A FUZZY-BASED TOOL FOR SPATIAL REASONING: A CASE STUDY ON ESTIMATING FOREST FIRE RISKY AREAS

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ABSTRACT:

The Mediterranean countries like many world countries have forest fire problem. Many forest fires have occurred each year and huge amount of forest areas in each country have been lost. 27% of Turkey's lands are covered by forest and 48% of these forest areas are productive, however 52% of them must be protected. There occurred 21000 forest fires due to several reasons between 1993 and 2002. It is estimated that 23477 ha area has been destroyed annually due to wildfires. The suitable response to forest fires depends on the evaluation of risks, hazards and values, which form the fire management strategies. In the case of the natural hazard "wildfire", the quantitative spatial analysis of wildfire risk that allows the generation of individual and collective risk maps. Since classical set theory is used in conventional decision making systems to model uncertain real world, the natural variability in the environmental phenomena can not be modelled appropriately. Because, pervasive imprecision of the real world is unavoidably reduced to artificially precise spatial entities when the conventional crisp logic is used for modelling. In this study fuzzy sets and fuzzy logic algebra were used in mapping the fire risky areas on a regional basis for Turkey. Three membership functions were used in the evaluation of the long term forest fire risk.

1. INTRODUCTION

Forests are one of the most valuable natural resources because of adjusting the natural balance, affecting the climate and water body of the region, preventing air pollution and erosion. In addition to this, they are important for community to meet the demand of products made of timber. Forest protection is an important part of silviculture, which are the science, art and practice of caring for forests with respect to human objectives. Forest fires are the most important injurious agencies. Forest fires occur either because of anthropological or natural causes. The majority of fires around the globe are caused by human activities. Lightning is probably the most common natural cause of fire. They have an instantaneous, often within a few hours, and enormous destruction. They consume forests, buildings and also cause damage to human life. Forest fires also produce gaseous and particle emissions that impact the composition and functioning of the jet stream and the global atmosphere, exacerbating climate change.

The Mediterranean Countries have forest fire problem due to their location and meteorological conditions. Turkey has also considerable amount of forest, which are extremely sensitive to fire, and they are located in west and south regions. The suitable response to forest fires depends on the evaluation of risks, hazards and values, which form fire management strategies. Risk is the chance of a fire starting. If the risk is high, fire prevention and detection are very cost-effective. Hazard is defined as simply the amount, condition and structure of fuels that will burn. Fire management requires an understanding of how fire starts and spreads; the behavior of fires, fuels and how they are suppressed. Many fire managers are searching the appropriate ways to manage fires rather than simply suppress those (Edmonds et al., 2000).

Forest fire prevention activities are more important than the activities realized after a fire starts. Some planning studies are needed in order to struggle against forest fires effectively. These plans can be regarded as fire protection, prevention and extinguishing plans. In fire protection plans, fire danger zone map using the information of former fires are prepared, precautions and law enforcements are determined. Studies including classification of the forest area according to fire danger, construction of fire safety roads and belts, construction of fire lookout stations, providing communication, transportation and location of the fire crews constitute the fire prevention plan. Spatial and statistical forest fire inventory relating to old fires should also be compiled for forest areas. These inventory databases can be used as basic data in taking measures and making decisions for probable fires.

Forest fire risk can be evaluated from several perspectives by taking into account the variability of the input layers in time. There are two basic types of indices that can be considered by a forest fire risk estimation system: the ones derived from factors that do not change in a short period of time and are referred as long-term indices, and the ones derived from factors that vary in short periods of time (vegetation status or the meteorological conditions) that are referred as dynamic indices (Iliadis, 2005). The main variables that can be used to complete the long term indices are fire history, fuel types, population, topography and soil types (Ayanz et al., 2003).

The objective of this study is to estimate the long-term forest fire risk on a country scale using fuzzy sets and fuzzy algebra concepts in spatial reasoning.

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2. MATERIALS AND METHODS

2.1 Fuzzy Set Theory

Fuzzy set theory provides a formal system for representing and reasoning with uncertain information. Linguistic variable concept in a fuzzy logic system enables to handle numerical data and linguistic knowledge simultaneously (Mendel,1995). Even L. A. Zadeh (1965), formulated the initial statement of fuzzy set theory (Maiers and Sherif, 1985), at first never expected fuzzy sets to be used in consumer products or in geographic information systems (Perry and Zadeh, 1995).

A collection of objects of any kind form a classical set and the objects themselves are called elements or members of the set. The elements of a classical set *A* in a universe of discourse *U* can be defined by specifying a condition. One other way to identify the elements of *A* is by introducing characteristic function for *A*, denoted as $\mu_A(x)$ such that $\mu_A(x) = 1$ if $x \in A$ and $\mu_A(x) = 0$ if $x \notin A$.

A fuzzy set is a generalization to classical set to allow objects to take membership values between zero and unity in vague concepts (Zadeh, 1965). A fuzzy set *F* defined on a universe of discourse *U* is characterized by a membership function $\mu_F(x)$ that maps elements of universe of discourse *U* to their corresponding membership values which is a real number in the interval [0, 1].

Fuzzy logic generalizes crisp logic to allow truth-values to take partial degrees. Since bivalent membership functions of crisp logic are replaced by fuzzy membership functions, the degree of truth-values in fuzzy logic becomes a matter of degree, which is a number between 0 and 1. Applications of fuzzy set theory ranging from consumer products, manufacturing, robotics, control systems, finance to earthquake engineering (Maiers and Sherif, 1985; Lee, 1990a) are mostly based on the use of fuzzy if-then rules. A fuzzy if-then rule in the form of a statement such as "IF *x* is *A* THEN *y* is *B*", where $x \in X$ and $y \in Y$ has a membership function defined as $\mu_{A\rightarrow B}(x, y)$. Note that $\mu_{A\rightarrow B}(x, y)$ describes the degree of truth of the implication relation between *x* and *y* (Mendel, 1995). Even though in most applications rules are connected using a t-conorm operator, there are a number of ways to connect rules (for discussions on connecting rules see (Kiszka et al., 1985a; Kiszka et al., 1985b; Lee, 1990b)). Since linguistic variables are used in the fuzzy if-then rules to describe elastic conditions (i.e., conditions that can be partially satisfied), a fuzzy if-then rule can capture knowledge about real world that is inexact by nature and involves imprecision (Yen and Langari, 1999; Yen, 1999). Another important feature of fuzzy if-then rules is its partial matching capability (Yen and Langari, 1999; Yen, 1999; Mendel, 1995).

2.2 Existing Approaches For the Estimation of Long-term Forest Fire Risk

The existing approaches that cluster the areas based on long-term degree of forest fire risk use the crisp sets. Based on this logic in order to cluster the areas belonging to the highest or to the moderate or to the lowest fire risk group are determined by drawing specific boundaries between the areas. In assessing the long-term fire risk, mainly probabilistic approaches are used. Probabilistic risk assessment can be defined as the process of estimating the probabilities of hazardous events taking place within a specified time period and in a specific context (Brillinger et al., 1986)

A system that estimates both the daily and the long-term forest fire risk is the European Forest Fire Information System that was developed by the Institute for Environmental and Sustainability Land Management, located in Italy (Ayanz et al., 2003).

The decision support system FFIREDESSYS uses fuzzy sets for the estimation of the structural forest fire risk on a global system (Iliadis, 2005).

Forest fire risk classes are obtained by General Directorate of Forest in Turkey. These maps are estimated by classifying the number of fires occurred in a particular year and areas burned in that year according to the size of the area burned.

2.3 Fuzzy Inference System

FuzzyCell, which is generic, enables decisionmakers to express their constraints and imprecise concepts that are used with geographic data through the use of natural language interfaces. FuzzyCell has been developed on a commercial GIS software namely, Arc-Map, which is a major GIS desktop system (Yanar and Akyürek, 2005). FuzzyCell can be viewed as a scheme for capturing experts knowledge on a specific problem. Through the use of linguistic variables, experts experiences in the problem domain, eventhough they naturally involve imprecision, are converted to fuzzy rules. Therefore, FuzzyCell allows users to handle imprecision in the decision making process by knowing only the fuzzy logic background.

Component Object Model (COM) environment is used for developing fuzzy inference system for ArcMap, where COM is a protocol that connects one software component, or module, with another and defining the manner by which objects interact through an exposed interface. The implementation of the fuzzy inference system tool for ArcMap is divided into two parts:

(1) Fuzzy Inference Engine implementation,
(2) Fuzzy Inference System Module implementation.

The general architecture design and workfow of the fuzzy inference system for cell-based information modeling is shown in Figure 1. Commercial GIS application uses Fuzzy Inference System (FIS) through public interface defined by Fuzzy Inference System Module. However, commercial GIS application and Fuzzy Inference System act as two separate applications, since Fuzzy Inference System is designed an ActiveX module.

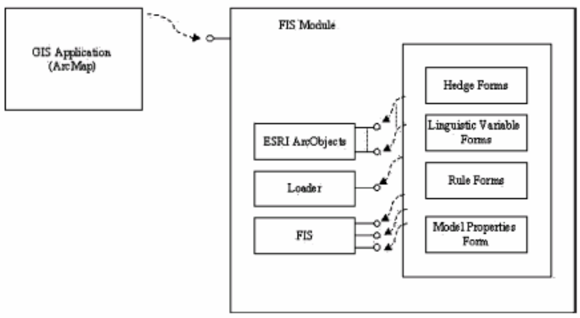


Figure 1. Architectural design and workflow of Fuzzy Inference System

2.4 Membership Functions

A membership function $\mu_F(x)$ maps each point in the input space to a degree of membership between zero and unity. Formally, if U is the universe of discourse and its elements are denoted by x, then a fuzzy set F in U is defined as a set of ordered pairs.

$$F = \{x, \mu_F(x) | x \in X\} \qquad (1)$$

where $\mu_F(x)$ is called the membership function of x in F. FIS provides most commonly used membership functions namely; trapezoidal, triangular, bell-shaped, Gaussian, Pi1, Pi2, S, Sigmoidal membership functions.

3. APPLICATION

3.1 Study Area

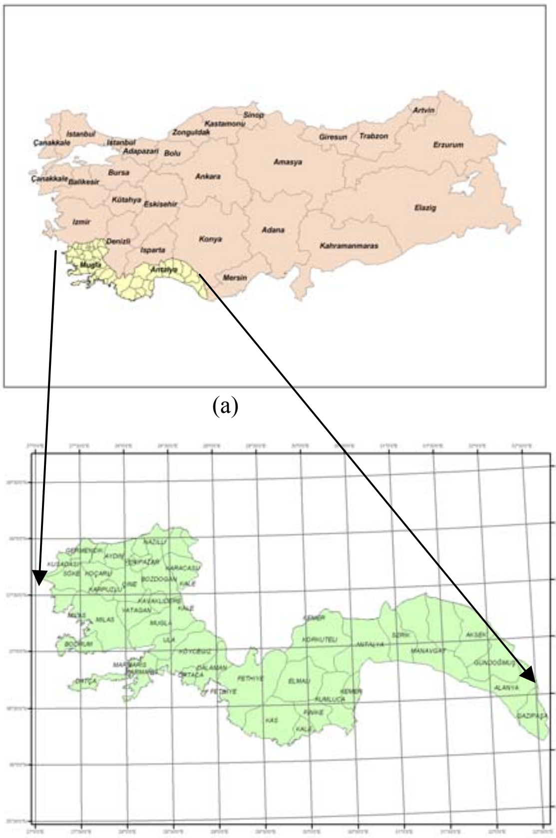
General Directorate of Forest that consists of 27 head offices manages the forests in Turkey. From 1937 to 2002, 1 549 506 ha area have been burned. When the last 10 years data have been examined in accordance with the Regional Head Offices, Muğla(1958 ha), İzmir (1475 ha) and Antalya (1352 ha) have taken the first 3 places in the ranking (General Directorate of Forest, 2004). Therefore in this study Antalya and Muğla Regional Head Offices are taken into consideration and the proposed methodology is applied to the prefectures belonging to these two Regional Head Offices (Figure 2)

3.2 Trapezoidal Membership Function

The choice of a shape for each particular linguistic variable is both subjective and problem dependent (Kecman, 2001). In this study three membership functions: trapezoidal, triangular and S membership functions are used in order to determine the degree of membership of an area to the fuzzy set.

A trapezoidal membership function can be defined as follows:

$$trapezoidal(x : a, b, c, d) = \begin{cases} 0 & x < a \\ (x-a)/(b-a) & a \le x < b \\ 1 & b \le x < c \\ (d-x)/(d-c) & c \le x < d \\ 0 & x \ge d \end{cases} \qquad (2)$$

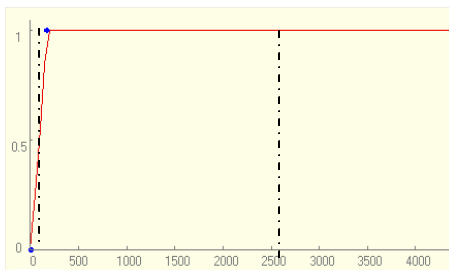


(a)

(b)

Figure 2. (a) The location of the study area in Turkey (b) The prefectures in the study area

In this definition "a" is the lowest bound, means that every region with a burned area of less than 1 ha has a degree of membership equal to zero to the corresponding fuzzy set. On the other hand, "b" and "c" denote the coordinates of tolerance. This means that all of the areas of interest with burned area from "b" to "c" ha have a degree of membership equal to one. It is obvious that the trapezoidal membership function can not be applied in the intervals [c,d] and [d,+∞] in this case, therefore the semi form of the trapezoidal membership function is used. Figure 3 depicts a Semi-Trapezoidal membership function. The values of "a", "b" and "c" are determined by a k-means clustering that was performed using SPSS program. The k-means clustering was done in order to determine the centres of the two most risky clusters and the centre of the least risky cluster. Forest fire data (burned areas) from 1997 to 2004 was used for the k-means clustering.



a b c

Figure 3. The semi-trapezoidal membership function

The prefectures of Turkey in the regional head offices of Antalya and Muğla were clustered in three groups of forest fire risk and centres of these groups determined the values of a, b, and c. The centres of the first two clusters are 4 443 167 and 17 552 700. These two centres are the coordinates of tolerance c and b, respectively. The centre of the last cluster, 82 521, is the lowest border a, of the semi-trapezoidal function.

3.3 Triangular Membership Function

A triangular membership function can be defined as follows:

$$triangle(x:a,b,c) = \begin{cases} 0 & x < a \\ (x-a)/(b-a) & a \le x \le b \\ (c-x)/(c-b) & b \le x \le c \\ 0 & x > c \end{cases} \quad (3)$$

For the same reasons as in the trapezoidal membership function, the triangular membership function can be used only in the semi-form. Using the same centres, c equals 17 552 700 and a is the centre of the cluster with the least risk which equals 82 521. Figure 4 illustrates a semi-triangular membership function.

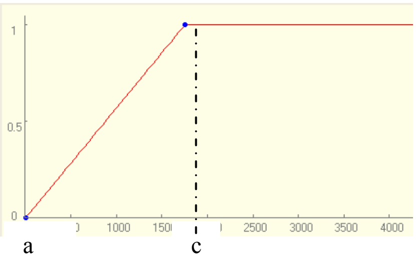


Figure 4. The semi-triangular membership function

3.4 S Membership Function

A S membership function can be defined as follows:

$$s(x:a,b) = \begin{cases} 0 & x < a \\ 2\left(\frac{x-a}{b-a}\right)^2 & a \le x \le \frac{a+b}{2} \\ 1 - 2\left(\frac{x-b}{b-a}\right)^2 & \frac{a+b}{2} \le x < b \\ 1 & x \ge b \end{cases} \quad (4)$$

Using the same centres, b equals 4 443 167 and a is the centre of the cluster with the least risk which equals 82 521. Figure 5 illustrates an S membership function.

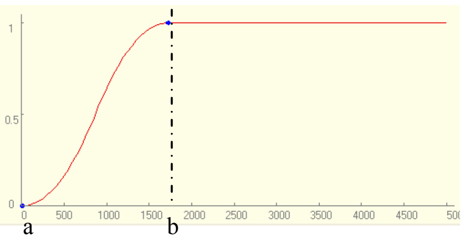


Figure 5. The S-membership function

4. RESULTS

Forest fire data is classified according to the number of fires occurred between 1997 and 2004 and total area burned for the prefectures in the regional head offices of Antalya and Muğla. The number of fires is classified in 5 classes and the map is presented in Figure 6. The classes for the burned area are determined according to the class intervals used by General Directorate of Forest and the classes are given in Table 1.

Table 1. The class limits used by General Directorate of Forest

Classes	A	B	C	D	E	F	G1	G2	G3
Area(ha)	<1	1.1-5.0	5.1-20	20.1-50	50.1-200	200.1-500	500.1-800	800.1-1500	>1500

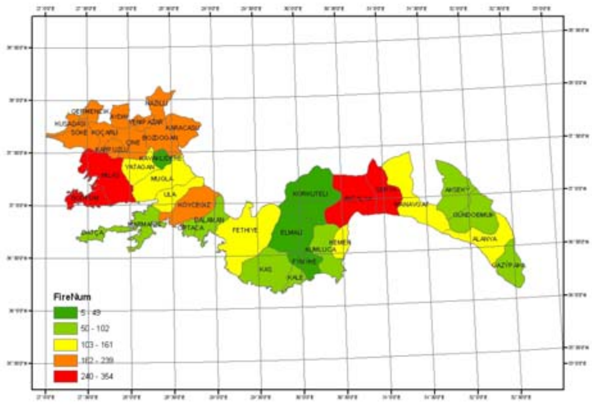


Figure 6. The distribution of number of fire occurred between 1997-2004

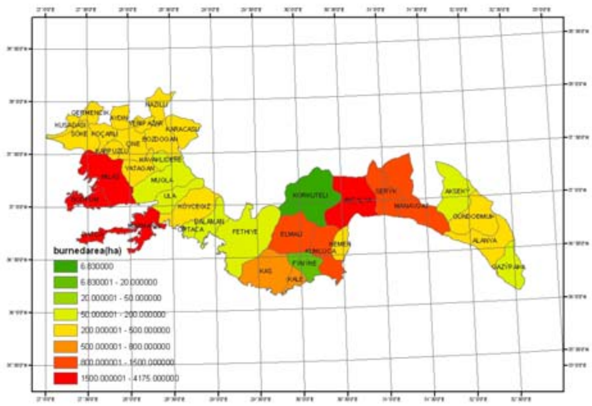


Figure 7. The distribution of the burned area between 1997-2004

The distribution of fire risky areas mapped by using semi-trapezoidal, triangular and S membership functions are presented in Figure 8-10, respectively.

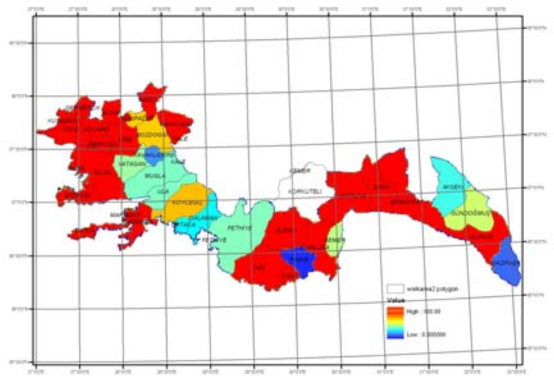


Figure 8. Fire Risky areas mapped by using semi-trapezoidal membership function

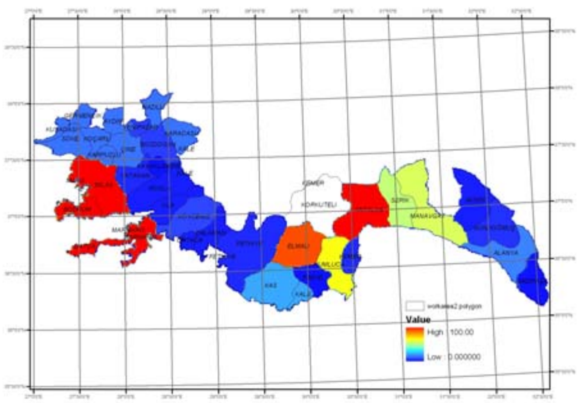


Figure 9. Fire Risky areas mapped by using triangular membership function

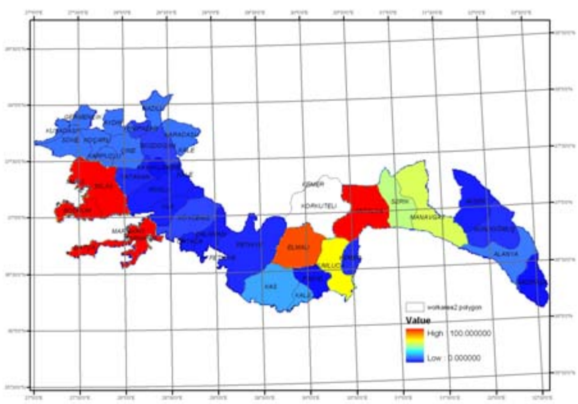


Figure 10. Fire Risky areas mapped by using S membership function

5. DISCUSSION

Eleven most risky prefectures were determined from semi-trapezoidal membership function. It characterizes the prefectures of Antalya, Kaş, Manavgat, Gündoğmuş, Kumluca, Serik, Alanya, Elmalı, Aydın, Marmaris, and Milas. Triangular and S membership functions identify three most risky prefectures. Triangular membership function characterizes the prefectures of Antalya, Marmaris, Milas and Elmalı, where the degrees of membership equal to 1 for Antalya, Marmaris and Milas and 0.935 for Elmalı. S membership function characterizes the prefectures of Antalya, Marmaris, Milas and Elmalı, where the degrees of membership equal to 1 for Antalya, Marmaris, Milas and 0.924 for Elmalı. There is a minor difference in the degrees of membership obtained from triangular and S membership functions in assessing the most risky areas, where the comparison for each prefecture can be seen in Figure 11.

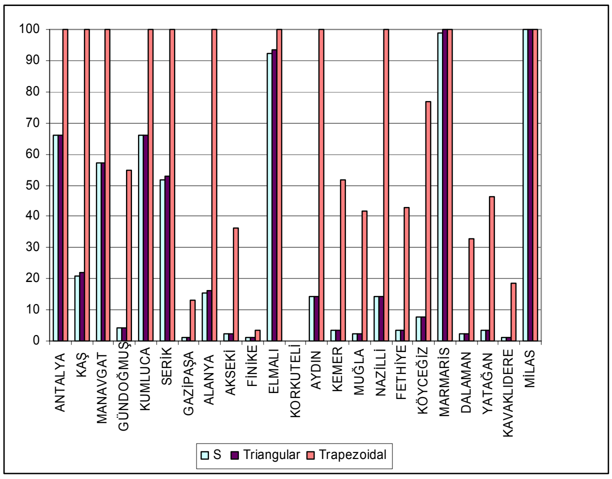


Figure 11. Comparison of degrees of three membership functions for the prefectures.

Triangular and S membership functions identify clear distinctions between the areas of highest risk. The prefectures classified as G3 class (Table 1) according to the burned area were estimated in the highest risk group. The degrees of membership were estimated for the other areas. The result shows that the system offers a much more reliable approach than the use of actual forest fire history and its evaluation will continue in the future.

The generic structure of Fuzzy Inference System makes the computation of fuzzy algebra possible. Although it provides different inference methods and aggregation methods, they are not used in this study and left for the future work.

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