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Gis and fuzzy logic approach for forest fire risk modeling in the Cajamarca region, Peru

Alex Vergara Anticona[a], Candy Ocaña Zúñiga[a*], Alexandre Rosa dos Santos[b], Alexandre Simões Lorenzon[c] and Plinio Antonio Guerra Filho[d]

[a]*Institute of Data Science, Remote Systems and Data Analysis Research Group. National University of Jaén, Jaén. Peru*
[b]*Federal University of Espírito Santo/UFES, Center of Agricultural Sciences, Alegre, ES, Brazil*
[c]*Federal University of Viçosa/UFV, Viçosa, MG, Brazil*
[c]*Federal University of Maranhão/UFMA, Campus Chapadinha, Chapadinha, MA, Brazil*

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A B S T R A C T

Forest fires are a potential threat to life, as they contribute to reducing forest areas, impact on the services we expect from ecosystems, the health of the inhabitants is affected by smoke and the economic costs for the recovery of affected areas is high. The objective of the study is to apply fuzzy logic to model the risk of forest fires in the Cajamarca-Peru region, incorporating variables that represent biological, topographic, socioeconomic, and meteorological factors. The analysis was based on the acquisition, editing and rasterization of the database, application of fuzzy membership functions and image fuzzification, fuzzy superposition and spatial reclassification of forest fire risk. The results obtained show that 71.68% of the area is under very low or medium forest fire risk. However, 28.32% of the study area has a high to very high fire risk, which makes the occurrence of fires susceptible to the lack of rain and water in the soil. It was found that biological, topographic, and socioeconomic factors with their respective variables are directly influenced by meteorological factor variables such as temperature, rainfall and water availability. Fuzzy logic offered flexibility in modeling wildfire risk in the region, proving to be a useful tool for predicting and mapping wildfire risk.

1. Introduction

In the last decades, forest fires have become a great concern in many world regions due to their exponential increase in terms of occurrence and severity, with emphasis on environmental impacts, material and human losses, among others (Gómez-Pazo and Salas, 2017; Westerling et al., 2006). Climate and land use change are considered to be the main factors that contribute to greater occurrence and spreading of forest fires (Díaz-Hormazábal and González, 2016; Rojas, 2013). Adult trees death, air pollution, soil without vegetation cover and propensity to erosion in inclined sites, among others, correspond to the main negative impacts of fires in forest ecosystems (Juárez-Martinez, 2003).

The forest fires risk is the result of constant and variable factors that affect beginning, spreading and difficulty to control the fire. These factors include topography, combustible material and weather availability, among others (Eugenio et al., 2019a; Mota et al., 2019). Chuvieco et al., (2014) mentions that modeling fire risk is important for planning and decision making in the short, medium and long term, aiming to avoid and mitigate adverse effects and environmental impacts of forest fires, especially in remote and most vulnerable areas. The complexity involved to spatially represent variables that allow inferences about forest fires vulnerability requires computational models and important tools of Geographic Information Systems (GIS) (Owen and Daskin, 1998; Saaty and Vargas, 2012; Teixeira et al., 2018). In this context, a lot

* Corresponding author.
E-mail address: candy.ocana@unj.edu.pe (C. O. Zúñiga)

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of mathematical models designed for the analysis of forest fires risk have been developed based on scientific and technological advances, which are available for use due to GIS implementations (Paëgelow et al., 2004).

GIS correspond to computational systems involving storage, analysis and visualization of geographic data (Burrough and McDonnell, 1998), which are essential for planning and generation of spatial information, mainly forest fires risk modeling (Eugenio et al., 2019b, 2019a, 2016a, 2016b; Mota et al., 2019; Santos et al., 2017, 2020). In a GIS, spatial and non-spatial data can be combined by mathematical and statistical models to simulate complex scenarios in order to support decision making (Teixeira et al., 2018). A lot of scientific works report the combining techniques, advantages and applications of artificial intelligence with GIS (Teixeira et al., 2018; Vieira et al., 2018). Multi-Criteria Analysis (MCA), for instance, allows to solve spatial problems involving various criteria and local candidates for a particular use (Aghajani Mir et al., 2016; Cortina and Boggia, 2014; Elaalem et al., 2010; Jiang and Eastman, 2000; Joss et al., 2008; Lewis et al., 2015; Oldeland et al., 2010; Phillips et al., 2011; Qiu et al., 2013; Santos et al., 2017; Teixeira et al., 2018; Tervonen et al., 2015; Triepke et al., 2008; Vieira et al., 2018). MCA is based on Boolean logic and Weighted Linear Combination (WLC) techniques. In Boolean logic, variables assume only 0 and 1 (true and false) values. However, WLC standardizes continuous values on a numerical scale by combining the criteria through weighted average (Jiang and Eastman, 2000; Santos et al., 2017; Teixeira et al., 2018). Unfortunately, Boolean logic and WLC rarely describe natural phenomena faithfully, especially when modeling involves a large number of variables (Jiang and Eastman, 2000; Santos et al., 2017).

Fuzzy logic constitutes an alternative for resolving MCA flaws (Santos et al., 2017). (Zanella et al., 2013). Zadeh (1965) developed the theory of fuzzy sets, defining it as the method for expressing subjective information in numerical language, such as uncertain and qualitative information usually found in nature (Silvert, 2000). In this sense, Fuzzy Logic stands out when modelling human reasoning in an approximate way to manipulate information from an uncertain environment and provide robust responses concerning the studied phenomena (Teixeira et al., 2018). In Fuzzy logic, true values assigned to variables can be any real number between 0 (corresponding to the false value) and 1 (corresponding to the true value) (Santos et al., 2017). Thus, Fuzzy logic enables conditions to treat information following natural reasoning rules (Bilobrovec et al., 2004; Silva and Lima, 2009). Its main applications concern risk mapping and environmental impacts (Álvarez, 2000; Chen et al., 2001; Juvanhol, 2014; Santos et al., 2017, 2020, 2018; Teixeira et al., 2018; Vadrevu et al., 2010; Vieira et al., 2018; Wang et al., 2011). The fuzzy logic integration with geographic information systems has been widely used in recent years ((Vadrevu et al., 2010). On the other hand, knowing the nature of the variables that are used to model forest fires risk, in recent years several authors have adopted fuzzy logic as a methodology for this purpose due to the reliability of the results obtained and the robustness provided by fuzzy logic for this subject, as can be seen in the works of Agarwal et al., (2013); Dieu et al., (2017); Erdin and Çağlar, (2021); Garcia-Jimenez et al., (2017), approach fuzzy logic for forest fires studies and all get reliable results. Also studying the forest fires risk, but using a different methodological approach, Abedi Gheshlaghi et al., (2020); Eskandari, (2017); Güngöroğlu, (2017); Medrano, (2017) implement fuzzy logic with other techniques such as analytical networks and AHP hierarchy to model forest fires risk.

In this sense and knowing that the main losses associated with forest fires are related to agricultural production, forest losses, CO2 emissions and threats to health, the main objective of this study was to apply Fuzzy logic to model forest fires risk in Cajamarca region, Peru.

2. Material and methods

2.1. Study area

Study area corresponds to the Amojú river basin, which is located in Jaén province and belongs to Cajamarca region, Peru. The aforementioned basin is composed of a lot of mountains that delimit it, and is very important as it covers territories of Pirias, Huabal, Bellavista and Jaén districts, and during its course it supplies an estimated population of 80,000 inhabitants, who use the water for their agricultural activities and human consumption (Corro and Tafur, 2014; Peña et al., 2007). It has an area of 354.52 km² and is located between 05º 41' and 05º 45' S latitude and 78º 40' and 78º 46' W longitude. The basin's relief ranges from 395 to 3,178 m above sea level. Climate is dry with an average annual temperature ranging from 14 to 33°C. The average annual rainfall varies from 712 to 1,222 mm, with a dry period from May to October and a highest rainy one between October and April (Fig. 1).

2.2. Methodological steps

The used model in this study combines Fuzzy logic and remote sensing. The Fig. 2 shows the Flow chart of the followed procedure including:

1. Database acquisition, editing and rasterization.
2. Application of Fuzzy membership functions and images fuzzification.
3. Fuzzy overlay.
4. Spatial reclassification of forest fires risk.

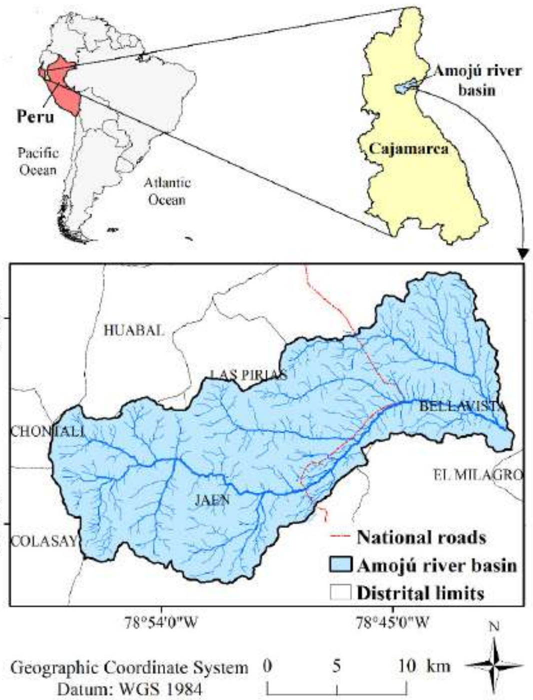

Fig. 1. Location map of the study area

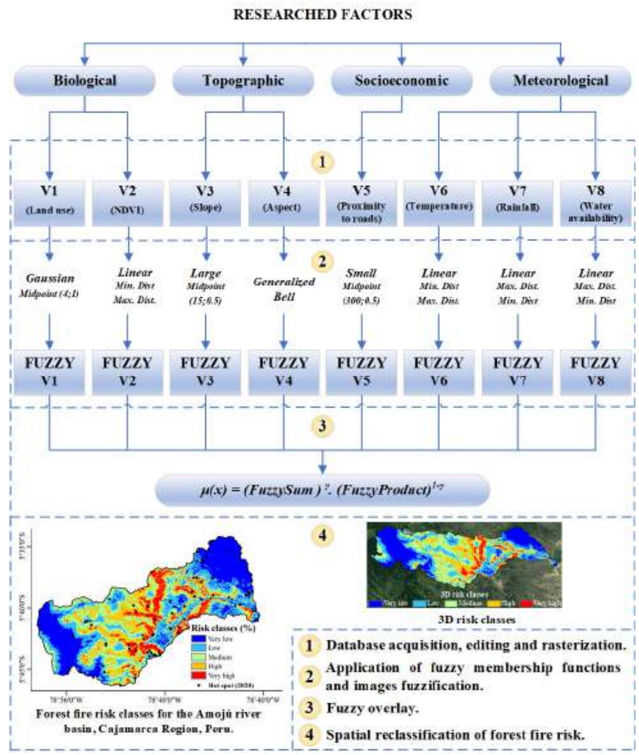

Fig. 2. Employed methodology

2.2.1. Database acquisition, editing and rasterization

Chuvieco et al. (2007) mention that to understand the forest fires risk, both the danger and the vulnerability of occurrence must be considered, in addition, it is known that the onset, spread and intensity depend on factors such as vegetation, topography, weather conditions and combustible materials (Silva et al., 2016). In this sense, the database used in the investigation included 04 types of factors with their respective variables that are related to the forest fires occurrence, presented as a) biological factors (land use and Normalized Difference Vegetation Index - NDVI), b) topographic (slope and aspect), c) socioeconomic (proximity to roads) and d) meteorological (temperature, rainfall and water availability). Database acquisition, as well as editing and rasterization of each variable according to its respective factor type was carried out in a GIS environment according to the following methodological procedures:

a) Biological factor

Vegetation, depending on structure, spacing and senescence, along with land use, influence the forest fires spread (Eugenio et al., 2019a, 2016a) with emphasis to the following variables:

Variable 1 (V1) – Land use: land use matrix image was generated by supervised classification technique employing the maximum likelihood algorithm (Lillesand and Kiefer, 1994), which was fed with Landsat 8 satellite orbital images (OLI sensor) from January 2019. Land use classes were based on the work proposed by Corine Land Cover and adapted for Peru (Chichipe et al., 2017; Trigoso et al., 2020), resulting in seven macroclasses adapted to the reality of the study area, corresponding to continuous urban area, high dense forest, low open forest, pastures, bare land, transient crops and water. The classification accuracy was validated using the Kappa coefficient (De León Mata et al., 2014; Vargas-Sanabria and Campos-Vargas, 2018), which were greater than 70%, as established by Jensen (1986). This evaluation considers all elements of the error matrix, instead of just those that belong to the main diagonal or the sum estimates of marginal rows and columns (Santos et al., 2010b). For this study, an accuracy of 92% was obtained, considered optimal, as Jensen, (1986) indicates for a land use classification to be accepted, the Kappa coefficient must be greater than 70%.

Variable 2 (V2) – NDVI: the NDVI variable indicates the amount of plant material present in the study area. Considering the fact that different types of vegetation have different chemical components, and when in contact with fire they become combustible material (Alavanja and Bonner, 2012; ILLERA et al., 1996; Kayet et al., 2020), these materials can determine both the beginning and forest fires spread. The acquisition, correction and resampling of NDVI images were based on Figueira Branco et al. (2019) and Silva et al. (2021) methodological steps. Thus, 2000-2019 product MOD13Q1 from Terra satellite (MODIS sensor) has been used. It presents 16 day temporal resolution and 250 meter spatial resolution (Didan, 2015), being made available at no cost by NASA website. In addition, the product is available as a compressed file in .hdf format (hierarchical data format), consisting of seven files, namely: NDVI image, EVI image, VI Quality image, Pixel Reliability image and reflectance images (Bands 1, 2 and 3). VI Quality and Pixel Reliability images were used to extract “spurious” pixels from NDVI images. The corrected NDVI images were converted to 30 m spatial resolution using the GIS function entitled "resampling”.

b) Topographic factor

Sloping relief with higher solar radiation incidence may contribute to forest fires occurrence (Eugenio et al., 2016a, 2016b, 2019b), whose variables correspond to:

Variable 3 (V3) – Slope: the surface slope is a variable that directly influences the direction and speed of fire propagation (Ajin et al., 2016; Gil, 2020; Jaiswal et al., 2002; Novo et al., 2020), slope matrix image was processed using GIS function titled “slope”. It received as input the pre-processed SRTM Digital Elevation Model (Shuttle Radar Topography Mission) with a 30 m spatial resolution. This data is available on the United States Geological Survey website (USGS). Subsequently, slope matrix image was reclassified into six relief classes, namely: flat, smoothly wavy, wavy, strong wavy, mountainous and craggy (Francelino et al., 2012). This process was performed with the GIS “reclassify” function. Subsequently, using the GIS function "reclassify", the slope matrix image was reclassified into six relief classes, as proposed by EMBRAPA, (1979): flat, smoothly wavy, wavy, strong wavy, mountainous and craggy (Francelino et al., 2012; Santos et al., 1995).

Variable 4 (V4) – Aspect: the aspect variable has great influence on forest fires risk because it indicates the amount of solar energy each area receives, directly influencing the beginning and propagation of forest fires (Adab et al., 2013; Ghobadi et al., 2012). The continuous aspect matrix image was derived from SRTM Digital Elevation Model using "Aspect" GIS function. Subsequently, the continuous aspect matrix image was reclassified into a discrete matrix image with nine spatial classes defined as flat, north, northeast, east, southeast, south, southwest, west and northwest (Santos et al., 2010a).

c) Socioeconomic factor

Socio-economic factors such as the road network can serve as both barriers and starting points for forest fires, in this sense, the selected variable is presented below:

Variable 5 (V5) – Proximity to roads: Considering most forest fires are caused by anthropogenic factors, the road network is understood as a variable that can determine the beginning of forest fires (Cipriani et al., 2011; Leal et al., 2019). Study area road network, including urban and interurban roads, was obtained from the Open Street Maps website. To generate the matrix image of proximity to roads, firstly, the GIS function entitled "buffer" was used, having as input the road network vector feature. An area of influence of 100 m (buffer) around roads was established according to (Jaiswal et al., 2002), due to greater displacement of vehicles and people in this range. Finally, the proximity to roads was obtained by the GIS function entitled "Euclidean distance", which calculates the closest distance in a straight line between two points, and is represented by the center of their corresponding cells. On a plane, the distance between points $A(X_a, Y_a)$ and $B(X_b, Y_b)$ is given by Pythagorean theorem (Louzada et al., 2010; Santos et al., 2017; Teixeira et al., 2018).

d) Meteorological factors

Given the water and energy importance in the soil-plant-atmosphere system and its influence on forest fires occurrence, the following variables and methodology were applied:

Variable 6 (V6) – Temperature and Variable 7 (V7) – Rainfall: Both rainfall and temperature of the study area are variables that directly influence the forest fires risk, since areas with higher temperatures and low precipitation are more prone to the start and spread of fires (Costa et al., 2011; Koutsias et al., 2013; Urrutia-Jalabert et al., 2018). Considering there are not enough meteorological stations within the study area for the generation of the monthly matrix image of temperature and precipitation, the 1970 to 2000 monthly matrix images of temperature and rainfall (January 2020 released version), with 30 s (1 km²) spatial resolution that have been used were obtained from WorldClim database (http://www.worldclim.org) version 2.1. Afterwards, matrix images were cut, reprojected and resampled (spatial resolution of 30 m) by “extract by mask”, “reproject coordinates” and “resampling” GIS functions, respectively.

Variable 8 (V8) – Water availability: The water availability for the study area is a determining variable for the propagation and initiation of a forest fires, because as the water availability decreases, the risk increases (Vilchis-Francés et al., 2015), in this sense, water availability matrix image was generated according to agroclimatological water balance proposed by Thornthwaite and Mather (1955). Data was obtained from WorldClim (http: //www.worldclim .org), corresponding to 1970-2000 matrix images of average monthly temperature, potential evapotranspiration and water capacity, which were processed by "BHCgeo" plugin (Cruz et al., 2013), available in QGIS software.

2.2.2. Application of Fuzzy membership functions and images fuzzification

Due to the fact there is no method that indicates which fuzzy membership function best suits each variable (Feizizadeh et al., 2013; Kamran et al., 2014), the fuzzy selection membership functions for each of variables used in this study was performed based on the behavior of each one of them in cases of fire, according to the consulted literature and the researchers' experience, which is a key factor in studies using Fuzzy Logic. Thus, the greatest risk of fire was indicated by the real value of 1, while the null risk was indicated by the real value of 0.

Variable 1 (V1) – Land use: land use matrix image was reclassified according to the influence of each class on fire risk, with aid of "reclassify" GIS function. In this context, assigned value to each class was defined according to type and characteristic of vegetation as well as the critical thinking of researchers and environmentalists. Finally, the land use reclassified image was fuzzified using the Fuzzy Gaussian membership function (Table 1 and Fig. 3a).

Table 1
Land use reclassification of classes proposed by Corine Land Cover and adapted for Peru.

Land Use Classes	Reclassified Value
Continuous Urban Area	1
High dense forest	2
Low open forest	3
Pastures	4
Bare land	5
Transient crops	6
Water	7

The Fuzzy Gaussian function defines a normal distribution around a midpoint, which is indicated by the slope value of the curve ranging from 0.01 to 1. The reclassified variable ranging from 1 to 7, had a midpoint value of 4 and slope value of 0.06 (adjusted) in the function (Fig. 3a).

Variable 2 (V2) – NDVI: in the study area there is a wide variety of wood species with different chemical components that, when in contact with fire or interacting with other factors, can trigger a forest fire. Therefore, for this study it was understood that the vulnerability to forest fires occurrence increases as NDVI is higher. In this sense, the continuous matrix image of NDVI was fuzzified using the Ascending Linear Fuzzy membership function (Fig. 3b).

Variable 3 (V3) – Slope: higher slope areas are more vulnerable to forest fires occurrence than flat areas. In this sense, the continuous matrix image of slope was fuzzified using the Large Fuzzy membership function (Fig. 3c). To adjust the membership function, the input values of slope were defined according to scientific studies that addressed its influence on the behavior of fire (Chandler et al., 1983; Juvanhol, 2014). In this context, a slope value of 15° at midpoint and a propagation value of 4 (adjusted) in function were considered for better representation of slope influence (Fig. 3c).

Variable 4 (V4) – Aspect: the reclassified matrix image of aspect was fuzzified using the Generalized Bell Fuzzy membership function. This fuzzification defines a bell-shaped distribution around the indicated midpoint, with a value to control the spreading amplitude of the function at midpoint. The defined value at the midpoint of the set assumes a degree of relevance equals to 1. Values between limits are in the transition zone of the set and assume a pertinence degree corresponding to the same value. To adjust the membership function, the North face (0° and 360°) was considered to be at the highest risk, while the South face (180°) was at the lowest. Fuzzy Generalized Bell was used for intermediate aspects. The curve slope was set at 45° and amplitude control at the central point set to 1 (Fig. 3d).

Variable 5 (V5) – Proximity to roads: areas located closer to the road network are more prone to forest fires occurrence than areas located further away. In this sense, the Euclidean distance matrix image was fuzzified using the Small Fuzzy membership function. The entry values were based on scientific studies developed by Soto, (2012) who addressed forest fires occurrence in relation to the distance of various road types. In this context, a distance value of 300 m to the road network at midpoint and a curve slope value of 6 (adjusted) in the function were defined so that shorter distances assume a greater degree of relevance in the Fuzzy set (Fig. 3e).

Variable 6 (V6) – Temperature: vulnerability to forest fires occurrence increases as temperature is higher. In this sense, the continuous matrix image of temperature was fuzzified using the Ascending Linear Fuzzy membership function (Fig. 3f).

Variable 7 (V7) Rainfall: vulnerability to forest fires occurrence increases as rainfall decreases. In this sense, the continuous matrix image of rainfall was fuzzified using the Descending Linear Fuzzy membership function (Fig. 3g).

Variable 8 (V8) – Water availability: vulnerability to forest fires occurrence increases as water availability decreases. In this sense, the continuous matrix image of water availability was fuzzified using the Descending Linear Fuzzy membership function (Fig. 3).

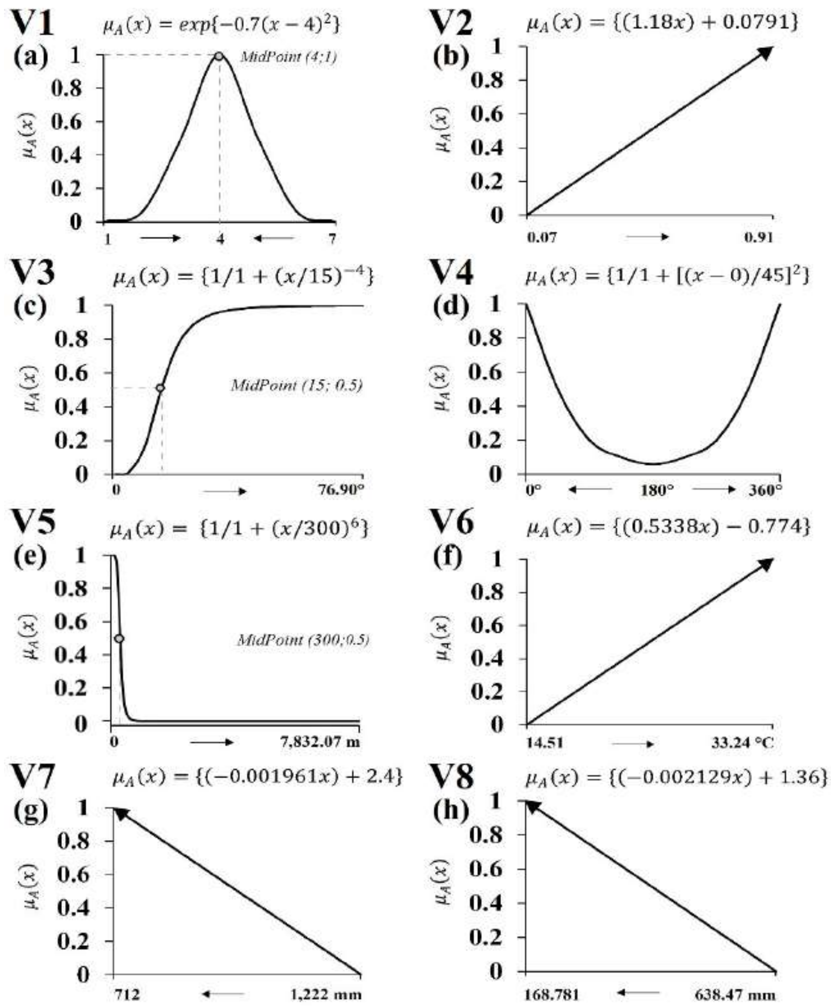

Fig. 3. Fuzzy membership function diagrams. (a) V1 – Land use – Fuzzy Gaussian; (b) V2 – NDVI – Fuzzy Linear; (c) V3 – Slope (º) – Fuzzy Large; (d) V4 – Aspect (º) – Fuzzy Generalized Bell; (e) V5 – Proximity to roads (m) – Fuzzy Small; (f) V6 – Temperature (ºC) – Fuzzy Linear; (g) V7 – Rainfall (mm) – Fuzzy Linear; (h) V8 – water availability (mm) – Fuzzy Linear.

2.2.3. Fuzzy overlay

After applying Fuzzy membership functions to variables used in modeling forest fires risk, the variables were combined by an overlay analysis to indicate the possibility that cells from a certain variable (matrix-image) belong, in fact, to another fuzzy set (variable) according to multiple entry criteria. Thus, overlay indicates the method that allows data to be combined based on the fuzzy set theory analysis (Juvanhol, 2014; Santos et al., 2017). The chosen overlay method was fuzzy gamma, which is an algebraic product of the fuzzy sum and fuzzy product, both raised to power of the gamma coefficient:

$$\mu(x) = \{1 - \prod_{i=1}^{n}(1-\mu_i)\}^{\delta} * \{\prod_{i=1}^{n}\pi_i\}^{1-\delta} \tag{1}$$

in which μi denotes the fuzzy membership values for i = 1, 2, … ,5; n denotes the total amount of variables in the study (number of raster images); and δ denotes a coefficient value between 0 and 1. The δ coefficient was defined according to the standard value of 0.9, in order to achieve the combined effect of total and gamma product. Fuzzy gamma allows to combine the growing effect of the fuzzy sum and the diminishing effect of the fuzzy product. As a result, it establishes the relationships among input criteria, not simply returning the value of a single fuzzy set (Juvanhol, 2014; Santos et al., 2017).

2.2.4. Spatial reclassification of forest fires risk

In this step, "reclassify" GIS function was applied to continuous matrix image of forest fires risk, using the optimization method proposed by Jenks to represent very low, low, medium, high and very high classes. Jenks optimization method, also known as Jenks natural breaks classification method, is a data clustering method designed to determine the best arrangement of different classes. This is done by minimizing average deviation within classes, while maximizing the average deviation among classes (Jenks, 1967; McMaster, 1997; Santos et al., 2017). Subsequently, the risk classes were also presented in 3D image, since this type of image provides a better understanding of results obtained in the study area (Kirschenbauer, 2005; Schmidt, 2012).

3. Results

The representative variables of Amojú river basin is shown in Fig. 4. The biological factors are represented by land use and NDVI variables (Fig. 4a and 4b), topographic factors by slope and aspect variables (Fig. 4c and Fig. 4d), socioeconomic factors by proximity to roads variable (Fig. 4e) and meteorological factors by the variable's temperature, rainfall and water availability (Fig. 4f, 4g and 4h).

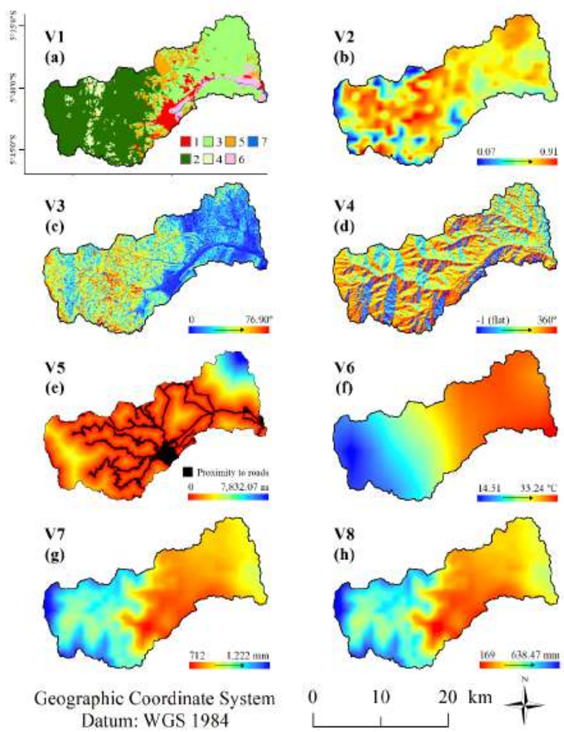

Fig. 4. Representative variables of Amojú river basin, Cajamarca region, Peru. (a) V1 – Land use, (b) V2 – NDVI, (c) V3 – Slope, (d) V4 – Aspect, (e) V5 – Proximity to roads, (f) V6 – Temperature, (g) V7 – Rainfall and (h) V8 – Water availability

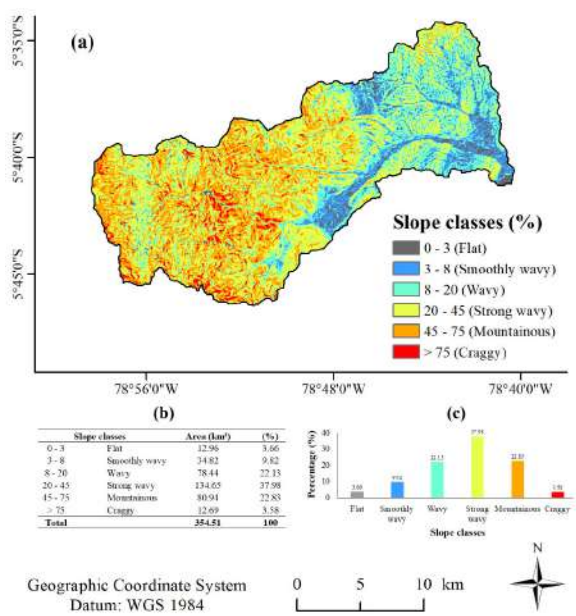

Fig. 5. Slope of Amojú river basin, Cajamarca region, Peru. (a) Map with slope classes, (b) Area (km²) and percentage (%) per class, (c) Distribution of slope classes (%)

In Fig. 5, slope of Amojú river basin is presented, with emphasis on the slope classes (Fig. 5a) and their respective area and percentage (Fig. 5b), as well as distribution (Fig. 5c). The result of applying the Fuzzy membership functions selected for each of variables is shown in Fig. 6, land use (Fig. 6a), NDVI (Fig. 6b), slope (Fig. 6c), aspect (Fig. 6d), proximity to roads (Fig. 6e) temperature (Fig. 6f), rainfall (Fig. 6g) and water availability (Fig. 6h).

Fig. 6. (a) V1 – Land use, (b) V2 – NDVI, (c) V3 – Slope, (d) V4 – Aspect, (e) V5 – Proximity to roads, (f) V6 – Temperature, (g) V7 – Rainfall and (h) V8 – Water availability. Fig.7. (a) Risk classes and hot spots, (b) Risk classes in 3D representation, (c) Hot spots, area (km²) and percentage of study area by class, (d) Percentage of study area by risk class.

The spatial relationship between risk classes and land use in Amojú river basin, Cajamarca region, Peru is also presented in Table 2.

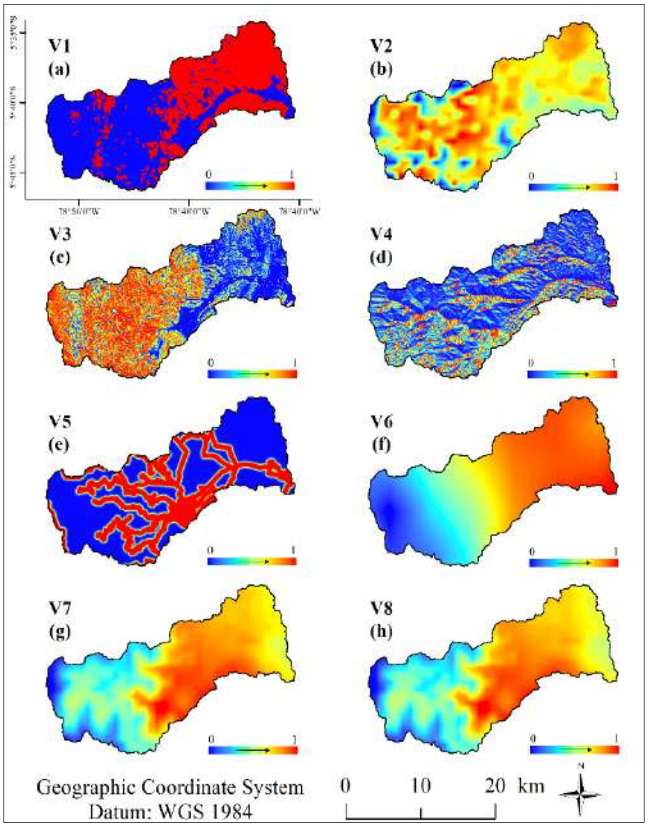

Fig. 6. Fuzzified images of variables used

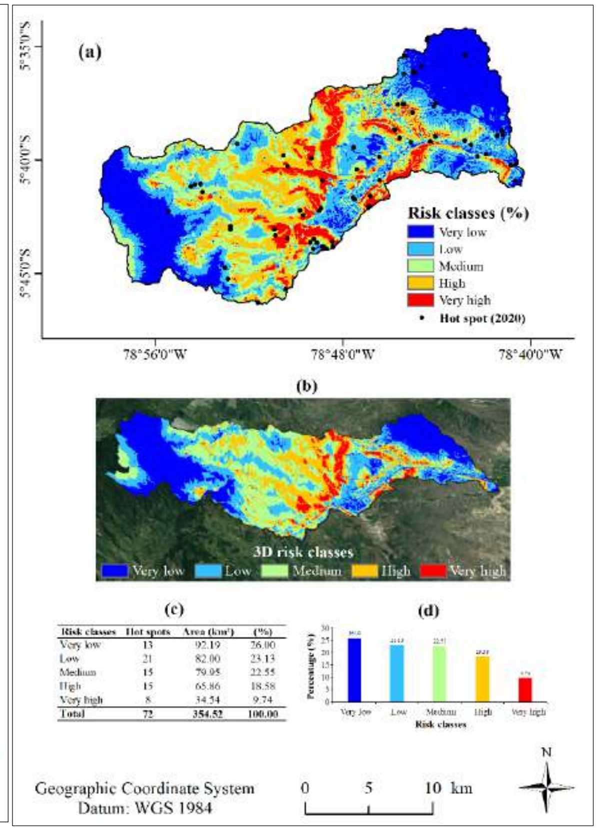

Fig. 7. Forest fires risk for Amojú river basin

Table 2

Spatial relationship between forest fires risk classes and land use in Amojú river basin.

Land use classes	Forest fires risk classes (%)				
	Very low	Low	Medium	High	Very high
Continuous Urban Area	5.48	12.03	4.25	0.54	0.40
High dense forest	42.61	42.63	56.67	55.22	6.40
Low open forest	45.56	26.72	20.78	24.94	52.60
Pastures	0.52	4.65	4.72	7.89	4.66
Bare land	2.05	5.10	8.82	10.56	35.81
Transient crops	3.20	8.42	4.63	0.83	0.11
Water	0.59	0.45	0.13	0.01	0.02
Total			**100**		

Table 3 shows the relationship between forest fire risk classes and slope classes in the study area. It was found that 59.87 % of the very high risk is found in the steep undulating slope class.

Table 3
Spatial relationship between forest fires risk classes and slope in Amojú river basin, Cajamarca region.

Slope classes	Forest fires risk classes (%)				
	Very low	Low	Medium	High	Very high
Flat	8.25	5.05	0.89	0.21	0.03
Smoothly wavy	14.30	16.67	7.64	1.50	0.20
Wavy	28.35	23.91	20.21	18.46	10.31
Strong wavy	31.32	30.56	39.46	45.33	59.87
Mountainous	15.51	20.65	27.17	29.53	26.47
Craggy	2.28	3.16	4.63	4.97	3.12
Total			**100**		

The relationship between the aspect of the terrain and the forest fire risk classes shows that the very high risk class is found in the northeast aspect zones with 21.60% and the greatest amount of areas with very low risk is found in the east aspect class with 18.55%, thus corroborating that the aspect of the terrain has a direct influence on the phenomenon in question because it is related to the amount of solar radiation that is received in these parts of the terrain (Table 4).

Table 4
Spatial relationship between forest fires risk classes and aspect in Amojú river basin, Cajamarca region

Aspect classes	Forest fires risk classes (%)				
	Very low	Low	Medium	High	Very high
Flat	4.78	6.00	4.47	6.49	12.50
North	3.77	5.40	5.09	9.64	15.08
Northeast	13.59	15.59	14.67	19.49	21.60
East	18.80	19.04	18.45	15.92	12.62
Southeast	18.55	18.25	18.45	13.24	10.39
South	13.79	13.28	14.13	11.98	6.24
Southwest	10.75	7.63	9.66	6.82	3.59
West	8.94	7.07	7.61	6.13	4.26
Northwest	7.04	7.74	7.48	10.29	13.72
Total			**100**		

4. Discussion

When modeling forest fires risk, it is necessary to consider biological, topographic, socioeconomic and meteorological factors, once their related variables, such as land use, NDVI, slope, aspect, proximity to roads, temperature, rainfall and water availability (Fig. 4), can directly or interactively influence the occurrence of fires. In this context, several authors (Barlow et al., 2012; Linn et al., 2012; Paz et al., 2011; Torres et al., 2017) report the importance of those variables in the beginning and spreading of fire.

The spatial relationship between forest fires risk classes and land use evidenced that bare lands and low open forest present the highest percentage for very-high fire risk, whose values correspond to 35.81 and 52.60, respectively (Table 2). Bare land and low open forest are mainly represented by xerophytic vegetation, which corresponds to a combustible material with high ignition power due to its suitability to long periods of drought and high temperatures. Both land use classes have been mentioned by other authors (Briones, 2001; Hoinka et al., 2009; Pereira et al., 2005; and Schoennagel et al., 2004) concerning their importance to forest fire. As reported by literature (Armenteras-Pascual et al., 2011; Bodi et al., 2012; and Juvanhol, 2014), water, transient crops and continuous urban areas behave as barriers to fire, which corroborates their respective values of 0.02, 0.11 and 0.40% in the very-high forest fires risk class.

Among studied variables, NDVI stands out as the closer to 1 the greater the vegetation or biomass vigor (Fig. 4b and Fig. 6b). A lot of authors report the relationship between NDVI and other variables (Ribeiro et al., 2008; Torres et al., 2014). Thus, literature corroborates results found in this study, once the quantitative values of NDVI may indicate the propensity of combustible material to ignite in situations of high temperature (Fig. 4f and Fig. 6f), low rainfall (Fig. 4g and Fig. 6g) and low water availability (Fig. 4h and Fig. 6h). Authors like (Kayet et al., (2020); Michael et al., (2021) corroborate results obtained in this research, as they indicate that NDVI acts as an indicator of combustible material due to chemical composition of different types of vegetation, also Burry et al., (2018) state this index is related to soil cover, plant productivity and indirectly to rainfall and temperature.

In Amojú River basin, 82.94% of the study area is represented in conjunctions by wavy, strong wavy and mountainous slope classes, while 3.58% corresponds to craggy slope (Fig. 5b and 5c). Regarding forest fires risk classes, the results obtained indicate the very high risk is located in a larger area on wavy, strong wavy and mountainous slopes. Presented results corroborate those found by other authors (Briones, 2001; Ganteaume and Jappiot, 2013; Muñoz, 2000; Ramiirez, 2017) who mention that slope directly influences forest fires propagation and speed, with a stronger effect in steeper areas.

The different relief orientations receive different amounts of solar radiation when compared to nearby flat areas in the same time of the year (Torres and Machado, 2008). In this context, results from applying Fuzzy membership function to aspect variable were similar to those found by Adab et al. (2011), Neto et al. (2016) and; Torres et al. (2014). Thus, the highest Fuzzy set values for fire risk occurred in sites facing Northeast, North and Northwestern, whose percentage values for very high fire risk correspond to 21.60, 15.08 and 13.72, respectively.

According to other authors (Martínez et al., 2008; Tian et al., 2013; Torres et al., 2014), the road network strongly relates with fire beginning because surrounding combustible material has greater likelihood of ignition (Fig. 4e and Fig. 6e) due to anthropogenic causes. In this sense, this behavior is confirmed by obtained results once the most vulnerable areas to forest fires occur close to the road network.

According to results (Fig. 7), 71.68% of Amojú river basin presents very low to medium forest fires risk. However, 28.32% of study area is under high to very high fire risk (Fig. 7a and 7b), which is strongly influenced by rain occurrence (Fig. 4g) and water availability in the soil (Fig. 4h). These statement is corroborated by Adámek et al. (2015).

The modeling of forest fires risk can contribute towards protection measures and fire-fighting assistance, such as indicate suitable places to install of observation towers, guide motorized patrol inspection, allocation of combat resources at strategic points, construction of preventive firebreaks, construction of fast access roads to risky places, among other measures. Since this study provides information concerning forest fires risk for study area, competent authorities can plan and better manage these events, as indicated by Cruz Espíndola et al., (2017) which mentions that forest fires risk models contribute to the planning of fire management strategies, such as fire prevention, control and fighting, thus ensuring resources are directed to areas with greater probability or danger, or where fire must be reintroduced for conservation, restoration or forestry purposes.

The proposed modeling by the present study is efficient; whose employment defines vulnerable areas to forest fires occurrence. At the same time, it is feasible for representing and interpreting fire as a natural phenomenon. Thus, this modeling helps to reduce rework and flaws, presenting itself as flexible and versatile approach that can be expanded to incorporate other variables as well as environmental, social, economic and political constraints, similar results were obtained by Juvanhol, (2014), which in its study also models forest fires risk using Fuzzy logic and obtains good results that indicate that its model is efficient. Soto, (2012) also mentions the construction of fuzzy-based multicriteria models using GIS provides better estimates in forest fire studies, while Abedi Gheshlaghi et al., (2020); Eskandari, (2017), Sharma et al., (2012) indicate Fuzzy logic obtains robust results when integrated with other methodologies, such as the AHP hierarchy and analytical networks (ANP).

5. Conclusions

This study shows that the proposed methodology, in which fuzzy logic is applied directly to a spatial model with integration of complex variables of different nature, such as vegetation, topography, climate, as well as social, economic and anthropic activities, to map the risk/vulnerability to forest fires is efficient. The map results showed that 71.68% of the area is under very low to medium forest fire risk. However, 28.32% of the study area has a high to very high fire risk.
Fuzzy logic offered flexibility in the modeling of forest fire risk in the Amojú river basin, Cajamarca region, Peru, elucidating, predicting and mapping the risk of forest fires, which is a great contribution to society in general, since the institutions and organizations in charge of disaster risk prevention and reduction can use the results obtained in this study to design management plans aimed at avoiding or reducing the effects of such events, safeguarding the inhabitants and the ecosystem of areas with medium, high and very high risk, mainly.

References

Abedi Gheshlaghi, H., Feizizadeh, B., & Blaschke, T. (2020). GIS-based forest fire risk mapping using the analytical network process and fuzzy logic. *Journal of Environmental Planning and Management*, *63*(3), 481-499. https://doi.org/10.1080/09640568.2019.1594726

Adab, H., Kanniah, K. D., & Solaimani, K. (2013). Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. *Natural hazards*, *65*(3), 1723-1743. https://doi.org/10.1007/s11069-012-0450-8

Adab, H., Kanniah, D., & Solaimani, K. (2011). GIS-based probability assessment of fire risk in grassland and forested landscapes of Golestan Province, Iran. In *International conference on environmental and computer science IPCBEE* (Vol. 19, p. 2011).

Adámek, M., Bobek, P., Hadincová, V., Wild, J., & Kopecký, M. (2015). Forest fires within a temperate landscape: a decadal and millennial perspective from a sandstone region in Central Europe. *Forest Ecology and Management*, *336*, 81-90. https://doi.org/10.1016/j.foreco.2014.10.014

Agarwal, J., Cohen, K., & Kumar, M. (2013). Fuzzy Logic Based Real-time Prediction Model for Wild-land Forest Fires. In *AIAA Infotech@ Aerospace (I@ A) Conference* (p. 5060). https://doi.org/10.2514/6.2013-5060

Aghajani Mir, M. A., Ghazvinei, P. T., Sulaiman, N. M. N., Basri, N. E. A., Saheri, S., Mahmood, N. Z., ... & Aghamohammadi, N. (2016). Application of TOPSIS and VIKOR improved versions in a multi criteria decision analysis to develop an optimized municipal solid waste management model. *Journal of environmental management*, *166*, 109-115. https://doi.org/10.1016/j.jenvman.2015.09.028

Ajin, R. S., Loghin, A. M., Vinod, P. G., & Jacob, M. K. (2016). Forest fire risk zone mapping using RS and GIS techniques: a study in Achankovil Forest Division, Kerala, India. *Journal of Earth, Environment and Health Sciences*, *2*(3), 109. https://doi.org/10.4103/2423-7752.199288

Alavanja, M. C., & Bonner, M. R. (2012). Occupational pesticide exposures and cancer risk: a review. *Journal of Toxicology and Environmental Health, Part B*, *15*(4), 238-263. https://doi.org/10.1080/10937404.2012.632358

Álvarez, R.Y. (2000). Aplicación de tecnología S.I.G. al Estudio del Riesgo y Prevención de Incendios Forestales en el área de Sierra Espuña-Gebas (Región de Murcia). TDR (Tesis Dr. en Red). Universidad de Murcia.

Armenteras-Pascual, D., Retana-Alumbreros, J., Molowny-Horas, R., Roman-Cuesta, R. M., Gonzalez-Alonso, F., & Morales-Rivas, M. (2011). Characterising fire spatial pattern interactions with climate and vegetation in Colombia. *Agricultural and Forest Meteorology*, *151*(3), 279-289. https://doi.org/10.1016/j.agrformet.2010.11.002

Barlow, J., Parry, L., Gardner, T. A., Ferreira, J., Aragão, L. E., Carmenta, R., ... & Cochrane, M. A. (2012). The critical importance of considering fire in REDD+ programs. *Biological Conservation*, *154*, 1-8.

https://doi.org/10.1016/j.biocon.2012.03.034
Bilobrovec, M., Marçal, R. F. M., & Kovaleski, J. L. (2004). Implementação de um sistema de controle inteligente utilizando a lógica fuzzy. *XI SIMPEP, Bauru/Brasil*, 42.
Bodí, M. B., Cerdà, A., Mataix-Solera, J., & Doerr, S. H. (2012). Efectos de los incendios forestales en la vegetación y el suelo en la cuenca mediterránea: revisión bibliográfica. *Boletín de la asociación de Geógrafos Españoles*. https://doi.org/10.21138/bage.2058
Briones, F.A. (2001). *Manual de formación de incendios forestales para cuadrillas*. 2nd ed. Zaragoza : Gobierno de Aragón., Zaragoza, España.
Burrough, P. A., McDonnell, R. A., & Lloyd, C. D. (2015). *Principles of geographical information systems*. Oxford university press. https://doi.org/10.2307/144481
Burry, L. S., Palacio, P. I., Somoza, M., de Mandri, M. E. T., Lindskoug, H. B., Marconetto, M. B., & D'Antoni, H. L. (2018). Dynamics of fire, precipitation, vegetation and NDVI in dry forest environments in NW Argentina. Contributions to environmental archaeology. *Journal of Archaeological Science: Reports*, *18*, 747-757. https://doi.org/10.1016/j.jasrep.2017.05.019
Chandler, C., Cheney, P., Thomas, P., Trabaud, L., & Williams, D. (1983). *Fire in forestry: forest fire behavior and effects*. J. Wiley & Sons, New York.
Chen, K., Blong, R., & Jacobson, C. (2001). MCE-RISK: integrating multicriteria evaluation and GIS for risk decision-making in natural hazards. *Environmental Modelling & Software*, *16*(4), 387-397. https://doi.org/10.1016/S1364-8152(01)00006-8
Chichipe, M. E. M., López, R. S., & Castillo, E. B. (2017). Análisis multitemporal de la deforestación usando la clasificación basada en objetos, distrito de Leymebamba (Perú). *INDES Revista de Investigación para el Desarrollo Sustentable*, *3*(2), 67-76. https://doi.org/10.25127/indes.201502.008
Chuvieco, E., Aguado, I., Yebra, M., Nieto, H., Martín, P., Vilar, L., ... & Salas, J. (2007). Generación de un Modelo de Peligro de Incendios Forestales mediante Teledetección y SIG. *Teledetección-Hacia un mejor entendimiento de la dinámica global y regional. Madrid: Editorial Martín*, 19-26.
Chuvieco, E., Aguado, I., Jurdao, S., Pettinari, M. L., Yebra, M., Salas, J., ... & Martínez-Vega, F. J. (2012). Integrating geospatial information into fire risk assessment. *International journal of wildland fire*, *23*(5), 606-619.
Cipriani, H. N., Pereira, J. A. A., Silva, R. A., Freitas, S. G. D., & Oliveira, L. T. D. (2011). Fire risk map for the Serra de São Domingos Municipal park, Poços de caldas, MG. *Cerne*, *17*, 77-83. https://doi.org/10.1590/s0104-77602011000100009
Corro, J. P., & Tafur, C. M. (2015). Calidad Biológica del agua del río Amojú, Jaén, Cajamarca. 2013. *SCIÉNDO*, *18*(1). https://doi.org/10.36955/riulcb.2014v1n2.005
Cortina, C., & Boggia, A. (2014). Development of policies for Natura 2000 sites: A multi-criteria approach to support decision makers. *Journal of environmental management*, *141*, 138-145. https://doi.org/10.1016/j.jenvman.2014.02.039
Costa, L., Thonicke, K., Poulter, B., & Badeck, F. W. (2011). Sensitivity of Portuguese forest fires to climatic, human, and landscape variables: subnational differences between fire drivers in extreme fire years and decadal averages. *Regional Environmental Change*, *11*(3), 543-551. https://doi.org/10.1007/s10113-010-0169-6
Cruz Espíndola, M. Á., Rodríguez Trejo, D. A., Villanueva Morales, A., & Santillán Pérez, J. (2017). Factores sociales de uso del suelo y vegetación asociados a los incendios forestales en Hidalgo. *Revista mexicana de ciencias forestales*, *8*(41), 139-163.
Cruz, J.C., Carvalho Neto, R.M., Cruz, R.C. (2013). Balanço Hídrico Climatológico Geoespacializado em Raster - BHCgeo.
da Silva, R. G., dos Santos, A. R., Pelúzio, J. B. E., Fiedler, N. C., Juvanhol, R. S., de Souza, K. B., & Branco, E. R. F. (2021). Vegetation trends in a protected area of the Brazilian Atlantic forest. *Ecological Engineering*, *162*, 106180. https://doi.org/10.1016/j.ecoleng.2021.106180
De León Mata, G.D., Pinedo Álvarez, A., & Martínez Guerrero, J.H. (2014). Application of remote sensing in the analysis of landscape fragmentation in Cuchillas de la Zarca, Mexico. *nvestigaciones geográficas,* 84, 42–53. https://doi.org/10.14350/rig.36568
Díaz-Hormazábal, I., & González, M.E. (2016). Spatio-temporal analyses of wildfires in the region of Maule, Chile. *Bosque 37*, 147–158. https://doi.org/10.4067/S0717-92002016000100014
Didan, K. (2015). MOD13Q1 MODIS / Índices de Vegetação Terra 16 dias L3 Global 250m Rede SIN V006 [Conjunto de dados]. DAAC, NASA EOSDIS LP. https://doi.org/10.5067 / MODIS / MOD13Q1.006
Bui, D. T., Bui, Q. T., Nguyen, Q. P., Pradhan, B., Nampak, H., & Trinh, P. T. (2017). A hybrid artificial intelligence approach using GIS-based neural-fuzzy inference system and particle swarm optimization for forest fire susceptibility modeling at a tropical area. *Agricultural and forest meteorology*, *233*, 32-44. https://doi.org/http://dx.doi.org/10.1016/j.agrformet.2016.11.002
Elaalem, M., Comber, A., & Fisher, P. (2010, May). Land evaluation techniques comparing fuzzy AHP with TOPSIS methods. In *13th AGILE international conference on geographic information science* (Vol. 2010, pp. 1-8).
EMBRAPA, E.B. de P.A. (1979). Sumula da X reunião técnica de levantamento de solos. Serviço Nac. Levant. E Conserv. Solos 10, 83.
Erdin, C., & Çağlar, M. (2021). Rural Fire Risk Assessment in GIS Environment Using Fuzzy Logic and the AHP Approaches. *Polish Journal of Environmental Studies*, *30*(6), 4971–4984. https://doi.org/10.15244/pjoes/136009
Eskandari, S. (2017). A new approach for forest fire risk modeling using fuzzy AHP and GIS in Hyrcanian forests of Iran.

Arabian Journal of Geosciences, *10*(8), 1-13. https://doi.org/10.1007/s12517-017-2976-2

Eugenio, F.C., Rosa dos Santos, A., Duguy Pedra, B., Macedo Pezzopane, J.E., Deleon Martins, L., Carlette Thiengo, C., Suemi Saito, N. (2019[a]). Choice of a wildfire risk system for eucalyptus plantation: a case study for FWI, FMA+ and horus systems in Brazil. *Natural Hazards and Earth System Sciences Discussions.* https://doi.org/10.5194/nhess-2019-350

Eugenio, F.C., Rosa dos Santos, A., Fiedler, N.C., Ribeiro, G.A., da Silva, A.G., Juvanhol, R.S., Schettino, V.R., Marcatti, G.E., Domingues, G.F., Alves dos Santos, G.M.A.D., Pezzopane, J.E.M., Pedra, B.D., Banhos, A., Martins, L.D. (2016a). GIS applied to location of fires detection towers in domain area of tropical forest. *Science Total Environment*, *562*, 542–549. https://doi.org/10.1016/j.scitotenv.2016.03.231

Eugenio, F.C., Santos, A.R., Fiedler, N.C., Ribeiro, G.A., da Silva, A.G., dos Santos, Á.B., Paneto, G.G., Schettino, V.R., (2016b). Applying GIS to develop a model for forest fire risk: A case study in Espírito Santo, Brazil. *Journal of Environmental Management, 173*, 65–71. https://doi.org/10.1016/j.jenvman.2016.02.021

Eugenio, F.C., Santos, A.R., Pedra, B.D., Macedo Pezzopane, J.E., Mafia, R.G., Loureiro, E.B., Martins, L.D., Saito, N.S., (2019b). Causal, temporal and spatial statistics of wildfires in areas of planted forests in Brazil. *Agricultural and Forest Meteorology,* 266–267, 157–172. https://doi.org/10.1016/j.agrformet.2018.12.014

Feizizadeh, B., Blaschke, T., & Roodposhti, M.S. (2013). Integrating GIS based fuzzy set theory in multicriteria evaluation methods for landslide susceptibility mapping. International Journal of Geoinformatics.

Figueira Branco, E.R., Rosa dos Santos, A., Macedo Pezzopane, J.E., Banhos dos Santos, A., Alexandre, R.S., Bernardes, V.P., Gomes da Silva, R., Barbosa de Souza, K., Moura, M.M., 2019. Space-time analysis of vegetation trends and drought occurrence in domain area of tropical forest. *Journal of Environmental Management*, *246*, 384-396. https://doi.org/10.1016/j.jenvman.2019.05.097

Francelino, M.R., de Rezende, E.M.C., da Silva, L.D.B. (2012). Proposta de metodologia para zoneamento ambiental de plantio de eucalipto. *CERNE, 18*, 275–283. https://doi.org/10.1590/S0104-77602012000200012

Ganteaume, A., & Jappiot, M. (2013). What causes large fires in Southern France. *Forest Ecology and Management*, *294*, 76-85. https://doi.org/10.1016/j.foreco.2012.06.055

Garcia-Jimenez, S., Jurio, A., Pagola, M., De Miguel, L., Barrenechea, E., Bustince, H. (2017). Forest fire detection: A fuzzy system approach based on overlap indices. *Applled Soft Computing Journal, 52*, 834–842. https://doi.org/10.1016/j.asoc.2016.09.041

Ghobadi, G. J., Gholizadeh, B., & Dashliburun, O. M. (2012). Forest fire risk zone mapping from geographic information system in Northern Forests of Iran (Case study, Golestan province). *International Journal of Agriculture and Crop Sciences*, *4*(12), 818-824.

Gil, M.J. eduardo (2020). Incendios forestales: causas e impactos. *El Antoniano 4*, 68–153.

Gómez-Pazo, A., & Salas, J. (2017). Modelado del peligro de ignición de incendios forestales en galicia (españa) * 7, 1–14.

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/Çakırlar. *Humman Ecological Risk Assessment, 23*, 388–406. https://doi.org/10.1080/10807039.2016.1255136

Hoinka, K. P., Carvalho, A., & Miranda, A. I. (2009). Regional-scale weather patterns and wildland fires in central Portugal. *International Journal of Wildland Fire*, *18*(1), 36-49.

Illera, P., Fernandez, A., & Delgado, J. A. (1996). Temporal evolution of the NDVI as an indicator of forest fire danger. *International Journal of remote sensing*, *17*(6), 1093-1105. https://doi.org/10.1080/01431169608949072

Jaiswal, R. K., Mukherjee, S., Raju, K. D., & Saxena, R. (2002). Forest fire risk zone mapping from satellite imagery and GIS. *International journal of applied earth observation and geoinformation*, *4*(1), 1-10. https://doi.org/10.1016/S0303-2434(02)00006-5

Jenks, G. F. (1967). The data model concept in statistical mapping. *International yearbook of cartography*, *7*, 186-190.

Jensen, J.R. (1986). *Introductory digital image processing*. Prentice – Hall, Englewood Cliffs.

Jiang, H., & Eastman, J. R. (2000). Application of fuzzy measures in multi-criteria evaluation in GIS. *International Journal of Geographical Information Science*, *14*(2), 173-184. https://doi.org/10.1080/136588100240903

Joss, B. N., Hall, R. J., Sidders, D. M., & Keddy, T. J. (2008). Fuzzy-logic modeling of land suitability for hybrid poplar across the Prairie Provinces of Canada. *Environmental monitoring and assessment*, *141*(1), 79-96. https://doi.org/10.1007/s10661-007-9880-2

Juárez-Martínez, A., & Rodríguez-Trejo, D. A. (2003). Efecto de los incendios forestales en la regeneración de Pinus oocarpa var. ochoterenae. *Revista Chapingo. Serie Ciencias Forestales y del Ambiente*, *9*(2), 125-130.

Juvanhol, R.S. (2014). Modelagem da vulnerabilidade à ocorrência e propagação de incêndios florestais. Universidade Federal Do Espírito Santo.

Kamran, K.V., Omrani, K., & Khosroshahi, S.S. (2014). Forest Fire Risk Assessment Using Multi- Criteria Analysis : A Case Study Kaleybar Forest. *International Conference on Agricultural Environmental Biological Science*, 30–33.

Kayet, N., Chakrabarty, A., Pathak, K., Sahoo, S., Dutta, T., & Hatai, B. K. (2020). Comparative analysis of multi-criteria probabilistic FR and AHP models for forest fire risk (FFR) mapping in Melghat Tiger Reserve (MTR) forest. *Journal of Forestry Research*, *31*(2), 565-579. https://doi.org/10.1007/s11676-018-0826-z

Kirschenbauer, S. (2005). Applying "True 3D" Techniques to Geovisualization: An Empirical Study, in: Dykes, J., MacEachren, A.M., Kraak, M.-J. (Eds.), Exploring Geovisualization. Elsevier, pp. 363–387. https://doi.org/10.1016/B978-008044531-1/50436-X

Koutsias, N., Xanthopoulos, G., Founda, D., Xystrakis, F., Nioti, F., Pleniou, M., ... & Arianoutsou, M. (2012). On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894–2010). *International Journal of Wildland Fire*, *22*(4), 493-507. https://doi.org/10.1071/WF12003

Leal, F.A., Souza, F.F.B. & de, Leal, G.D.S.A. (2019). Zoneamento De Riscos De Incêndios Florestais Em Regiões Hot Spot De Focos De Calor No Estado Do Acre. *Nativa 7*, 274. https://doi.org/10.31413/nativa.v7i3.6768

Lewis, S.M., Gross, S., Visel, A., Kelly, M., & Morrow, W. (2015). Fuzzy GIS-based multi-criteria evaluation for US Agave production as a bioenergy feedstock. *GCB Bioenergy 7*, 84–99. https://doi.org/10.1111/gcbb.12116

Lillesand, T.M., & Kiefer, R.W. (1994). *Remote sensing and image interpretation*. 2nd ed. John Wiley & Sons, Chichester.

Linn, R. R., Canfield, J. M., Cunningham, P., Edminster, C., Dupuy, J. L., & Pimont, F. (2012). Using periodic line fires to gain a new perspective on multi-dimensional aspects of forward fire spread. *Agricultural and Forest Meteorology*, *157*, 60-76. https://doi.org/10.1016/j.agrformet.2012.01.014

Louzada, F.L.R. d. O., Alexandre Rosa dos Santos, Aderbal Gomes da Silva, André Luiz Nascente Coelho, Saito, N.S., Peluzio, T.M. de O., Thiago de Oliveira Tuler, André Luiz Campos Tebaldi, & Garcia, G. de O. (2010). Delimitação de corredores ecológicos.

Martínez, J., Chuvieco, E., Martín, P., & Gonzalez-Caban, A. (2008). Estimation of risk factors of human ignition of fires in Spain by means of logistic regression. In *Proceedings of the Second International Symposium on Fire Economics, Planning, and Policy: A Global View* (pp. 265-278). Albany, Calif.: US For. Serv..

McMaster, R. (1997). In memoriam: George f. jenks (1916-1996). *Cartography and Geographic Information Systems*, *24*(1), 56-59. https://doi.org/10.1559/152304097782438764

Medrano, A.W.O. (2017). Análisis de cambio de uso de suelo al sur del cantón Samborondón mediante Sistemas de Información Geográfica y Teledetección. Universidad de Guayaquil.

Michael, Y., Helman, D., Glickman, O., Gabay, D., Brenner, S., & Lensky, I.M. (2021). Forecasting fire risk with machine learning and dynamic information derived from satellite vegetation index time-series. *Science Total Environment, 764*, 142844. https://doi.org/10.1016/j.scitotenv.2020.142844

Mota, P.H.S., da Rocha, S.J.S.S., de Castro, N.L.M., Marcatti, G.E., França, L.C. de J., Schettini, B.L.S., Villanova, P.H., dos Santos, H.T., & dos Santos, A.R. (2019). Forest fire hazard zoning in Mato Grosso State, Brazil. *Land use policy 88*, 104206. https://doi.org/10.1016/j.landusepol.2019.104206

Muñoz, R.V. (2000). Las quemas incontroladas como causa de incendios forestales. Cuad. la S.E.CE 9, 13–26.

Nebot, À., & Mugica, F. (2021). Forest fire forecasting using fuzzy logic models. *Forests 12.* https://doi.org/10.3390/f12081005

Neto, G.B.S., Bayma, A.P., de Faria, K.M.S., de Oliviera, E.G., & Menezes, P.H.B.J. (2016). Riscos de incêndios florestais no parque nacional de Brasília. *Brasilian Territorium 23*, 161–170. https://doi.org/10.14195/1647-7723_23_13

Novo, A., Fariñas-Álvarez, N., Martínez-Sánchez, J., González-Jorge, H., Fernández-Alonso, J.M., & Lorenzo, H. (2020). Mapping Forest Fire Risk — A Case Study in. Remote Sens. 12.

Oldeland, J., Dorigo, W., Lieckfeld, L., Lucieer, A., & Jürgens, N. (2010). Combining vegetation indices, constrained ordination and fuzzy classification for mapping semi-natural vegetation units from hyperspectral imagery. *Remote sensing of Environment*, *114*(6), 1155-1166. https://doi.org/10.1016/j.rse.2010.01.003

Owen, S. H., & Daskin, M. S. (1998). Strategic facility location: A review. *European journal of operational research*, *111*(3), 423-447. https://doi.org/10.1016/S0377-2217(98)00186-6

Paëgelow, M., Camacho Olmedo, M.T., & Menor Toribio, J. (2004). Modelizacion prospectiva del paisaje mediante Sistemas de Informacion Geografica. *Geofocus 3*, 22–24.

Paz, S., Carmel, Y., Jahshan, F., & Shoshany, M. (2011). Post-fire analysis of pre-fire mapping of fire-risk: a recent case study from Mt. Carmel (Israel). *Forest Ecology and Management*, *262*(7), 1184-1188. https://doi.org/10.1016/j.foreco.2011.06.011

Peña, M. J. L., Reynel-Rodríguez, C., Zevallos-Pollito, P., Bulnes-Soriano, F., & Pérez-Ojeda del Arco, A. (2007). Diversidad, composición florística y endemismos en los bosques estacionalmente secos alterados del distrito de Jaén, Perú. *Ecología aplicada*, *6*(1-2), 9-22. https://doi.org/10.21704/rea.v6i1-2.336

Pereira, M. G., Trigo, R. M., da Camara, C. C., Pereira, J. M., & Leite, S. M. (2005). Synoptic patterns associated with large summer forest fires in Portugal. *Agricultural and Forest Meteorology*, *129*(1-2), 11-25. https://doi.org/10.1016/j.agrformet.2004.12.007

Phillips, T., Leyk, S., Rajaram, H., Colgan, W., Abdalati, W., McGrath, D., & Steffen, K. (2011). Modeling moulin distribution on Sermeq Avannarleq glacier using ASTER and WorldView imagery and fuzzy set theory. *Remote Sense Environment, 115*, 2292–2301. https://doi.org/10.1016/j.rse.2011.04.029

Qiu, F., Chastain, B., Zhou, Y., Zhang, C., & Sridharan, H. (2013). Modeling land suitability/capability using fuzzy evaluation. *GeoJournal 79*, 167–182. https://doi.org/10.1007/s10708-013-9503-0

Ramiirez, D.E.U. (2017). Zonificación de amenaza a incendios forestales en el municipio de Riohacha, La Guajira. Trabajo de especialización en Geomática.Universidad Militar Nueva Granada, Facultad de Ingeniería, Especialización En Geomática, Bogota, Colombia.

Ribeiro, L., Koproski, L. de P., Stolle, L., Lingnau, C., Soares, R.V., & Batista, A.C. (2008). Zoneamento de riscos de incêndios florestais para a fazenda experimental do Canguiri, Pinhais (PR). *Floresta 38*, 561–572. https://doi.org/http://dx.doi.org/10.5380/rf.v38i3.12430

Rojas, M.F.C. (2013). Evaluación de zonas vulnerables a incendios forestales en bosques de alta montaña del Estado de México. Universidad Autónoma del Estado de México Programa de Maestría y Doctorado en Ciencias Agropecuarias y Recursos Naturales.

Saaty, T.L., & Vargas, L.G. (2012). *Models, Methods, Concepts & Applications of the Analytic Hierarchy Process*, 2nd ed, …-Driven Demand and Operations Management Models. Kluwer Academic Publishers, Boston. https://doi.org/10.1007/978-1-4614-3597-6

Santos, A.R., Eugenio, F.C., & Louzada, F.L.R. de O., (2010a). ArcGIS 9.3 Total: Aplicação para Dados Espaciais.

Santos, A.R., Machado, T., & Saito, N. (2010b). Spring 5.1.2 passo a passo: aplicações práticas, Alegre, ES: CAUFES.

Santos, A.R., Paterlini, E.M., Fiedler, N.C., Ribeiro, C.A.A.S., Lorenzon, A.S., Domingues, G.F., Marcatti, G.E., de Castro, N.L.M., Teixeira, T.R., dos Santos, G.M.A.D.A., Juvanhol, R.S., Branco, E.R.F., Mota, P.H.S., da Silva, L.G., Pirovani, D.B., de Jesus, W.C., Santos, A.C. de A., Leite, H.G., Iwakiri, S. (2017). Fuzzy logic applied to prospecting for areas for installation of wood panel industries. *Journal of Environmental Management, 193*, 345–359. https://doi.org/10.1016/j.jenvman.2017.02.049

Santos, A.R. dos, Araújo, E.F., Barros, Q.S., Fernandes, M.M., de Moura Fernandes, M.R., Moreira, T.R., de Souza, K.B., da Silva, E.F., Silva, J.P.M., Santos, J.S., Billo, D., Silva, R.F., Nascimento, G.S.P., da Silva Gandine, S.M., Pinheiro, A.A., Ribeiro, W.R., Gonçalves, M.S., da Silva, S.F., Senhorelo, A.P., Heitor, F.D., Berude, L.C., & de AlmeidaTelles, L.A. (2020). Fuzzy concept applied in determining potential forest fragments for deployment of a network of ecological corridors in the Brazilian Atlantic Forest. Ecol. Indic. 115, 106423. https://doi.org/10.1016/j.ecolind.2020.106423

Santos, H.G. dos (1995). HOCHMÜLLER, D.P., CAVALCANTI, A.C., RÊGO, R.S., KER, J.C., PANOSO, L.A., AMARAL, J.A.M. do. *Procedimentos normativos de levantamentos pedológicos. Rio de Janeiro, RJ.*

Santos, J. S., Leite, C. C. C., Viana, J. C. C., dos Santos, A. R., Fernandes, M. M., de Souza Abreu, V., ... & de Mendonça, A. R. (2018). Delimitation of ecological corridors in the Brazilian Atlantic Forest. *Ecological Indicators*, *88*, 414-424. https://doi.org/10.1016/j.ecolind.2018.01.011

Schmidt, M.A.R. (2012). Uso de mapas 3D para navegação virtual: uma acordagem cognitiva. Universidade Federal do Paraná.

Schoennagel, T., Veblen, T.T., & Romme, W.H. (2004). The Interaction of Fire , Fuels , and Climate across Rocky Mountain Forests. *Bioscience 54.*

Sharma, K.L., Kanga, S., Nathawat, S.M., Sinha, S., & Pandey, C.P. (2012). Fuzzy AHP for forest fire risk modeling. Disaster Prev. Manag. An Int. J. 21, 160–171. https://doi.org/10.1108/09653561211219964

Silva, I., Gomes, D., & Valle, M.E. (2016). Estimativa de Risco e Perigo de Incêndios Florestais Utilizando Subconjuntos Fuzzy , k-NN Fuzzy e Subtractive Clustering.

Silva, S. de A., & Lima, J.S. de S. (2009). Lógica fuzzy no mapeamento de variáveis indicadoras de fertilidade do solo. Idesia 27, 41–46. https://doi.org/10.4067/s0718-34292009000300007

Silvert, W. (2000). Fuzzy indices of environmental conditions. *Ecological modelling*, *130*(1-3), 111-119. https://doi.org/10.1016/S0304-3800(00)00204-0

Soto, M.E.C. (2012). The identi fi cation and assessment of areas at risk of forest fi re using fuzzy methodology. *Applied Geography, 35*, 199–207. https://doi.org/10.1016/j.apgeog.2012.07.001

Teixeira, T.R., Soares Ribeiro, C.A.A., Rosa dos Santos, A., Marcatti, G.E., Lorenzon, A.S., de Castro, N.L.M., Domingues, G.F., Leite, H.G., da Costa de Menezes, S.J.M., Santos Mota, P.H., de Almeida Telles, L.A., da Silva Vieira, R. (2018). Forest biomass power plant installation scenarios. *Biomass and Bioenergy 108*, 35–47. https://doi.org/10.1016/j.biombioe.2017.10.006

Tervonen, T., Sepehr, A., & Kadziński, M. (2015). A multi-criteria inference approach for anti-desertification management. *Journal of Environmental Management, 162*, 9–19. https://doi.org/10.1016/j.jenvman.2015.07.006

THORNTHWAITE, C.W., & MATHER, J.R. (1955). *The water balance, in: Publications in Climatology. Drexel Institute of Technology*, Centerton, NJ, p. 104.

Tian, X., Zhao, F., Shu, L., & Wang, M. (2013). Distribution characteristics and the influence factors of forest fires in China. *Forest Ecology and Management*, *310*, 460-467. https://doi.org/https://doi.org/10.1016/j.foreco.2013.08.025

Torres, F.T.P., & MACHADO, P.J.O. (2008). Introdução à Climatologia, Geographic. ed. Geographica, Ubá.

Torres, F.T.P., Ribeiro, G.A., Martins, S.V., & Lima, G.S. (2014). Mapeamento da suscetibilidade a ocorrências de incêndios em vegetação na área urbana de Ubá-MG. Rev. Arvore 38, 811–817. https://doi.org/10.1590/S0100-67622014000500005

Torres, F. T. P., Roque, M. P. B., Lima, G. S., Martins, S. V., & Faria, A. L. L. D. (2017). Mapeamento do risco de incêndios florestais utilizando técnicas de geoprocessamento. *Floresta e Ambiente*, *24*. https://doi.org/10.1590/2179-8087.025615

Triepke, F. J., Brewer, C. K., Leavell, D. M., & Novak, S. J. (2008). Mapping forest alliances and associations using fuzzy systems and nearest neighbor classifiers. *Remote Sensing of Environment*, *112*(3), 1037-1050. https://doi.org/10.1016/j.rse.2007.07.014

Trigoso, D.I., López, R.S., Briceño, N.B.R., López, J.O.S., Fernández, D.G., Oliva, M., Huatangari, L.Q., Murga, R.E.T., Castillo, E.B., Gurbillón, M.Á.B., 2020. Land Suitability Analysis for Potato Crop in the Jucusbamba and Tincas Microwatersheds. *Agronomy 10*, 18. https://doi.org/10.3390/agronomy10121898

Urrutia-Jalabert, R., González, M.E., González-Reyes, Á., Lara, A., & Garreaud, R. (2018). Ecosphere - 2018 - Urrutia-

Jalabert - Climate variability and forest fires in central and south-central Chile. *ECOSPHERE, 9*(2), 1–17.
Vadrevu, K. P., Eaturu, A., & Badarinath, K. (2010). Fire risk evaluation using multicriteria analysis—a case study. *Environmental monitoring and assessment*, *166*(1), 223-239. https://doi.org/10.1007/s10661-009-0997-3
Vargas-Sanabria, D., & Campos-Vargas, C. (2018). Sistema multi-algoritmo para la clasificación de coberturas de la tierra en el bosque seco tropical del Área de Conservación Guanacaste, Costa Rica. Rev. Tecnol. en Marcha 31, 58. https://doi.org/10.18845/tm.v31i1.3497
Vieira, G. C., de Mendonça, A. R., da Silva, G. F., Zanetti, S. S., da Silva, M. M., & Dos Santos, A. R. (2018). Prognoses of diameter and height of trees of eucalyptus using artificial intelligence. *Science of the Total Environment*, *619*, 1473-1481. https://doi.org/10.1016/j.scitotenv.2017.11.138
Vilchis-Francés, A.Y., Díaz-Delgado, C., Magaña-Lona, D., Bâ, K.M., & Gómez-Albores, M.Á. (2015). Territorial modeling for danger of wildfires with daily prediction in the Balsas River basin | Modelado espacial para peligro de incendios forestales con predicción diaria en la cuenca del Río Balsas. *Agrociencia, 49*, 803–820.
Wang, Y., Li, Z., Tang, Z., & Zeng, G. (2011). A GIS-based spatial multi-criteria approach for flood risk assessment in the Dongting Lake Region, Hunan, Central China. *Water resources management*, *25*(13), 3465-3484. https://doi.org/10.1007/s11269-011-9866-2
Westerling, A. L., Hidalgo, H. G., Cayan, D. R., & Swetnam, T. W. (2006). Warming and earlier spring increase western US forest wildfire activity. *science*, *313*(5789), 940-943.
Zadeh, L.A. (1965). Fuzzy sets. *Information Control, 8*, 338–353. https://doi.org/10.1016/S0019-9958(65)90241-X
Zanella, M. E., Olímpio, J. L., Costa, M. C. L., & Dantas, E. W. C. (2013). Vulnerabilidade socioambiental do baixo curso da bacia hidrográfica do Rio Cocó, Fortaleza-CE. *Sociedade & Natureza*, *25*, 317-332.

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