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Fire risk evaluation using multicriteria analysis—a case study

Krishna Prasad Vadrevu · Anuradha Eaturu · K. V. S. Badarinath

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Abstract Forest fires are one of the major causes of ecological disturbance and environmental concerns in tropical deciduous forests of south India. In this study, we use fuzzy set theory integrated with decision-making algorithm in a Geographic Information Systems (GIS) framework to map forest fire risk. Fuzzy set theory implements classes or groupings of data with boundaries that are not sharply defined (i.e., fuzzy) and consists of a rule base, membership functions, and an inference procedure. We used satellite remote sensing datasets in conjunction with topographic, vegetation, climate, and socioeconomic datasets to infer the causative factors of fires. Spatial-level data on these biophysical and socioeconomic parameters have been aggregated at the district level and have been organized in a GIS framework. A participatory multicriteria decision-making approach involving Analytical Hierarchy Process has been designed to arrive at a decision matrix that identified the important causative factors of fires. These expert judgments were then integrated using spatial fuzzy decision-making algorithm to map the forest fire risk. Results from this study were quite useful in identifying potential "hotspots" of fire risk, where forest fire protection measures can be taken in advance. Further, this study also demonstrates the potential of multicriteria analysis integrated with GIS as an effective tool in assessing "where and when" forest fires will most likely occur.

Keywords Forest fires · Spatial decision-making · AHP · Fuzzy sets

K. P. Vadrevu (✉)
Agroecosystem Management Program, Ohio Agricultural Research and Development Center (OARDC), The Ohio State University, 201 Thorne Hall, 1680 Madison Avenue, Wooster, OH 44691, USA
e-mail: krisvkp@yahoo.com

A. Eaturu
Department of Mathematics, Kent State University, Kent, OH USA

K. V. S. Badarinath
Department of Space-Government of India, Atmospheric Science Section, National Remote Sensing Center, Balanagar, India

Introduction

Over the past few decades, forest fires in India have received increasing attention because of the wide range of ecological, economic, social, and political impacts. Fire plays an important role in the creation and maintenance of landscape structure, composition, function, and ecological integrity (Covington and Moore 1994; Goldammer 1999; Morgan et al. 2001) and can influence the rates and processes of ecological succession and encroachment. The impact of fires at local, regional, and global scales has been recently reviewed in Stolle and Lambin (2003) and Lentile et al. (2006). For example, at the local scale, fire can stimulate soil microbial processes and combust vegetation ultimately altering the structure and composition of both soils and vegetation (Goldammer 1999; Lentile et al. 2006). Also, at the regional and global scales, combustion of forest and grassland vegetation releases large volumes of radiatively active gases, pyrogenic aerosols, and other chemically active species that significantly influence Earth's radiative budget and atmospheric chemistry (Andreae and Merlet 2001), impacting air quality (Hardy et al. 2001) and raise concern about risks to human health (Brauer 1999). Considering these impacts, understanding the causative factors of fire including fire effects and ecosystem response is a challenge to both research and management.

Most importantly, the overriding role of anthropogenic factors in regulating fire events in addition to climate, vegetation, and topographic factors makes fire risk prediction highly challenging (Perry 1998). A relevant question in this context is whether it is possible to delineate the vulnerable areas under study as "forest fire risk" zones. Important definitions of fire risk along with fire danger and vulnerability were reviewed in Chuvieco et al. (2003a, b). According to FAO's terminology (FAO 1986), forest "fire risk is the chance of a fire starting as determined by the presence and activity of any causative agent". In this study, we adopt the terminology of Chuvieco and Congalton (1989), who defined the fire risk as "the union of two components of fire hazard and fire ignition." The overall risk depends on the fuel and its susceptibility to burn (i.e., hazard) and on the presence of external causes (both anthropogenic and natural) leading to fire ignition. Other sources consider risk as "the potential number of ignition sources" (Canadian Forest Service 1997). Also, Chuvieco et al. (2003a, b) inferred fire risk as a combination of two terms, the fire danger (the probability of fire ignition and propagation) and fire vulnerability (as outcome or consequences of fires). Further, fire danger has been referred to an assessment of both fixed and variable factors of the fire environment (i.e., fuels, weather, and topography) that determine the ease of ignition, rate of spread, difficulty of control, and impact of wild land fires (Merril and Alexander 1987; Taylor and Alexander 2006).

A great range of techniques have been used to model fire risk, from pure "crisp" mathematical models (usually based on the Rothermel (1983) equations), to cellular automata and computational intelligence techniques (Allgower et al. 2003). The more complex fire models require spatial information that is furnished by remote sensing and Geographic Information Systems (GIS) (Bonazountas et al. 2005). Additionally, integration of multicriteria decision-making (MCDM) methods in spatial domain provides a novel framework for addressing several environmental problems, including quantifying "fire risk." For example, MCDM methods have been developed to solve conflicting preferences among criteria (Keeney and Raiffa 1976). Rational decision-making requires combining both objective and subjective criterion (Pomerol and Barba-Romero 2000), most notably in a collaborative participatory framework for which MCDM methods can provide useful framework (Saaty 1994; Malczewski 2002; Tangestani 2004; Sadiq and Husain 2005). The study area is dominated by forests, where most of the stakeholders are local indigenous people, and their dependence on forest resources is immense. Also, the forest fire problem in the study area is spatially diverse in nature and involves both biophysical and socioeconomic parameters, providing an ideal scenario to test MCDM methodologies. There are several districts where fires are relatively intense compared to others. Also, each of biophysical (climate, topography, vegetation) and socioeconomic parameters (population density, literacy rates, agricultural workers, nutritional density, etc.) have spatial dimension, i.e., they vary across districts. Combining these multiple parameters using decision-making methods in a collaborative framework may yield good results (Saaty 1994; Malczewski 2002). Of the several algorithms, since fuzzy linguistic models permit the translation of verbal expressions into numerical values, MCDM methods based on fuzzy relations were used quite successfully (Malczewski 2002; Kahraman et al. 2003). Fuzzy set theory is an extension of classical set theory (Zadeh 1965). Fuzziness is a type of imprecision, associated with sets in which there is no sharp transition from membership to nonmembership (Bellman and Zadeh 1970). The membership grade of an object can range from 0 to 1. The value of 1 denotes full membership, whereas the closer the value is to 0, the weaker the object's membership is in the fuzzy set. Fuzzy set eliminates the sharp boundary, which divides members and nonmembers in a crisp set, by providing a transition between the full membership and nonmembership (Leung and Cao 2001). Continuous fuzzy classes can be constructed based on the central concepts of classes that are defined a priori using experience and scientific or heuristic knowledge. The linguistic knowledge can be used to summarize information about a complex phenomenon and then converted to numerical data for further processing (Yanar and Akyurek 2006).

A detailed review on the basic concepts of fuzzy sets and integration of the same using GIS can be found in Robinson (2003). Integration of fuzzy logic with GIS in a decision-making framework has been used for different purposes, including land suitability based upon soil profiles (Burrough et al. 1992), soil classification (Lark and Bolam 1997), landfill site screening (Charnpratheep et al. 1997), soil erosion (Mitra et al. 1998), crop land suitability analysis (Ahmed et al. 2000), ranking burned forests to evaluate the risk of desertification (Sasikala and Petrou 2001), seeking optimum locations for real estate (Zeng and Zhou 2001), assessing vulnerability to natural hazards (Rashed and Weeks 2003; Tangestani 2004; Dixon 2005), estimating risk (Sadiq and Husain 2005), incorporating farmer's knowledge for land suitability classification (Sicat et al. 2005), fuel type mapping (Nadeau and Englefield 2006), assessing spatial extent of dry land salinity (Malins and Metternicht 2006), etc. Therefore, many studies have been performed using fuzzy logic integrated with GIS in a MCDM framework demonstrating that the methods are robust and valid. However, we know of no such studies that used fuzzy logic integrated with GIS in a MCDM framework for quantifying fire risk in tropical deciduous forests of south India.

In this study, we explore the direct and the indirect causes of fires at the landscape scale, using a fuzzy decision-making model in a GIS framework that is capable of predicting the future fire threats as a function of biophysical, socioeconomic, topographic, and climatic conditions. The method presented in our study integrates analytic hierarchy process (AHP) in a participatory decision-making framework along with fuzzy logic to quantify fire risk focusing on tropical deciduous forests of Andhra Pradesh, south India.

Study area

Andhra Pradesh state lies between 12°41′ and 22°N latitude and 77° and 84°40′E longitude of the Indian region (Fig. 1). It covers an area of 275,608 km^2 and is bounded by Maharashtra, Chhattisgarh, and Orissa in the north, the Bay of Bengal in the east, Tamil Nadu to the south, and Karnataka to the west. Andhra Pradesh is the fifth largest state and is considered the rice bowl of India. Agriculture has been the chief source of income for the state's economy. Two important rivers of India, the Godavari and Krishna, flow through the state. The state has 23 local administrative districts, and Hyderabad is the capital of the state. Forests of Andhra Pradesh occupy an area of about 63,814 km^2. Forest area to geographical area is about 23.2% with dense forests occupying 23,048 km^2, open forests 19,859 km^2, and mangrove vegetation of about 383 km^2. Most dominant forests are dry deciduous and moist deciduous forests. Nearly 3.2 million indigenous people live in different districts of Andhra Pradesh. Their habitat is spread along the coastal and mountain strip of the Bay of Bengal from the Bhadragiri agency in Srikakulam district to the Bhadrachalam agency in Khammam and Godavari districts. Important among them are the Khonds, Kolamis, Nayakpods, Koyas,

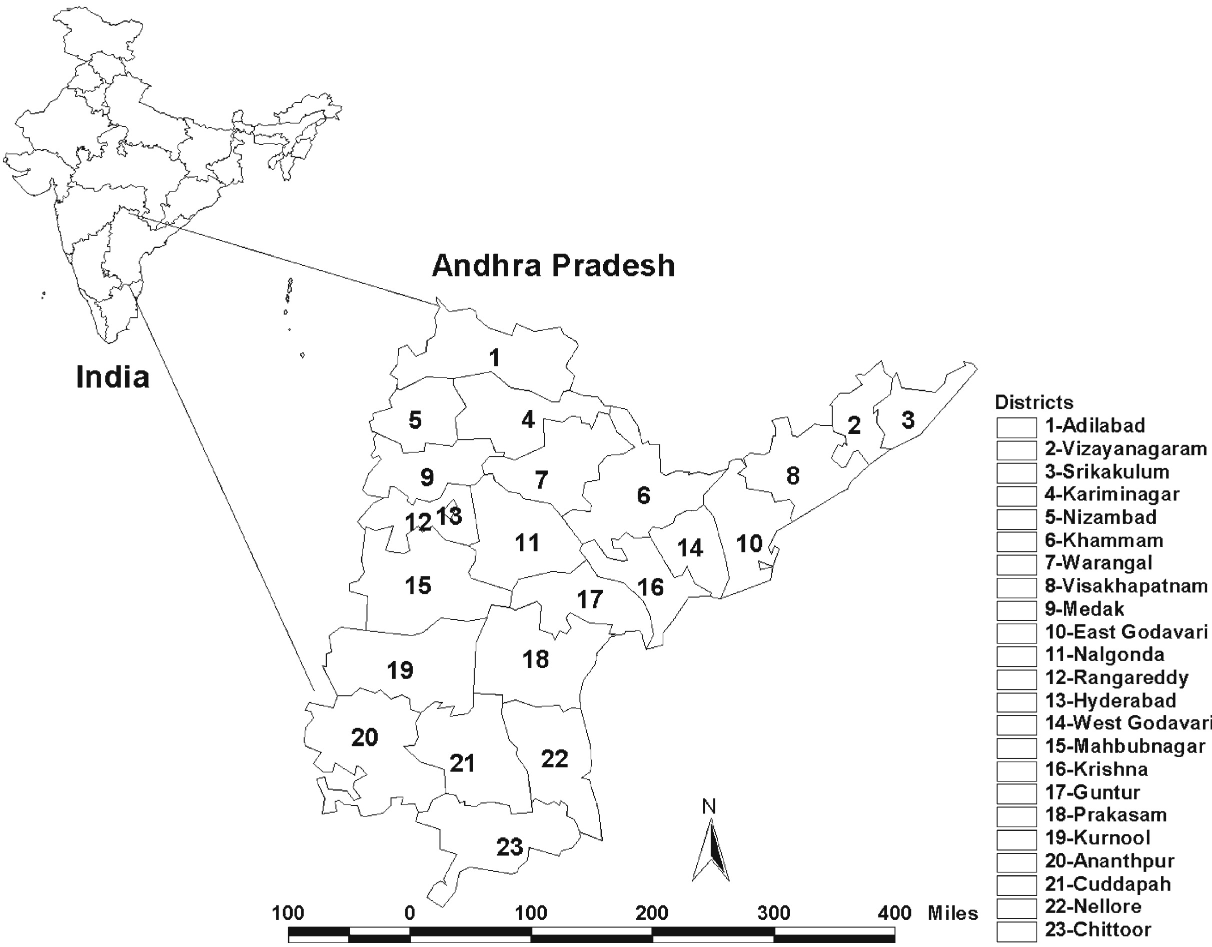

Fig. 1 Study area location map

Kondadoras, Valmikis, Bhagatas, Savaras, Jatayus, Gadabas, Yanadis, and Chenchus. Several of these indigenous communities depend on forest resources for food, fuel and fodder.

Methodology

In this study, we used Saaty's (2000) analytical hierarchy process, a MCDM methodology in conjunction with fuzzy logic, in a participatory decision-making framework to rank and prioritize the causative factors of fire risk in the study area. Our methodology consisted of four different components: (1) hierarchical structure development of fire risk criteria, (2) weights determination at different levels of hierarchy using linguistic variables and fuzzy sets, (3) assigning criteria weights in GIS, and (4) fire risk quantification using decision rule.

Hierarchical structure development of fire risk criteria

We used topographic, vegetation, climatic, and socioeconomic parameters for evaluating the fire risk in the study area. These data were arranged in raster-based maps for further analysis. The hierarchical structure for quantifying fire risk has

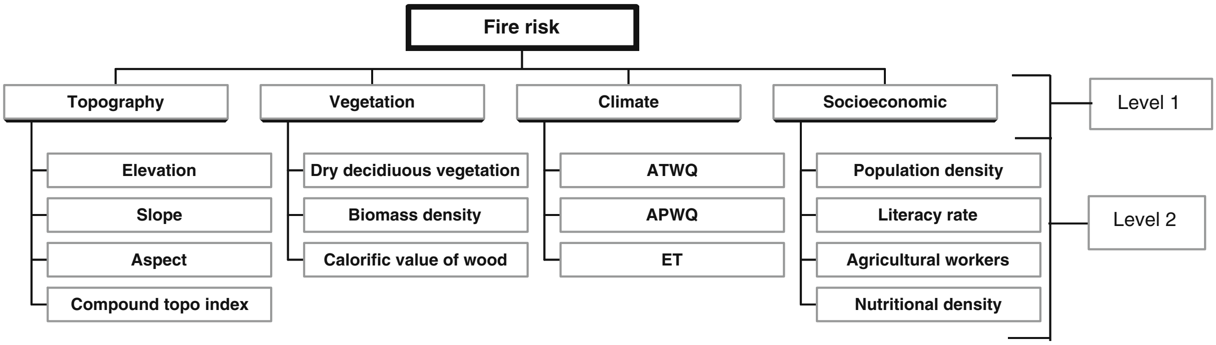

Fig. 2 Hierarchical data organization for quantifying fire risk in the study area

been designed following the Analytical Hierarchy model (Saaty 2000) and is given in Fig. 2. Detailed explanation for causative factors of fires is given below.

Topographic parameters

For the past several years, fire behavior models have incorporated the interaction of fire spread with fuels, weather, and terrain (Albini 1976; Rothermel 1983). Some effects were accounted for fire line intensity (Rothermel 1983). Other terrain effects on fire intensity and spread were incorporated indirectly through fuel type and moisture. The effect of terrain attributes on forest survival following wildfire has been assessed by Kushla and Ripple (1997) and others. We used four different topographic parameters explained below, as causative factors of fires; these included elevation, slope, aspect, and a compound topographic index. Most of these parameters were derived from GTOPO digital elevation model (DEM) and specifically the south Asia GIS database (Hearn et al. 2001).

(a) Elevation: It is an important physiographic factor that is related to wind behavior and hence affects fire proneness (Rothermel 1983). Fire travels most rapidly up-slope and least rapidly down-slope. Elevation values (m) for fire pixels have been extracted from GTOPO30 DEM with a horizontal grid spacing of 30 arc sec (∼1 km).

(b) Slope: It is an indicator of rate of change of elevation (degrees). Slope affects both the rate and direction of the fire spread. Fires usually move faster uphill than downhill (Rothermel 1983; Kushla and Ripple 1997).

(c) Aspect: Describes the direction of the maximum rate of change in elevation between each cell and its neighbors. A slope with an east aspect will get direct sunlight earlier in the day than a slope with a west aspect. Also, a north-facing slope receives less sunlight than a south facing slope. Thus, Southern aspects receive more direct heat from the sun, drying both the soil and the vegetation.

(d) Compound topographic index (CTI): CTI, also known as the wetness index, is a function of upstream contributing area and the slope of the landscape (Moore et al. 1991). The spatial distribution of water on a field is influenced by lateral flow and thus controlled by elevation differences. CTI is a compound terrain attribute calculated from specific catchment area of a point (A_s) and the local slope gradient tan β (Beven and Kirby 1979). CTI is given as

$$\mathrm{CTI} = \frac{\ln(a)}{\tan\beta} \tag{1}$$

where ln is the natural logarithm, "a" is the upslope area per unit width of contour, and β is the slope angle (Moore et al. 1991). In general, the index essentially is a measure of the tendency of water to accumulate at any point on a slope. The index has been widely used for both prediction of runoff and hydrological conditions. The CTI maps indicate zones of high potential soil moisture (high values) and zones that dry up first (low values). Thus, higher CTI values are a good indicator of lower fire probability. CTI values have been calculated for individual pixels using GTOPO 30 elevation datasets.

Vegetation parameters

Vulnerability of the forest fuels to fire has been mapped based on vegetation type and biomass data. Vegetation must be considered because some vegetation types are more flammable than others, thereby increasing the fire hazard. Fuels represent the organic matter available for fire ignition and combustion (Rothermel 1983; Albini 1976). Thus, a spatial mapping of fuels is fundamental to assess fire hazard across a landscape. In this study, we used three different vegetation parameters, (a) percent dry deciduous vegetation, (b) biomass densities, (c) calorific value of wood material.

(a) Percent dry deciduous vegetation: Flammability increases if the vegetation is dry. Vegetation types for the study area have been characterized from Satellite Pour l'Observation de la Terre (SPOT) 1 km satellite vegetation datasets.
(b) Biomass densities: The higher the quantity of fuel, the higher the flammability. As the amount of flammable material in a given area increases (such as due to litter accumulation), the amount of heat produced by the fire also increases (Albini 1976). Biomass density values at district level have been aggregated from local forest records and then calculated for individual pixels to arrive at a biomass density map (km^2).
(c) Calorific value of wood material: High calorific value, together with burning efficiency, governs the heat energy of wood material (Bhatt and Todaria 1992). Thus, higher calorific value produces more energy and thus facilitates fire spread and dispersal. Calorific values (kJ/g) for plant species have been collected from literature and calculated based on biomass densities (km^2) and dominant species at a district level. These values were then assigned to individual pixels using SPOT vegetation type dataset.

Climatic parameters

Fire occurrence, frequency, as well as intensity are primarily dependent on climate, directly through weather conditions, which allow ignition, and indirectly through the supply of sufficient vegetation fuel load to sustain fire. Climatic and weather factors also play an important role in fire spread and behavior. In this study, we used temperature as well as precipitation (summed over different time periods) as modulating parameters of forest fires in the study region, in addition to evapotranspiration. The data for these parameters has been obtained from local meteorological records at a district level.

(a) Average temperature of the warmest quarter: Higher temperature (°C) makes fuels highly susceptible to fires, mainly due to dryness.
(b) Average precipitation of the warmest quarter: Higher values (in mm) contribute to high moisture in fuels, thus are a negative indicator of fire spread. The scale has been reversed to fit the linear trend in accordance to other parameters.
(c) Evapotranspiration (ET): ET (in mm) is a measure of evaporative demand and is calculated based on Penman Monteith equation. Values are aggregated only from March to June. Fuels are highly prone to fires with increasing evapotranspiration.

Socioeconomic parameters

The demand for fuel wood by tribal people in the study region is closely linked with shifting cultivation, i.e., slash and burn agriculture, in which the biomass is clear cut and then subsequently burnt for land-clearing purpose. The tribal dependence on forests for fuel wood is also a major source of energy, causing serious deforestation in several parts of the study area. Commercial fuel is beyond the means of the tribal communities due to their poor socioeconomic conditions. Also, due to ever-increasing population, fuel wood consumption in some of the districts is increasing rapidly. Because the majority of the population live in rural areas where fuel wood, along with crop residues, provide most of the energy requirements, we used socioeconomic indices obtained from locally available district census handbooks that combined anthropogenic measures with forest and agriculture parameters as causative factors of fire. These variables included population density, literacy rate, agricultural workers, and nutritional density to model fires as explained below.

(a) Population density (PD): The higher the PD, higher the dependence on surrounding forest resources. Fires in several districts of the study area are caused mainly due to land clearing for agriculture purpose (slash and burn agriculture).
(b) Literacy rate (LR): LR is a positive indicator of awareness relating to forest sustainability and accidents that may cause forest fires. The scale has been reversed to match other criteria, i.e., the lower the literacy rate, the higher the rate of susceptibility of fire risk.
(c) Agricultural workers (AGRI-W): A surrogate measure of land use intensity and also farming systems influence. Several local farmers use fire to clear forests and higher number of AGRI-W provide opportunities for land owners to clear large tracks of land (Stolle and Lambin 2003).
(d) Nutritional density (ND): This is calculated as total rural population/total agricultural area. In a traditional society, the nutritional density can be considered as one of the socioeconomic constraints on the land use/cover. The index forms one of the indirect indicators for forest cover proportions. Because the major occupation of the rural as well as indigenous population inhabiting the study area is slash and burn agriculture, the high value of ND can have a negative impact on forest cover proportion.

Weights determination at different levels of hierarchy

A fuzzy set is a multivalent generalization of a crisp set whose membership function takes on bivalent values {0,1}. The central concept of the fuzzy-set theory is the membership function, which represents the degree with which an element belongs to a set. A fuzzy subset A of a universe of discourse U is characterized by a membership function μ_A.

That is,

$$\mu_A : U \to [0, 1]; \tag{2}$$

where $\mu_A(x)$ is the membership of x in A; that is, μ_A serves as the membership function by which a fuzzy set A is defined (Bellman and Zadeh 1970). This function associates with each element x of U a number $\mu_A(x)$ in the interval [0,1].

This fuzzy set A can be formally written as:

$$A = \left\{x1/\mu\left(x_1\right), x_2/\mu\left(x_2\right), \ldots\ldots x_n/\mu\left(x_n\right)\right\} \tag{3}$$

For all A, $\mu_A(x)$ takes on the values between and including 0 and 1. Various types of fuzzy membership functions have been proposed. Multiple methods can be used to determine the membership values, e.g., depending on the amount of a priori information available. In our study, we used a trapezoidal fuzzy function. A trapezoidal fuzzy number (Fig. 3) can be expressed as (a_1, a_2, a_3, a_4), and its membership function ($\mu_{x)}$ is defined as (Zadeh 1965)

$$\mu_a(x) = \begin{cases} 0, x < a_1 \\ (x - a_1)/(a_2 - a_1), a_1 \le x \le a_2 \\ 1a_2 \le x \le a_3 \\ (x - a_4)/(a_3 - a_4), a_3 \le x \le a_4 \\ 0, x > a_4 \end{cases} \tag{4}$$

The fuzzy operations for the trapezoidal numbers are given in Dubois and Prade (1979).

Application of fuzzy sets, in particular the theory of linguistic variables (Zadeh 1965) in spatial analysis is given in Leung and Cao (2001). The merit of using a fuzzy approach is to express the relative importance of the alternatives and the criteria with fuzzy numbers instead of using crisp

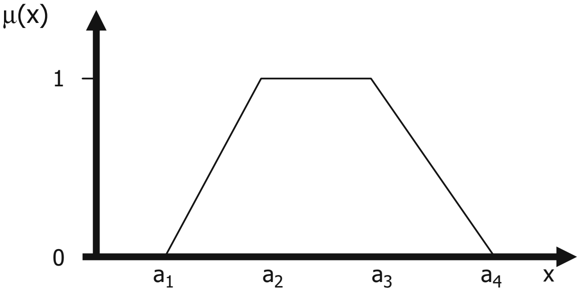

Fig. 3 Trapezoidal fuzzy membership functions

numbers. To suit the trapezoidal fuzzy numbers, we used the standard membership functions from Chen and Hwang (1992) that are based on linguistic variables. For determining the weights at level for key variables (topography, vegetation, climate, and socioeconomic parameters) we used AHP. Our study comprised nine experts (four academic researchers, two from government organizations, and three from nongovernment organizations who work closely in forested areas). The core of the AHP Saaty's (2000) method is an ordinal pairwise comparison of all criteria. In other words, it addresses preference statements. Per pair of criteria, the decision maker is asked to which degree a criterion is more important than the other. By means of these comparisons, the method defines the relative position of one criterion in relation to all other criteria. By using an eigenvalue matrix technique, quantitative weights can be assigned to the criteria. The Saaty's method employs a semantic nine-point scale for the assignment of priority values. This scale relates numbers to judgments, which express the possible results of the comparison in qualitative terms. In this way, different elements can be weighted with a homogenous measurement scale. Through this method, the weight assigned to each single criterion reflects the importance which every expert involved in the project attaches to the objectives. Although the discrete scale of 1 to 9 has the advantages of simplicity and ease of use, it does not take into account the uncertainty associated with mapping of one's perception (or judgment of a number). To address the uncertainty, we used fuzzy trapezoidal numbers (Chen and Hwang 1992) in order to capture the vagueness (Table 1). Each weight obtained through the decision-making process was assigned to fuzzy sets. The pairwise comparisons were then used to calculate vector of weights and then multiplied by the matrix of criterion scores to compute a single aggregate value. The priorities of the criteria were estimated by finding the principal eigenvector "w" of the matrix "A", as

$$Aw = \lambda_{\max} w \tag{5}$$

where λ_{max} is the largest eigenvalue of the matrix "A," and the corresponding eigenvector "w" contains only positive entries. The eigenvector "w" is then normalized to yield a vector of weights for each of the individual attributes contributing to the aggregate value (Ramanathan 2001). The logical consistency of comparison matrices was evaluated using the consistency ratio (CR), defined as,

$$\mathrm{CR} = \mathrm{CI}/\mathrm{RI} \tag{6}$$

where CI is the consistency index defined as,

$$\mathrm{CI} = (\lambda_{\max} - n)/(n-1) \tag{7}$$

Table 1 Linguistic values and corresponding Fuzzy numbers (Chen and Hwang 1992)

Intensity of fuzzy scale	Linguistic variable	Fuzzy sets
1	Equally important; very low	(0,0,0.1,0.2)
3	Weakly important; low	(0.1, 0.25, 0.25,0.4)
5	Essentially important; medium	(0.3,0.5,0.5,0.7)
7	Very strongly important; high	(0.6,0.75,0.75,0.9)
9	Absolutely important; very high	(0.8,0.9,1.0,1.0)
2,4,6,8	Intermediate values between two adjacent judgments	

where λ_{max} is the maximum eigenvalues, n is the number of key variables; and RI is the Random Inconsistency Index (Saaty and Vargas 1993). The mean Random Inconsistency Index table that is given in Saaty (1980), obtained by averaging the CIs of many randomly generated pairwise comparison matrices, was used to compute the CR. The CR was computed for each matrix of pairwise comparisons, and only those with CR $\leq$ 0.10 were included in a combined matrix. In general, CR $\leq$ 0.10 is considered to be tolerable (Saaty and Vargas 1993). The pairwise comparison matrices for each expert that met the consistency criterion were than aggregated by calculating a geometric mean for each element in the matrix (Saaty 2000). The detailed equations involved in AHP calculation are provided in Saaty (2000) and also in Wang et al. (2006), Ying et al. (2008), and Wu et al. (2007).

Assigning criteria weights in GIS

At the level-two hierarchy (Fig. 2), each criterion is represented in the form of GIS maps. Detailed procedures for generating the fuzzy criteria maps and weights using the linguistic variables and corresponding fuzzy membership functions are given in Malczewski (1999). In this study, we used the fuzzy membership functions (also called standard fuzzy numbers) from Chen and Hwang (1992) (Table 1) to generate the

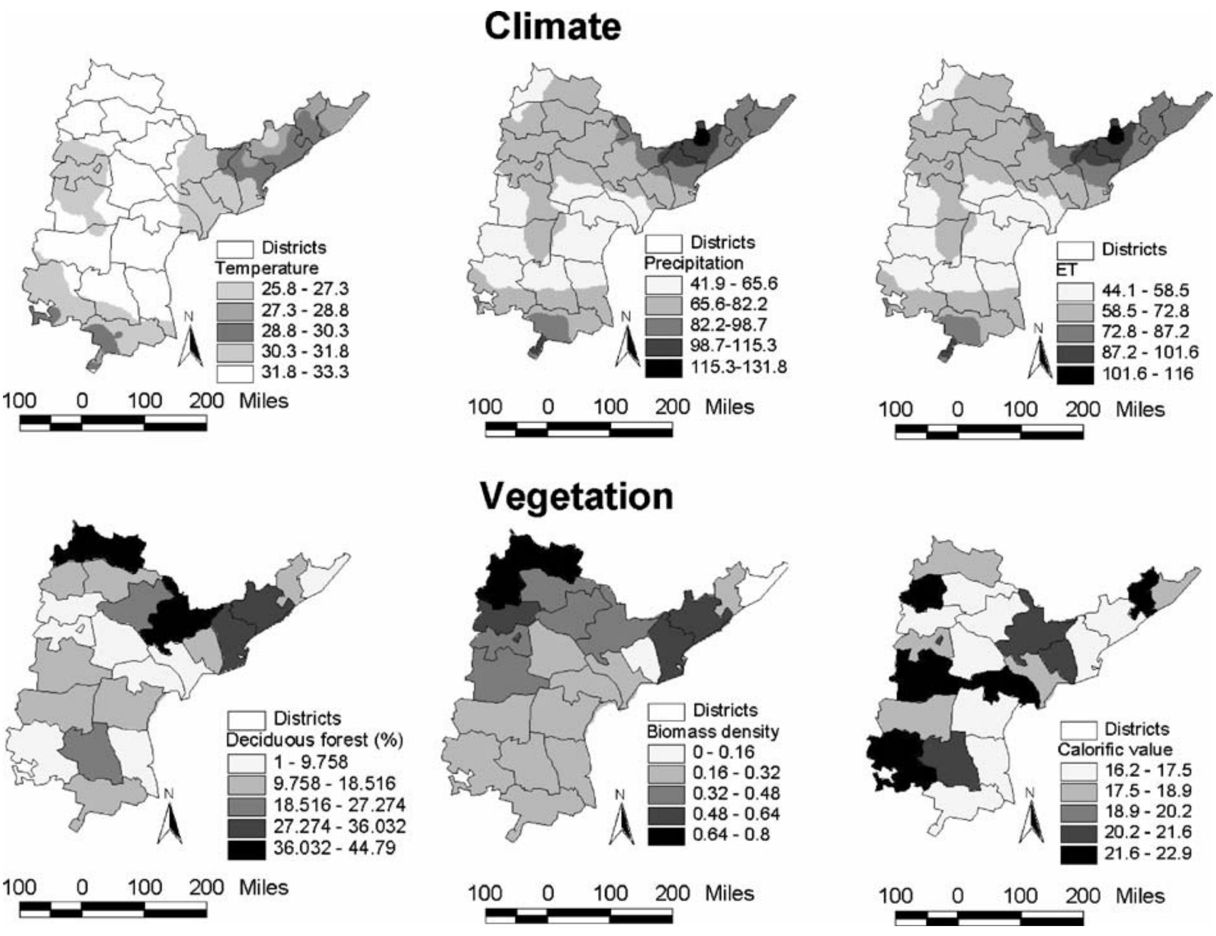

Fig. 4 Criterion maps depicting five-point scale for climate and vegetation key variables

commensurate criterion map layers for individual variables (elevation, slope, aspect, compound topographic index for key variable of topography, and so on...) in ARCGIS (ESRI 9.0x). The ranges of values from "very low" to "high" with five-point scale for individual key variables are shown in Figs. 4 and 5. Specifically, the fuzzy numbers are states of the linguistic variable (Table 1). The states are represented by linguistic terms such as "very high," "high," "medium," "low," "very low" (e.g., for population density variable in socioeconomic category), or "very steep," "steep," "small," "medium," "large" (e.g., slope category in biophysical category), and so on. The maps depicted in Figs. 4 and 5 with five-point scale were converted to standardized form using the fuzzy numbers (Table 1). Each pixel value represented by a particular attribute is assigned the fuzzy membership function ranging from 0 to 1, indicating the degree of membership in the fuzzy set (Malczewski 1999). For example, in the PD map (first map in Fig. 5, socioeconomic variables) "very low" values corresponding to population range of 154–462.8/sq.km) were assigned the fuzzy membership values of (0,0,0.1,0.2). In the raster-based map of population density, each pixel corresponding to the individual population density range was assigned four elements of the trapezoidal fuzzy number, i.e., the values of 0,0,0.1,0.2. Thus, a single attribute (e.g., "very low" population density) is represented by a set of four raster GIS layers (Malczewski 1999; Eastman et al. 1995). The above process was achieved through ARCGIS (9.0x) Spatial Analyst using raster calculator option and through building map algebra expressions. A similar exercise was done for all the other key variables. Although tedious to implement in GIS, the above procedure allowed assigning the membership functions in a systematic manner (Eastman et al. 1995; Heywood et al. 1995). Once fuzzy criterion maps are created, they were multiplied by AHP weights with their corresponding fuzzy numbers. Also, to handle the no-data problem in raster-based computations, the values were replaced with the smallest possible fuzzy membership number, which does not affect

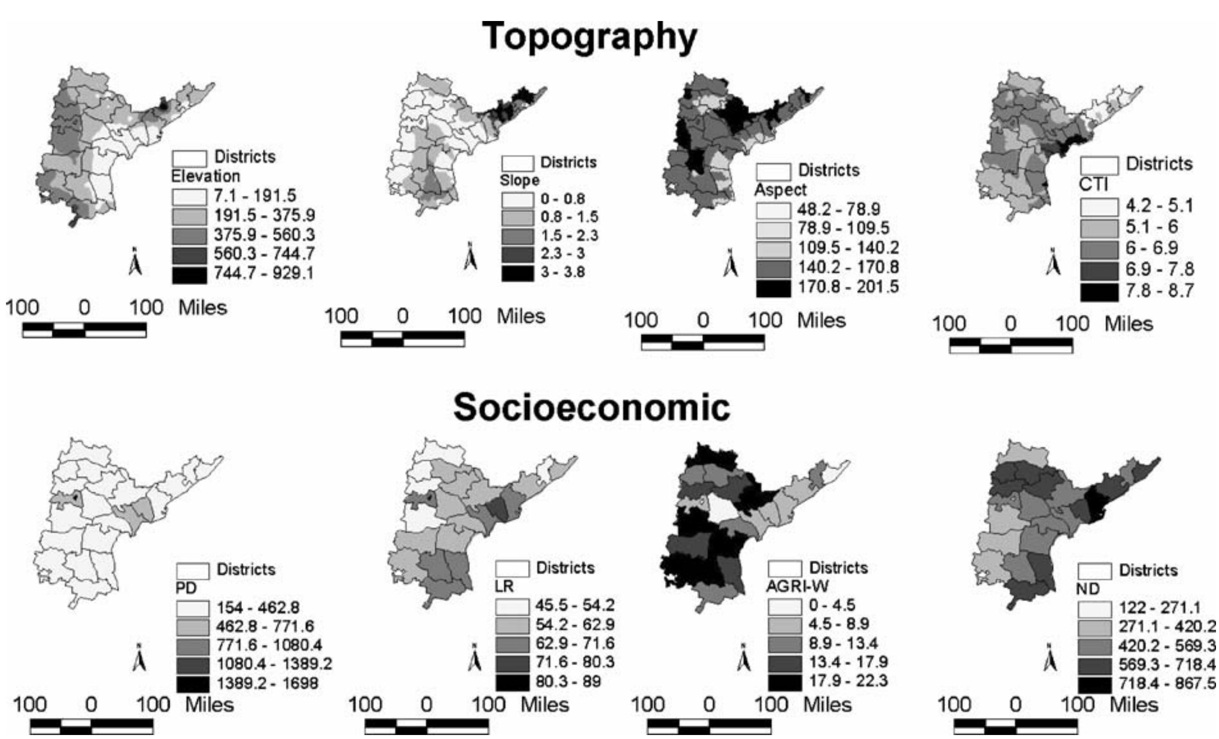

Fig. 5 Criterion maps depicting five-point scale for topography and socioeconomic key variables

the prospectivity results but still allows these areas to be included in the analysis (D'Ercole et al. 2000).

Fire risk quantification using decision rule

We used the fuzzy-weighted sum model (F-WSM) to prioritize the fire risk from fuzzy sets as

$$P_{\mathrm{F-WSM-score}} = \max \sum_{j=1}^{n} a_{ij} w_j \text{for } i = 1, 2, 3, 4 \ldots, m \tag{8}$$

where $P_{\mathrm{F-WSM-score}}$ is the fuzzy weighted performance score for the ith alternative in terms of the jth criterion obtained from trapezoidal fuzzy number denoted as $a_{ij} = (a_{ij1}, a_{ij2,} a_{ij3,} a_{ij4})$ (Fishburn 1967; Triantaphyllou and Lin 1996).

Results

The composite "fire risk" map derived from integrating AHP and fuzzy functions is shown in Fig. 6. In the fire risk map, the individual cells were ranked from very low to very high, based on their predicted "risk" of fire. These results clearly suggest that districts of Adilabad, Khammam, East Godavari, Visakhapatnam, Vizayanagaram, Cuddapah, and Prakasam showed "medium to very high" fire risk, compared to other districts having "low to very low" fire risk values. Also, fire risk varied from "medium to high" for different areas of the same district, such as for Visakhapatnam and Khammam. Of the different causative factors of fire risk at the first level of hierarchy (Fig. 2), the normalized priority vector from the AHP analysis yielded the highest weight for socioeconomic factors (0.312) followed by vegetation (0.255), climate (0.233), and topography (0.204). These weights were based on the com-

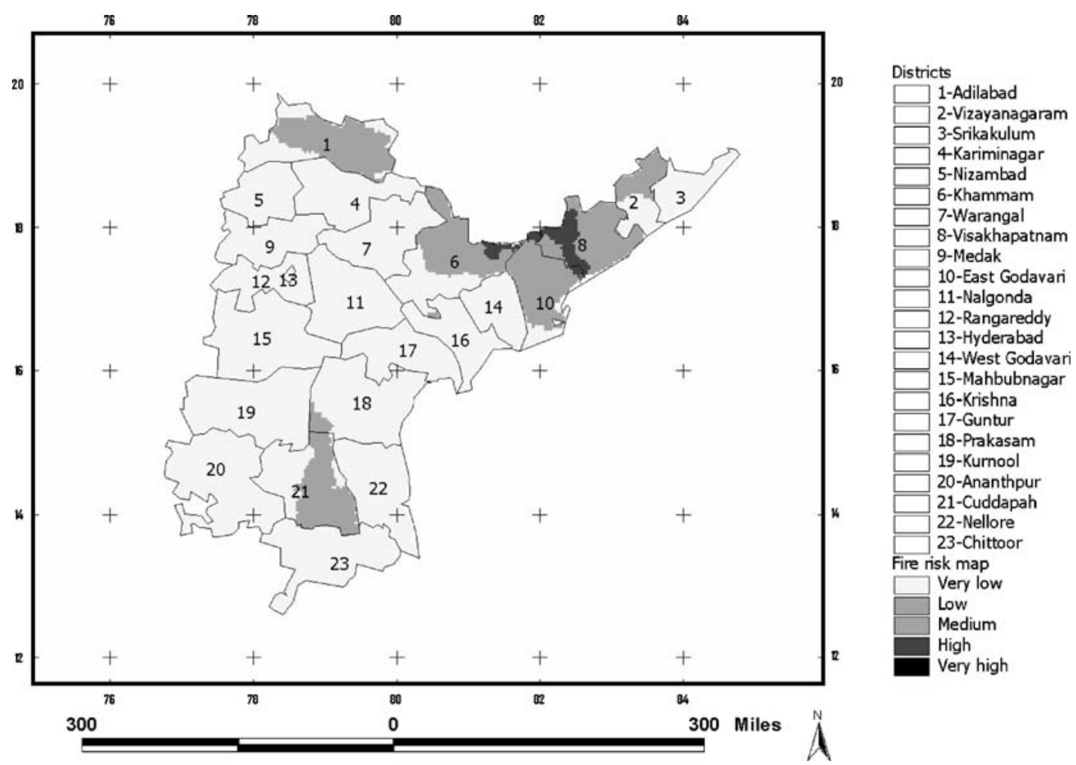

Fig. 6 Forest fire risk map

bined matrix of judgments obtained from different experts and had the consistency ratio less than 0.1. The above expert information in the form of weights has been combined with fuzzy criterion maps followed by defuzzification to arrive at the "fire risk" map for the study area. Thus, the final map is a combined map of both objective as well as subjective (expert judgment) data. In this study, we also tested the accuracy of the "fire risk" using one of the most readily available SPOT satellite-derived fire dataset, a global product available for the year 2000 (Gregoire et al. 2003; Tansey et al. 2004). A global fire map has been subset for the study area and overlaid on "fire risk" map (Fig. 7), for assessing the overall accuracy. Although direct comparison between these two maps is not totally valid, mainly due to temporal and dynamic nature of fire events, this exercise is considered the "starting point" for understanding the predictive capability of "fire risk" map. Results suggested that satellite-derived fire patterns largely followed the fuzzy-AHP-derived "fire risk" patterns, however, with varying accuracy. For example, satellite-derived fire pixels matched very closely with fuzzy-AHP-derived "very high fire risk" in districts of Visakhapatnam and Khammam, followed by "medium to high" in districts of Vizaynagaram, Adilabad, East Godavari, Cuddapah, etc. In contrast, several districts such as Warangal, Nizambad, Medak, Mahbubnagar, Ananthpur, etc., that showed "very low risk" for fires in fuzzy-AHP-derived map had fires recorded by the SPOT satellite data. With respect to the accuracy, the fire risk map for the three classes alone could predict only 64.4% of the total fire pixels (6,369) in Andhra Pradesh state, recorded during year 2000. The predictive capacity was highest for the medium class (42.3%), followed by high (12%) and very high (10.1%) categories.

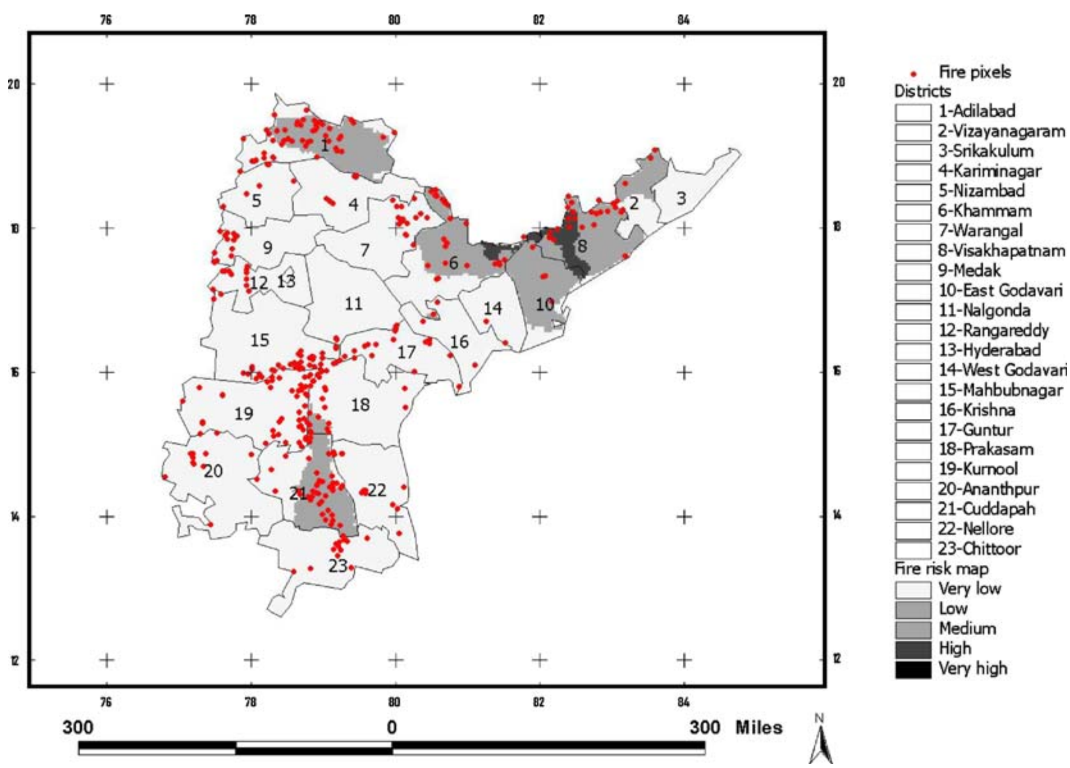

Fig. 7 Map depicting the accuracy assessment of fire risk. Fire pixels derived from SPOT satellite datasets for year 2000 have been overlaid on fire risk map, for overall accuracy

Discussion

The above results clearly suggest highly dynamic and spatial nature of fire events in the study area. To manage growing forest fires and associated fire hazards, as well as prioritize prescription efforts, it is essential to improve our understanding of the causative factors of fires. Earlier research relating to forest fire risk involved identifying the potentially contributing variables and integrating them into a mathematical expression, i.e., an index. In creating such an index, most of the earlier researchers focused on using meteorological data alone (Goncalves and Lourenco 1990; Van Wagner 1993) or vegetation parameters (Maselli et al. 2003; Hernandez-Leal et al. 2006). Predicting the nature of “fires” may not be easy through using such indices alone. The fuzzy AHP-integrated GIS model attempted in our study takes a different approach, compensating MCDM through codifying the expert knowledge for forest fire risk variables and combining it with the human-biophysical dimension. Most importantly, several of the causative factors of fire have inherent fuzzy characteristics. Zadeh (1965), in his seminal papers, proposed fuzzy set theory as the means for quantifying the inherent fuzziness that is present in ill-posed problems. Fuzziness is a type of imprecision, which may be associated with sets in which there is no sharp transition from membership to nonmembership (Bellman and Zadeh 1970). In particular, the qualitative fuzzy decision-making techniques use linguistic assessments which are quite useful to convey the vagueness of the existing knowledge (Chen and Hwang 1992). The fire risk mapping attempted in this study not only furnished the qualitative information about causative factors of fire in a spatial domain but also suggested a reliable way of combining objective and subjective data in a decision-making process. Most importantly, fuzzy set theory in our case provided a novel and formal framework to process linguistic knowledge/expert judgments and their corresponding numerical data through membership functions (Yen 1999). Also, we inferred that rapid protocols can be developed and expanded to include the decision representation of local people in assessing the forest sustainability and risks using GIS-based methodologies. For integrating the judgments, we used AHP as it is easy to compute and provides a way for inconsistencies to be measured. Integration of the priority weights derived from the AHP through fuzzy combination in GIS framework yielded a satisfactory result in our present case as evaluated from accuracy of fire risk map. However, it may be mentioned that, when the number of evaluation criteria increase, pairwise comparisons through AHP method can be tedious. In such cases, several other alternate computer-based approaches have been developed to deliver MCDM, or elements thereof, in a range of forms; e.g., ELECTRE III (Opperhuizen and Hutzinger 1982; Roy 1991); DEFINITE (Janssen and Herwijnen 1994); routines in IDRISI GIS (Eastman and Jiang 1995); ASSESS (Veitch and Bowyer 1996; Hill et al. 2005); GIWIN (Ren 1997); MULINO-DSS (Giupponi et al. 2004); HERO for heuristic multi-objective optimization (Kangas et al. 2000); FORM (Kazana et al. 2003); and MEACROS (Mazzetto and Bonera 2003). On the other hand, decision makers may not necessarily be proficient in computer science and information technology, and they may need appropriate tools in order to easily participate in the discussion. This parallels the vision of the decision support system community pioneers; that is, by supporting and not replacing human judgment, the system comes in second and the users “first” (Karacapilidis and Pappis 2000; Kahraman et al. 2003). In such context, we infer that the methodology followed in this study is relatively easy (AHP) to implement in a group decision-making framework. Nevertheless, there is considerable scope for further improvement through internet web-based GIS framework to integrate a greater number of decisions into forest planning. With respect to limitations, although the overall accuracy of the fire risk map has been found to be only 64.4% using the sample dataset from SPOT satellite data, we infer that robust accuracy assessments using other real-time fire data sets are needed to test the potential of fuzzy-AHP-derived fire risk map. Also, a variety of other information layers or other key variables in the form of criterion maps can be added to our basic model, making it more flexible. However, problems can occur with respect to inclusion of dynamic factors of fire risk in a spatial domain. Yet, the combination of ground-based data in conjunction with the analytical power of GIS and decision-making framework such as fuzzy AHP can be effectively used for assessing fire risk in the study area. The novelty of our approach lies in using linguistic variables in fuzzy classification in addition to several biophysical and new socioeconomic parameters such as nutritional density, agricultural workers, etc., for inferring fire risk in the study area. The results identify important biophysical and socioeconomic parameters of fire risk in the study area. The maps produced can answer important questions concerning the causative factors of fire in the spatial domain and will be useful to forest managers to undertake necessary mitigation measures at a local level.

Conclusion

Forest fires in the tropical regions are the result of several underlying factors. In this study, we quantified fire risk in tropical deciduous forests, India, as a function of topographic, vegetation, climatic, and socioeconomic attributes. To address the "fuzziness" in the spatial datasets and also to include the subjective judgments in the modeling process, we implemented fuzzy analytical hierarchy approach in GIS to assess fire risk in the study area. Results were quite useful in delineating potential "fire risk" zones at a district level. These results can be used both as a strategic planning tool to address broad-scale fire hazard concerns and also as a tactical guide to help managers in designing effective fire control measures at local level. Also, the criterion maps relating to topographic, biophysical, and socioeconomic predictors produced in this study can also be used to assess the susceptibility of any vegetation to fire and for determining future fire risks. In overall, this study demonstrates the potential of GIS technology and its viability in integrating objective as well as subjective data using fuzzy-AHP approach for assessing fire risk in the study area.

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