Evaluation of the wildfire ignition risk by the aid of fuzzy logic

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Abstract

The danger of destructive wildfires has become a major issue in the U.S. due to decades of fuel accumulation from fire suppression efforts. With more people moving closer to or living in the wildland-urban interface, the risk of wildfires has increased dramatically. Wildfire risk analysis is aiming at predicting when and where wildfires will likely occur, and measures can be taken in advance to reduce the number and the intensity of disasters. In general, wildfire risk analysis can be divided into ignition risk analysis and fire behavior risk analysis. This study focuses on an ignition fire risk analysis in Rabun County, Georgia. Four fire risk related factors — human activity, illumination, elevation and vegetation type — were derived from spatial datasets. Three of them were used as linguistic variables, and then fuzzy set theory and fuzzy inference were applied to these variables to model wildfire risk levels (low, possible, substantial and high). The final result is a thematic risk level map that suggests that fuzzy logic can be used as a powerful tool in the field of fire risk analysis to predict more interpretable

risk levels for a certain area. Some advantages and disadvantages of using fuzzy logic over traditional approaches were also discussed in the paper.

Keywords: wildfire risk, fuzzy logic, fuzzy inference, linguistic variables, membership function

Introduction

Over 8,600,000 acres of land were burned by 66,552 wild fires in US. in 2005, according to national interagency fire center. A wildfire (wildland fire), also known as a forest fire, vegetation fire, grass fire, or bushfire (in Australasia), is often an uncontrolled fire occurring in wildland areas. Wildfire is a major issue in natural resource management, and the severe threat posed to human being’s property and life is evident. However, it is not very easy to predict future wildfire risk, since wildfires can be caused by many different reasons, such as lighting, arson, and dry climates, and each of which varies in different regions at different times. Combinations of many factors and dynamic characteristics of landscapes and weather have made the study of fire risk very complex.

In general, wildfire risk analysis can be broken down into ignition risk analysis and behavior risk analysis (or fire spreading risk analysis) (Salas and Chuvieco, 1994). Ignition risk analysis concentrates on what may cause a fire or increase the possibility of fire occurrence, while behavior risk analysis examines the potential factors which may affect the intensity, the speed, and the direction of the existing fire. In this study, I only focused on the ignition risk, leaving the behavior risk for further study.

The most common approach to establish a fire ignition risk assessment model is to use fire history data to develop a statistical regression model. In most cases, the number of fire occurrences is regressed on factors associated with fire risks —

environmental factors and human factors. Therefore, we can predict future wildfire risks in a region based on an established model. Logistic regression between the seasonal southern oscillation index and total acreages burned has been applied to predict wildfire events in the Hawaiian Islands (Chu, 2002). Multivariate analysis has been carried out to examine the influences of fuel, weather and topography on lightning-caused forest fires in Southern British Columbia and Alberta, Canada (Wiezchowski, 2002).

Geographic Information Systems (GIS) and Remote Sensing (RS) are integrated into fire risk modeling for spatial analysis, mapping, and information derivation. RS images, such as Landsat TM and AVHRR, are the most common satellite data used in wildfire field. For example, AVHRR images were used to derive Canadian drought code values in Canada (Aguado et al., 2001) and fuel moisture content in Mediterranean grasslands (Chuvieco et al., 2004), and they were also used for wildfire mapping (Pu et al., 2004). GIS techniques are commonly used in acquisition of required datasets in wild fire risk analysis. Salas and Chuvieco (1994) developed a fire hazard model in the city of Madrid in Spain, which incorporated GIS data layers of vegetation type, illumination, elevation, slope, aspect and human factors. Several advanced GIS techniques, such as cellular automaton, have also been applied to the simulation of fire behavior and wildfire prediction.

All the traditional fire risk analysis models attempt to evaluate risk in a quantitative context, which requires one to assign a value to each risk-related factor, even if those factors may be qualitative in nature, such as human activity. These traditional methods take advantage of easy computing of quantitative values by modern computing techniques and provide us a practical way to understand the location and severity of potential fires. However, an alternative method to assess risk can be implemented using fuzzy inference techniques, which provide us a better way to manipulate and calculate qualitative data.

The remainder of this article is organized as follows: Section 2 introduces basic concepts of fuzzy logic and the research background of risk analysis aided by fuzzy logic; section 3 describes the study area — Rabun county, GA; section 4 illustrates methods and the process used in this study; section 5 provides the result and discusses the pros and cons of the fuzzy approach compared to traditional ways. Also, some future work that may improve this research is suggested in this section.

Concepts of fuzzy logic and applications of risk analysis by fuzzy logic

The first idea related to fuzzy logic was introduced by Lofti A. Zadeh in the field of electrical engineering and computer science in 1964. He felt that “traditional system analysis techniques were too precise for many complex real-world problems” (Yen and Langari, 1998). The grade of membership function that he first thought of became the backbone of the theory of fuzzy sets afterwards. There are numerous concepts in the field of fuzzy logic, and among them five basic concepts formed the foundation of this field, which are:

(1) Fuzzy sets: sets with smooth boundaries instead of sharp distinctions. For example, if we have three crisp sets which have different colors: green, blue and red, then orange is not in any of these sets since it is neither green nor blue nor red. But if these sets are fuzzy sets which have no sharp boundaries, and green suggests a set with more objects than just green, and blue suggests a set with more objects than just blue, and the same for red, then the orange object may be grouped into the red category with high

confidece, but it can also be grouped into the other two color categories with less confidence. Fuzzy sets are useful when it is difficult to make clear boundaries between different groups.

(2) Linguistic variables: a qualitative variable that uses words in natural languages as the values (Sii et al., 2001). In this study, three variables are considered linguistic variables which values are based on fuzzy sets with membership functions.

(3) Fuzzy if-then rules: a knowledge representation which takes if-then form and derives conclusions in the 'then' part by reasoning from the 'if' part. Basically, it is a database of knowledge for the fuzzy sets under study. For example:

Rule 1: if the elevation is high, then the fire risk is low;

Rule 2: if the human activity is high and the elevation is low, then the fire risk is high.

(4) Membership function: a function used to define a projection from the domain values to the membership values. For example, function $f(x) = 0.1x\ (2 \le x \le 5)$ describes a mapping from the original value x to the membership value $f(x)$ which is limited in a range from 0 to 1. There are two types of commonly used membership functions: triangular membership functions and trapezoid membership functions. It is believed that in different areas under varying situations, the membership function forms should vary correspondingly.

(5) Fuzzy inference: a reasoning process operated on fuzzy sets. A simple form is expressed as the following:

Rule: If x $\in$ Q then y $\in$ P (Q and P are fuzzy sets)

What we know is $x \in Q$, and after reasoning we obtain the conclusion $y \in P$. This is the same reasoning process as the normal logic syllogism, except that the normal logic syllogism is performed only on crisp sets, while fuzzy inference is performed on fuzzy sets. We need to notice that fuzzy inference is both as mathematical and logical rigorous as it should be. However, the details of mathematical proofs were not provided in this paper. One can refer to Chang et al. (1991) for further study, in which fuzzy reasoning is presented in a logical rigor. In general, a fuzzy inference process involves 4 steps:

(1) Fuzzy matching: assignment of membership functions.

(2) Inference: calculate conclusions with membership values based on fuzzy if-then rules.

(3) Combination: combine conclusions inferred by all fuzzy rules into a final conclusion.

(4) Defuzzification: convert a fuzzy conclusion into a crisp output.

Fuzzy logic has been widely used in various fields, such as control engineering systems, artificial intelligence, fuzzy database management, fuzzy classification, and fuzzy pattern recognition. Recently, fuzzy logic has been applied to risk analysis, since risk is in nature uncertain, which is the main feature of fuzzy sets. Horgby (1998) applied fuzzy inference to the risk classification in life insurance and pointed out that by using fuzzy logic the insurer can evaluate risk in the same manner that human underwriters evaluate risk. Wang (2001) developed a safety assessment model for maritime and offshore safety based on a fuzzy logic approach. Wang (2005) also proposed a risk assessment model in an electronic business project by using fuzzy set and grey theory. Fuzzy logic has also been used in medical risk field. Brand et al. (2004) use fuzzy modeling to predict the risk of colon cancer in HNPCC patients. All the above research explicitly pointed out or implicitly indicated that fuzzy approach is a better alternative to evaluate risks with respect to the preciseness, compared to the traditional statistical approach.

Research has also been carried out in the area of wildfire risks evaluation. For example, a lightening risk assessment model used fuzzy logic techniques to estimate the subjectiveness involved in risk analysis and determine whether a risk level is acceptable (Gallego et al., 2004). In Greece, Iliadis (2005) classified forest fire risk zones by using fuzzy sets and presented a decision support system to estimate long-term forest fire risk by applying semi-triangular membership and semi-trapezoidal membership functions. These studies suggested that fuzzy logic can be adequately applied to wildfire risk analysis and thus support decision making process with more precise and interpretable risk prediction. However, few studies have integrated fuzzy logic techniques into a spatial context in their analysis to predict the future wildfire risk level. In this study, spatial information of the study area is being derived from both vector and raster datasets, and then fuzzy inference is performed upon raster spatial calculation to derive fire risk levels for each geographical unit.

Study area

Rabun County is located in the northeast of Georgia, U.S., with a latitude of 34.84 N and a longitude of -83.43 W. The entire county is within the Blue Ridge Mountains (figure 1). The highest point is 1,431.34 m (4,696 feet) above sea level and several other mountains in this county ranges in height from 762 m (2,500 feet) to 1,371.6 m (4,500 feet) above sea level. According to the 2000 U.S. Census, Rabun County has a total area of 976 km^2 (377 mi^2) and a total population of 15,050. The Chattahoochee National Forest covers the majority of the county, thus most of the land is covered by a large areas of forest.

Data sources

The 1998 Georgia vegetation/land cover GAP data is one of the main data sources in our study (figure 2). This land cover map was originally produced from Landsat TM imagery classification with a spatial resolution of 30 m. The overall statewide accuracy for classification is 75.46%, which suggests for some areas the data accuracy may be even lower. However, we do not consider this issue in this study and assume that landcover types in the map represent the real land surface quite well. Such simplification of assumptions may result in a slight bias in determining the fire risk level for each 30 m area, but it is beyond the scope of this research. The other data source is Georgia DLG-F Roads and Highways published by Georgia GIS Data Clearinghouse in 1997, which includes all interstate highways, state highways, county roads, and city streets. A third data source is 7.5-Minute Digital Elevation Model (DEM), which is available from the USGS. Using these three datasources, factors used for evaluating fire risks were derived for Rabun County.

Methods

The objective of this study is to analyze wildfire ignition risk in Rabun County by using a fuzzy inference approach. I demonstrated this approach based on county level datasets, but the methodology can be easily applied to larger areas with different resolutions.

The inference process follows: to identify linguistic variables, to set up if-then rules, and to make inference of conclusions. After the final result was deduced, we converted it back to an interpretable crisp output.

a. identification of risk-related factors

There are various factors that may cause wildfire or increase the possibility of fire occurrence, such as arson, lightening, dry weather, high temperature, and high illumination. Among them, human activity is one of the most important causes in the southern U.S., especially in wildland-urban interface areas where high amounts of human activities occur close to or within wildland areas. In order to evaluate this factor, I decided to use ‘distance to roads’ as one of linguistic variables, since the closer one is to roads, the more likely human activities occur, and thus the higher the fire risk. This factor information is calculated and derived from the original vector dataset of Georgia DLG-F Roads and Highways (figure 3). Elevation is another influential factor, which can be derived from DEM (figure 4). This factor is negatively correlated with the fire risk, since the higher the elevation, the lower the average temperature. Actually, in some areas of Rabun County, wildfires are almost impossible to occur due to the very high elevation and the very low temperature. Another linguistic variable is the illumination. Illumination data (figure 5) can also be derived from DEM by specifying two parameters — sun altitude and azimuth. (71° and 149.5° respectively) which is calculated at the location of N34° 53’, W 83° 24’ at noon (12:00 p.m.) on the day of July 31st, 2005 by U.S. Naval Observatory.

Besides these three linguistic variables, another crucial factor which affects wildfire risk levels, but not considered a linguistic variable, is the vegetation type/land cover. Since the assumption has been made that landcover data represents the true land surface, there is little uncertainty in this variable with respect to the wildfire ignition risk. Different vegetation types have different flammability levels. For example, conifer stands are the easiest ones to burn due to their physical characteristics and their high flammability level of both live and dead fuels, while crops and grass lands are not very susceptible to fires.

For each linguistic variable, linguistic categories were identified to represent three levels: low, medium and high. For example, elevation is in a low category if it is lower than 400 m, in a medium category if its range is between 300 m and 800 m, and in high category if it is higher than 700 m. Each category overlaps with its neighbors since fuzzy sets were applied to these categories. Therefore, a certain value may belong to different groups, and such classification is more appropriate to the real world. Triangular membership functions and trapezoid membership functions were used to calculate membership values for each fuzzy set with respect to each linguistic variable, and they are described in Table 1. Figure 6 shows these functions graphically.

The vegetation factor was divided into 6 groups based on their flammability: conifer, mixed forest, hardwood, crop/grass, urban, and water, and different fire risk weights were given to them as 100%, 90%, 80%, 50%, 10% and 0, respectively.

The conclusion variable fire risk was grouped into 4 fuzzy sets: low, possible, substantial and high based on a 0 - 10 scale (table 2). A trapezoid membership function was used to match risk probability and membership values (figure 7).

b. Fuzzy Inference:

The process of fuzzy inference is the process by which we obtain fire risk levels given the predefined values for each factor. The essence of fuzzy inference is embedded in fuzzy if-then rule system. Based on knowledge acquisition, 27 rules were composed and were described as follows:

If the distance to roads is close AND the illumination is high AND the elevation is low, THEN the risk level is high; Rule #1;

IF the distance to roads is close AND the illumination is high AND the elevation is medium, THEN the risk level is substantial; Rule #2;

IF the distance to roads is close AND the illumination is high AND the elevation is high THEN the risk level is possible; Rule #3;

IF the distance to roads is close AND the illumination is medium AND the elevation is low THEN the risk level is substantial; Rule #4;

IF the distance to roads is close AND the illumination is medium AND the elevation is medium, THEN the risk level is possible; Rule #5;

IF the distance to roads is close AND the illumination is medium AND the elevation is high, THEN the risk level is low; Rule #6;

IF the distance to roads is close AND the illumination is low AND the elevation is low, THEN the risk level is possible; Rule #7;

IF the distance to roads is close AND the illumination is low AND the elevation is medium, THEN the risk level is low; Rule #8;

IF the distance to roads is close AND the illumination is low AND the elevation is high, THEN the risk level is low; Rule #9;

IF the distance to roads is medium AND the illumination is high AND the elevation is low, THEN the risk level is substantial; Rule #10;

IF the distance to roads is medium AND the illumination is high AND the elevation is medium, THEN the risk level is possible; Rule #11;

IF the distance to roads is medium AND the illumination is high AND the elevation is high THEN the risk level is low; Rule #12;

IF the distance to roads is medium AND the illumination is medium AND the elevation is low THEN the risk level is possible; Rule #13;

IF the distance to roads is medium AND the illumination is medium AND the elevation is medium, THEN the risk level is possible; Rule #14;

IF the distance to roads is medium AND the illumination is medium AND the elevation is high, THEN the risk level is low; Rule #15;

IF the distance to roads is medium AND the illumination is low AND the elevation is low, THEN the risk level is possible; Rule #16;

IF the distance to roads is medium AND the illumination is low AND the elevation is medium, THEN the risk level is low; Rule #17;

IF the distance to roads is medium AND the illumination is low AND the elevation is high, THEN the risk level is low; Rule #18;

IF the distance to roads is far AND the illumination is high AND the elevation is low, THEN the risk level is possible; Rule #19;

IF the distance to roads is far AND the illumination is high AND the elevation is medium, THEN the risk level is possible; Rule #20;

IF the distance to roads is far AND the illumination is high AND the elevation is high THEN the risk level is low; Rule #21;

IF the distance to roads is far AND the illumination is medium AND the elevation is low THEN the risk level is possible; Rule #22;

IF the distance to roads is far AND the illumination is medium AND the elevation is medium, THEN the risk level is low; Rule #23;

IF the distance to roads is far AND the illumination is medium AND the elevation is high, THEN the risk level is low; Rule #24;

IF the distance to roads is far AND the illumination is low AND the elevation is low, THEN the risk level is low; Rule #25;

IF the distance to roads is far AND the illumination is low AND the elevation is medium, THEN the risk level is low; Rule #26;

IF the distance to roads is far AND the illumination is low AND the elevation is high, THEN the risk level is low; Rule #27;

The distance to roads variable, which represents human activity, was given more weight in these rules because it is the main cause of wildfire ignition in the southern U.S. (Salas and Chuvieco, 1994).

The inference calculation was performed on each of 30 m cells. The following example shows how our predefined 'if-then' rules were used to find a wildfire risk level for one cell. For instance, if a cell with the conifer vegetation cover type, has a value 60 for the distance factor, 195 for the illumination factor, and 250 for the elevation factor, how do we calculate the fire risk according to rules given above? First, we need to fuzzify those quantitative values by fuzzy membership functions. After fuzzification, the cell is one which has a ‘close’ distance to roads with a membership value of 0.35, a ‘high’ illumination value with a membership value of 0.89, and a ‘low’ elevation value with a membership value of 0.75. Then the minimum function was used to perform fuzzy matching in order to obtain the degree of matching from all the input data. Since min(0.35,0.89,0.75)=0.35, 0.35 is the degree of matching, i.e. membership value, for the ‘high’ category with respect to fire risk levels based on Rule 1. It was also observed from the human activity membership function (figure 6a.) that the distance to roads of 70 m also falls in the medium category with a membership value of 0.15. Therefore, based on Rule 10, this same cell can also be classified into an area with the ‘substantial’ fire risk level with a confidence of 0.15, since min(0.15,0.89,0.75)=0.15. Thus, the fuzzy inference calculation leads to a combination of two risk levels for one cell, which can be expressed as follows:

Risk Level= (0.35, high; 0.15, substantial)

c. Defuzzification:

In order to make a thematic risk level map, we need to use a single output value to represent the risk value for each of 30 m cells, and thus we must combine all conclusions inferred by different rules into one final conclusion set for each unit and then defuzzify this combined fuzzy set into a crisp set. Amongst various defuzzification methods, COA (center of average) is “the most commonly used defuzzifier in fuzzy systems” (Sii et al., 2000). Formulas for both discrete domain set and continuous domain set are as follows:

$$y = \frac{\sum_i \mu_A(y_i) * y_i}{\sum_i \mu_A(y_i)} \qquad \text{for discrete,}$$

$$y = \frac{\int \mu_A(y_i) * y_i \; dy}{\int \mu_A(y_i) \; dy} \quad \text{for continuous.}$$

Where y_i is an arbitrary domain value, $\mu_A(y_i)$ refers to the membership value corresponding to y_i on the fuzzy set ✌, and y is the converted final crisp output for corresponding conclusion fuzzy set.

Applying the formula for the continuous case to the previous example, we obtained 1.089 as a fire risk level value for this particular cell. For the final result, the vegetation factor was used as a weight to modify the output generated from the fuzzy inference.

ArcObjects (AO) provided by ESRI and VBA embedded in ArcGIS are the tools used to implement the fuzzy inference process. The entire process is based on the raster calculation.

Results and Discussions

The thematic raster map of risk levels is the final result (figure 8). We can observe a clear pattern that areas along roads have a relatively high risk level and areas far from roads have a comparably low risk level. Some areas along roads have higher risk than other areas on the opposite side of the road, most likely a function of illumination. The map also shows different risk levels due to different land covers. For example, water has the lowest risk value 0 (bright green color in the map); crop and grass land is not at high risk either. However, it is not easy to distinguish between conifer stands and hardwood stands on the risk map, probably because they are all mixed together geographically and their flammability potential is similar.

The resulting map is the representation of the rule system that was employed. If rules are changed, the resulting map will likely appear differently. The rule system is also the representation of our knowledge and experience about the wildfire risk in Rabun County. Therefore, as long as our knowledge is correct, the result will be accurate enough. As the knowledge and experiences about wildfires are accumulating, the rule system can be easily adjusted to obtain better results.

There are some advantages using the fuzzy logic approach to predict future wildfire risk over traditional methods. One is its flexibility to adjust membership functions and if-then rules. The other advantage is that we can easily interpret the pattern from the final result, which also facilitates the future validation. The third advantage is that by using the if-then rule system we can communicate efficiently with foresters and rangers who are more experienced in certain small areas, and then refine our rule system.

This study demonstrates that fuzzy logic can be properly applied to wildfire risk analysis and lead to reasonable results. However, there are still some problems which may need further study. Setting up rules is one primary task in the inference process, but it is also difficult and tedious work. The number of rules increases exponentially with more variables entering the model. We hope future studies can use computer tools to generate rules automatically using existing expert knowledge techniques, and such human-free tools would also reduce the subjectiveness caused by system maintaining individuals.

Another important aspect which requires more attention is the sensitivity analysis of membership functions. How do different kinds of membership functions affect the final result? In which situation, are triangular membership functions better than trapezoid functions? In order to answer such questions, an experiment should be carefully designed to capture and separate differences due to varied membership functions from ones due to other situations. Also, field work is highly suggested to check and validate the quality of analysis results.

We have used four main factors to predict wildfire risk level in Rabun County. Some other factors are suggested to be considered in the future study, such as the distance to streams, because streams themselves and buffer zones around them usually have moister soil and air conditions than the surrounding uplands. Also, in order to improve the usefulness and suitability of this research, we should consider dynamic changes of weather and report constant changing risks by dynamic maps. All of these possible improvements are left for further study.

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Appendix

Figure 1: Triangular membership function and trapezoid membership function

Figure 2. Rabun County (GA) topography and location

Figure 3. GAP data of Rabun County (GA)

Figure 4. Human activity measurement (distance to roads) for Rabun County (GA)

Figure 5. Elevation factor (DEM) for Rabun County (GA)

Figure 6. Illumination factor for Rabun County (GA)

Figure 7. Membership functions of three linguistic variables

Figure 8. Membership functions of the resulting fire risk levels

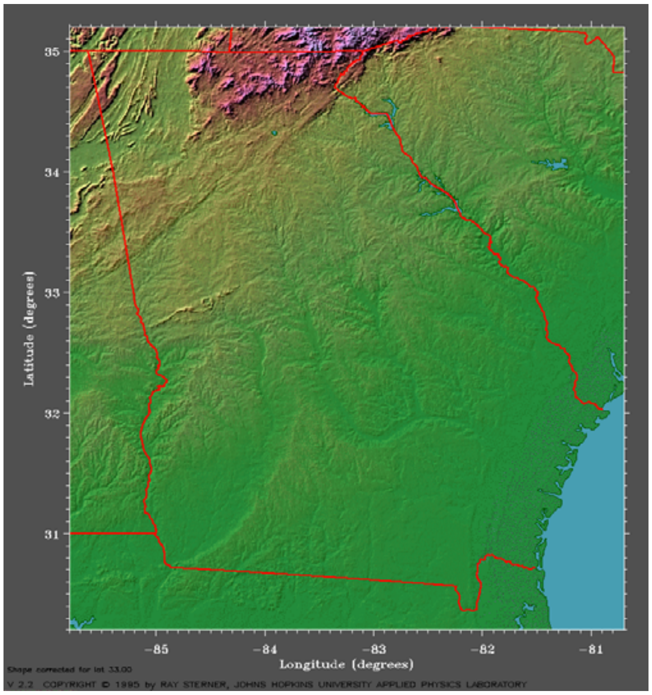
Figure 9. Final map of fire risk levels for Rabun County (GA)

Table 1. Membership functions of three linguistic variables

Table 2. Membership functions of the resulting fire risk levels

Figure 1. Rabun County (topography and location)

a. Georgia topographic relief map



b. County boundary map

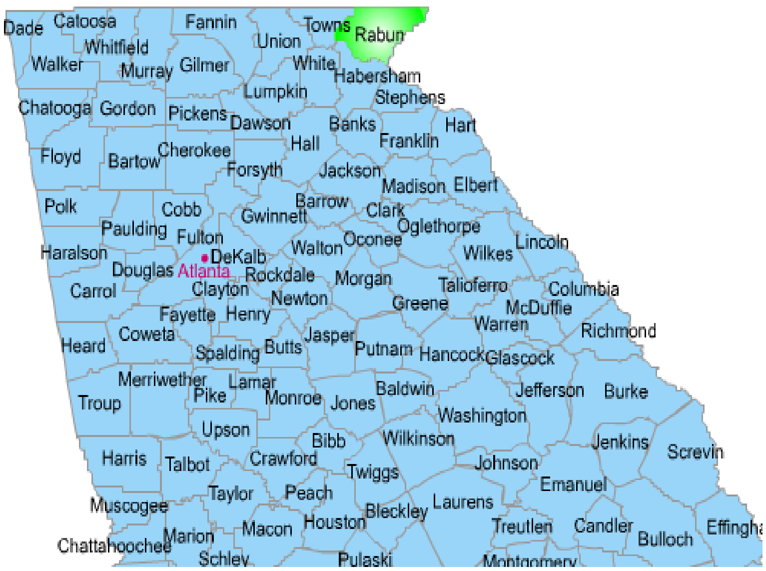


Figure 2. GAP data of Rabun County (GA)

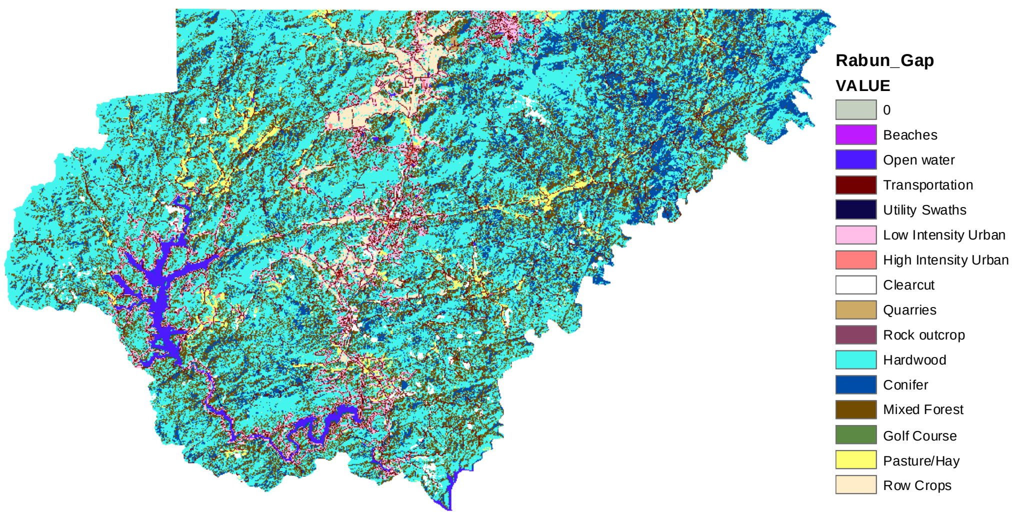


Figure 3. Human activity measurement (distance to roads) for Rabun County (GA)

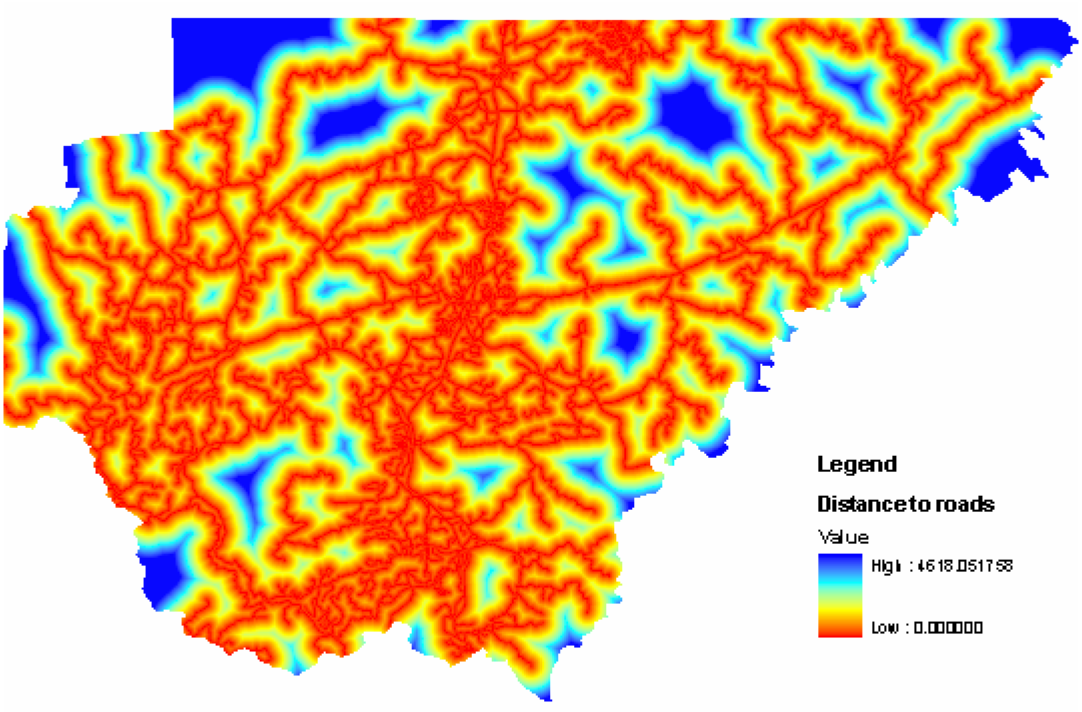


Figure 4. Elevation factor (DEM) for Rabun County (GA)

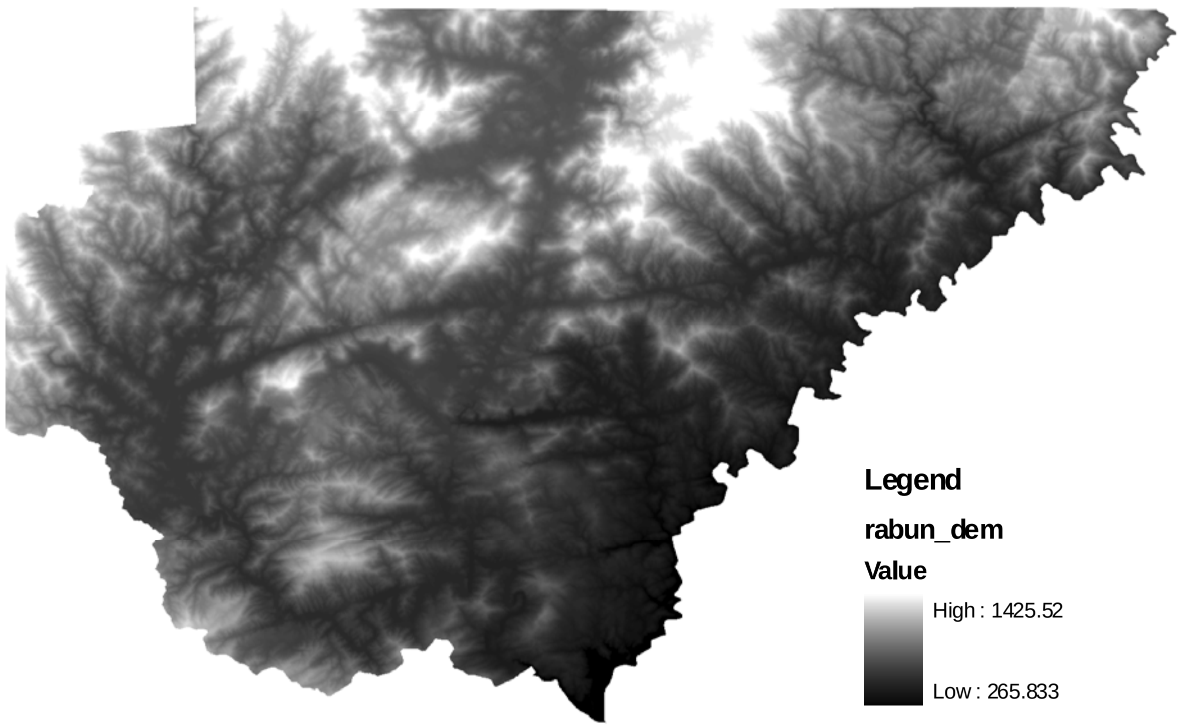


Figure 5. Illumination factor for Rabun County (GA)

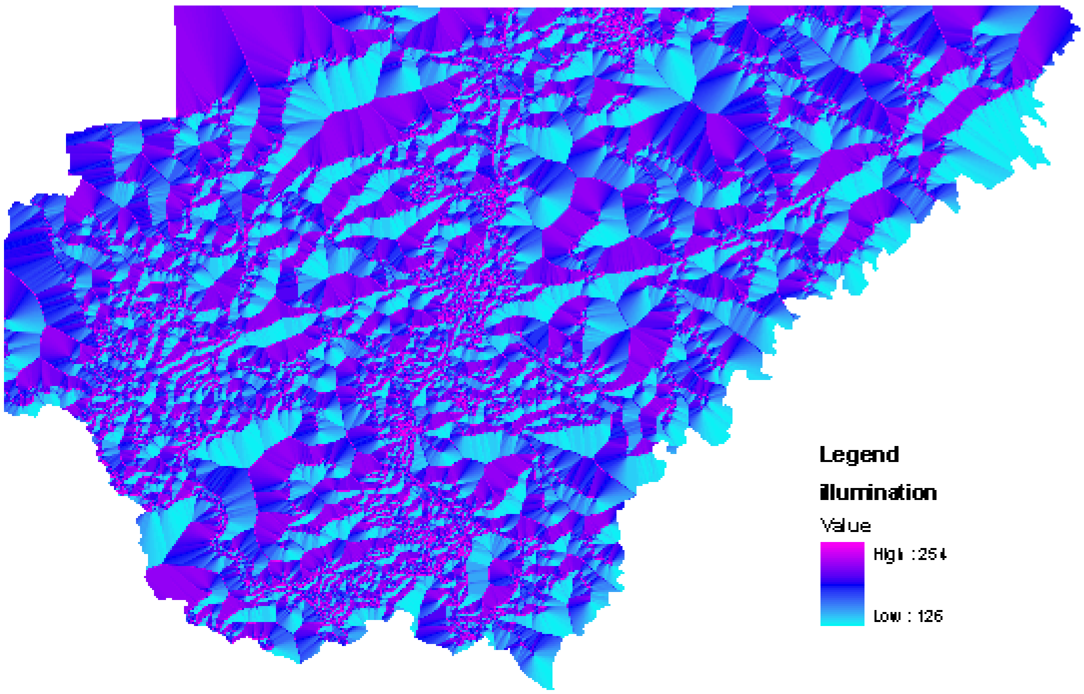
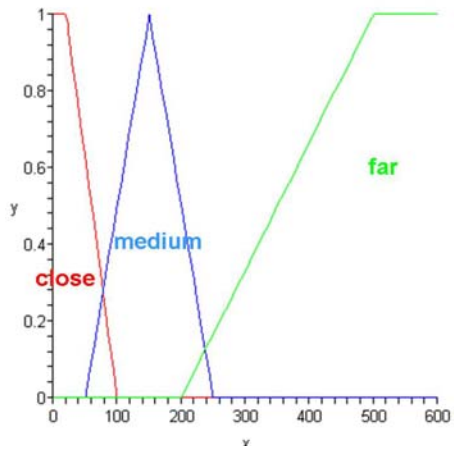
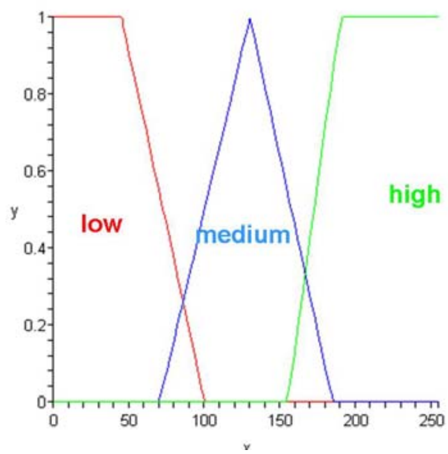


Figure 6. Membership functions of three linguistic variables

a. membership function of the variable of the distance to roads



b. membership function of the illumination variable



c. membership function of the elevation variable

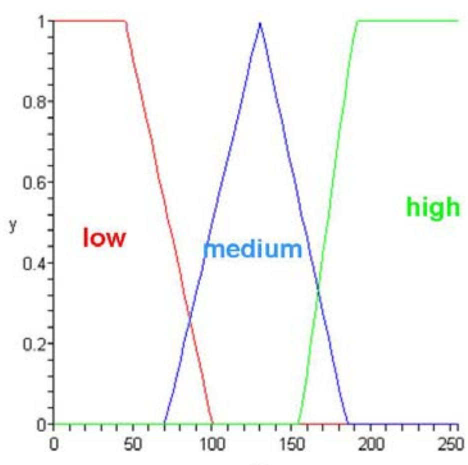


Figure 7. Membership function of the resulting fire risk levels

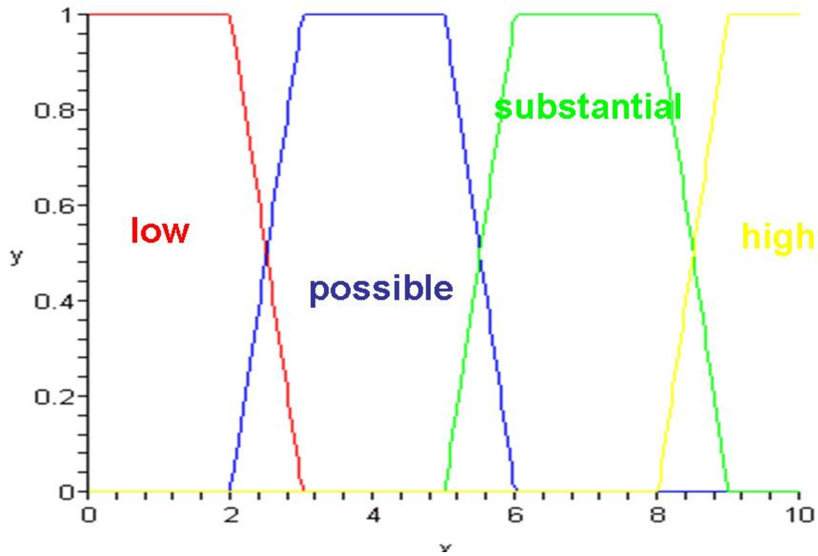


Figure 8. Final map of fire risk levels for Rabun County

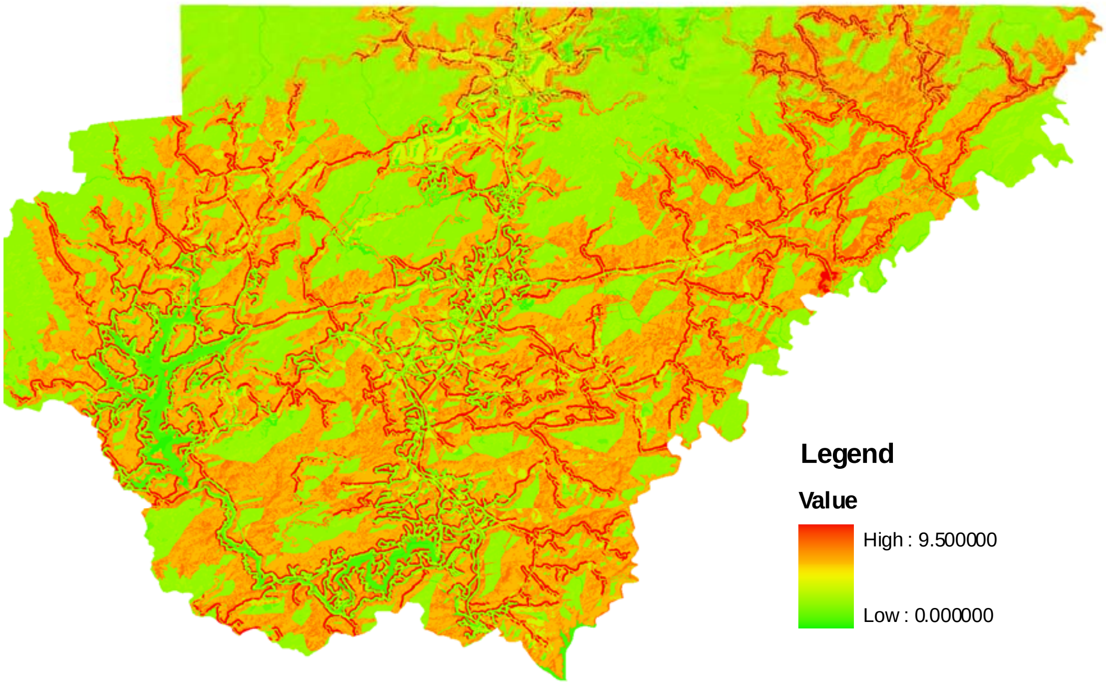


Table 1. Membership functions for three linguistic variables

Variable	Category	Functions
Distance to roads	Close	$f\_dist\_close := \begin{cases} 1 & 0 \le x \textbf{ and } x < 20 \\ -\frac{1}{80}x + \frac{5}{4} & 20 \le x \textbf{ and } x < 100 \end{cases}$
	Medium	$f\_dist\_mid := \begin{cases} \frac{1}{100}x - \frac{1}{2} & 50 \le x \textbf{ and } x < 150 \\ \frac{5}{2} - \frac{1}{100}x & 150 \le x \textbf{ and } x < 250 \end{cases}$
	Far	$f\_dist\_far := \begin{cases} \frac{1}{300}x - \frac{2}{3} & 200 \le x \textbf{ and } x < 500 \\ 1 & 500 \le x \end{cases}$
Illumination	Low	$f\_illum\_low := \begin{cases} 1 & 0 \le x \textbf{ and } x < 45 \\ -\frac{1}{55}x + \frac{20}{11} & 45 \le x \textbf{ and } x < 100 \end{cases}$
	Medium	$f\_illum\_mid := \begin{cases} \frac{1}{60}x - \frac{7}{6} & 70 \le x \textbf{ and } x < 130 \\ -\frac{1}{55}x + \frac{37}{11} & 130 \le x \textbf{ and } x < 185 \end{cases}$
	High	$f\_illum\_high := \begin{cases} \frac{1}{45}x - \frac{31}{9} & 155 \le x \textbf{ and } x < 200 \\ 1 & 200 \le x \textbf{ and } x \le 255 \end{cases}$
Elevation	Low	$f\_ele\_low := \begin{cases} 1 & 0 \le x \textbf{ and } x < 200 \\ -\frac{1}{200}x + 2 & 200 \le x \textbf{ and } x < 400 \end{cases}$
	Medium	$f\_ele\_mid := \begin{cases} \frac{1}{250}x - \frac{6}{5} & 300 \le x \textbf{ and } x < 550 \\ -\frac{1}{250}x + \frac{16}{5} & 550 \le x \textbf{ and } x < 800 \end{cases}$
	High	$f\_ele\_high := \begin{cases} \frac{1}{300}x - \frac{7}{3} & 700 \le x \textbf{ and } x < 1000 \\ 1 & 1000 \le x \end{cases}$

Table 2. Membership functions for the resulting fire risk levels

Variable	Category	Functions
Risk level	Low	$f\_risk\_low := \begin{cases} 1 & 0 \leq x \textbf{ and } x < 2 \\ -x+3 & 2 \leq x \textbf{ and } x < 3 \end{cases}$
	Possible	$f\_risk\_poss := \begin{cases} -2+x & 2 < x \textbf{ and } x \leq 3 \\ 1 & 3 < x \textbf{ and } x \leq 5 \\ -x+6 & 5 < x \textbf{ and } x < 6 \end{cases}$
	Substantial	$f\_risk\_subs := \begin{cases} -5+x & 5 < x \textbf{ and } x \leq 6 \\ 1 & 6 < x \textbf{ and } x \leq 8 \\ -x+9 & 8 < x \textbf{ and } x < 9 \end{cases}$
	High	$f\_risk\_high := \begin{cases} -8+x & 8 < x \textbf{ and } x \leq 9 \\ 1 & 9 < x \end{cases}$