An Acad Bras Cienc (2021) 93(Suppl. 3): e20190726 DOI 10.1590/0001-3765202120190726
Anais da Academia Brasileira de Ciências | *Annals of the Brazilian Academy of Sciences*
Printed ISSN 0001-3765 I Online ISSN 1678-2690
www.scielo.br/aabc | www.fb.com/aabcjournal

FORESTRY SCIENCE

Gis and fuzzy logic applied to modelling forest fire risk

RONIE S. JUVANHOL, NILTON CESAR FIEDLER, ALEXANDRE R. DOS SANTOS, GILSON F. DA SILVA, MOISÉS S. OMENA, FERNANDO C. EUGENIO, CHRISTIANO JORGE G. PINHEIRO & ANTÔNIO CARLOS FERRAZ FILHO

Abstract: Fire risk mapping is a basic planning and protection element. This study presents the application of fuzzy logic in a geographic information system (GIS) as an alternative multi-criteria analysis for determining the areas of highest risk of forest fire in natural forest remnants in the Brazil. In the decision-making process, a set of factors that are relevant to fire safety were identified in the study area. For each input variable chosen for the model, a pertinence function was defined that best described its influence on fire risk. Subsequently, the variables were combined for the presentation of the final fire risk map. Concluded in the study that an increased risk of fire occurs at the wildland - urban interface. A strong relationship was observed between the fire ignition points and proximity to roads and urban areas. The proposed model was efficient to integrate the variables and determine areas of greatest risk.

Key words: forestry protection, geotechnology, multi-criteria analysis, spatial analysis.

INTRODUCTION

Forests are an important natural resource with a role in maintaining environmental balance. Forest fires can significantly change natural ecosystems and affect Brazil and other countries with large extents of forest cover, such as the United States, Canada, Australia, and countries of the European Union and southeast Asia. Accordingly, concerns about the possible impacts of forest fires have shaped research interests over the last decade (Argañaraz et al. 2015, Carvalho et al. 2014, Ikemori et al. 2015, Martins et al. 2012, Wu et al. 2014, 2015).

Studies that model the risk of forest fires are important tools for planning the protection of natural resources, as they provide a visualisation of the spatial distribution of the areas that are most susceptible to the phenomenon of fire and ensure that adequate resources and equipment are available for fire prevention and control, in accordance with the characteristics of each region.

Geographic information systems (GIS) are employed as an effective tools for forest resource management due to, among other things, its computer modelling capacity. A wide variety of techniques have been used for to model fire risk. When forest fire occurrence data is available, statistical models can be used to map risk areas. These models range from multiple linear regression (Oliveira et al. 2012, Syphard et al. 2008) to logistic regression (Catry et al. 2009, Martínez et al. 2009). More recently, machine learning algorithms were used to evaluate the predictive capacity of fire occurrence, such as Random Forest (Arpaci et al. 2014, Wu et al. 2014), MaxEnt (Arpaci et al. 2014), Boosted Regression Trees (Argañaraz et al. 2015) and Classification and Regression Trees (Juvanhol et al. In Press)

However, in regions with no fire records maintained by fire agencies, the integration of factors considered influential in forest fire risk modelling and prediction is performed by application of subjective indexes. These methods that can incur in insufficient data standardization and have the difficulty of establishing weights consistent with reality (Eugenio et al. 2016, Omena et al. 2016, Tetto et al. 2012, Torres et al. 2017). Against these shortcomings, the integration of spatial multi-criteria decision-making methods provide a new framework for addressing various environmental problems, including quantification of fire risk.

The need for frequent preliminary judgements, due to the complexity and uncertainty of the real world, prompts the incorporation of expert opinion into models. This is accomplished by employing a specific class of models know as specialist systems, which are designed to perform reasoning (Krueger et al. 2012). The two uncertainty models most widely used are probability theory and fuzzy set theory. A probabilistic approach generally follows the Bayesian interpretation of probability; the latter is equivalent to possibility theory. Zadeh (1983) stated that probability theory does not provide a systematic basis to address the inherent imprecision of knowledge. Ross et al. (2008) considered possibility theory as more flexible and intuitive than probability theory for framing the opinion of experts.

Fuzzy logic consists of bringing the computational decision process closer to human decision-making, turning machines more capable of handling complex problems. This is done in such a way that the decision of a machine is coded not only a “yes” or “no”, but generating more nuanced responses such as “a little more” or “maybe” and many other types that represent decisions made by human beings. It is a way of inherently interconnecting analog processes that move across a continuous band to a computer, emphasizing the relative importance of alternatives and criteria with fuzzy instead of crisp numbers.

One of the main potentialities of fuzzy logic, when compared to other schemas that deal with inaccurate data such as neural networks, is that its knowledge bases, which are in the form of rules, are easy to examine and understand. This rule format also makes it easy to maintain and update the knowledge base.

A detailed review of the basic concepts of fuzzy sets and their integration using GIS can be found in Robinson (2003). The integration of fuzzy logic with GIS in a decision-making structure has been used for different purposes in environmental studies, including geotechnical disaster risk management (Machado et al. 2018), landscape analysis (França et al. 2014), analysis of environmental degradation in rivers (Lopes et al. 2016, Vidal et al. 2015), forest planning (Boyland et al. 2006, Diaz-Balteiro & Romero, 2008), and more specifically, the modeling of the risk of forest fires (Güngöroğlu 2017, Mehta et al. 2018, Semeraro et al. 2016, Sharma et al. 2012). Thus, many studies have been carried out using fuzzy logic integrated with GIS, demonstrating that the methods are robust and valid. However, none of these studies used fuzzy logic integrated with GIS to quantify fire risk in tropical forests in southeastern Brazil.

In this study, the direct and indirect causes of fires at a landscape scale were considered, using a fuzzy decision making model in a GIS environment that is capable of predicting future fire threats as a function of biophysical and socioeconomic conditions. The presented method integrates a participatory decision-making structure together with fuzzy logic to quantify the fire risk in an important remnant of Atlantic forest in the state of Espírito Santo, Brazil.

MATERIALS AND METHODS

Study area

Recognised as a Natural Heritage Site in 1999 by The United Nations Educational, Scientific and Cultural Organization (UNESCO), the Vale Natural Reserve (Reserva Natural Vale - RNV) is one of 14 centres of high diversity and endemism of plant and animal life in Brazil and one of the best protected conservation areas in South America (Gentry et al. 1997, Peixoto & Silva, 1997). With 22 thousand hectares, it is the second largest reserve of the Mata dos Tabuleiros or Costal Zone (Hiléia Baiana) of the Espírito Santo state (Martin et al. 1993). It is located in the northern region of the state in the municipalities of Linhares, Sooretama and Jaguaré, between the geographical coordinates 18° 58' and 19° 16' S and 39°50' and 40°7' W (Figure 1). The area surrounding the reserve, which determines the range of monitoring and protection of the reserve performed by the park employees, is represented by a 3 km radius that extends the entire length of the reserve and a small part of the Biological Reserve (Reserva Biológica - REBIO) of Sooretama, which is bordered by federal Highway BR-101. The total study area encompasses 68,243 thousand hectares.

Model development

For this research, a specialist system model was employed to determine the areas of greatest risk of occurrence and spread of forest fire. The first step to achieve this is to identify relevant criteria. Five factors were considered: biological

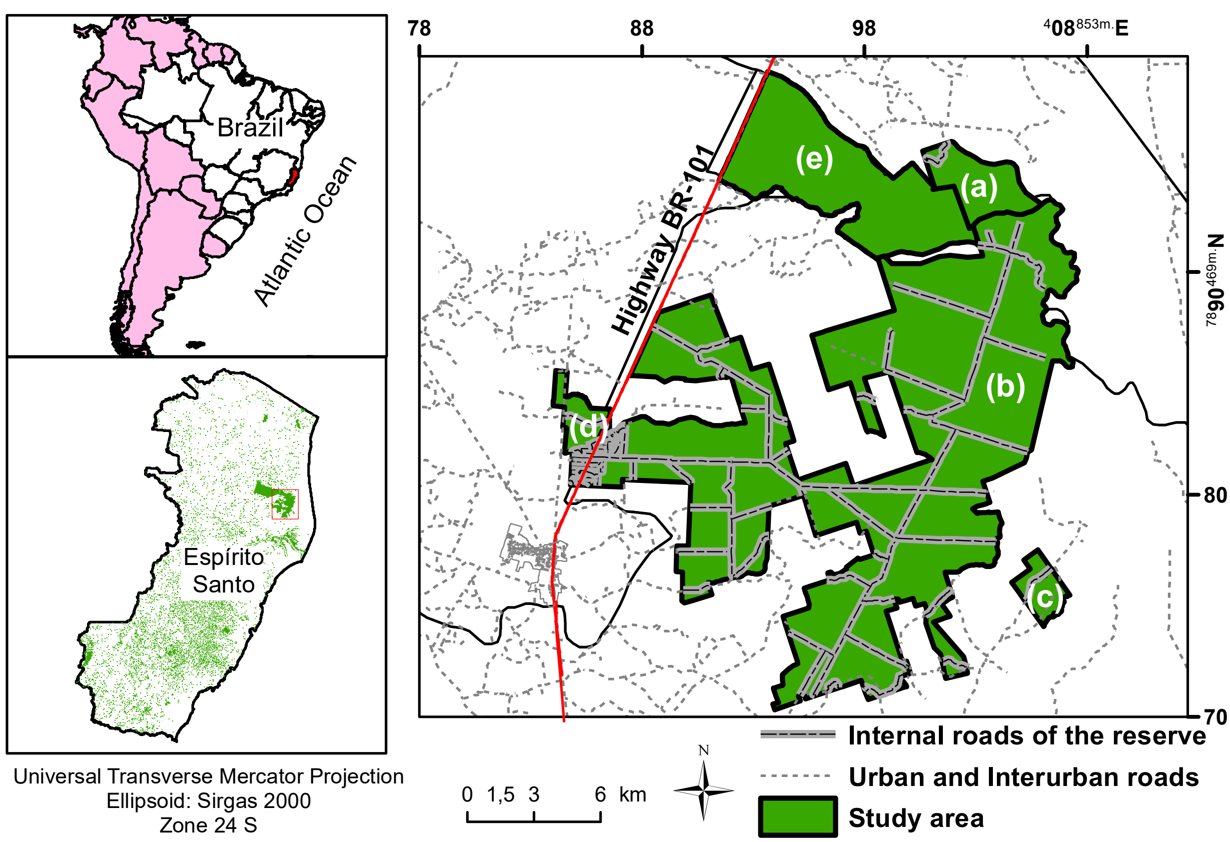

Figure. 1. Location of the area of study. The RNV consists of four matrices: (a) Jaguaré, (b) Linhares, (c) Imbiribas and (d) Rancho Alto. The surrounding area includes a small part of the REBIO of Sooretama (e), which is bordered by federal Highway BR-101, which traverses the study area.

factors (land use and occupation), physical factors (relief orientation and slope) and socioeconomic factors (proximity to roads and proximity to residences). The selected variables were determined according to the procedures described in the Supplementary Material - Supplementary Appendix.

Fuzzy logic was applied for the integration of the variables. This multi-criteria analysis can be used to aggregate precision in the mathematical model of classical sets with the inaccuracy of the real world. Classical set theory only identifies if an element belongs to a given set. Zadeh (1965) proposed a broader characterization that attributes a degree of pertinence, which can vary on a scale from 0 (element not belonging to the set) to 1 (element completely belonging to the set). Therefore, fuzzy logic is a form of managing uncertainties by the expression of terms with a degree of certainty in a numerical range [0,1]. Thus, a fuzzy relevance vector is also referred to as a possibility vector or a possibility distribution.

The central concept of fuzzy set theory is the function of association, which represents the degree to which an element belongs to a set. A fuzzy subset A of a universe of speech U is characterized by a function of association μA (x), as shown in equation (1).

$$\mu_A(\mathrm{x}) : U \rightarrow [0,1] \qquad (1)$$

where μ_A (x) is the association of *x* in *A*; *i.e.* μ_A serves as the association function by which a fuzzy set *A* is defined (Bellman & Zadeh 1970). This function associates each *x* element of *U* with a number μ_A(x) in the interval [0,1]. This *A* fuzzy set can be formally written as:

$$A = \{x_1 / \mu(x_1), x_2 / \mu(x_2), \ldots\ldots x_n / \mu(x_n)\} \qquad (2)$$

For all of *A*, μ_A(x) assumes the values between and including 0 and 1. All numbers within a percent error will have a membership factor of 1, and all the others a factor of 0 (Figure 2a). For the precise case, the pertinence factor is 1 only for the exact number, being 0 for all the others (Figure 2b). When a number is more a member of a set than another it is possible to express the pertinence factor through several types of fuzzy pertinence functions. Several methods can be used to determine membership values, depending on the amount of information available *a priori*. For example, to express the idea that a temperature has its value around 25, a triangular pertinence function (Figure 2c), with the peak at 25, can be used to suggest the idea that the closer the number to 25, the more it identifies with the concept represented.

In this sense, in the computer program *ArcGIS/ArcINFO* 10.2, for each fuzzy set that was represented by the matrix image of the input variable, a function of pertinence that best

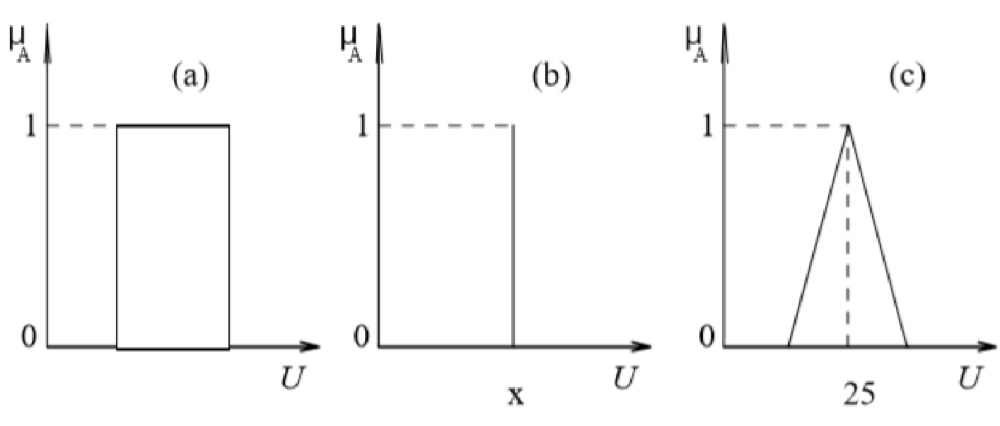

Figure 2. **Pertinence functions (Gomide & Gudwin 1994).**

described the influence of each variable on forest fire risk was defined. The greatest risk of fire was indicated when the value of the variable was 1, and the risk was null when the value of the variable was 0.

The variable land use and occupation was classified in relation to the influence of each class on the risk of forest fire, as it is a discrete variable, and applied to the fuzzy Gaussian pertinence function. The value assigned to each class in the matrix image was defined according to the type and characteristics of the vegetation, such as composition, stage of development and type of management, or by the use of the natural resources in the region. The opinions of researchers and environmentalists were considered for selecting the value of the mapped class (Table I).

The fuzzy Gaussian function (Eq. 3) defines a Gaussian or normal distribution around a midpoint indicated with a slope value of the curve, which may range from 0.01 to 1. The reclassified variable with values from 0 to 21 had a median point value of 11 and a slope of 0.05 (adjusted) in the function (Figure 3a).

$$\mu_A(x) = exp\left\{-\sigma(x-a)^2\right\} \quad (3)$$

where σ is the parameter that determines the slope of the curve, x is the land use and occupation class in the matrix image and a corresponds to the value at the midpoint, which defines the central point for the function, in which $\mu_A(x)$ is 1.

To represent the influence of the proximity to roads with regards to fire risk, the variable was modelled as a function of the fuzzy small pertinence function (Eq. 4). This function represents the variation in the degree of relevance of the matrix image with smaller input values, which are more likely to be a member of the set and assume a value of 1. The value defined at the midpoint gives a degree of pertinence of 0.5 in the function with a degree of propagation of the curve from 1 to 10, which determines the shape and characteristic of the transition zone.

$$\mu_A(x) = \left\{1/1+(x/c)^b\right\} \quad (4)$$

where x is the value of distance (meters) to the roads in the matrix image, b is the parameter that determines the slope of the curve and c corresponds to the value at the midpoint, defining the centre point for the function at which $\mu_A(x)$ is 0.5.

Table I. Land use and occupation classes reclassified as a function of the potential for risk of forest fires.

Class of land use and occupation	Reclassified value	Class of land use and occupation	Reclassified value
Water course	0	Native grasslands	11
Primary forest / Riparian forest	1	Pasture	13
Mussununga forest	3	Forestry	15
Sand extraction	5	Oil extraction	17
Area under regeneration	7	Periodically flooded area	19
Agricultural cultivation	9	Marsh and swamp forest / urban area	21

The input values in the function for the variable were defined according to Rodríguez-Silva et al. (2010) and Soto (2012) to obtain a parameter for the occurrence of forest fires based on the distance to various types of roads. According to the characteristics of the roads and how they are presented in the study area, a distance of 300 m for the road network was defined at the midpoint and a curve slope value of 3 (adjusted) was defined in the function; thus, shorter distances assumed a greater degree of pertinence in the fuzzy set (Figure 3b).

The slope was best described by the fuzzy large pertinence function (Eq. 5), which represents the variation in the degree of pertinence of the matrix image with higher input values, which are most likely to be a member of the set and assume a value of 1. The value defined at the midpoint provides a degree of pertinence of 0.5 in the function with a degree of propagation for the curve from 1 to 10, which determines the shape and characteristic of the transition zone.

$$\mu_A(x) = \left\{1/1+(x/e)^{-d}\right\} \quad (5)$$

where *x* is the value of slope (degrees) in the matrix image; *d* is the parameter that determines the slope of the curve and *e* corresponds to the value at the midpoint, which defines the centre point for the function at which $\mu_A(x)$ is 0.5.

The input values for the slope variable in the function were defined by a literature review

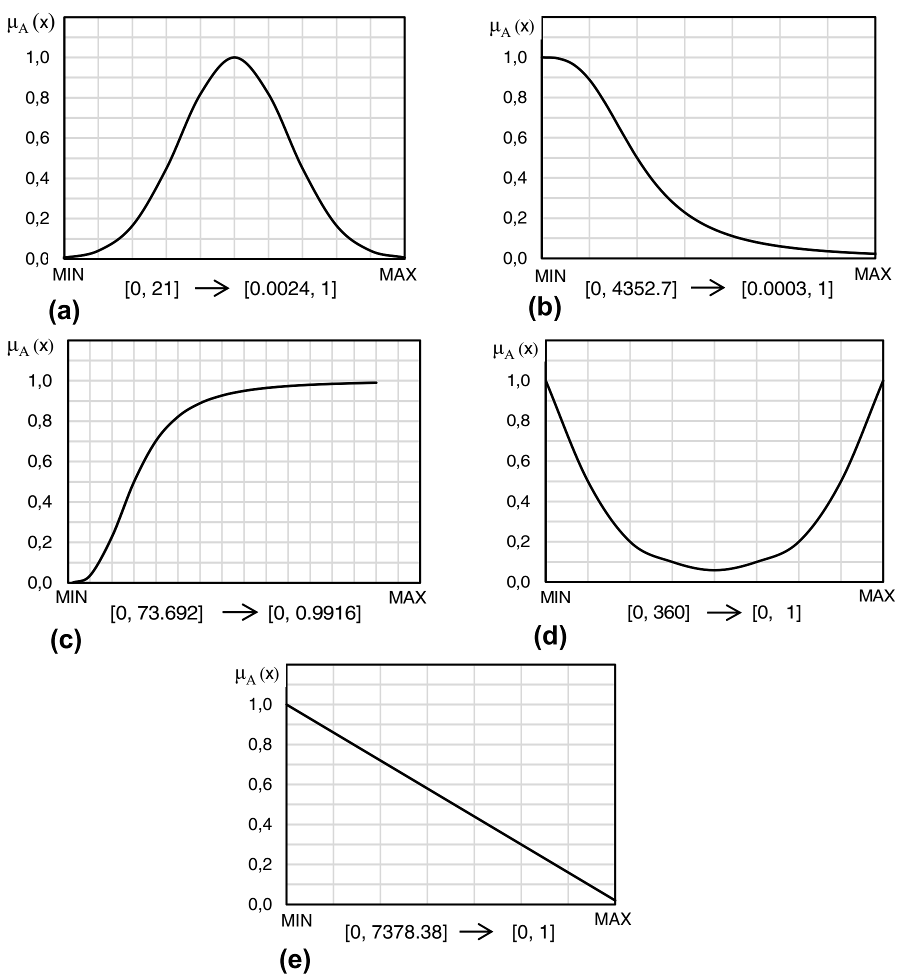

Figure 3. Diagrams of the fuzzy pertinence functions. (a) Land use and occupation - fuzzy Gaussian; (b) Proximity (meters) to roads - fuzzy small; (c) Slope (degrees) - fuzzy large; (d) Relief orientation (degrees) - fuzzy generalised bell; (e) Proximity (meters) to residences - fuzzy linear.

of studies on fire behaviour as a function of the increase in slope (Chandler et al. 1983, Luke & McArthur 1978), considering a slope value of 15° at the midpoint and a propagation value of 3 (adjusted) in the function for a greater control of the slope of the curve (Figure 3c).

The relief orientation was modelled by the fuzzy generalised bell pertinence function (Eq. 6), which defines a bell-shaped distribution around a midpoint that is indicated with a propagation value in the function and a value to control the amplitude at the midpoint. The value defined in the midpoint of the set assumes a degree of pertinence of 1. Values that fall between the two limits are observed in the transition zone of the set and assume a degree of pertinence of equal value.

$$\mu_A(x) = \left\{ 1/1 + \left[(x-g)/f \right]^{2h} \right\} \tag{6}$$

where x is the relief orientation value (degrees) in the matrix image; f is the parameter that determines the slope of the curve; g corresponds to the value at the midpoint, which defines the centre point for the function at which $\mu_A(x)$ is 1; and h controls the amplitude at the central point.

The influence of the relief orientation on the risk of fires was programmed in the language Python in ArcGis/ArcInfo 10.2, in which the northern face (O° and 360°) has the highest risk and the southern face (180°) has the lowest risk (supplementary material 2). For intermediate aspects, the fuzzy generalised bell was utilised. The slope of the curve was adjusted to 45°, and a value of 1 was used for amplitude control of the central point (Figure 3d).

The variable proximity to residences was modelled by the fuzzy linear pertinence function, in which the largest euclidean distance was considered for the minimum value in the fuzzy set and the shortest distance for the maximum value. The minimum value produces a degree of pertinence of 0 (min $\mu_A(x) = 0$), and the maximum value is assigned a pertinence of 1 (max $\mu_A(x) = 1$) for $x \in U$ (Figure 3e). This means that A is in the fuzzy set, based on the proximity to residences x in a continuous universe of discourse U.

Fuzzy overlay

In modelling fire risk in a GIS environment, the variables that influence the onset and spread of fire should be combined by an overlap analysis to indicate the potential of a cell of the matrix image for one variable to be a member of each fuzzy set of the remaining variables by multiple input criteria. Thus, the type of overlap indicates the method that enables the data to be combined based on an analysis of the set theory, and not simply combined using a subjective importance ranking. The overlay method selected for the matrix image input was the fuzzy gamma operator, which is an algebraic product of the fuzzy sum operator and the fuzzy product operator; both operators are raised to the power of the gamma coefficient (Eq. 7).

$$\mu_A(x) = \left\{ 1 - \prod_{i=1}^{n} (1-\mu_i) \right\}^{\delta} * \left\{ \prod_{i=1}^{n} \mu_i \right\}^{1-\delta} \tag{7}$$

where μ_i represents the fuzzy association values for i=1, 2, ..., 5; n corresponds to the raster data layer, *i.e.*, the number of variables in the study; and δ is the coefficient with values between 0 and 1.

The coefficient δ was defined by the standard value of 0.9 to achieve the combined effect between the total and the gamma product. The fuzzy gamma enables the increasing effect of the fuzzy sum and the decreasing effect of the fuzzy product to be combined. It establishes the relationships among the various input criteria and does not simply return the value of a single fuzzy set.

The Jenks natural breaks classification was used to discriminate different levels of fire risk, both to minimize each mean deviation of the class (Jenks, 1967) and to determine the best arrangement of values of fire risk in three different classes: low, medium and high.

Measuring the neighbourhood effects by spatial autocorrelation

Statistical analysis of spatial correlation was used to measure the neighbourhood effects of the locations of high-risk of forest fires in the study area and the corresponding land use and occupation class. Given a set of characteristics and an associated attribute, a spatial autocorrelation tool evaluates whether the distribution of the attribute is clustered, dispersed or random. A positive spatial autocorrelation exists if the occurrence of one spatial phenomenon event tends to attract similar events in its neighbourhood, which usually produces a group distribution pattern. If the occurrence of a spatial phenomenon event tends to prevent these events from occurring in the immediate vicinity, it produces a dispersed distribution pattern, and the phenomenon exhibits a negative spatial correlation. Neither of the two extreme types may dominate the distribution, which produces a pattern of relative random distribution. In this case, the spatial correlation is not significant.

Moran's "I" coefficient (Moran 1948 – Equation 8) was adopted to evaluate the neighbourhood effects.

$$\mathrm{I} = \frac{\mathrm{N}}{\sum\sum \mathrm{W}_{ij}} \frac{\sum\sum \mathrm{W}_{ij}\left(\mathrm{X}_i - \mathrm{X}\right)(\mathrm{X}_j - \bar{x})}{\sum(\mathrm{X}_i - \bar{x})^2} \quad (8)$$

where N is the number of geographical units, X_i is the observed value of the variable X for the unit *i*, and W_{ij} are the elements of the normalised matrix of spatial proximity. According to Cliff and Ord (1981), the expected value of Moran's "I" under the assumption that the random variable X is normally distributed is given by Eq. 9:

$$E(I) = I/(1-N) \quad (9)$$

The expected value is always negative and approaches zero as the number of polygons tends towards infinity. The variance is given by Eq. 10:

$$VAR(I) = \frac{N^2 S_1 - NS_2 + 3(\sum\sum W_{ij})^2}{(\sum\sum W_{ij})^2\left(N^2 - 1\right)} \quad (10)$$

where

$S_1 = (1/2)\sum\sum(W_{ij} + W_{ji})^2$ and $S_2 = \sum(\sum W_{ij} + \sum W_{ji})^2$

The normal standard deviation Z, which is based on the mean and variance of Moran's "I", is suitable for significance tests of spatial correlation (Eq. 11).

$$Z = \left[I - E(I)\right]/d_I \quad (11)$$

where d_i indicates the standard deviation of *I*.

Model validation

Many areas of the world frequently affected by fires do not have reliable spatially explicit long-term records of fire occurrence. Global satellite systems are a major source of information for these data-poor regions. To evaluate the accuracy of the proposed fire risk model, were used a database of hotspots from the satellites for fire monitoring in the landscape under the supervision of the National Institute for Space Research (INPE 2019). Database of hotspots from 2001 to 2014 were used to evaluate the frequencies of hotspots in the different risk classes. Due to the dynamic and temporal nature of fire events, this undertaking is considered the starting point for understanding the predictive capacity of the fire risk map.

In this context, the *extract values to point* function was applied to determine the number of hotspots in each fire risk class. To analyse the

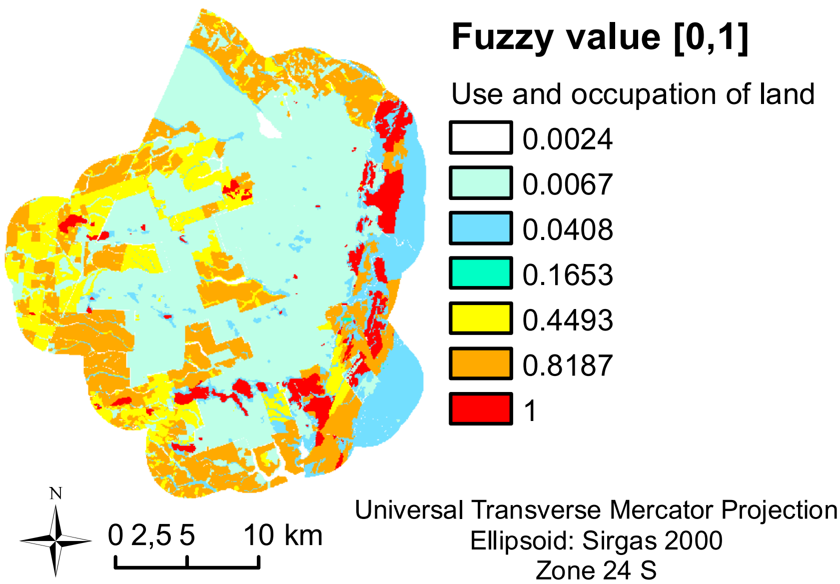

Figure 4. Effect of the fuzzy Gaussian function on fire risk probability in different land use and occupation classes. Lower values in the set are primarily represented by natural forests, and higher values are primarily represented by the pastures, monocultures and native grasslands.

possible differences between the observed and expected frequencies in the number of hotspots and the percentage of area corresponding to each fire risk class, the nonparametric hypothesis test chi-square (X^2) was used (Eq. 12).

$$\chi^2 = \sum_{i,j} \frac{\left(O_{ij} - E_{ij}\right)^2}{E_{ij}} \qquad (12)$$

where O_{ij} is the observed frequency for each class, and E_{ij} is the expected frequency for each class.

RESULTS

The main factor that affects the propagation of a forest fire is the type and characteristics of vegetation, which represent the amount of fuel available for a fire. The results of this study indicated that water courses comprise the class of lowest fire hazard (0.0024), as they are natural barriers against fire (Fig. 4). The natural forest and urban area represent a low risk of fire; for this reason, a value of 0.0067 in the fuzzy set is assumed. Equally insignificant to the risk of fire, the class of Mussununga forest and areas with periodic flooding assumed a risk value of 0.04, whereas sand and oil extraction sites presented a value of 0.16. Forest plantations and natural forest regeneration areas assumed a value of 0.44 in the fuzzy set, and the agricultural crops and pastures assumed a high risk with a value of 0.81, a function of the use of fire in soil preparation and renewal of pasture. Native grasslands was considered to have the highest risk of fire, with a value of 1.

Considering proximity to roads, the concentration of the risk of fire values, as shown in Fig. 5a, primarily corresponds to areas at the wildland - urban interface. As a result of this grouping value, the areas of risk are considerably larger than in more distant areas (Fig. 5b). In the fuzzy set, 45.72% or 3119977 pixels were found to be 0.91 and 1, which indicates that the study area represents a high risk of fire for the variable proximity to roads.

The increased risk of fire determined by the slope was restricted to areas surrounding the reserve (Fig. 5c), with the highest value of the set presenting lower pixel frequencies (Fig. 5d). The highest concentration of pixels was observed for the lowest values, with 49.39% or 2775926 pixels

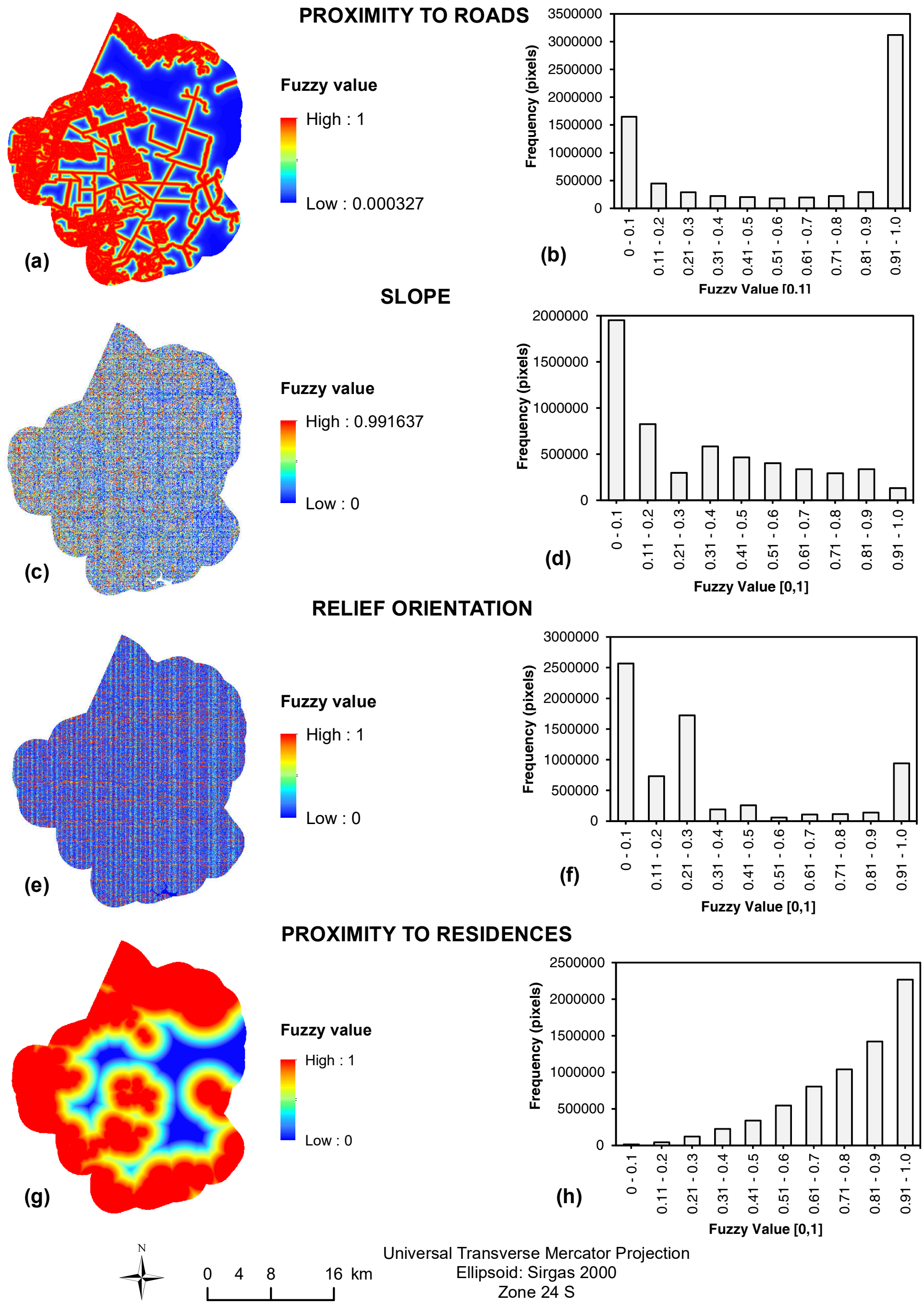

Figure 5. Fuzzy map of the variables proximity to roads (a), slope (c), relief orientation (e), and proximity to residences (g) and the pixel frequency values in the set classified into ten categories for proximity to roads (b), slope (d), relief orientation (f) and proximity to residences (h).

exhibiting a fuzzy value in the range of 0 – 0.2, which indicates that the study area presents a risk of fire that ranges from medium to low for this variable. In this case, the slope of the terrain exerts a minimal influence on the intensity and the direction of fire propagation.

For the relief orientation, the values presented in the histogram (Fig. 5f) showed the highest pixel concentration for the lower values of the set, with 73.57% of the pixels in the fuzzy value range of 0 – 0.3. Although the study area presents a low fire risk, which is associated with the surfaces with low exposure to solar radiation, the results indicate that the highest values in the fuzzy set, in the class of greatest risk (0.91 – 1), correspond to 13.77% of the pixels, which are primarily associated with the north face. Therefore, knowledge of the relief orientation in the forest landscape is important for establishing management plans for areas that are at risk of fire.

The proximity to residences is important in the distribution of forest fires. The modelled risk of fire by the variable revealed an increased risk within the limits of the reserve (Fig. 5g). The grouping of values in the fuzzy set, which were showed by a histogram (Fig. 5h), indicated that the highest values in the set (0.71 – 1.0) represented 69.31% of the pixels. Thus, the results indicate that the variable proximity to residences is the main factor that influences the risk of forest fires in the study area by the distance from the wildland - urban interface.

Risk of forest fire

The risk of forest fire determined by the combination of variables presented areas of greatest risk, especially at the wildland - urban interface (Fig. 6a). Medium-risk areas surround the reserve and are conditioned by the land use and occupation, and internal roads. The lowest risk is represented by the natural Tabuleiro forest areas, where human access is managed or relatively limited. Locations of medium risk and low risk predominate with 38.33 and 33.12%, respectively (Fig. 6b). Although high risk areas have the lowest percentage (28.55%), a significant area is under risk (19,429 ha).

The main regions at high risk are occupied by agricultural cultivation (6,408.55 ha), forestry (5,063.06 ha) and pasture (5,051.37 ha). Note that the natural forest of the reserve is under threat from fire in the native grasslands (1,503.57 ha), primary forest (148.64 ha) and Mussununga forest (139.54 ha), as shown in Table II.

The spatial autocorrelation of the high-risk of forest fire areas indicates a distribution

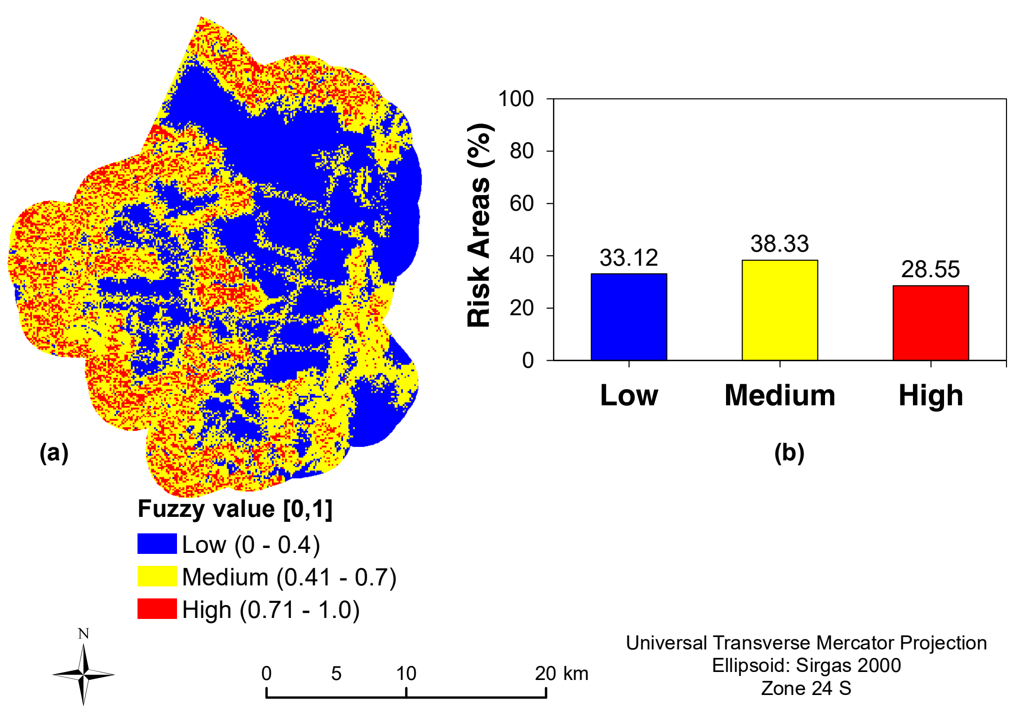

Figure 6. Risk of forest fire in the study area represented by three categories of risk, in accordance with the degree of relevance for the start and spread of fire (a), and the area of risk as a percentage of each category (b).

Table II. Main areas of high risk for the land use and occupation classes in the study area.

Land use and occupation class	Total area (ha)	Area of high risk (ha)	%
Agricultural cultivation	7,974.34	6,408.55	80.36
Forestry	7,091.82	5,063.06	71.39
Pasture	8,302.73	5,051.37	60.84
Native grasslands	3,846.14	1,503.57	39.09
Regeneration	1,223.28	800.08	65.40
Periodically flooded area	5,840.28	197.51	3.38
Primary forest	25,387.32	148.64	0.59
Mussununga forest	2,186.21	139.54	6.38
Total	61,852.12	19,312.32	-

pattern in clusters relative to the classes of land use and occupation, as observed in Table III. The risk of fire is positively spatially autocorrelated, *i.e.*, in adjacent areas of high risk, there is potential for increased risk of fire. An important implication of the results found in this study is that a spatial dependence term to represent the neighbourhood effects is needed to better represent the risk of forest fire.

Model validation

A high number of hotspots were observed in the high-risk class from the years 2001 to 2014. The percentage of hits from the total of hotspots observed in medium and high risk areas is 78%. The best performances were observed in the years 2005, 2011, 2012 and 2014, with 100% of hits (Fig. 7).

Table III. Spatial autocorrelation of the high fire risk in the study area and class corresponding of land use and occupation.

Global Moran's I	Summary
Moran's Index	0.426001
Expected Index	-0.000291
Variance	0.000904
Z-score	14.178807
p-value	< 0.001

The X^2 test showed that there are no divergences between the observed and expected frequencies in relation to the evaluated parameters (Table IV). Therefore, the results were quite proficient in describing the potential delineation of fire risk zones in the study area.

DISCUSSION

In investigating forest fires, the type of vegetation and the differences that can cause changes in the development of fires should be considered. Goldammer (1982) suggested that the natural forest, particularly in moist areas or valleys, works as a natural barrier against fire. Studies by Uhl et al. (1990) in the region of Paragominas, Pará, Brazil, affirmed that protected forests of the humid tropics are not typically at risk of fire, as they preserve high moisture levels. However, in the surrounding grasslands that are employed for cattle pasture, the maximum air temperature may be 10 °C higher than the temperature inside the forest, and the relative humidity decreases from 86 to 51%, which significantly increases the incidence and propagation speed of fire.

An important activity for forest management in the area is to prevent the edges of production forest stands from directly contacting areas of

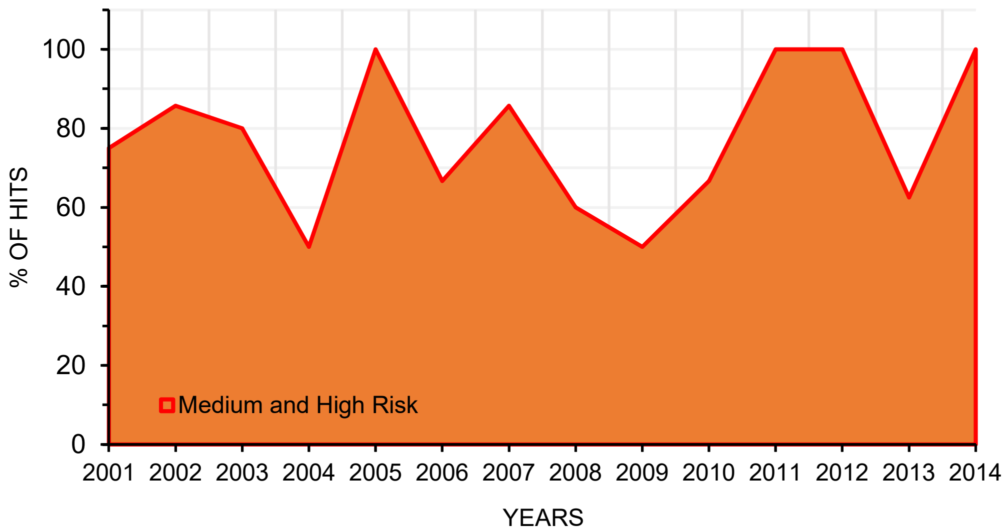

Figure 7. **Percentage of hits from the total of hotspots observed in the medium and high risk classes from 2001 to 2014.**

adjacent pastures or the edges of roads that are usually dominated by grasses, which are highly susceptible to fire. This mitigation can be achieved by ensuring that the edges of forest stands are always protected by permanent corridors composed of fire resistant tree species. These permanent corridors not only improve the appearance of the landscape but also protect and prevent the spread of fire, as they always maintain a greater amount of moisture in their understory.

The role played by the Vale Natural Reserve for the conservation of tropical forests goes far beyond its territorial extension. It assumes the role of the greatest centers of diversity of species of the Atlantic Forest (Thomaz 2010), favored by the great diversity of environments in which this tropical forest developed (Lima & Capobianco 1997).

One of the most intriguing feature of Atlantic Forests is the presence of large forest-grassland ecotone areas. According to De Oliveira & Passacantili (2010), two hypotheses were proposed to explain this occurrence, which occurs also in other brazilian ecosystems: natural origin of the grasslands and anthropic origin. The hypothesis of the anthropic origin of the grasslands permeated the brazilian scientific literature from the twentieth century. For Pillar (2003), which defends the anthropic hypothesis, the use of fire and land use for pasture are the main factors for the occurrence or at least for the maintenance of the ecotone forest-grassland in the Atlantic Forest domain.

A small factor analyzed in relation to the problem of the origin of the savanna islands, within forest areas, is the intensity and frequency of fires as determinants of vegetation type. In an analysis of charred particles, De Oliveira & Passacantili (2010) evaluated the impact of fires on the possible expansion of the grassland vegetation in the study area. According to the authors, the results indicate that, in recent times, fire had a large impact on the reserve, and although it is not the main and determinant factor of the grassland vegetation studied; it can contribute to the process of ecological succession and slow the forest regeneration.

This study also showed that tropical rainforests of the Atlantic Forest region, despite its location being in one the most humid areas of Brazil, where the average annual rainfall exceeds 1500 mm, suffer sporadically with fire. According to Hammond (2006), humid forest

Table IV. Observed and expected frequencies in the number of hotspots and the percentage of area corresponding to each fire risk class by the X^2 test.

Risk class	Observed hotspots	Expected hotspots	% area for each risk class observed	% area for each risk class expected	Total observed
Low	20	26.2323	33	26.7677	53
Medium	37	37.1212	38	37.8788	75
High	41	34.6465	29	35.3535	70
	X^2 parcials				
Risk class	Hotspots	% area for each risk	X^2 value	X^2 tabulated (p<0.05, DF= 2)	
Low	1.4807	1.4511	5.2395^{ns}	5.991	
Medium	0.0004	0.0004			
High	1.1651	1.1418			

ns: not significant.

frequently suffer with fire in the Guianas due to human impacts. Carcaillet et al. (2002) report that in the last 2000 years, in the Amazonia, fires were also present in the paleoenvironmental record associated with anthropic influence. The occurrence of anthropogenic forest fires in humid Amazonia, observed in forests by Nelson (1994), Nelson and Irmão (1998), suggests that without human presence, forest regions would hardly be naturally burned. Most Amazon forests are not expected to burn unless they are first cut and allowed to dry out, because of the high water content of the biomass and dampness of the litter layer. More recent studies in temperate forests have found similar results in large areas that transform from forest to shorter-statured or open-canopy vegetation under altered fire regimes in the face of climatic and land-use change (Paritsis et al. 2015, Tepley et al. 2016).

Mapping fire risk is critical for ecosystem management, including restoration efforts. The results of this study provide a contribution to the understanding of fire ecology in South America and in subtropical forests in general. The main causes of fires in the reserve are related to criminal activity that is associated with the threat of local fauna hunting. Rural property, human accessibility and population density were important determinants of the spatial location of fires, where locations close to roads (<150 m) were generally associated with a higher incidence of fire. There is a strong relationship between points of fire ignition and places of greatest risk in wildland - urban interface.

The influence of roads on the spatial distribution of risk of fire presented similar values in the studies by Rodríguez-Silva et al. (2010) for the frequency of fire at different distances from roads for different road types. Soto (2012) also observed that the risk of fire does not follow a uniform spatial distribution in the trajectory for each type of road network, as the results attributed to the concentration of fire consider additional factors, such as population centres and agricultural and forestry activities in the area of direct influence. These arguments highlight the importance of effective monitoring in areas surrounding roads and along the entire length of BR-101 due to the intense flow of vehicles and proximity to the reserve.

For protection plans, controlled burning in a region of great potential fire risk can be applied to minimise fire potential in the area and reduce the likelihood of fire in adjacent areas due to neighbourhood effects.

Changes in behaviour and lifestyle (*e.g.*, increased recreational activity and urbanization in forest areas) are the main factors that drive the distribution of people in forest areas and the increase in fire events (Badia-Perpinyà & Pallares-Barbera 2006, Mundo et al. 2013, Paritsis et al. 2013). These alterations indicate a potential change in the nature of fire risk in the study area due to the urbanization of rural areas. The results of the predictive model indicate a strong relationship between points of fire ignition and proximity to urban areas. These results provide new insight into the spatial distribution of human-caused fires, as the human factors have received little attention in quantitative risk analysis. According to Rindfuss et al. (2004), the reasons for this lack of attention are diverse, but one of the most important is the difficulty in integrating socioeconomic and biophysical data for spatial analysis.

The proposed fuzzy logic approach demonstrates the predictive ability of the forest fire risk map given the highly dynamic and spatial nature of fires. The observed and expected frequencies of hotspots in the risk classes showed that the fuzzy model is suitable for determining a risk area by Chi-square test. When fire-fighting agency data are present and reliable, a brute-force analysis can be used to verify the best function of pertinence and degrees of pertinence.

The spatial modelling approaches employed here provide useful tools to integrate socioeconomic and biophysical data, not only to analyse characteristics of fire risk, but also to explain the patterns of distribution fire risk. The results indicate the need for control plans and the allocation of resources for protection measures, as well as mitigation of major damage and the effects caused by fire in interface areas. In natural forests with a predicted high risk, measures such as inspection by motorized patrols, allocation of combat resources at strategic points, construction of preventive firebreaks and road construction for rapid access to risk sites are important protective mechanisms that will aid firefighting.

Finally, it is possible to infer that rapid protocols can be developed and expanded to include the representation of local population in assessing the forest sustainability. Although these specific results are not expected to be extended to other regions, fuzzy modelling of the risk of forest fire can be applied in other areas with sufficient information about the factors that can influence in the forest fires events.

CONCLUSIONS

The results reveal an efficient model for estimating the risk of fire; fuzzy modelling efficiently analysed the influence of different variables on the risk of fire in the study area. The method can be employed to evaluate the possible changes in the risk of fire occurrence in response to any type of proposed treatment and changes to the landscape. The forest fire risk model can be expanded to include additional variables that are relevant to the start and spread of fire. The proposed methodology can be adapted to areas of other countries. When these data are available, the same model construction process can be performed and a more accurate distribution of the risk of fire can be obtained.

Acknowledgments

The authors would like to thank the Coordination for the Improvement of Higher Education Personnel (CAPES) and the Research and Innovation Support Foundation of the Espírito Santo (FAPES). Thanks also to the Pos-Graduate Program in Forest Science of the Federal University of Espirito Santo, Vale Natural Reserve and the research group Geotechnology Applied to Global Environment (GAGEN).

REFERENCES

ARGAÑARAZ JP, PIZARRO GG, ZAK M, LANDI MA & BELLIS LM. 2015. Human and biophysical drivers of fires in Semiarid Chaco mountains of Central Argentina. Sci Total Environ 520: 1-12.

ARPACI A, MALOWERSCHING B, SASS O & VACIK U. 2014. Using multi variate data mining techniques for estimating fire susceptibility of Tyrolean forests. Appl Geog 53: 258-270.

BADIA-PERPYNIÀ A & PALLARES-BARBERA, M. 2006. Spatial distribution of ignitions in Mediterranean periurban and rural areas: the case of Catalonia. Int J Wildland Fire 15 (2): 187-196.

BELLMAN RE & ZADEH LA. 1970. Decision making in a fuzzy environment. Manage Sc 17: 141-164.

BOYLAND M, NELSON J, BUNNELL FL & D'EON RG. 2006. Human and biophysical drivers of fires in Semiarid Chaco mountains of Central Argentina. Sci Total Environ 520: 1-12.

CARCAILLET C et al. 2002. Holocene biomass burning and global dynamics of the carbon cycle. Chemosphere, 49: 845-863.

CARVALHO FP, OLIVEIRA JM & MALTA, M. 2014. Exposure to radionuclides in smoke from vegetation fires. Sci. Total Environ 472: 421-424.

CATRY FX, REGO FC, BACAO FL & MOREIRA F. 2009. Modeling and mapping wildfire ignition risk in Portugal. Int J Wildland Fire 18: 1-11.

CHANDLER C, CHENEY P, THOMAS P, TRABAUD L & WILLIAMS D. 1983. Fire in forestry: forest fire behavior and effects. New York: J. Wiley & Sons.

CLIFF AD & ORD JK. 1981. Spatial processes: Models and applications, Pion, London.

DE OLIVEIRA PE & PASSACANTILI MGSB. 2010. Influência antrópica em três ecótonos floresta/campo da Floresta Atlântica do Sudeste do Brasil: análise de micropartículas carbonizadas em solos superficiais. Hoehnea 37 (4): 777-789.

DIAZ-BALTEIRO L & ROMERO C. 2008. Making forestry decisions with multiple criteria: A review and an assessment. Forest Ecol Manag 255: 3222-3241.

EUGENIO FC, SANTOS AR, FIEDLER NC, RIBEIRO GA, SILVA AG, SANTOS AB, PANETO GG AND SCHETTINO VR. 2016. Applying GIS to develop a model for forest fire risk: A case study in Espírito Santo, Brazil. J Environ Manage173: 65-71.

FRANÇA LVG, BRESSANE AS, FÁBIO N, PECHE FILHO A, MEDEIROS GA, RIBEIRO AI, ROVEDA JAF & ROVEDA SRMM. 2014. Modelagem fuzzy aplicada à analise da paisagem: uma proposta para o diagnóstico ambiental participativo. Fronteiras 3(3): 124-141.

GENTRY A, HERRERA-MACBRYDE O, HUBER O, NELSON BW & VILLAMIL CB. 1997. Regional overview: South America. In: Davis SD et al. (Eds), Centres of plant diversity: A guide and strategy for their conservation. Cambridge: WWF/IUCN, p. 269-307.

GOLDAMMER JG. 1982. Forest fires problems in the Federal Republic Germany. In: Nao TV (Ed), Forest fire prevention and control. For Sci, p. 143-147.

GOMIDE FAC & GUDWIN RR. 1994. Modelagem, controle, sistemas e lógica fuzzy. SBA Controle & Automação 4(3): 97-115.

GÜNGÖROĞLU C. 2017. Determination of forest fire risk with fuzzy analytic hierarchy process and its mapping with the application of GIS: The case of Turkey/Çakirlar. Hum Ecol Risk Assess 23(2): 388-406

HAMMOND DS, STEEGE H & VAN DER BORG K. 2006. Upland soil charcoal in the wet Tropical Forests of Central Guyana. Biotropica 39:153-160.

INPE - INSTITUTO NACIONAL DE PESQUISAS ESPACIAIS. 2019. Available at: http://queimadas.dgi.inpe.br/queimadas/bdqueimadas.

IKEMORI F, HONJYO K, YAMAGAMI M & NAKAMURA T. 2015. Influence of contemporary carbon originating from the 2003 Siberian forest fire on organic carbon in PM2.5 in Nagoya, Japan. Sci Total Environ 530-531: 403-410.

JENKS GF. 1967. The data model concept in statistical mapping. International Yearbook Cartogr J 7: 186-190.

JUVANHOL RS, FIEDLER NC, SANTOS AR, PELUZIO TMO, SILVA WB, PINHEIRO CJG & SOUSA HCP. IN PRESS. Machine Learning as a tool for determining fire management units in the Brazilian Atlantic Forest. An Acad Bras Cienc: In press.

KRUEGER T, PAGE T, HUBACEK K, SMITH L & HISCOCK K. 2012. The role of expert opinion in environmental modelling. Environ Model Softw 36: 4-18.

LIMA AR & CAPOBIANCO JPR. 1997. A Mata Atlântica: avanços legais e institucionais para sua conservação.

Documentos do Instituto Socioambiental nº 4. São Paulo, Instituto Socioambiental - ISA.

LOPES AAS, SANTOS SHL, RIOS MAS & SOUZA RO. 2016. Lógica fuzzy como ferramenta para avaliação da degradação ambiental em rios: relação entre os parâmetros DBO/OD. Geintec 6(2):3035-3048.

LUKE RH & McARTHUR AG. 1978. Bushfires in Australia. Canberra: Australian Government Publishing Service.

MACHADO B, MEDEIROS I & RUIZ FILHO R. 2018. Aplicabilidade da lógica fuzzy na gestão de risco de desastres geotécnicos do estado de Santa Catarina. R Gest Sust Ambient 7: 66-85.

MARTIN L, SUGUIO K & FLEXOR JM. 1993. As flutuações de nível do mar durante o quaternário superior e a evolução geológica de “deltas” brasileiros. Boletim. IG-USP. Publicação Especial. 15: 1-186.

MARTÍNEZ J, VEJA-GARCIA C & CHUVIECO E. 2009. Human-caused wildfire risk rating for prevention planning in Spain. J Environ Manage 90:1241-1252.

MARTINS V, MIRANDA AI, CARVALHO A, SCHAAP M, BORREGO C & SÁ E. 2012. Impact of forest fires on particulate matter and ozone levels during the 2003, 2004 and 2005 fire seasons in Portugal. Sci Total Environ 414: 53-62.

MEHTA D, BAWEJA PK & AGGARWAL RK. 2018. Forest fire risk assessment using Fuzzy Analytic Hierarchy Process. Curr World Environ 13(3): 307-316.

MORAN PAP. 1948. The interpretation of statistical maps. J R Stat Soc. Series B 37: 243-251.

MUNDO IA, WIEGAND T, KANAGARAJ R & KITZBERGER T. 2013. Environmental drivers and spatial dependency in wildfire ignition patterns of northwestern Patagonia. J Environ Manage 123: 77-87.

NELSON BW. Natural forest disturbance and change in the Brazilian Amazon. 1994. Remote Sensing Reviews 10: 105-125.

NELSON BW & IRMÃO MN. 1994. Fire penetration in standing Amazon forests. In: Anais IX SBSR p. 1471-1482.

OLIVEIRA S, OHELER F, SAN-MIGUEL-AYANZ J, CAMIA A & PEREIRA JMC. 2012. Modeling spatial patterns of fire occurrence in Mediterranean Europe using Multiple Regression and Random Forest Ecol Manag 275:117-129.

OMENA MTRN, ARAKI EK, SCHIMALSKI MB, TANIWAKI MH & SANTOS PS. 2016. Zoneamento do risco de incêndio florestal para o Parque Nacional de São Joaquim - SC. Biodiv Bras 6(2): 173-186.

PARITSIS J, HOLZ A, VEBLEN TT & KITZBERGER T. 2013. Habitat distribution modeling reveals vegetation flammability and land use as drivers of wildfire in SW Patagonia. Ecosphere 4(5): 1-20.

PARITSIS J, VEBLEN TT & HOLZ A. 2015. Positive fire feedbacks contribute to shifts from *Nothofagus pumilio* forests to fire-prone shrublands in Patagonia. J Veg Sci 26(1): 89-101.

PEIXOTO AL & SILVA IM. 1997. Tabuleiro forests of northern Espirito Santo, Southeastern Brazil. In: Davis SD et al. (Eds), Centres of plant diversity: A guide and strategy for their conservation. Cambridge: WWF/IUCN, p. 369-372.

PILLAR VP. 2003. Dinâmica da expansão florestal em mosaico de floresta e campo no Sul do Brasil. In: Claudino-Sales V (Ed), Ecossistemas brasileiros: manejo e conservação. Fortaleza: Expressão Gráfica, p. 209-216.

RINDFUSS RR, WALSH SJ, TURNER BL, FOX J & MISHRA V. 2004. Developing a science of land change: challenges and methodological issues. PNAS 101(39): 13976-13981.

ROBINSON V. 2003. A perspective on the fundamentals of Fuzzy sets and their use in Geographic Information Systems. T GIS 7: 3-30.

RODRÍGUEZ-SILVA F, JULIO G, CASTILLO M, MOLINA JR, HERRERA MA, TORAL M, CERDA C & GONZÁLEZ L. 2010. Aplicación y adaptación del modelo SEVEIF para la evaluación socioeconómica del impacto de incêndios forestales em la Provincia de Valparaíso, Chile: Agencia Española de Cooperación Internacional para el Desarrollo.

ROSS J, OZBEK M & PINDER GF. 2008. Kalman filter updating of possibilistic hydraulic conductivity. J Hydrol 354 (1-4): 149-159.

SEMERARO T, MASTROLEO G, ARETANO R, FACCHINETTI G, ZURLINI G & PETROSILLO I. 2016. Gis Fuzzy Expert System for the assessment of ecosystems vulnerability to fire in managing Mediterranean natural protected areas. J Environ Manage 168: 94-103.

SHARMA LK, KANGA S, NATHAWAT MS, SINHA S & PANDEY PC. 2012. Fuzzy AHP for forest fire risk modeling. Disaster Prev Manag 2(2):160-171.

SOTO MEC. 2012. The identification and assessment of areas at risk of forest fire using fuzzy methodology. Appl Geogr35 (1-2): 199-207.

SYPHARD AD, RADELOFT V, KEULER NS, TAYLOR RS, HAWBAKER TJ, STEWART SI & CLAYTON MK. 2008. Predicting spatial patterns of fire on a southern California landscape. Int J Wildland Fire: 602-613.

TEPLEY AJ, VEBLEN TT, PERRY GLW, STEWART GH & NACIFY CE. 2016. Positive feedbacks to fire-driven deforestation following human colonization of the South Island of New Zealand. Ecosystems 19 (8): 1925-1344.

TETTO AF, BATISTA AC & SOARES RV. 2012. Zoneamento de risco de incêndios florestais para a Floresta Nacional de Irati, Estado do Paraná, Brasil. Sci For 40(94): 259-265

TORRES FTP, ROQUE MPB, LIMA GS, MARTINS SV & FARIA ALL. 2017. Mapeamento do risco de incêndios florestais utilizando técnicas de geoprocessamento. Floresta e Ambiente, 24: e00025615.

THOMAZ LD. 2010. A Mata Atlântica no estado do Espírito Santo, Brasil: de Vasco Fernandes Coutinho ao século 21. Boletim do Museu de Biologia Mello Leitão 27: 5-20.

UHL C, KAUFFMAN JB & SILVA ED. 1990. Os caminhos do fogo na Amazônia. Ciência Hoje 11(65): 25-32.

VIDAL TF, CHAGAS PF & SOUZA RO. 2015. Aplicação da teoria fuzzy em modelos de transporte de poluentes em rios, para estudar funções de pertinência relacionadas com campos de concentração, em função das características do rio. Fórum Ambiental 11(6):173-187.

WU Z, HE HS, YANG J, LIUA Z & LIANG Y. 2014. Relative effects of climatic and local factors on fire occurrence in boreal forest landscapes of northeastern China. SciTotal Environ 493: 472-480.

WU Z, HE HS, YANG J, LIUA Z & LIANG Y. 2015. Defining fire environment zones in the boreal forests of northeastern China. Sci Total Environ 518-519: 106-116.

ZADEH LA. 1965. Fuzzy sets. Infor Control 8(3): 338-353.

ZADEH LA. 1983. The role of fuzzy logic in the management of uncertainty in expert systems. Fuzzy Set Syst 11(3): 199-227.

SUPPLEMENTARY MATERIAL

Supplementary Appendix. **Database of model variables.**
Table SI. Programming command lines in Python in ArcGIS/ArcInfo 10.2 for spatialization in fuzzy logic of the influence of the relief orientation on the risk of fires.

How to cite

JUVANHOL RS, FIEDLER NC, SANTOS AR, SILVA GF, OMENA MS, EUGENIO FC, PINHEIRO CJG & FERRAZ FILHO AC. 2021. Gis and fuzzy logic applied to modelling forest fire risk. An Acad Bras Cienc 93: e20190726. DOI 10.1590/0001-3765202120190726.

Manuscript received on June 24, 2019;
accepted for publication on May 24, 2021

RONIE S. JUVANHOL[1]
https://orcid.org/0000-0002-0040-3382

NILTON CESAR FIEDLER[2]
https://orcid.org/0000-0002-4376-3660

ALEXANDRE R. DOS SANTOS[2]
https://orcid.org/0000-0003-2617-9451

GILSON F. DA SILVA[2]
https://orcid.org/0000-0001-7853-6284

MOISÉS S. OMENA[3]
https://orcid.org/0000-0002-7735-0899

FERNANDO C. EUGENIO[4]
https://orcid.org/0000-0002-1148-1167

CHRISTIANO JORGE G. PINHEIRO[5]
https://orcid.org/0000-0003-2898-8738

ANTÔNIO CARLOS FERRAZ FILHO[1]
https://orcid.org/0000-0001-9178-918X

[1]Federal University of Piaui/UFPI, Campus Professora Cinobelina Elvas, Av. Manoel Gracindo, s/n, Km 01, Planalto Horizonte, 64900-000 Bom Jesus, PI, Brazil

[2]Federal University of Espírito Santo/UFES, PostGraduate Programme in Forest Sciences, Av. Governador Lindemberg, 316, Centro, 29550-000 Jerônimo Monteiro, ES, Brazil

[3]Federal Institute of Education, Science and Technology of Espírito Santo, Campus Serra, Rodovia ES-010, Km 6,5, Manguinhos, 29173-087 Serra, ES, Brazil

[4]Federal University of Santa Maria/UFSM, 322, Campus Cachoeira Paulista, Rua. Ernesto Barros, 1345, Santo Antonio, 96506-310 Cachoeira do Sul, RS, Brazil

[5]Federal University of Espírito Santo/UFES, Department of Rural Engineering, Alto Universitário, s/n, Guararema, 29500-000 Alegre, ES, Brazil

Correspondence to: **Ronie Silva Juvanhol**
E-mail: roniejuvanhol@gmail.com

Author contributions

JUVANHOL RS: Conceptualization, Investigation, Methodology, Writing – review & editing. FIEDLER NC, SANTOS AR: Participated of the study supervision. DA SILVA GF, PINHEIRO CJG; EUGENIO FC, FILHO ACF: Formal analysis. OMENA MS: Performed the programming computational.