000 simulations). For comparison purposes, the input parameters were individually perturbed in an interval from -10% to +10%, considering their original value. The ±10% variation was adopted since it was compatible with the projections presented by the Intergovernmental Panel on Climate Change (IPCC), which indicated an increase in temperature of 1.5 °C and the intensification of extreme precipitation events (positive and negative anomalies) by 2050, and which could increase forest fires in the region (Hoegh-Guldberg et al. 2018). The individual sensitivity of the parameters was analyzed by considering the average percentual change in the fuzzy system's output.

The interaction of the four inputs of the proposed fuzzy system enabled the generation of 81 association rules. Figure 2 presents the schematic diagram of the fuzzy model implemented from the *R* software (R Core Team, 2020).

RESULTS

Model Input Data

Figure 3 presents the maps of the spatial distribution of the average observed temperature (a) and precipitation (b) between August and October 2018, as well as the distance from highways (c) and land use (d) for the respective period evaluated.

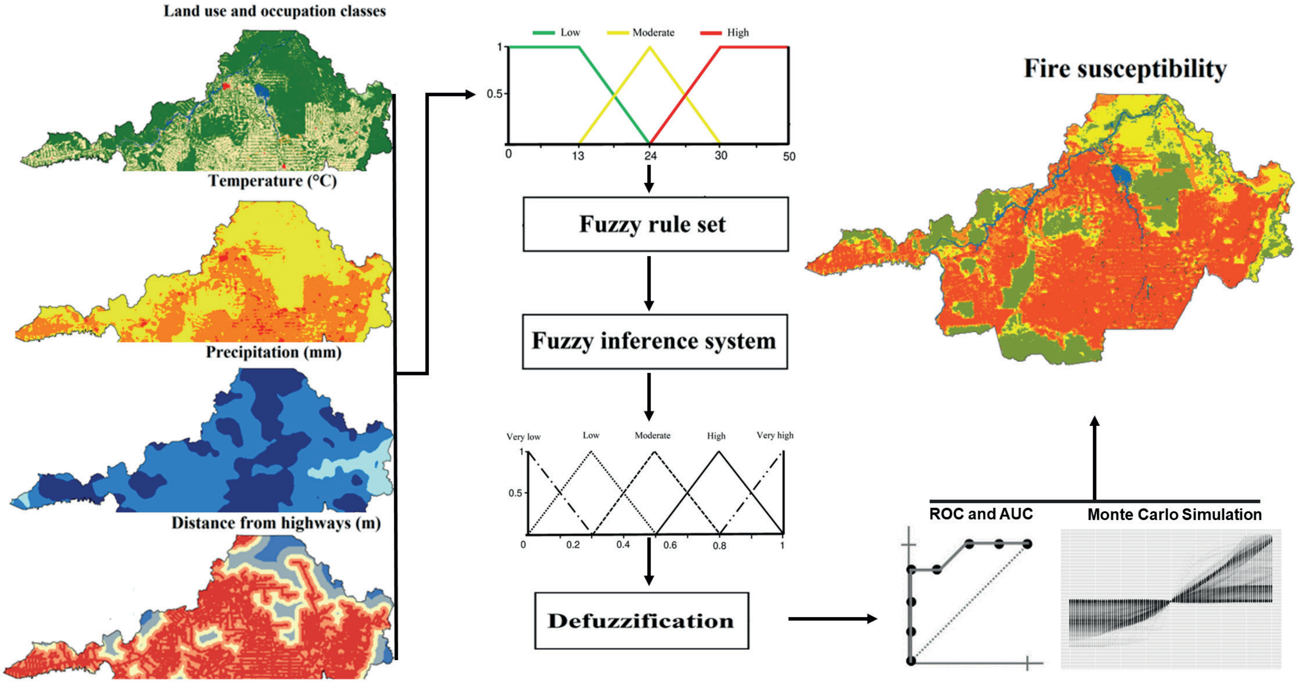

Fig. 2. Schematic diagram of the developed fuzzy inference system

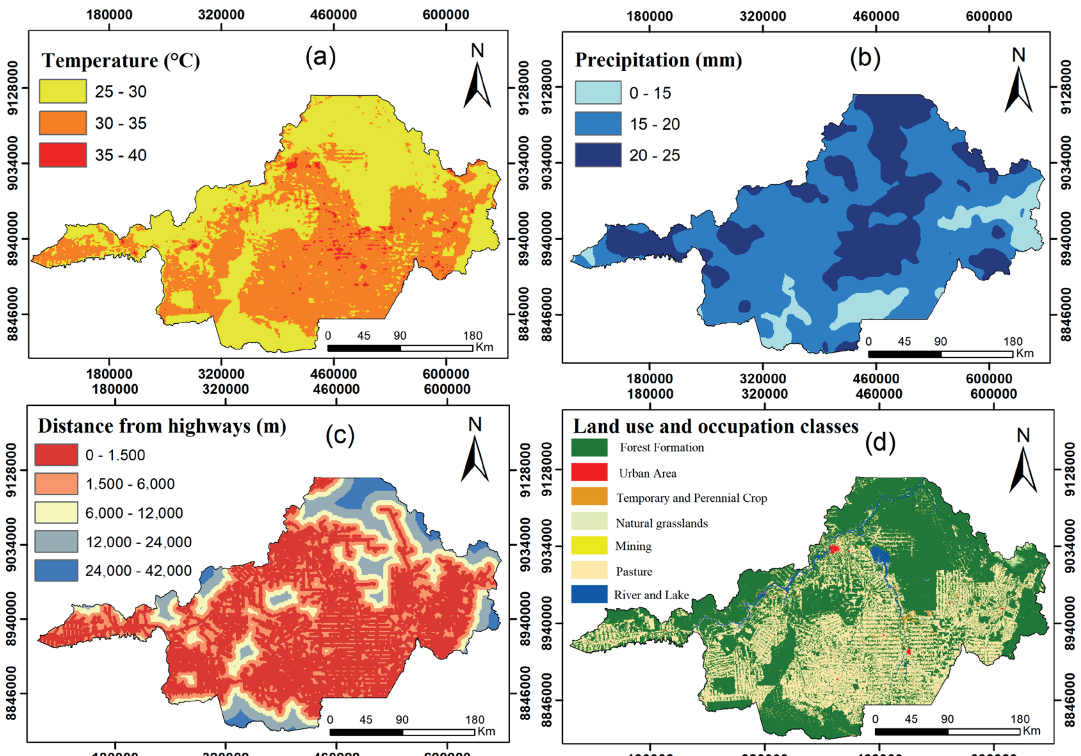

Fig. 3. Input data of the fuzzy system regarding monthly average temperature between August and October 2018 (a) retrieved via the MODIS satellite, monthly average precipitation between August and October 2018 (b) retrieved via the GPM satellite, distance from highways (c) obtained based on DNIT and OpenStreetMap data, and land use and occupation (d) obtained from MapBiomas

The surface temperature map obtained via the MODIS sensor (Figure 3 a) between August and October 2018 shows that the average values ranged from 25 °C to 40 °C, with the highest temperatures occurring in anthropized areas, mainly in urban and agricultural areas. Meanwhile, the lowest temperatures occurred in areas occupied by forests and natural grasslands. Regarding the average precipitation accumulated from August to October registered by the GPM sensor (Figure 3 b), it is evident that most of the study area had precipitation of 15-20 mm, with small areas in the central and extreme northern parts receiving 20-25 mm, and precipitation of 0-15 mm found in the outer eastern and southern parts.

Regarding the distance from highways and minor roads (Figure 3 c), the study area primarily presented high density of road network (dark red), especially in the south, where the majority of rural settlements are concentrated. This high density can also be observed on the land-use map (Figure 3 d), which illustrates the characteristic "herringbone" areas that correspond to deforestation advance around the minor roads.

The land-use map for 2018 shows the predominance of areas occupied by native forests (58.30%), followed by pasture areas (38.72%), rivers and lakes (1.88%), annual and perennial agriculture (0.46%), natural fields (0.41%) urban areas (0.21%), and mining areas (0.01%) during the studied period. Out of all areas occupied by forests, around 40% corresponded to areas protected by conservation units, and the other 10% protected by indigenous lands. In other words, 50% of the areas occupied by forests in the region were within protected areas, and the rest consisted of small forest fragments out of legal reserves and environmental protection areas. The predominance of anthropogenic pastures shows that the region was a part of the agricultural frontier, concentrating 34.02% of the cattle in Rondônia (IDARON, 2018).

Mapping of Fire Susceptibility

Figure 4 shows the fire susceptibility classification map generated by the fuzzy system for the north of Rondônia. 47% of the area were classified as having very high susceptibility, 16% as having high susceptibility, 18% as having moderate or low susceptibility, and just 0.17% as having very low susceptibility.

The reliability of the fuzzy system was evaluated using the overlap between the mapped fire susceptibility classes with the density of fire outbreaks that were observed by satellites between August and October 2018, as shown in Table 2.

It can be noted there is significant agreement between the fire susceptibility classes mapped by the fuzzy system and the density of fire outbreaks per km^2 observed between August and October 2018 in the region (Table 2). Notably, the very low and low susceptibility classes show a hotspot density of 0.01 and 0.09 per km^2. Meanwhile, the hotspots increase substantially in moderate, high, and very high susceptibility areas. The response of the model built by the fuzzy system was also evaluated by considering two extreme weather events (Figure 5). In the period corresponding to the rainy summer (Figure 5 a), the study area was predominantly classified as having low

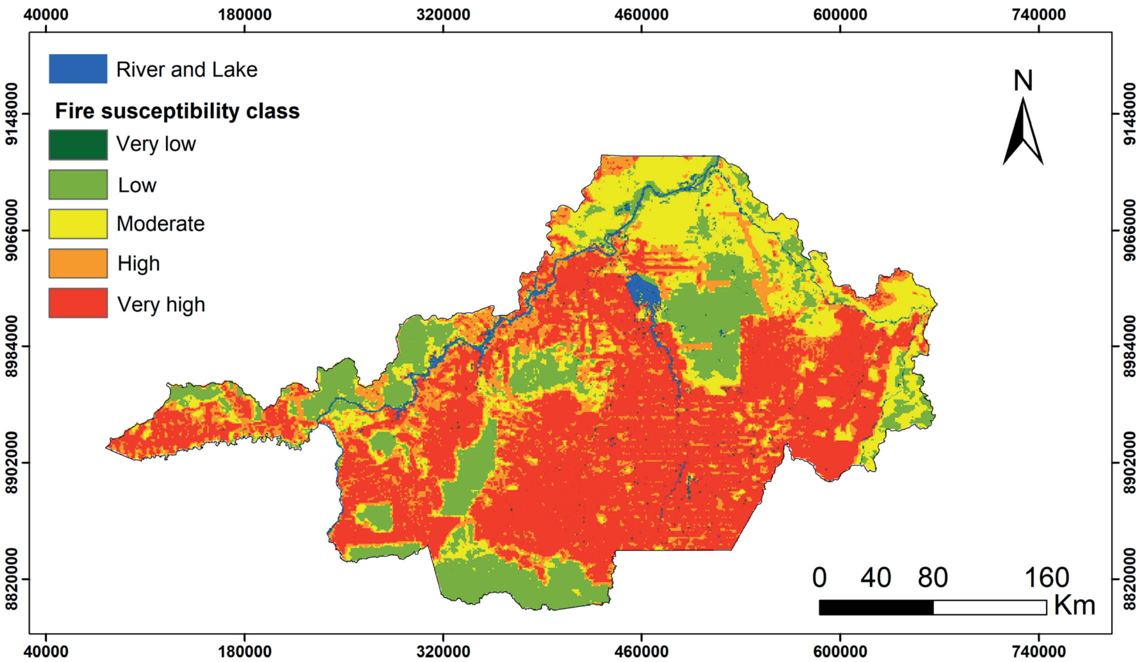

Fig. 4. Fire susceptibility map for the study area

Table 2. Relationship between the classes of fire susceptibility and observed fire outbreaks in 2018

Susceptibility Classes	Area (km^2)	Area (%)	Number of outbreaks of fire	Density of fires/km^2
Very low	1,731.74	0.17	15.00	0.01
Low	15,861.60	18.28	1,437.00	0.09
Moderate	16,059.00	18.29	9,890.00	0.62
High	14,248.90	16.27	23,514.00	1.65
Very high	41,789.80	47.00	59,910.00	1.43

susceptibility to fire. In contrast, for the dry summer period (Figure 5 c), the fuzzy system model classified the area as having a predominance of very high susceptibility.

Regarding the density of fire outbreaks per km^2, the rainy summer period showed low density (Figure 5 c), while the dry summer period showed high density (Figure 5 d). It is worth noting that the density of fire outbreaks aligns with the mapped susceptibility classes. The occurrence distribution is denser in areas classified with high and very high susceptibility and lower in areas classified with low and very low susceptibility, as shown in Figure 5 c and Figure 5 d.

To assess the accuracy of the results, which was a crucial step in the modelling process (Pourghasemi et al. 2020), the AUC and ROC were used. Figure 6 presents the AUC values for the ROC curve in 2018, as well as for 2001 and 2007. The AUC values for the proposed fuzzy model range from 0.709 to 0.879, thus indicating that the model has a good predictive capacity.

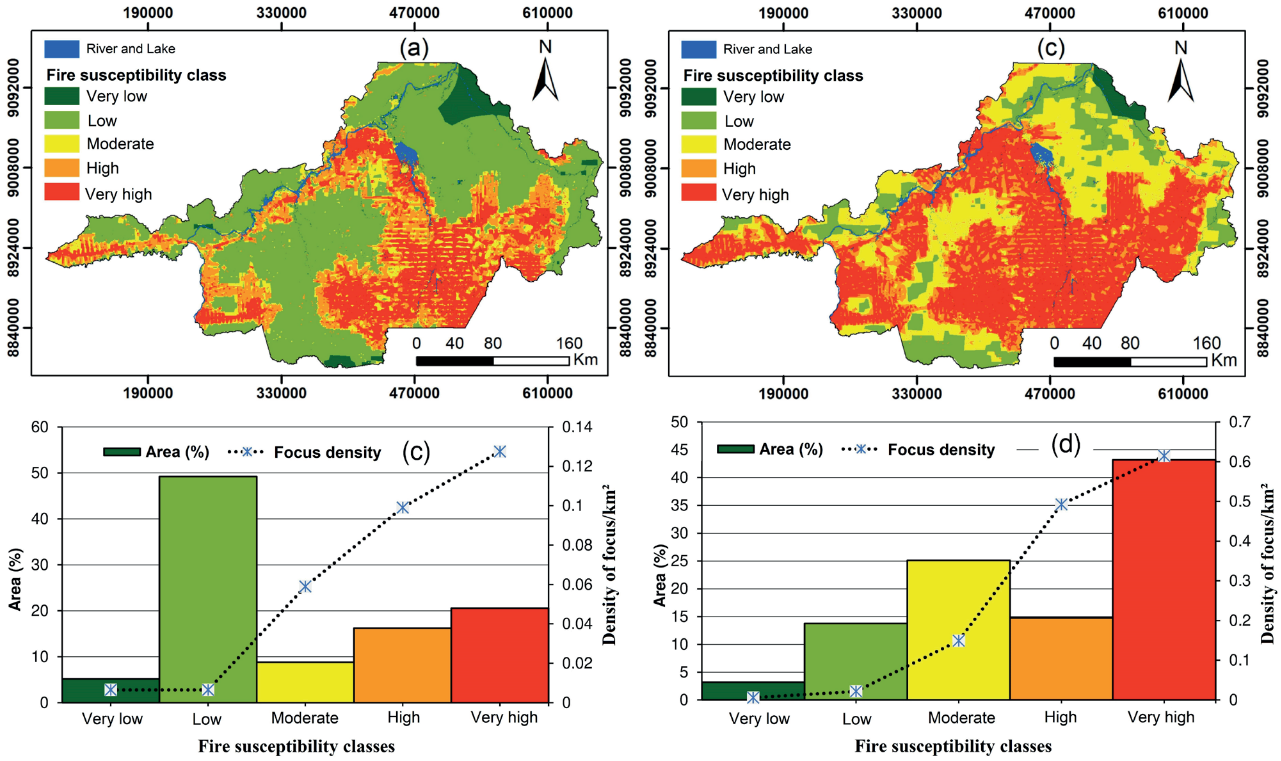

Fig. 5. Mapping of the fire susceptibility for a rainy (a) and dry (b) summer, and respective density of fire outbreaks per km^2 (c and d)

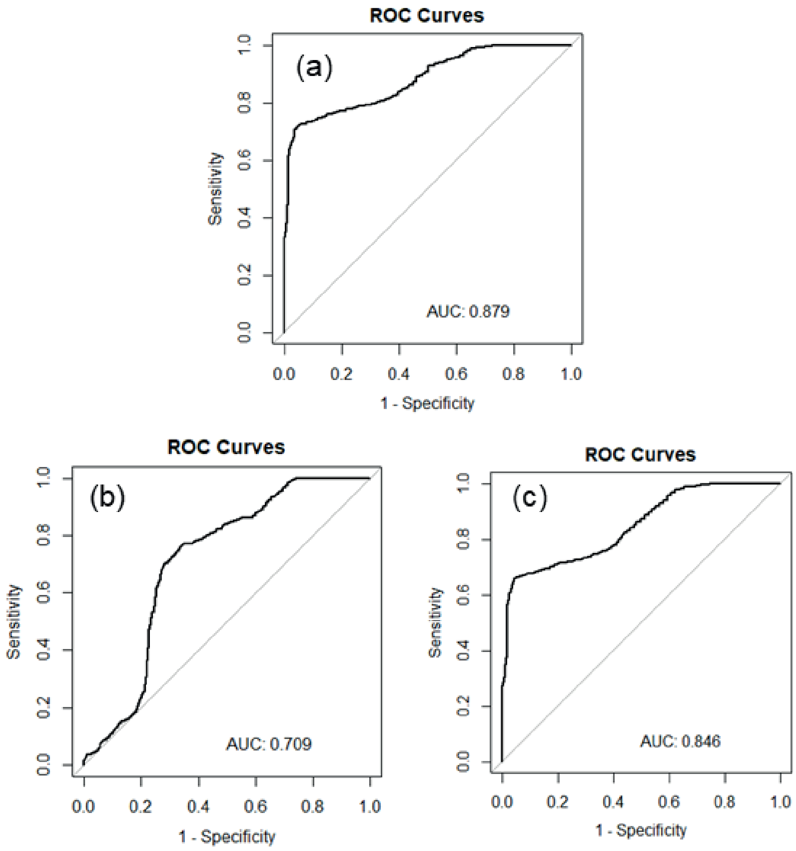

Fig. 6. Prediction rate curve of the forest fire susceptibility map using the fuzzy model for 2018 (a), 2001 (b) and 2007 (c)

Figure 7 represents the sensitivity analysis of the fuzzy system performed using 1,000 Monte Carlo simulations. The graphs show the percentage contribution of each variable to the model output when individually disturbed between -10% and +10%.

In random simulations of up to ±2.5% in temperature (Figure 7 a), fire susceptibility can be altered by an average of ±20%. In other words, a 2.5% increase in regional temperature can result in a 20% increase in fire susceptibility compared to what is normally observed. Meanwhile, precipitation showed considerably lower sensitivity when compared to temperature (Figure 7 b). Disturbances of up to ±2.5% of precipitation alter the average fire susceptibility by up to ±10%. Thus, a 2.5% reduction in precipitation can cause an average 10% increase in fire susceptibility to fire in the study area. Regarding the distance from highways and minor roads (Figure 7 c) and land use (Figure 7 d), the random simulations showed less significant variations in the proposed model.

DISCUSSION

Proper mapping of forest fire susceptibility is an important task within its management. However, this is still a complicated challenge due to the complexity and non-linearity of these fires (Moayedi et al. 2020; Sahiner et al. 2022). This study used the fuzzy inference system composed of four input parameters (temperature, precipitation, distance from roads, and land use and occupation), with a map output showing the spatial distribution of fire susceptibility. The used method made it possible to incorporate expert knowledge into the model and, with the use of linguistic variables and degrees of pertinence, to smoothen the transition from one class to another (Zadeh, 1965; Cheng et al. 2022). This allowed the values of the influencing factors to belong simultaneously to several levels of susceptibility with different degrees of association, thus better reflecting the real characteristics of the events.

The proposed fuzzy system applied in this study indicated the predominance of areas that were classified as having very high fire susceptibility in 2018. These areas were distributed mainly throughout the south of the study area, where most of the agricultural and cattle-ranching lands and the highest road network density could be found. When these factors were combined with low precipitation and high temperatures observed during the evaluated period, they contributed to the predominance of high and very high fire susceptibility, similar to Cardozo et al. (2014). On the other hand, the areas identified as having low and very low fire susceptibility corresponded to protected areas represented by conservation units and indigenous lands distributed throughout the north of the region. However, these areas have recently suffered from the advancement of anthropogenic activities due to the construction of unofficial minor roads and land grabbing, as also demonstrated by Fonseca et al. (2018). Although the study area had around 58.30% native forest coverage, 19.25% of them were classified as having high susceptibility to fire, and other 21% as having very high susceptibility. These areas corresponded to border zones with proximity to highways and unofficial minor roads. When road proximity is combined with the fuel stored in the forest litter, high temperatures, and low precipitation rates, it becomes a dominant component for the start of forest fires.

Furthermore, forest fires have become increasingly frequent because during intense dry seasons the Amazon Forest has become more flammable, and thus more susceptible to fires, as already described by Aragão et al. (2018) and Staver et al. (2020), and shown by the model results for the dry summer period in 2007. There is a high alignment between mapping results based on the proposed methodology and the recorded fire instance data both for 2018 and for 2001 and 2007 with extreme weather conditions. These results show that the developed fuzzy model system can adjust to climatic variations (temperature and precipitation) that occur during extreme weather events. This emphasizes the high adequacy of the applied method, which was confirmed by the AUC values of 0.879 for the year 2018, 0.709 for the rainy summer period, and 0.846 for the dry summer period.

The results achieved in this research are considered satisfactory when compared with the AUC values found in

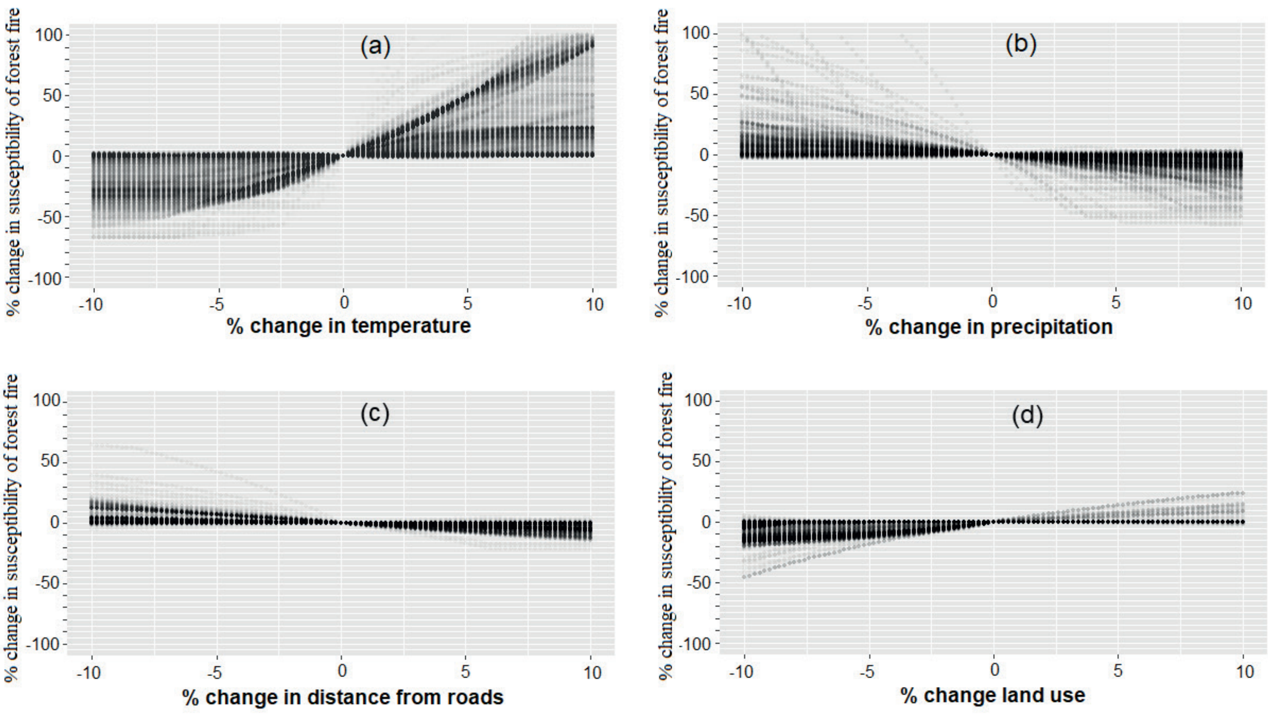

Fig. 7. Sensitivity analysis of the fuzzy system output with a disturbance at -10% and +10% of precipitation (a), temperature (b), distance from highways, and land use and occupation (d)

previous research. For example, Pourghasemi et al. (2020), when employing methods such as mixture discriminant analysis (MDA) and boosted regression tree (BRT), obtained AUC values ranging from 82.5% to 88.90%. By employing joint approaches, Eskandari et al. (2021) observed that the generalized additive model – multivariate adaptive regression spline – support vector machine (GAM-MARS-SVM) method achieved an AUC of 83.00%, which surpassed the individual models used by the authors. These findings are consistent with those of Mohajane et al. (2021), who observed an AUC of 98.90% for the forest random frequency ratio (RF-FR) method. In both cases, the models were considered satisfactory and appropriate for the mapping of fire susceptibility in the respective analysed areas.

Regarding the sensitivity of the input variables of the fuzzy inference system, the proposed model proved to be more sensitive to the factors that can alter the flammability of combustible materials, such as precipitation and temperature during seasonal changes. In variations of up to 2.5% in temperature, the model indicated an average 20% increase in fire susceptibility in the region, which is a worrisome scenario. According to the Intergovernmental Panel on Climate Change (IPCC), for the Amazon, there is a projected 1.5 °C increase in temperature by 2050 (Hoegh-Guldberg et al. 2018), which can result in an increase in fire susceptibility beyond what was calculated by the model.

It is worth mentioning the influence of anthropogenic activity on fire susceptibility. In this study, anthropogenic areas had an average temperature that was 5 °C higher than in natural areas (Figure 3a and 3d), which resulted in greater fire susceptibility, as reported in other studies (Oliveira et al. 2021; Silva et al. 2023).

Moreover, regional atmospheric conditions, such as strong anticyclones over the continent, for example, the South Atlantic Subtropical High, inhibit the formation of rain clouds north of the state of Rondônia. These conditions contribute to low precipitation between August and October in this region, which increases the flammability and burning potential of the combustible material (Tejas et al. 2012; França, 2015; Aragão et al. 2018; Ribeiro et al. 2020).

Thus, adopting an integrated command and control system that encompasses public policies and includes prevention techniques for fighting and controlling fires is essential for the region. As such, the methodology presented for fire susceptibility mapping, which integrates the fuzzy system with data obtained from remote sensing techniques and GIS, can provide the basis for local environmental planning.

It is worth noting that, although the Brazilian Forest Code, Law No. 12,651, of May 25, 2012, provides for the creation of the National Integrated Fire Management Policy (PNMIF), this system has not been completed yet (Brasil, 2020). The reflection of the absence of the system that centralizes firefighting efforts in Brazil makes these events historically excessive, such as those observed in the study area between August and October 2018, with about 94,766 registered fire outbreaks.

The absence of an effective fire control system, combined with the anthropogenic activity in the region, which includes deforestation for shifting agricultural practices and pastures and the practice of using fire to clear degraded pastures, and extreme droughts, are the main reasons for the high fire rates in this region (Cardozo et al. 2014; Aragão et al. 2018; Chuvieco et al. 2019; Barlow et al. 2019; Caúla et al. 2019; Staver et al. 2019; Ribeiro et al. 2020).

Advantages and Limitations

The ability of fuzzy inference systems to handle most inaccuracy sources in remote sensing data, such as uncertainties in sensor measurements, parameter variations due to limited sensor calibration, and class mixing due to limited spatial resolution, and other (Benz et al. 2004), gives the fuzzy system an advantage over other methods that are usually implemented for mapping forest fire susceptibility.

In this study, the uncertainties related to the disagreement between the expert class intervals were considered using fuzzy sets, which were defined by membership functions and allowed the incorporation of a combination of subjective data into a fuzzy domain, thus making it possible to build inference systems based on expert experience and deal with inaccurate data (Zadeh, 1965). In addition, it allowed influencing factors to belong simultaneously to more than one susceptibility class, however, with different degrees of association (Zadeh, 1965; Cheng et al. 2022) to better reflect the real characteristics of fire susceptibility that are observed in the region.

Nonetheless, it is worth mentioning that in a grid-type partition fuzzy inference system the number of rules is given by the combination of linguistic values, in other words, the number of rules can increase exponentially as a function of the number of input variables (Bressane et al. 2020; Fernandes et al. 2023). In this study, only four inputs were selected to compose the model; however, for cases in which a greater number of explanatory factors are introduced, this would negatively affect the transparency and interpretability of the fuzzy inference system, and, consequently, its replication (Ojha et al. 2019). One of the solutions would be the optimization of input factors using metaheuristics (Moayed et al. 2022).

CONCLUSIONS

The methodology presented for mapping fire susceptibility by integrating a fuzzy inference system with data obtained via remote sensing techniques and GIS tools proved to be highly effective, especially when implemented for precipitation, temperature, distance from highways, and land use as input variables. The findings indicate that the study area had a predominantly high fire susceptibility, especially when considering the climatic characteristics observed between August and October (during the dry season) and the land use patterns of the region.

The areas classified with very high susceptibility by the fuzzy system were located predominantly in the south of the study area, where agricultural and livestock activity prevails. On the other hand, the areas that had low and very low susceptibility were concentrated primarily in conservation units and indigenous lands, which shows the importance of these protected areas.

The comparison between the mapped fire susceptibility classes and the density of registered fire outbreaks showed a strong spatial coincidence, which reinforces the credibility of the fire susceptibility mapping based on the proposed methodology, and these results were confirmed by the AUC values (mean of 0.81), thus indicating an impressive predictive capacity of the model.

Thus, the results obtained in this study can be used to inform the community, fire departments, and local authorities about areas that are most susceptible to fires. The findings can also be used to highlight areas that are conducive to controlled burning, with the aim of reducing the accumulation of combustible material, contributing to the prevention of uncontrollable fires.

Finally, the obtained results can significantly contribute to land management and planning policies, including the possibility of integrating similar data in other regions. They can also assist the decision-making process when fighting fires. However, for implementation in other regions, it is necessary to incorporate sufficient information regarding local factors that can influence forest fires.

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