ALEX JOEL VERGARA ANTICONA

FUZZY LOGIC APPLIED TO FOREST FIRE RISK MODELING IN THE CAJAMARCA REGION, PERU

Dissertation submitted to the Forest Science Graduate Program of the Universidade Federal de Viçosa in partial fulfillment of the requirements for the degree of *Magister Scientiae.*

Adviser: Alexandre Rosa dos Santos

Co-adviser: Alexandre Simões Lorenzon

VIÇOSA - MINAS GERAIS
2021

Ficha catalográfica elaborada pela Biblioteca Central da Universidade Federal de Viçosa - Campus Viçosa

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Vergara Anticona, Alex Joel, 1994-
Fuzzy logic applied to forest fire risk modeling in the Cajamarca region, Peru/ Alex Joel Vergara Anticona. – Viçosa, MG, 2021.
41 f. : il. (algumas color.) ; 29 cm.

Orientador: Alexandre Rosa dos Santos.
Dissertação(mestrado) - Universidade Federal de Viçosa.
Referências bibliográficas: f. 31-41

1. Engenharia geotécnica. 2. Análise espacial (Estatística). 3. Processo decisório por critério múltiplo. I. Universidade Federal de Viçosa. Departamento de Engenharia Florestal. Programa de Pós-Graduação em Ciência Florestal. II. Título

CDO adapt. CDD 634.9431

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APPROVED: April 09, 2021.

Assent:

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“We will ask our heart when we do not know what to do, because that is where the soul is and we will take care of what we sow in our heart because life flows from it” W.S.S.

ACKNOWLEDGEMENTS

To God for the gift of life.

My mother Olivia Anticona and my father Danid Vergara for their love and support.

To my brothers Cristhiam, Sara and Fabiola for being my life companions.

To Mirtha Cerdan, for the love, affection, companionship, advice and for being my support in the most difficult times.

To Professor Dr. Alexandre Rosa dos Santos and Dr. Alexandre Simões Lorenzon for sharing their knowledge and for the guidance for the development of this research.

To the Federal University of Viçosa, for the opportunity to complete the postgraduate course.

To the Forest Engineering department of the Federal University Viçosa.

To the Graduate Program in Forest Science of the Federal University of Viçosa.

To the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior (CAPES), to granting the scholarship.

To the colleagues of the post-graduation that made my adaptation easier.

To those in charge of the PPG Secretariat for Forestry Sciences Alexandre and Dilson for their availability and the help provided.

To all my friends that I met at UFV and made my stay much more friendly

To all who have contributed to this work in some way.

ABSTRACT

Anticona, Alex Joel Vergara, M.Sc., Universidade Federal de Viçosa, April, 2021. **Fuzzy logic applied to forest fire risk modeling in the Cajamarca region, Peru**. Adviser: Alexandre Rosa dos Santos. Co-adviser: Alexandre Simões Lorenzon.

Forest fires have become more frequent due to anthropogenic activities and climate change. Besides being also a natural phenomenon in all plant ecosystems of the world, it contributes to reduce forest areas when occurs in tropical, boreal and temperate vegetation. The objective of this study was apply Fuzzy logic as an alternative to multicriteria analysis, in order to model forest fire risk in Cajamarca region, Peru. Eight variables have been incorporated to represented biological, topographic, socioeconomic and meteorological factors. Necessary methodological steps for this study were as follows: a) Database acquisition, editing and rasterization, b) Application of Fuzzy membership functions and images fuzzification, c) Fuzzy overlay and d) Spatial reclassification of forest fire risk. According to results, 71.68% of the area is under very low to medium forest fire risk. However, 28.32% of the study area has high and very high fire risk, which makes fire occurrence susceptible to lack of rain and water in the soil. It was found that biological, topographic and socioeconomic factors with their respective variables were directly influenced by the meteorological factor variables, which were temperature, rainfall and water availability. The proposed methodology integrates geotechnology and artificial intelligence to model the complex interactions between vegetation, topography and climate, as well as social, economic and anthropic activities, in order to map vulnerable areas to forest fires. Fuzzy logic provided flexibility to model forest fire risk in Cajamarca region, Peru. By elucidating and mapping fire risk, this approach can provide great environment, economic and social benefits through initiatives that mitigate fire environmental impacts, which improves income, life quality and local population GDP. This methodology can be applied to other areas around the world to provide information about the risk of forest fires.

Keywords: Geotechnology. Spatial analysis. Multi-criteria analysis. Membership functions.

RESUMO

Anticona, Alex Joel Vergara, M.Sc., Universidade Federal de Viçosa, abril de 2021. **Lógica fuzzy aplicada à modelagem de risco de incêndio florestal na região de Cajamarca, Perú**. Orientador: Alexandre Rosa dos Santos. Coorientador: Alexandre Simões Lorenzon.

Os incêndios florestais têm se tornado mais frequentes devido às atividades antrópicas e às mudanças climáticas. Além de ser também um fenômeno natural em todos os ecossistemas vegetais do mundo, contribui para a redução de áreas florestais quando ocorre em vegetação tropical, boreal e temperada. O objetivo deste estudo foi aplicar a lógica Fuzzy como alternativa à análise multicritério, a fim de modelar o risco de incêndio florestal na região de Cajamarca, Peru. Oito variáveis foram incorporadas a fatores biológicos, topográficos, socioeconômicos e meteorológicos representados. As etapas metodológicas necessárias para este estudo foram as seguintes: a) Aquisição, edição e rasterização do banco de dados, b) Aplicação de funções de pertinência Fuzzy e fuzzificação de imagens, c) Sobreposição fuzzy e d) Reclassificação espacial do risco de incêndio florestal. De acordo com os resultados, 71,68% da área está sob risco de incêndio florestal de baixíssimo a médio. Porém, 28,32% da área de estudo apresenta risco alto e muito alto de incêndio, o que torna a ocorrência de incêndio suscetível à falta de chuva e água no solo. Constatou-se que os fatores biológicos, topográficos e socioeconômicos com suas respectivas variáveis foram influenciados diretamente pelas variáveis dos fatores meteorológicos, que foram temperatura, pluviosidade e disponibilidade hídrica. A metodologia proposta integra geotecnologia e inteligência artificial para modelar as complexas interações entre vegetação, topografia e clima, bem como atividades sociais, econômicas e antrópicas, a fim de mapear áreas vulneráveis a incêndios florestais. A lógica fuzzy forneceu flexibilidade para modelar o risco de incêndio florestal na região de Cajamarca, Peru. Ao elucidar e mapear o risco de incêndio, essa abordagem pode proporcionar grandes benefícios ambientais, econômicos e sociais por meio de iniciativas que mitiguem os impactos ambientais dos incêndios, o que melhora a renda, a qualidade de vida e o PIB da população local. Essa metodologia pode ser aplicada em outras áreas do mundo para fornecer informações sobre o risco de incêndios florestais.

Palavras-chave: Geotecnologia. Análise espacial. Análise multicritério. Funções de associação.

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SUMMARY

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; 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; GONZÁLEZ, 2016; KEELEY, 1999; 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; RODRIGUEZ-TREJO, 2003).

The risk of forest fires 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., 2016a, 2016b; MOTA et al., 2019). Chuvieco et al., (2014) mentions that the modeling fire risk is important for planning and decision making in the short, medium and long term, aiming 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 fire vulnerability requires computational models and important tools of Geographic Information Systems (GIS) (OWEN; DASKIN, 1998; SAATY; VARGAS, 2012; TEIXEIRA et al., 2018). In this context, several mathematical models designed to the analysis of forest fire risk have been developed based on scientific and geotechnological advances, which are available for use due to GIS implementations (PAËGELOW; CAMACHO OLMEDO; MENOR TORIBIO, 2004; VETTORAZZI; FERRAZ, 1998).

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 fire risk modeling (Coelho Eugenio et al., 2019; Eugenio et al., 2019, 2016a, 2016b; Mota et al., 2019; Santos et al., 2017; Santos et al., 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).

Several scientific works report the advantages of combining techniques 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; BOGGIA, 2014; ELAALEM; COMBER; FISHER, 2010; JIANG; 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; SEPEHR; KADZIŃSKI, 2015; TRIEPKE et al., 2008; VIEIRA et al., 2018). MCA is based on Boolean logic and Weighted Linear Combination (WLC) technique. 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; 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; EASTMAN, 2000; SANTOS et al., 2017).

Fuzzy logic constitute 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 uncertain environment and provide robust response concerning the studied phenomena (TEIXEIRA et al., 2018). In Fuzzy logic, the 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 enable conditions to treat information following natural reasoning rules (BILOBROVEC; MARTINS; KOVALESKI, 2004; GOMIDE; GUDWIN, 1994; SILVA; LIMA, 2009). Its main applications concern risk mapping and environmental impacts (Álvarez, 2000; Chen et al., 2001; Juvanhol, 2014; Rosa et al., 2012; Santos et al., 2017, 2018; Santos et al., 2020;Teixeira et al., 2018; Vadrevu et al., 2010; Vieira et al., 2018; Wang et al., 2011).

Given the importance of forest fires and knowing that their main costs are associated with agricultural production, forest losses, CO_2 emissions and health threat, this work presents a suitable model for assessment of areas vulnerable to forest fire occurrence. The application of such model may yield environmental, economic and social benefits. In this context, the objective of this study was to apply Fuzzy logic as an alternative of multicriteria analysis, in order to model forest fire risk in the Cajamarca region, Peru.

2. MATERIALS AND METHODS

2.1. Physical aspects of the study área

Study area corresponds to the Amojú river basin, which is located in Jaén province and belongs to Cajamarca region, Peru. 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 annual average temperature that ranges 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 (Figure 1).

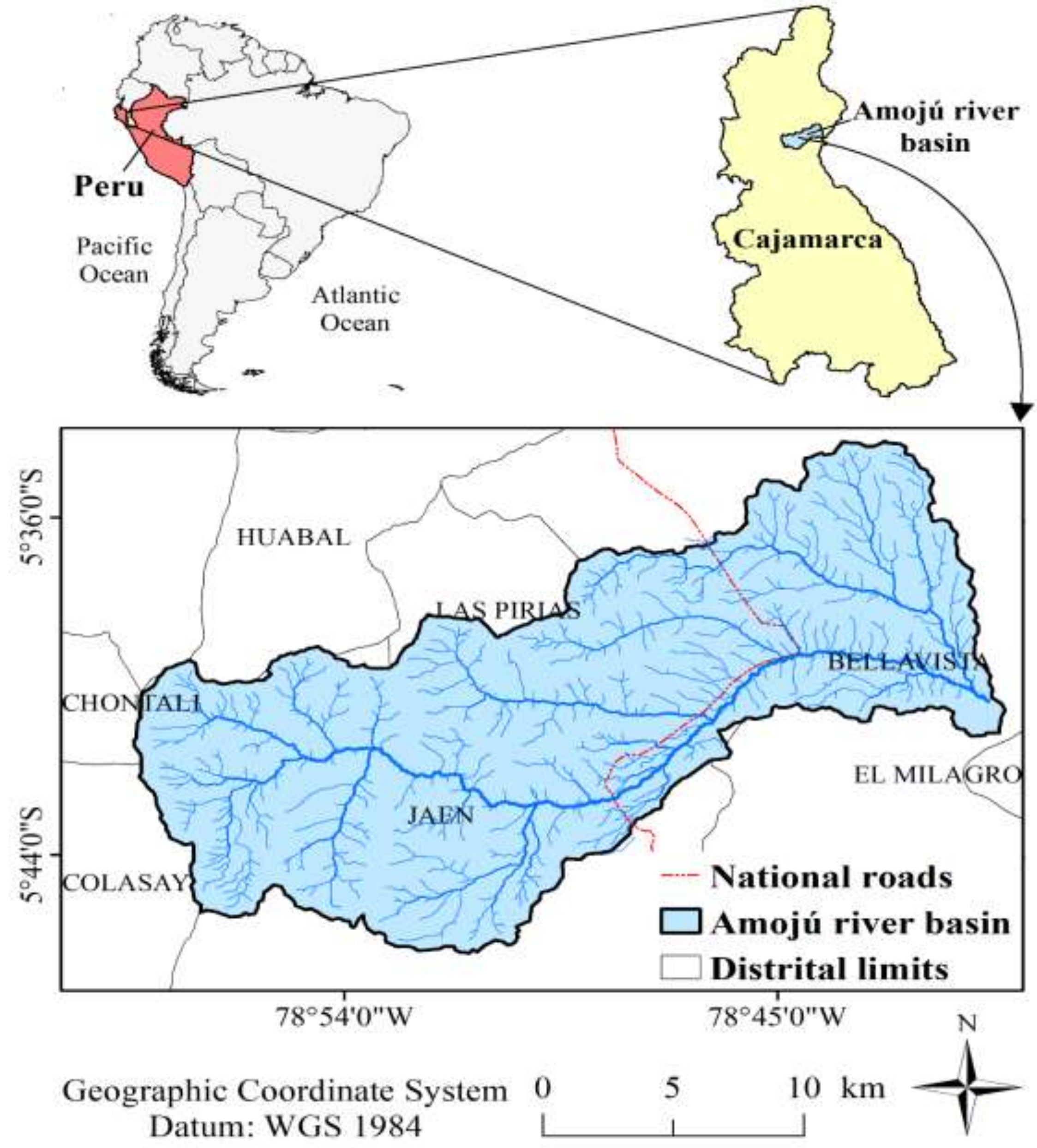


Figure 1 - Amojú river basin, Cajamarca Region, Peru.

2.2. Methodological steps

The methodological flowchart containing the necessary steps to model forest fire risk in Cajamarca region, Peru is shown in Figure - 2.

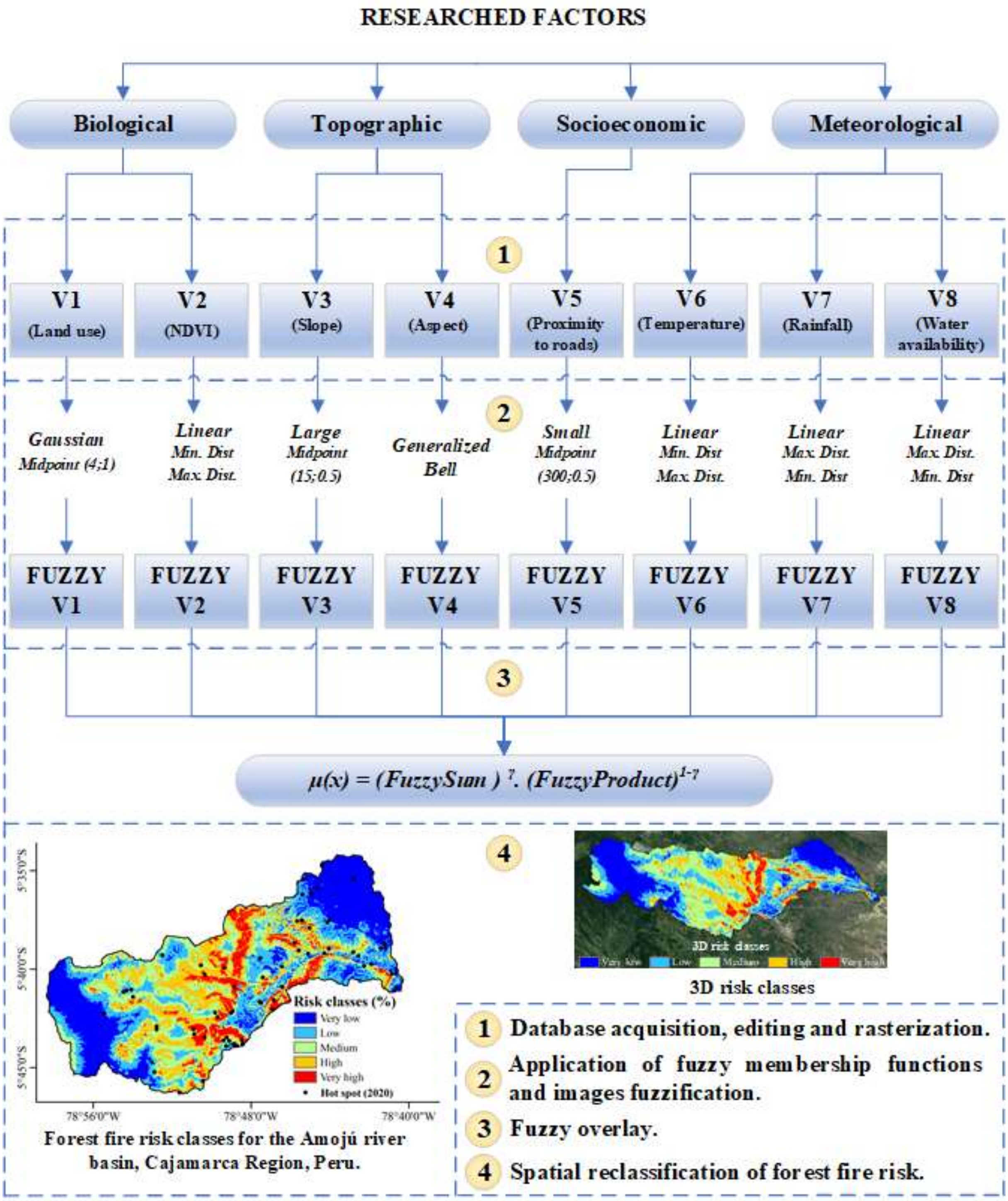


Figure 2 - Methodological steps needed to model risk of forest fire in the Cajamarca region, Peru.

The following methodological steps were needed to model forest fire risk with Fuzzy logic in the Cajamarca region, Peru:

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

Step 1. Database acquisition, editing and rasterization.

Employed database included 04 types of factors with their respective variables that are related to the occurrence of forest fires 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 spread of forest fires (EUGENIO et al., 2016a, 2016b, 2019) 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; KIEFER, 1994), which was fed with Landsat 8 satellite orbital images (OLI sensor) from January 2019. Seven macro-classes were 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 verified according to Kappa coefficient 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; MACHADO; SAITO, 2010).

Variable 2 (V2) – NDVI: 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 composition 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 the occurrence of forest fires (EUGENIO et al., 2016a, 2016b, 2019), whose variables correspond to:

Variable 3 (V3) – Slope: 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 in 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; REZENDE; SILVA, 2012). This process was performed with GIS "reclassify" function.

Variable 4 (V4) – Aspect: aspect continuous matrix image was derived from SRTM Digital Elevation Model using "Aspect" GIS function. Subsequently, the aspect continuous 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; EUGENIO; LOUZADA, 2010).

c) Socioeconomic factor

Road network can act either as a barrier or a starting point for forest fires (EUGENIO et al., 2016a, 2016b; MOTA et al., 2019), being processed as follows:

Variable 5 (V5) – Proximity to roads: 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, that are represented by the center of their corresponding cells. On a plane, the distance between points $A(X_a, Y_a)$ and $\mathrm{B}(X_b, Y_b)$ is given by the Pythagorean theorem (LOUZADA et al., 2010; SANTOS et al., 2017; TEIXEIRA et al., 2018).

d) Meteorological factors

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

Variable 6 (V6) – Temperature and Variable 7 (V7) – Rainfall: 1970 to 2000 monthly matrix images of temperature and rainfall (January 2020 released version), with 30 s (1 km²) spatial resolution have been used. They 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: water availability matrix image was generated according to the 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 monthly average temperature, potential evapotranspiration and water capacity, which were processed by "*BHCgeo*" plugin (CRUZ; CARVALHO NETO; CRUZ, 2013), available in QGIS software.

Step 2. Application of Fuzzy membership functions and images fuzzification.

The best suitable pertinence function was defined for each Fuzzy set, or variable, in order to describe its influence over fire risk. Thus, the greatest fire risk was indicated by the real value of 1, while null risk 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, the 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 reclassified image of land use was fuzzified using the Fuzzy Gaussian membership function (Table 1 and Figure. 3a).

Table 1 - Land use class reclassification according to forest fire risk.

Class of Land Use/Cover	**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 (Figure. 3a).

Variable 2 (V2) – NDVI: vulnerability to fire occurrence increases as NDVI is higher. In this sense, the continuous matrix image of NDVI was fuzzified by the Ascending Linear Fuzzy membership function (Figure. 3b).

Variable 3 (V3) – Slope: higher slope areas are more vulnerable to forest fire occurrence than flat areas. In this sense, the continuous matrix image of slope was fuzzified using the Large Fuzzy membership function (Figure. 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; LUKE; MCARTHUR, 1978). In this context, a slope value of 15 ° at midpoint and a propagation value of 4 (adjusted) in the function were considered for better representation of the slope influence (Figure. 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 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 °) 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 (Figure. 3d).

Variable 5 (V5) – Proximity to roads: areas located closer to road network are more prone to forest fire 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 Rodríguez Silva et al. (2010) and Soto (2012), who addressed forest fire 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 (Figure. 3e).

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

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

Variable 8 (V8) – Water availability: vulnerability to forest fire 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 (Figure. 3h).

Step 3. Fuzzy overlay.

When modeling forest fire risk, the variables were combined by an overlay analysis to indicate the possibility of 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 analysis of fuzzy set theory (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 the power of the gamma coefficient:

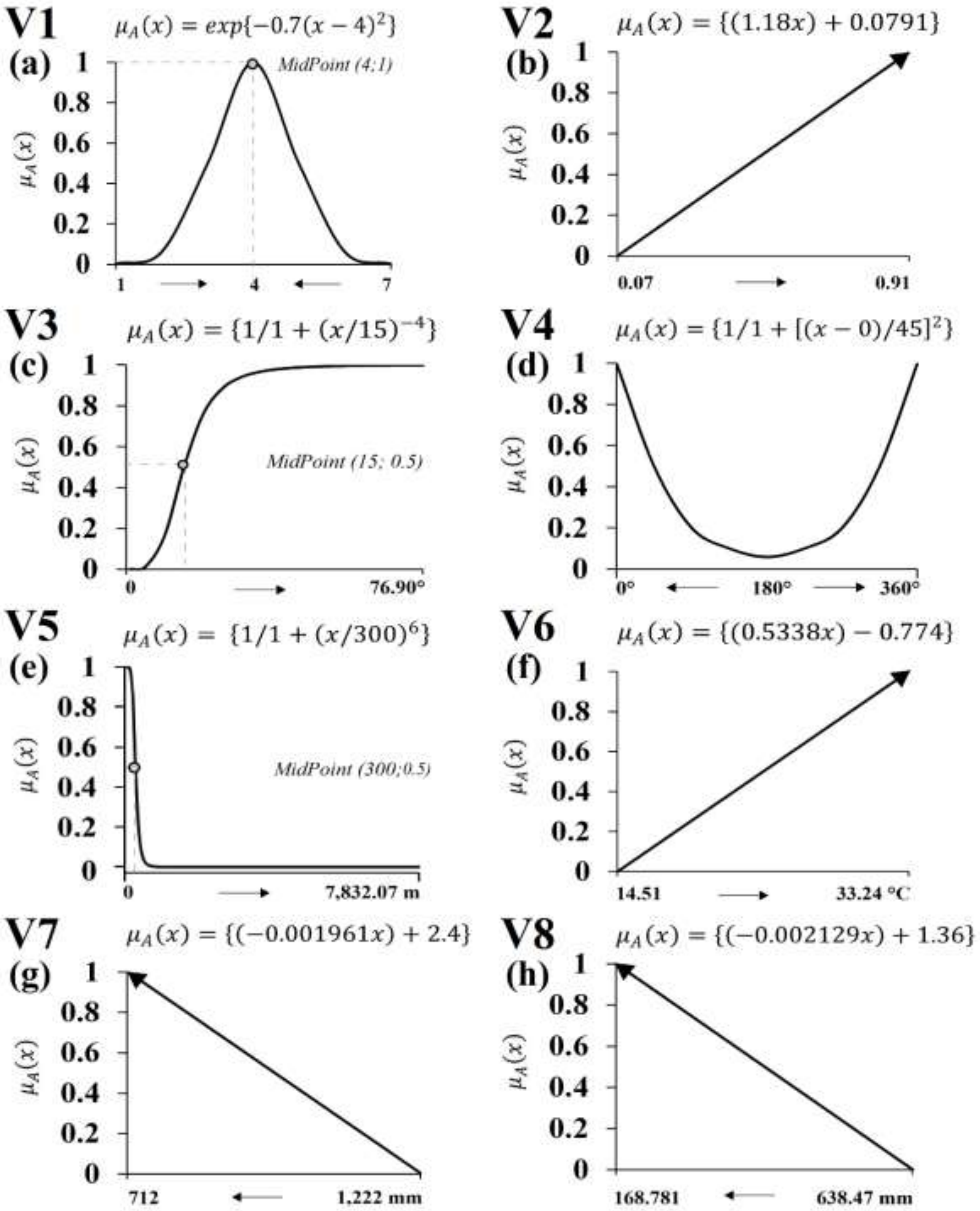


Figure 3 - Fuzzy membership function diagrams. (a) V1 – Land use – Fuzzy Gaussian; (b) V2 – NDVI – Fuzzy Linear; (c) V3 – Slope (º) – Fuzzy Large; (d) V4 – Aspect (º) – Fuzzy Generalized Bell; (e) V5 – Proximity to roads (m) – Fuzzy Small; (f) V6 – Temperature (ºC) – Fuzzy Linear; (g) V7 – Rainfall (mm)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

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

in which μ_i 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).

Step 4. Spatial reclassification of forest fire risk.

In this step, "reclassify" GIS function was applied to the continuous matrix image of forest fire 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 the average deviation within classes, while maximizing the average deviation among classes (JENKS, 1967; MCMASTER, 1997; SANTOS et al., 2017).

3. RESULTS

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

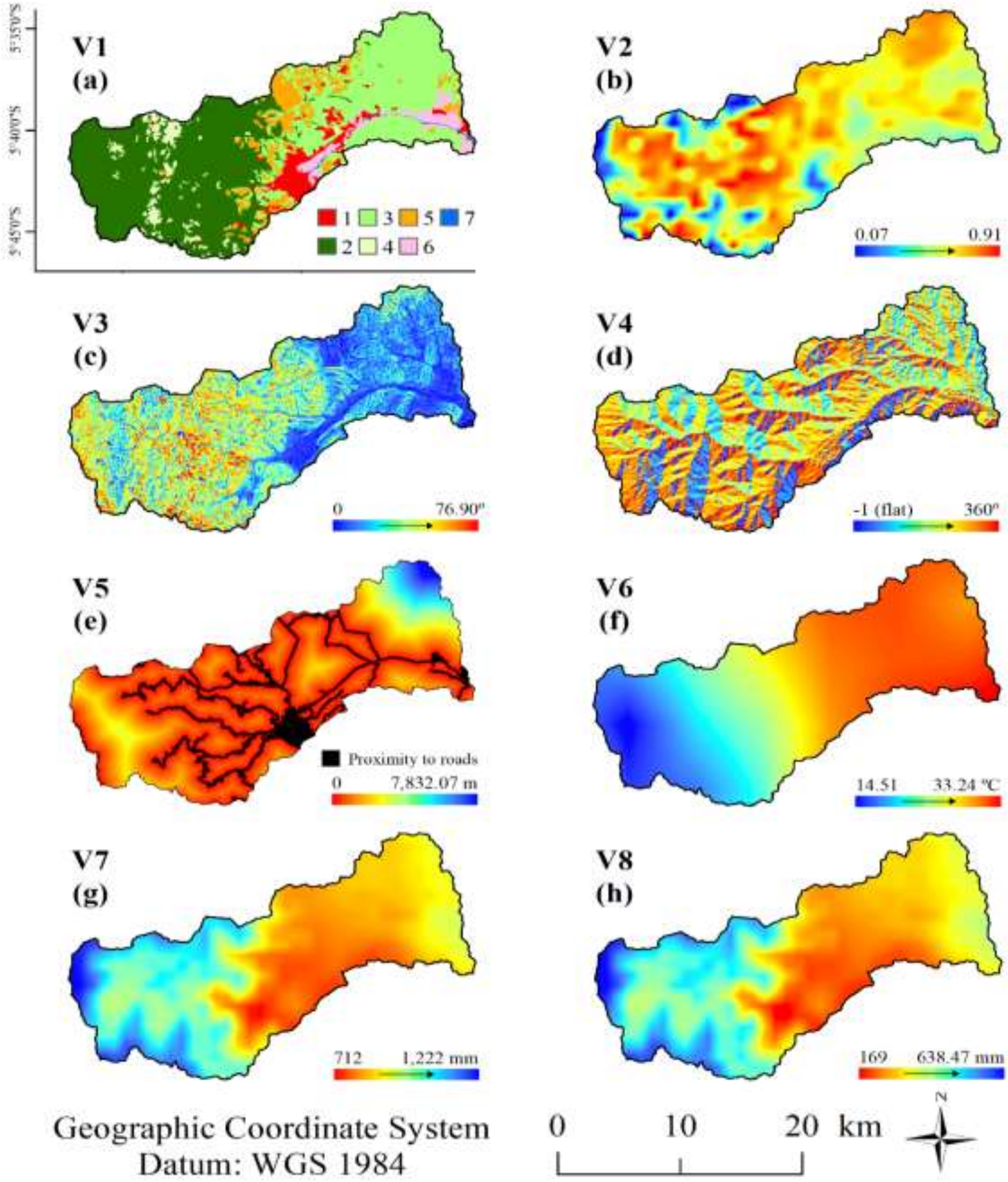
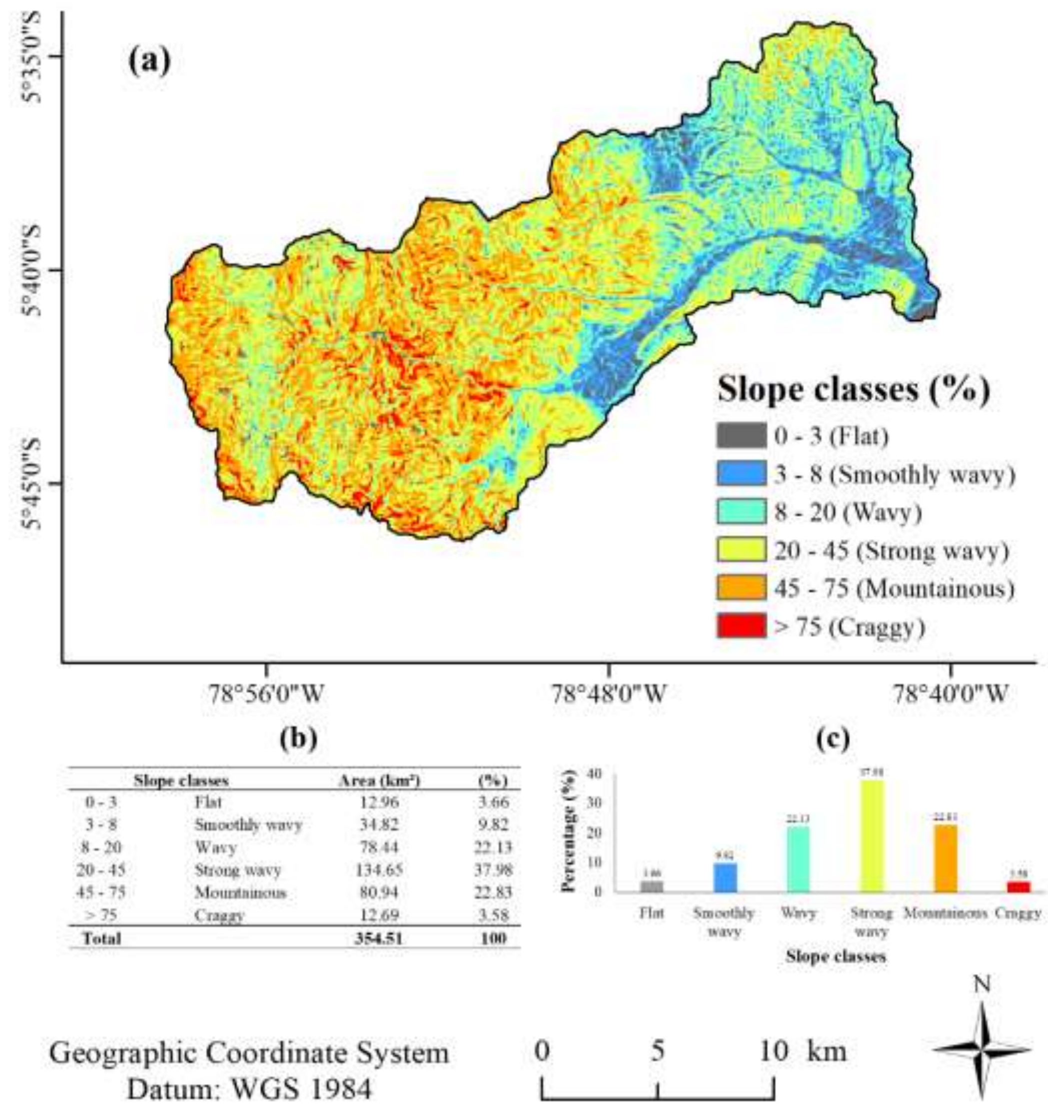


Figure 4 - Representative variables of Amojú river basin, Cajamarca region, Peru. (a) V1 – Land use, (b) V2 – NDVI, (c) V3 – Slope, (d) V4 – Aspect, (e) V5 – Proximity to roads, (f) V6 – Temperature, (g) V7 – Rainfall and (h) V8 – Water availability.

In Figure. 5, slope of Amojú river basin is presented, with emphasis on the slope classes (Figure. 5a) and their respective area and percentage (Figure. 5b), as well as distribution (Figure. 5c).



Slope classes		Area (km²)	(%)
0 - 3	Flat	12.96	3.66
3 - 8	Smoothly wavy	34.82	9.82
8 - 20	Wavy	78.44	22.13
20 - 45	Strong wavy	134.65	37.98
45 - 75	Mountainous	80.94	22.83
> 75	Craggy	12.69	3.58
Total		**354.51**	**100**

Figure 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 (%).

The Fuzzy logic derived from representative variables of Amojú river basin, Cajamarca region is shown in Figure. 6, with emphasis on fuzzified variables of land use (Figure. 6a), NDVI (Figure. 6b), slope (Figure. 6c), aspect (Figure. 6d), proximity to roads (Figure. 6e) temperature (Figure. 6f), rainfall (Figure. 6g) and water availability (Figure. 6h).

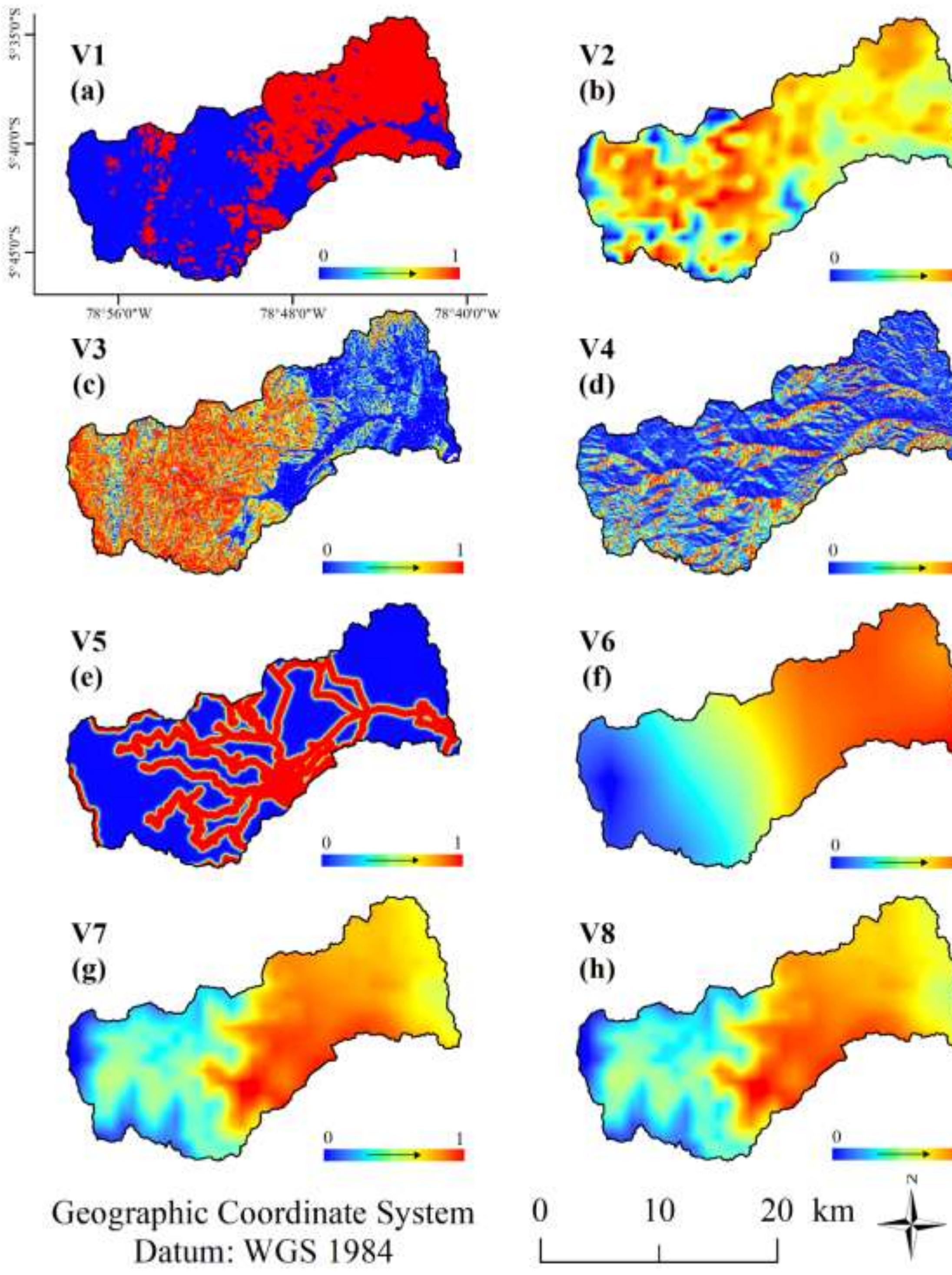
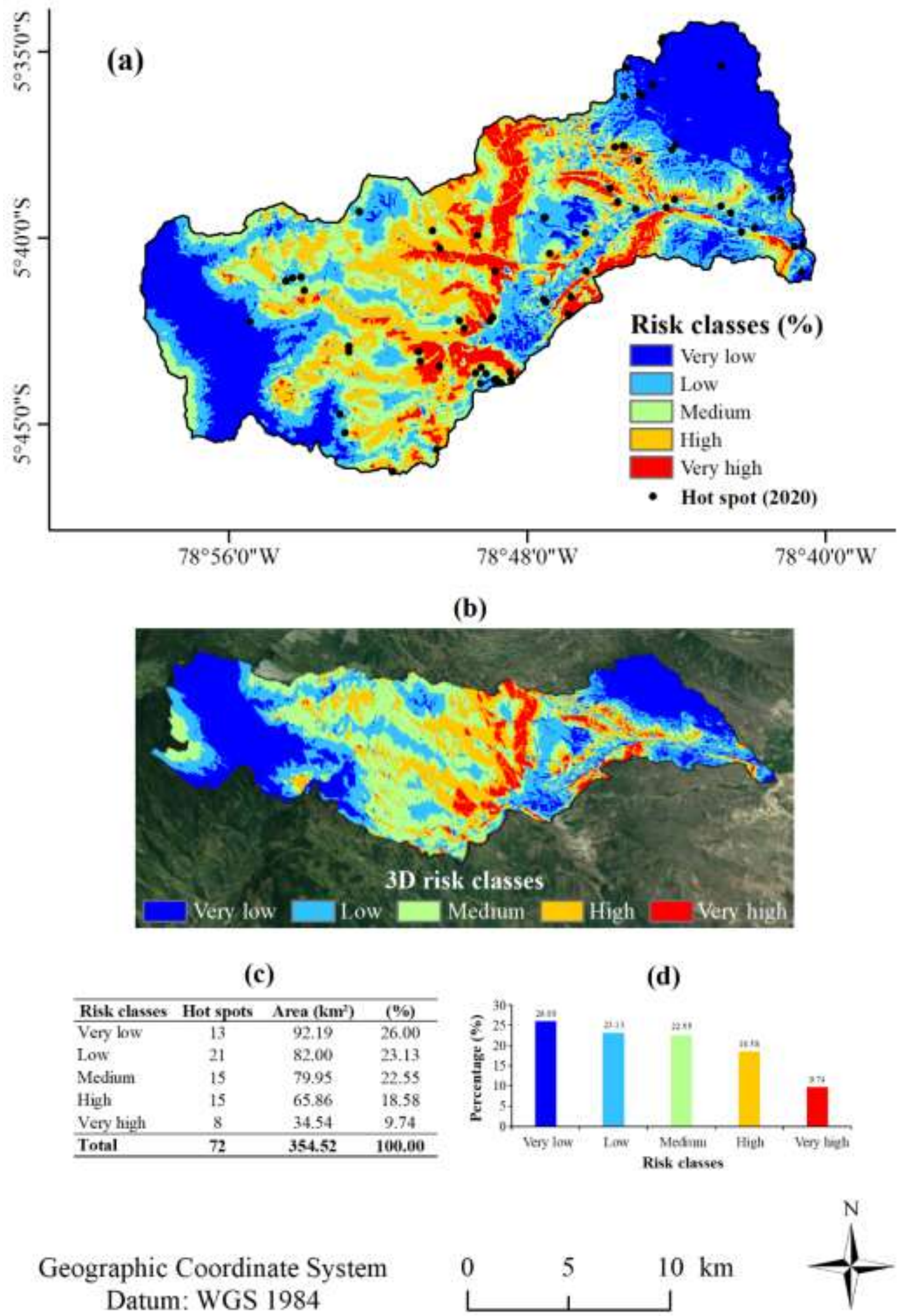


Figure 6 - Fuzzy logic derived from representative variables of Amojú river basin, Cajamarca region, Peru. (a) V1 – Land use, (b) V2 – NDVI, (c) V3 – Slope, (d) V4 – Aspect, (e) V5 – Proximity to roads, (f) V6 – Temperature, (g) V7 – Rainfall and (h) V8 – Water availability.

In Figure. 7, the risk of forest fire in Amojú river basin, Cajamarca region, Peru, is presented being characterized by risk classes (Figure. 7a), 3D risk classes (Figure. 7b), their respective hot spots, area and percentage (Figure. 7c), as well as distribution (Figure. 7d).



Risk classes	Hot spots	Area (km²)	(%)
Very low	13	92.19	26.00
Low	21	82.00	23.13
Medium	15	79.95	22.55
High	15	65.86	18.58
Very high	8	34.54	9.74
Total	**72**	**354.52**	**100.00**

Figure 7 - Risk of forest fire in Amojú river basin, Cajamarca region, Peru. (a) Risk classes, (b) 3D risk classes, (c) Hot spots, area (km²) and percentage (%) per class, (d) Risk class distribution (%).

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

Table 2 - Spatial relationship between classes of forest fire risk and land use in Amojú river basin, Cajamarca region, Peru.

Land use classes	**Classes of forest fire risk (%)**				
	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**				

The spatial relationship between risk classes and slope in Amojú river basin, Cajamarca region, Peru is shown in Table 3.

Table 3 - Spatial relationship between classes of forest fire risk and slope in Amojú river basin, Cajamarca region, Peru.

Slope classes	**Classes of forest fire risk (%)**				
	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**		

In Table 4, the spatial relationship between risk classes and aspect in Amojú river basin, Cajamarca region, Peru is presented.

Table 4 - Spatial relationship between classes of forest fire risk and aspect in Amojú river basin, Cajamarca region, Peru.

Aspect classes	**Classes of forest fire risk (%)**				
	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 fire 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 (Figure. 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 fire 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 (AGUIRRE, 2001; HOINKA; CARVALHO; MIRANDA, 2009; PEREIRA et al., 2005; SCHOENNAGEL; VEBLEN; ROMME, 2004) concerning their importance to forest fire subject. As reported by literature ((ARMENTERAS-PASCUAL et al., 2011; BODI et al., 2012; 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 fire risk class.

Among studied variables, NDVI stands out as the closer to 1 the greater the vegetation or biomass vigor (Figure. 4b and Figure. 6b). Several authors report the relationship between NDVI and other variables (RIBEIRO et al., 2007; TORRES et al., 2014). Thus, literature corroborate the results found in this study, once the quantitative values of NDVI may indicate the propensity of the combustible material to ignite in situations of high temperature (Figure. 4f and Figure. 6f), low rainfall (Figure. 4g and Figure. 6g) and low water availability (Figure. 4h and Figure. 6h).

In Amojú River basin, 82.94% of the study area is represented in conjunct by wavy, strong wavy and mountainous slope classes, while 3.58% corresponds to craggy slope (Figure. 5b and 5c). Presented results corroborate those found by other authors (AGUIRRE, 2001; GANTEAUME; JAPPIOT, 2013; MUÑOZ, 2000; RAMIIREZ, 2017) who mention that slope directly influences forest fire 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; MACHADO, 2008). In this context, the results from applying Fuzzy membership function to the 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; CHUVIECO; MARTÍN, 2008; TIAN et al., 2013; TORRES et al., 2014) the road network strongly relates with fire beginning because the surrounding combustible material has greater likelihood of ignition (Figure. 4e and Figure. 6e) due to anthropogenic causes. In this sense, this behavior is confirmed by obtained results once the most vulnerable areas to forest fire occur close to the road network.

In this study, it was verified that biological, topographic and socioeconomic factors and their respective variables were directly influenced by the meteorological factor, which is represented by temperature, rainfall and water availability variables (Figure. 4f, 4g and 4h).

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

Multidisciplinary and harmonic integration among different fields of knowledge, such as artificial intelligence and geotechnology, is fundamental for spatial modeling, in addition of being useful for analyzing, for instance, fire risk and its distribution pattern. The results indicate the need to implement mitigation measures, vegetation management and resources allocation in order to minimize potential damage and effects caused by fire in interfacing areas.

The modeling of forest fire 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.

The proposed modeling by the present study is efficient; whose employment defines vulnerable areas to the occurrence of forest fires. 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.

5. CONCLUSIONS

The modeling proposed in this study integrates geotechnology and artificial intelligence to assess the complex interactions between vegetation, topography, climate, as well as social, economic and anthropic activities in order to map the risk/vulnerability of forest fires, whose results are corroborated by reality and occurrence of the phenomenon within study area.

Fuzzy logic provided flexibility for modeling forest fire risk in Amojú River basin, Cajamarca region, Peru. By elucidating, anticipating and mapping forest fire risk, the proposed modeling can provide great environmental, economic and social benefits, including initiatives that reduce both environmental impacts and potential damages caused by fire. Consequently, improvements of income, life quality and local population GDP can be expected, mainly in the most likely sites to forest fire occurrence. This methodology can be applied to other areas around the world to generate information about forest fire risk.

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