

# Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques

Hamed Adab · Kasturi Devi Kanniah · Karim Solaimani

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**Abstract** Fire in forested areas can be regarded as an environmental disaster which is triggered by either natural forces or anthropogenic activities. Fires are one of the major hazards in forested and grassland areas in the north of Iran. Control of fire is difficult, but it is feasible to map fire risk by geospatial technologies and thereby minimize the frequency of fire occurrences and damages caused by fire. The fire risk models provide a suitable concept to understand characterization of fire risk. Some models are map based, and they combine effectively different forest fire-causing variables with remote sensing data in a GIS environment for identifying and mapping forest fire risk. In this study, Structural Fire Index, Fire Risk Index, and a new index called Hybrid Fire Index were used to delineate fire risk in northeastern Iran that is subjected to frequent forest fire. Vegetation moisture, slope, aspect, elevation, distance from roads, and vicinity to settlements were used as the factors influencing accidental fire starts. These indices were set up by assigning subjective weight values to the classes of the layers based on their sensitivity ratio to fire. Hot spots data derived from MODIS satellite sensor were used to validate the indices. Assessment of the indices with receiver operating characteristic (ROC) curves shows that 76.7 % accuracy of the HFI outperformed the other two indices. According to the Hybrid Fire Index, 57.5 % of the study area is located under high-risk zone, 33 % in medium-risk zone, and the remaining 9.5 % area is located in low-risk zone.

**Keywords** Forest fire risk · GIS · RS · Structural Fire Index · Fire Risk Index · Hybrid Fire Index

## 1 Introduction

Wildfires are complex events that occur as a result of natural processes and human factors (Vasilakos et al. 2009). Wildfires are considered as a disaster that distresses terrestrial

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environments and causes economic destruction for people, such as missing income relative to the land use, destruction and loss of property, damages to the agriculture, and loss of biodiversity (Merlo and Rojas Briales 2000; Wenliang et al. 2010). Deforestation and desertification are among the more important effects of wildfires (Hernandez-Leal et al. 2006). Usually, fire starts from ignition points, attributable to either people or lightning (Braun et al. 2010).

To manage wildfires effectively, proper planning is needed to achieve fire risk reduction, fire regime restoration, and maintenance (Keifer et al. 1999). The terms hazard and risk have been used in fire controlling issues since the beginning of modern fire science in the 1920s in the United States (Hardy 2005). Based on the MiSRaR project from European Union (MiSRaR 2010), risk is defined as a combination of hazard and potential damage (Fig. 1). Generally, forest fire management contains four steps of analysis and assessment of effective response to fires, namely, mapping both potential fire hazard and risk, detecting hot spots, monitoring active fires, and assessing post-fire degradation (Roy 2003). Determining fire risk is the most important step because knowing where the risk is highest is essential to minimize threats to life, property, and natural resources. Therefore, in this study, we focused on determining geographic distribution of fire risk in northeast Iran.

Many environmental and anthropogenic variables are relevant to fire, and knowing them is required to understand fire occurrences and to determine fire risk (Krivtsov et al. 2009). Vegetation species and density, humidity, vicinity to settlements, distances from roads are among the variables (Chuvieco and Congalton 1989; Roy et al. 1991; Jain et al. 1996). Three groups of indices are proposed to determine fire risk based on their temporal scale by the European Union's (EU) Joint Research Center (Joint Research Center (JRC) 2002) as follows:

1. Structural or long-term indices. These indices mostly show static information at the global scale (Chéret and Denux 2011). They do not change over short timeframes. Such indices include elevation, vegetation type, land cover, land use, slope, aspect, distance to roads and vicinity to settlement areas (Pelizzari et al. 2008; Puri et al. 2011), climatic variables, soils (Sebastián-López et al. 2008), and population density (Li et al. 2009). These indices are more adapted to identifying fire risk and thus can be calculated before the fire season to recognize any risk due to fire (Carrao et al. 2003).
2. Dynamic or short-term indices. These types of indices change moderately continuously over time due to vegetation or weather condition. These indices are formulated



**Fig. 1** Conceptual model of risk (Probability: fire occurrence probability in a position; Susceptibility: potential damage from the fire in a position; Vulnerability: degree of loss of a component at risk; Economic value: value (in €, \$) of a component at risk) (MiSRaR 2010)

to detect the flammability of forest fuels during the fire season. Hence, dynamic indices use variables that are changing in a short period of time, so these are focused on probability of forest fire ignition and spread (Salinero and Chuvieco 2003). For example, the flammability of vegetation is influenced by the amount of live and dead fuels, their moisture content, and vegetation type (Albini 1976; Rothermel et al. 1986). Because the vegetation moisture content is related to meteorological conditions for each fuel type and greenness, a dynamic fire model should be calculated daily by updated fuel map and meteorological variables such as temperature, precipitation, relative humidity with an approximation of the amount of live and dead fuels (Carrao et al. 2003).

3. Combined indices. These indices include both structural and dynamic factors as mentioned above (Graña and Duro 2008). The most critical subject in this approach is how to combine effectively the relevant variables to get a rational concept. Because the integration of both structural and dynamic variables is usually based on the specific knowledge of experts and their personal judgment (Caetan et al. 2002), it is really difficult to establish which variables are correctly related to fire.

Structural, dynamic, and combined indices have been used extensively in different countries (Table 1). They have different strengths to recognize forest fire risk because they are developed for special environment. But, there have not any comparisons been carried out between the indices to assess their robustness in the northeast of Iran. Thus, in this study, we tried to use and compare the Structural Fire Index (SFI) that has been adopted by (Chuvieco and Congalton 1989), the Fire Risk Index (FRI) that has been introduced by (Erten et al. 2004), and a new index combining both SFI and FRI to identify fire risk in northeast Iran.

Iran is one of the countries in the Middle East and North of Africa that face high risk in terms of wildfire occurrence in forested areas. The average number of fires per year is 130, and the average area burnt per year is 5,400 ha. Record shows that the largest fire occurred in 1993 and destroyed 33,000 ha of forested land (Alexandrian and Esnault 1998). Forest fires are considered as a frequent hazard in Golestan Province, especially in Golestan National Park in the Alborz Mountains in the northeast of Iran (Fig. 2). Fires frequently occur from August to the end of December mainly due to decrease in humidity and increase in wind speed. However, fires are predominantly ignited by humans in this region (Allard 2001). Some forest areas of Golestan Province were destroyed by fires due to extreme temperature and reduction in precipitation that increase the fire risk and alter the behavior of fires dramatically. Therefore, zonation of fire risk is needed to recognize critical areas.

The objective of the study is to develop an index to aid forest planners in defining areas of great risk and take appropriate actions to minimize risky conditions. The way this is accomplished is proposing a Hybrid Fire Index (HFI) and showing it to be valid and a better predictor than already existing indices in Golestan Province, Iran. In addition, a probability distribution technique is applied to define the level of risk for fire risk zonation.

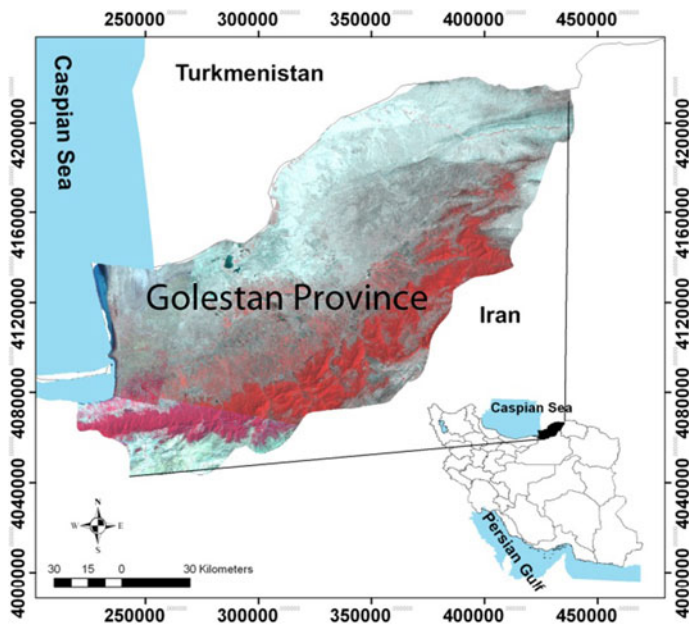
Forest fire risk has both spatial and temporal components (Chuvieco et al. 2010). Spatial techniques can be used to process fire risk from data integration to risk assessment and then to risk decision-making using spatial modeling (Dlamini 2011; Chen et al. 2003). Remote sensing data are extensively used for forest fire danger monitoring (Leblon 2005) and geographic information system for processing, and managing spatial information, as well as for visually representing the results (Chuvieco et al. 2010).

**Table 1** Previous studies that have used Structural Fire Index (SFI), Dynamic Fire Index (DFI), and Integrated Index (II) to study fire risk

No	Variables	Country	Index	Authors	Result
1	Vegetation, altitude, slope, aspect, and proximity to roads	Spain	SFI	Chuvieco and Congalton (1989)	The model performed properly, but more researches should be done by including new variables such as climatic data or by establishing, or to establishing statistical methods between fire hazard groups within these variables.
2	Temperature, humidity, and rainfall	Spain	DFI	Alonso-Betanzos et al. (2002)	The accuracy of the model was quite good, but other information such as socio-economic and terrain factors (e.g., existence of a road, type of vegetation, etc) can be used to further improve the modelling of forest fire risk.
3	Vegetation type, slope, proximity to settlements, and distance from roads	India	SFI	Jaiswal et al. (2002)	The model was found to be in strong agreement with actual fire-affected sites. Correlation of the risk areas with actual sites affected was assumed to be a major test for the reliability of the model.
4	Vegetation, slope, aspect, distance from roads, and distance from settlements	Turkey	SFI	Erten et al. (2004)	The model was set up in a pilot zone and the satellite images both before and after the fire were used for visual validation. However the model needs more investigation and can not explain any fire risk condition.
5	Insolation hours, vegetation cover, altitude, slope, proximity to main roads, and NDVI	Canary Islands	SFI@DFI	Hernandez-Leal et al. (2008)	The index represented a clear positive correlation in the levels of fire risk associated with 15 days prior to the fire event. However additional data from ground based stations (air temperature, wind velocity, humidity, etc.), and high voltage networks maps will improve the modeling of risk.
6	Species composition, stand crown closure, stand development stage, insolation, slope, proximity of agricultural lands to forest, and distance from settlement areas	Turkey	SFI	Saglam et al. (2008)	Results showed that ignition in the study area is mostly triggered by human activities.
7	Vegetation moisture, slope, aspect, and distance from roads and settlements	Greece	SFI	Siachalou et al. (2009)	Overlaying the fire risk zones to the classified burned areas provided a good reliability of the approach. The model can be further improved by using daily measurements of meteorological data such as speed and direction of the wind, atmosphere's dryness, rainfall etc.

**Table 1** continued

No	Variables	Country	Index	Authors	Result
8	Fuel model, solar radiation, topographic wetness, and populations density	US	II	Lein and Stump (2009)	The results were reasonable when compared to the historic pattern. However information regarding the fire location, ignition source, type of fuel ignited, size of the burn areas, and etc are critical for better characterizations of wildfire modeling.
9	NDWI, NDVI, temperature, and relative humidity	Spain	DFI	Huesca et al. (2009)	The autoregressive models were found to accurately simulate and predict fire potential. The model was accounted for 26–32 % of the total error in the temperate region.
10	Road, buildings, land-use/cover, land slope, altitude, and slope orientation	Brazil	SFI	Henrique et al. (2011)	Structural fire index is useful as a preliminary approach because because it can identify most vulnerable zones.



**Fig. 2** Location of Golestan Province (Iran) forests is in south and arid area near to desert of Turkmenistan (False Color Composite of Landsat ETM + dated July 20, 2010)

## 2 Data and methodology

### 2.1 Study area

Golestan Province (North East Iran) is one of the most important forest areas in Iran. The total area of this province is 20,381 km<sup>2</sup> (1.3 percent of the total area of Iran), and it is

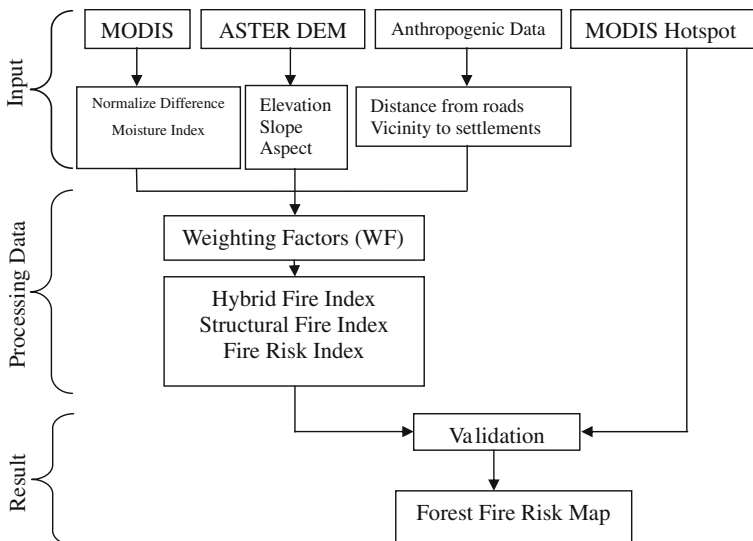
located in the southeast of the Caspian Sea (Fig. 2). Total forest area in Golestan Province is ~426 ha (Forests Range and Watershed Management Organization of Iran (FRWOI) 2005). Climate conditions in this area are controlled by several factors such as latitude and topographic features (the Alborz Mountain Ranges), distance from the Caspian Sea, and the desert areas in south of Turkmenistan. Most of Golestan Province experiences moderate Caspian climate (Mediterranean), except for the low-elevation Gorgan plains, which has a relatively semi-desert climate due to its distance from the sea and proximity to the desert of Turkmenistan (Statistical Centre of Iran (SCI) 2009). The highest rainfall areas in Golestan Province are located in the southwest with 1,000 mm rainfall per year and the lowest one in the northern region with 150 mm per year. The average annual rainfall is around 550 mm. Air humidity ranges between 17 and 100 %, and the average temperature in Gorgan airport synoptic station is between 12.7 and 22.8 °C (I.R. of Iran Meteorological Organization (IRIMO) 2005). Fires frequently occur in June and July (summer season) because of high availability of green vegetation that provides fuel for ignition. Also, fires occur during autumn season (October, November, and December) and during drought period when forest floor becomes dry due to low precipitation, high temperature, and hot-dry winds (Shafiei et al. 2010; Ardakani et al. 2011).

### 2.2 Datasets

The datasets and overall methodology adopted to achieve the objectives of this study are illustrated in Fig. 3. The parameters that are responsible for forest fire risk and thus used in this study to calculate fire risk are as follows:

#### 2.2.1 Vegetation moisture

Vegetation moisture condition is very influential in fire risk determination because it influences the flammability of the fuel (Siachalou et al. 2009). Vegetation moisture



**Fig. 3** Overall methodology adopted to produce forest fire risk maps for the Golestan Province

condition can be assessed using many bio-spectral indices from remote sensing data. The viability of the use of greenness indices has been tested to evaluate fire hazard (Fiorucci et al. 2007). Vegetation moisture content was obtained in this study using vegetation indices calculated from MODIS (Moderate Resolution Imaging Spectro-radiometer) Terra Level 1B data (500 meter spatial resolution). MODIS image dated August 2, 2002, was downloaded from the Land Processes Distributed Active Archive Center (LPDAAC) and used in this study.

### 2.2.2 Elevation

Elevation is a crucial physiographic variable that is associated with temperature, moisture, and wind (Xiangwei et al. 2011). Therefore, it has an important role in fire spreading (Jaiswal et al. 2002). Elevation influences vegetation structure, fuel moisture, and air humidity (Castro and Chuvieco 1998). It has been analyzed that humidity and temperature have higher influence on fire at higher-altitude areas than lower ones (Hernandez-Leal et al. 2006). It has also been reported that fire behavior trends are less severe at higher altitude because of higher rainfall (Chuvieco and Congalton 1988).

### 2.2.3 Slope

Slope is one of the parameters that influence fire spread rate (Weise and Biging 1997). Fire moves more quickly up the slope and less quickly down slope (Kushla and Ripple 1997). Also, fire spread rate may rise on steeper slopes due to flames being angled closer to the ground surface, and the process of heat convection can be enhanced by wind effects due to fire behavior (Whelan 1995; DeBano et al. 1998).

### 2.2.4 Aspect

Aspect is correlated with the amount of solar energy an area receives. South aspects experience more sun light, higher temperatures, robust winds, low humidity, and low fuel moistures in the North Hemisphere. Therefore, vegetation is typically drier and less dense on south-facing slopes than north-facing ones (Prasad et al. 2008; Anderson 1982). Because of that, drier fuels are more exposed to ignition (Noonan 2003; Iwan et al. 2004). In addition, earlier in the day, east aspects get more ultraviolet and direct sunlight than west aspect. Consequently, east aspects become drier faster (Prasad et al. 2008; Anderson 1982).

Elevation, slope, and aspect data were extracted in this study from the Digital Elevation Model (DEM), which were determined by remote sensing satellites such as Shuttle Radar Topography Mission (SRTM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER). ASTER DEM version 2 was obtained from the ASTER Global Digital Elevation Model (GDEM) Explorer tool (DEMEX) of United States Geological Survey (USGS). Meanwhile, SRTM DEM was downloaded from the US Geological Survey's EROS Data Center.

### 2.2.5 Distance from roads and vicinity to settlement areas

Anthropogenic factors are important variables that influence fire occurrences as represented by factors such as proximity to roads and settlements (Avila-Flores et al. 2010). It is

recognized that human activities are one of the basic factors that affect fire occurrences (Dong et al. 2005). Due to the more intense human activities, fire risk is increased and it provides much opportunity for unexpected man-made ignition (Alencar et al. 2004). Distance to roads and road density are potentially important parameters because roads allow people to go into the forested and grassland areas and cause ignitions. Also, forested and grassland areas near to settlements are more prone to fire ignition because accidental fires can be caused by residents inside the forest (Jaiswal et al. 2005).

The road network includes all the major and minor roads and settlements in the study area. These data were digitized from the thematic (1:50,000 scale) and scanned topographic maps of Golestan at 1:250,000 scale that were obtained from the National Cartographic Center of Iran (NCC). These data are made available in a GIS database in a vector format (Shp files).

### 2.2.6 MODIS hotspot data

The MODIS hot spot product is available from the National Aeronautics and Space Administration (NASA) Web site at <http://earthdata.nasa.gov/firms> (Csiszar et al. 2006; Justice et al. 2002; Davies et al. 2009). We downloaded two tiles of the product covering MOD14A1 or MYD14A1 as a daily 1-km pixel product to validate the output of this study (forest fire risk locations/areas). These data were obtained for a period of 3 years (2001–2003).

## 2.3 Methodology

### 2.3.1 Validation of DEM

The NASA Shuttle Radar Topographic Mission (SRTM) has provided digital elevation data (DEMs) for over 80 % of the globe. The SRTM DEMs are derived from interferometric radar data from NASA's Space Shuttle mission in February 2000 (Gallant and Read 2009). So far, the DEMs of ASTER have covered 99 % of the Earth's land surface (Wang et al. 2011). ASTER and SRTM DEMs have been validated in many geographic areas (ASTER GDEM Validation Team (NASA.USGS.LPDAA.EROS) 2009) such as North Shaanxi, China, with RMSE between  $\pm 7$  and  $\pm 15$  m for ASTER DEMs (Yang et al. 2011) and Crete Island in Southern Greece with 16 m RMSE for SRTM DEMs (Miliaresis and Paraschou 2005).

Nevertheless, we also assessed the absolute accuracy of ASTER and SRTM DEMs in this study using the digital topographic map of northeast Iran (1:250,000 scale) obtained from the National Cartographic Center of Iran (NCC). A total of 4,523 elevation points were extracted based on the digitized topographic map. The extracted elevations from the digitized topographic map were compared with the SRTM and ASTER DEM values. The results are shown in the Results and Discussion section (Table 4).

### 2.3.2 Calculation of vegetation index

High moisture content in vegetation is represented by the high absorption of short-wave infrared (SWIR) band in thin layers of canopy, and the high reflectance of near-infrared (NIR) band by healthy green vegetation (Siachalou et al. 2009). By this definition, Normalized Difference Moisture Index (NDMI—Equation 1) has been used for assessing



vegetation water content. Moisture condition of vegetation canopies greatly influences fire behavior (Wilson and Sader 2002; Sader et al. 2003; Hemmleb et al. 2006; Meng-Lung et al. 2009). Low NDMI values show very dry vegetation is more flammable than fresh vegetation that has high NDMI value. This index is sensitive to changes in liquid water content in vegetation canopies (Bo-cai 1996). Several studies have shown that NDMI is a more reliable indicator of canopy relative water content (Serrano et al. 2000) compared to NDVI (Normalized Difference Vegetation Index) for assessing canopy water content and vegetation stress (Hardisky et al. 1983; Wilson and Sader 2002).

MODIS data Level 1B (calibrated and geolocated) onboard Terra satellite dated August 2, 2002 were obtained and preprocessed (re-projected from its original sinusoidal to the

**Table 2** Parameters used to model fire risk in northeast of Iran and their data sources (SFI: Structural Fire Index, FRI: Fire Risk Index, and HFI: Hybrid Fire Index)

Parameters for fire risk modeling	Source of data	Source	Spatial resolution	Purpose
NDMI (normalized difference moisture index)	Terra-MODIS	NASA	500 m	Inputs to SFI, FRI, and HFI models
DEM	ASTER	DEMEX of USGS	30 m	Inputs to SFI, and HFI models
Slope	ASTER	DEMEX of USGS	30 m	Inputs to SFI, FRI, and HFI models
Aspect	ASTER	DEMEX of USGS	30 m	Inputs to SFI, FRI, and HFI models
Distance from roads	Digitized topographic map	National Cartographic Center of Iran	30 m	Inputs to SFI, FRI, and HFI models
Vicinity to settlements	Digitized topographic map	National Cartographic Center of Iran	30 m	Inputs to FRI, and HFI models
HOT SPOT	MODIS	FIRMS of NASA	1 km	Validate SFI, FRI, and HFI models

**Table 3** Weights assigned to each variable and classes for forest fire risk modeling

Variables	Classes	Ratings of hazard/risk	Description of fire hazard/risk
NDMI (−1/+1)	>0.36, 0.26–0.36, 0.16–0.26, 0–0.16, <0	1,2,3,4,5	Very low, low, medium, high, very high
Elevation (m)	>2,000, 1,000–2,000, 500–1,000, 200–500, <200	1,2,3,4,5	Very low, low, medium, high, very high
Slope (°)	<5 %, 10–5 %, 25–10 %, 35–25 %, >35 %	1,2,3,4,5	Very low, low, medium, high, very high
Aspect (°)	North, East, West, South	2,3,4,5	Low, medium, high, very high
Distance from roads (m)	>400, 300–400, 200–300, 100–200, <100 m	1,2,3,4,5	Very low, low, medium, high, very high
Vicinity to settlements (m)	>2,000, 1,500–2,000, 1,000–1,500, 500–1,500, <500 m	1,2,3,4,5	Very low, low, medium, high, very high

UTM zone 40 cartographic projection). The imagery was cloud-free, and after pre-processing, the following equation was used to calculate NDMI (Sader and Jin 2006):

$$\text{NDMI} = \frac{(\text{NIR} - \text{MIR})}{(\text{NIR} + \text{MIR})} \quad (1)$$

where NIR is the near-infrared spectral wavelength and MIR is mid-infrared spectral wavelength (Bands 2 and 6 of MODIS data, respectively).

All the parameters extracted/calculated/obtained in this study and their data sources are shown in Table 2. Weights assigned to each of the parameters are described in Table 3. These parameters were used to calculate the following three fire risk indices:

### 2.3.3 Structural Fire Index (SFI)

The SFI is an empirical index that is based on the combination of five influential variables on fire risk, namely, vegetation moisture, slope, aspect, elevation, and distance from roads (Chuvieco and Congalton 1989). This index has been used in Spain (Chuvieco and Congalton 1989) and Portugal (Pelizzari et al. 2008) to map forest fire risk. The following equation to calculate SFI was applied in this study to obtain first risk in Golestan Province (Table 3):

$$\text{SFI} = 1 + 100v + 30s + 10a + 5r + 2e \quad (2)$$

where  $v$ ,  $s$ ,  $a$ ,  $r$ , and  $e$  show vegetation moisture, slope, aspect, distance from roads, and elevation. The parameter portion in fire risk is represented by the number value of 100, 30, 20, 5, and 2. The variables in the index are the basic factors that affect forest fires in the Mediterranean areas (Chuvieco and Congalton 1989). Vegetation moisture has a weight of 100, which means vegetation plays a major role in fire risk, whereas elevation has the least importance with a weight of just 2.

### 2.3.4 Fire Risk Index (FRI)

The FRI is an empirical index that has been applied in Turkey (Erten et al. 2004) and Greece (Siachalou et al. 2009) for forest fire risk mapping. It is based on five variables, namely, vegetation moisture, slope, aspect, distance from roads, and vicinity to settlements (Erten et al. 2004). In order to calculate the risk index, all the mentioned variables are ranked according to their influence on fire hazard. Hence, the variables are separated into different classes. First class shows highest fire hazard, and the last one shows lowest fire hazard (Table 3). The index is described by the following equation:

$$\text{FRI} = 7 \times V_t + 5 \times (S + A) + 3 \times (D_r + D_s) \quad (3)$$

where  $V_t$ ,  $S$ ,  $A$ ,  $D_r$ , and  $D_s$  indicate vegetation moisture, slope, aspect, distance from roads, and vicinity to settlements. The parameters' importance is denoted by the number value of 7, 5, and 3. These values show the weight of parameters in forest fire risk. Vegetation moisture is the most influential factor, and distance from roads and vicinity to settlements are the least important factors in this index.

### 2.3.5 Hybrid Fire Index (HFI)

The SFI and FRI do not use vicinity to settlement and elevation. These missing parameters can affect the reliability of the indices to present fire risk because each parameter has its

own influence on fire hazard. Hence, it is assumed that the integration of all parameters from the two indices (SFI and FRI) can improve the result. Therefore, Hybrid Fire Index (HFI) is developed in this study by integrating 6 parameters as follows:

$$\text{HFI} = (100_v + 50_s + 25_a + 10 \times (r + c) + 5_e)/10 \quad (4)$$

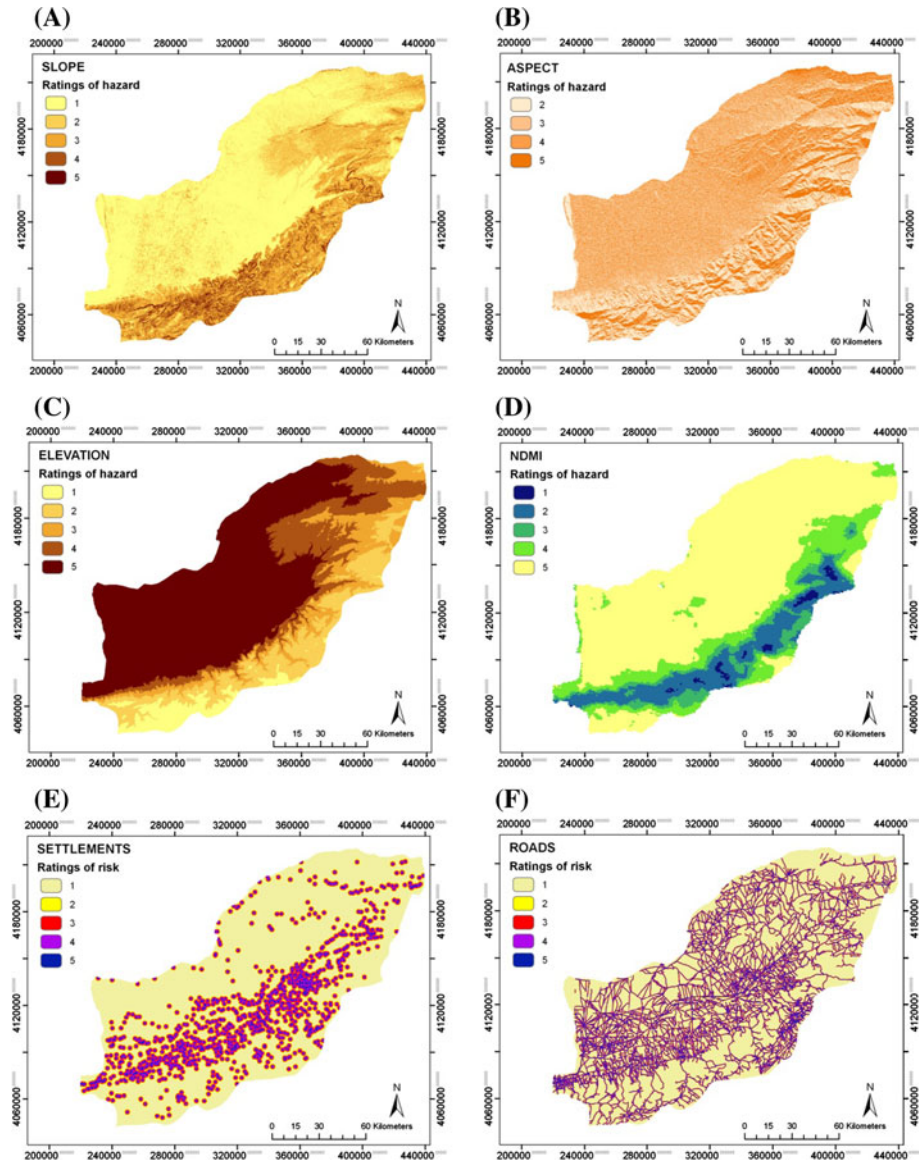
where  $v$ ,  $s$ ,  $a$ ,  $r$ ,  $c$ , and  $e$  indicate vegetation moisture, slope, aspect, distance from roads, vicinity to settlements, and elevation. Weightages are given to each of the variable as per their influence on fire risk based on field observation, knowledge of the experts, and also literature survey (Saglam et al. 2008; Chuvieco and Congalton 1989; Erten et al. 2004; Jaiswal et al. 2002) (Table 3). The weight factor contributes to the rank of influence in the modeling. Considering that the vegetation moisture has a weight of 100, this means that it has the major role in ranking fire risk in the study area. Slope is the second most important variable in this index. This is because slope can influence the wind velocity when the local hot and dry wind often starts in the summer season. Aspect can influence relative humidity, temperature, evapotranspiration, and fuel moisture content, and therefore, it is the third critical parameter in this index. Distance from roads and vicinity to settlements are two anthropogenic parameters. They have the same weight in HFI because they play same role in terms of distance in fire risk modeling. Elevation, which does not necessarily influence the probability of an ignition but has a strong influence on the behavior of fire, was assigned the least weight in HFI.

### 2.3.6 Forest fire risk mapping

Each of the parameters (vegetation moisture, elevation, slope, aspect, and distance) was assigned different weighting coefficients before they were used in fire risk indices. Four to five rating classes were used based on their relative importance to fire risk (Table 3). Higher weighting value shows very high hazard, and the hazard become less with lower weighting value. These weighted criteria of parameters were used in previous studies (Chuvieco and Congalton 1989; Jaiswal et al. 2002; Siachalou et al. 2009). However, they were modified in this study based on knowledge and experience of forest experts.

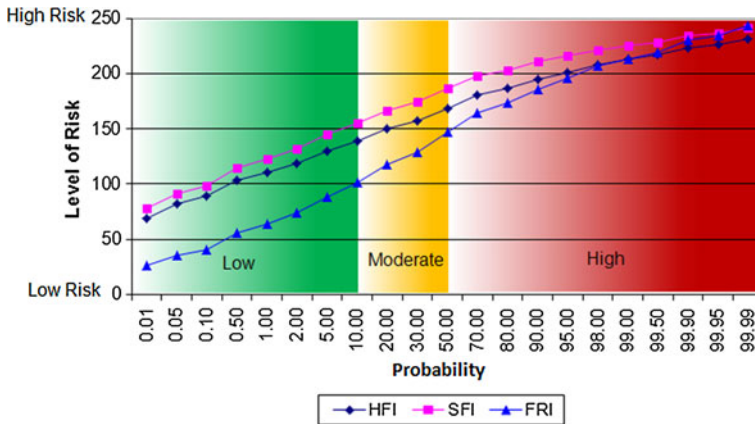
The reclassification functions of Arc Map 10 were used to reclassify the values of parameters in the input raster with new values that show the weight values. Then, the Raster Calculator was used to apply mathematical operators for performing Structural Fire Index, Fire Risk Index, and Hybrid Fire Index (Fig. 4).

The main objective of the current study is to define a new fire risk index on the basis of weightage assignments followed by indexing to layers that are important input to forest fire risk. For this purpose, the results of the three indices were normalized between 0 with low risk and 255 with high risk. The risk value of each hot spot was extracted from the outcomes of the three indices, and the probability distribution of risk value of hot spots was used for each index. The probability distribution shows which level of risk is more probable to occur for each index. Several probability distributions were fitted to estimate forest fire risk probability such as Pearson type 3 (P3), Log Pearson type 3 (LP3), Normal, Lognormal 2 (LN2), Weibull and Pearson type III. These were used to test whether or not Structural Fire Index, Fire Risk Index, and Hybrid Fire Index follow forest fire occurrences by these types of distribution. The visualization results of the fitting showed that Weibull and Pearson type III were the best distribution for definition of fire risk level (low, moderate, and high) of Structural Fire Index, Fire Risk Index, and Hybrid Fire Index respectively. Each index has different levels of risk based on their probability distribution.



**Fig. 4** The input parameters used to model fire risk in northeast of Iran: **a** slope, **b** aspect, **c** elevation, **d** NDMI (normalized difference moisture index), **e** vicinity to settlements, and **f** distance from roads

For definition of fire risk, three classes of risk were arranged, namely, low, moderate, and high. Based on the minimum and maximum statistically possible values of Weibull and Pearson type III, low risk is defined as values between 1 and 10, moderate risk has values between 10 and 50, and high risk has values between 50 and 100. It shows all the possible values and likelihoods that a risk can take within a given range, and the maps of indices were classified based on that (Fig. 5).



**Fig. 5** Level of low, moderate, and high fire risk of three indices based on probability distribution

**Table 4** Validation result of SRTM and ASTER DEM

DEM datasets	Mean	SD	Pearson correlation TOPO map	MAE	RMSE
SRTM	525	673.3	0.997	−8.4	46.6
ASTER	527.3	675.1	0.997	−6.2	46.3

### 3 Results and discussion

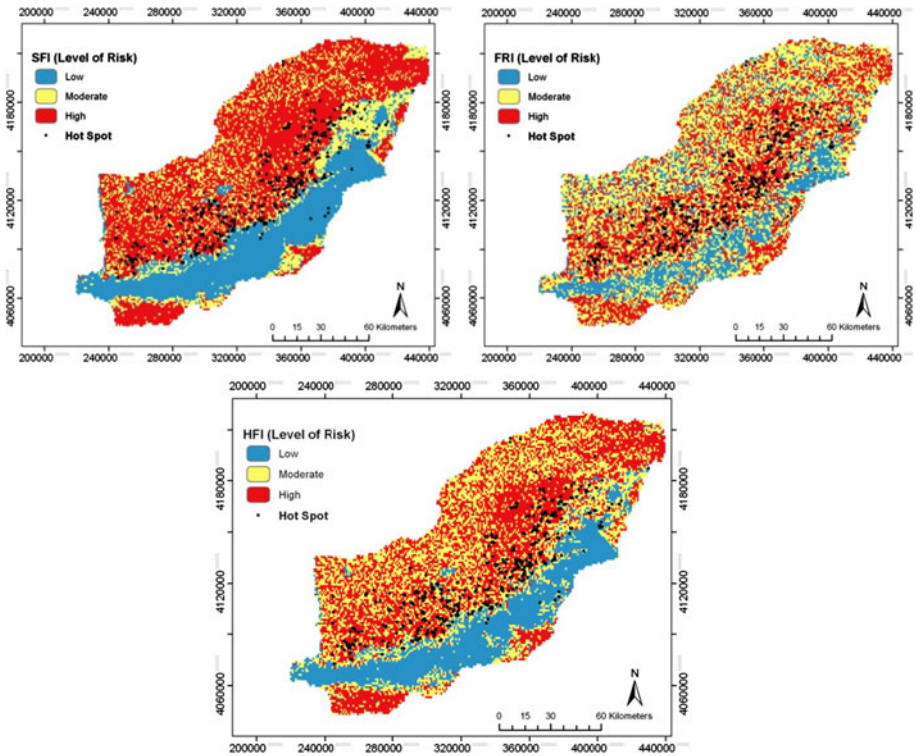
#### 3.1 Accuracy of DEMs

ASTER and SRTM DEMs should be verified before extracting terrain slopes and aspects by ground data (GPS points) and other data, such as thematic and topographic maps. The digitized topographic data were used for validation of DEMs, as the GPS points were not available for the entire study area. According to Pearson correlation, ASTER and SRTM DEM values match well with elevation values derived from the topographic map. The root-mean-square error (RMSE) of ASTER DEM is less than the that of SRTM DEM (Table 4). Therefore, we used the DEMs of ASTER for extracting slope and aspect values using spatial analyst tools available in ArcGIS, version 10.

#### 3.2 Forest fire risk in Golestan Province

Probability distributions (Fig. 5) can be used to estimate the fire risk probabilities in a given region or in a forest district. We used the probability distributions to further classify the forest fire risk modeled from each index into three levels of fire risks, that is, low, moderate, and high (Fig. 6). These maps represent the spatial distribution of forest fire risk in Golestan Province, Iran. The result of each index is different because the number of parameters contributing and the relative weight of parameters for each index are different.

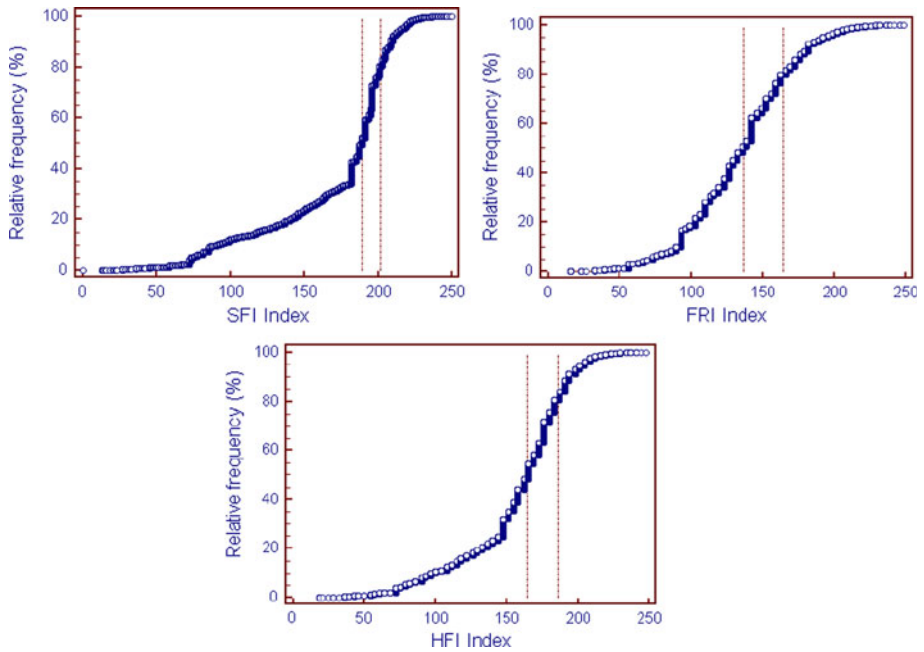
Relative frequency was used to represent the proportion of the total frequency that is in any given fire risk class interval in the frequency distribution. One of the important types of



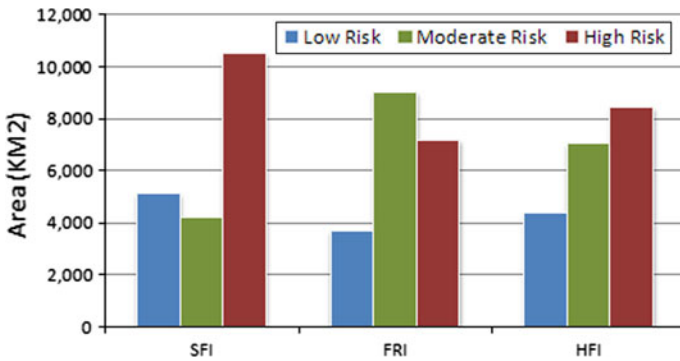
**Fig. 6** The fire risk zone maps based on Structural Fire Index, Fire Risk Index, and Hybrid Fire Index

frequency distribution is cumulative frequency distribution. The cumulative frequency for each class interval of fire risk is the frequency for that class interval added to the preceding cumulative total. Therefore, the cumulative relative frequency distribution curves (CRFD) were used to present the percentage of fire risk pixels that lie above or below a particular value of index. Figure 7 shows line graph of the cumulative frequencies for each index. According to CRFDs, the ranges of indices are between 0 and 250, and high fire risk is illustrated by values from 147 to 250 for FRI, from 169 to 250 for HFI, and from 187 to 250 for SFI.

The total areas affected by low-, moderate-, or high-risk fire as estimated by all the three indices/models are shown in Fig. 8. Results show that Structural Fire Index (SFI) classified most of the area ( $10,500 \text{ km}^2$ ) into potentially highly risky areas in terms of fire occurrences. This covers about 53 % of the total forested area in Golestan Province. Meanwhile, total areas that fall under the categories of moderate and low risks are  $5,100$  and  $4,200 \text{ km}^2$ , respectively. Other two forest fire risk indices estimated about  $8,500 \text{ km}^2$  (HFI) and  $7,000 \text{ km}^2$  (FRI) of forested areas in the study area as highly risky fire areas. These numbers represent about 42 % (HFI) and 36 % (FRI) of the total forested areas in the Golestan Province. It is found that each index represented different area of low, moderate, and high fire risk. It means that the weights and ratings assigned to variables for each index have different effect on area of fire risk.



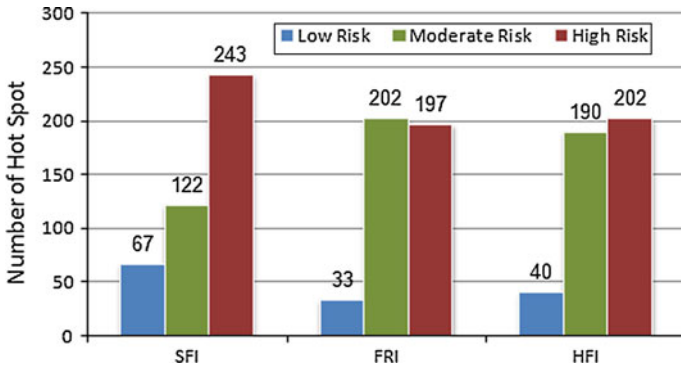
**Fig. 7** The cumulative relative frequency distribution curves of forest fire risk maps for the study area



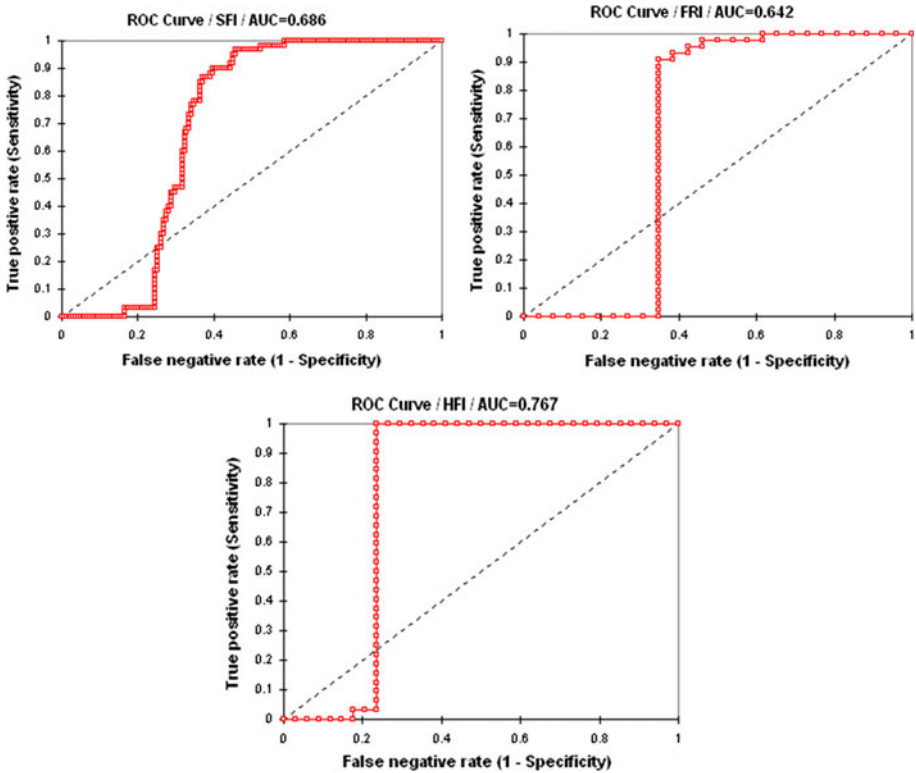
**Fig. 8** Area of fire risks as estimated by Structural Fire Index (SFI), Fire Risk Index (FRI), and Hybrid Fire Index (HFI)

### 3.3 Model validation

Model validation is an essential part in any natural hazards assessment. It refers to comparing the model predictions with a real-world dataset for assessing its accuracy or predictive power (Beguería 2006). Therefore, in this study, we used hot spot data from MODIS to validate our results of forest fire risk areas. For evaluation of each index, the number of hot spots in each risk class was counted. It would be justified that the most hot spots should be located in high-risk zone and the less in low-risk zone. The results in Fig. 9 show that most of the hot spots as derived from MODIS are found in high-risk zone (243)



**Fig. 9** Number of hot spots extracted from MODIS satellite data in each risk zones (high, moderate, and low) as estimated by Structural Fire Index (SFI), Fire Risk Index (FRI), and Hybrid Fire Index (HFI)

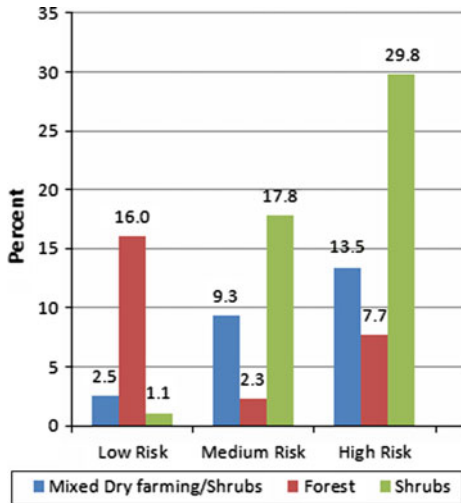


**Fig. 10** Estimation accuracy of forest fire risk indices for the study area. Estimation accuracy is highest (76.7 %) for Hybrid Fire Index (HFI), followed by Structural Fire Index (SFI) with 68.6 % and Fire Risk Index (FRI) with 64.2 %

as classified by SFI model. Similarly, HFI also shows large number of hotspots (202) in high-risk zones. However, FRI shows slightly lower number of hotspots in high-risk zones (197) compared with moderate-risk zones (202).



**Fig. 11** Three different land-use classes that are affected by fire risk based on Hybrid Fire Index (HFI)



For the effective comparison of the forest fire maps, all of the three fire risk indices were assessed by comparing them separately with the hot spot data obtained from MODIS fire product using the receiver operating characteristics (ROC) technique. The area under the ROC curve (AUC) expresses the quality of a prediction model by describing its performance to assess the occurrence or non-occurrence of predefined ‘events’ (Yesilnacar and Topal 2005). Thus, AUC measures the accuracy of model if the AUC is close to one, and the result of the model is excellent. On the contrary, the fairer is the result of the model when the AUC is closer to 0.5. The ROC curves for the three indices are shown in Fig. 10. The computed *p* value of HFI and SFI represents 0.0002 and 0.0001, respectively, at 95 % confidence level. As the computed *p* value of FRI (0.12) is greater than the significance level, one should accept that the AUC is equal to 0.5. The area under the curve for HFI, SFI, and FRI is 0.76, 0.68, and 0.64 which means the accuracy of forest fire risk is 76, 68, and 64 %, respectively. According to AUC, Hybrid Fire Index is the most accurate index to represent the forest fire risk in the Golestan Province.

### 3.4 Land use affected by forest fire

Since HFI yielded the highest accuracy among the three forest fire risk indices analyzed in this study, we used the index to examine which land use in Golestan Province is subjected to high risk of forest fire. The result (Fig. 11) shows that shrubs land cover class faces high risk (~ 30 %), and this is followed by mixed dry farming/shrubs (13.5 %) and finally forest (7.7 %).

## 4 Conclusions

The present study is an attempt to integrate remote sensing data and GIS concept to determine high-risk locations in a forest area in northeastern Iran. Three forest fire risk indices, namely Structural Fire Index, Fire Risk Index, and Hybrid Fire Index, were used to identify high-fire-risk area in northeastern Iran. Fire risk indices are great approaches for

precautionary measures to protect natural resources lands. This paper has introduced Hybrid Fire Index (HFI) as a new GIS-based forest fire risk index.

The results of SFI, FRI, and HFI are dissimilar because the number of input parameters and weight criteria assigned to each of the inputs are subjectively different. Therefore, it can affect the degree of fire risk substantially in different environmental conditions. ROC analysis indicated that HFI gives a better result than the other two indices, and therefore this index can be considered as a reliable index because it combines all variables of SFI and HFI.

The findings of this study can help forest managers and forest agencies to locate high-fire-risk zones/locations (as presented in Fig. 11) easily and take preventive policies and try to limit loss of human life, natural resources, and properties.

Subjective weights are simple method to contribute the human decision-making and formulate the experience and knowledge of experts. These indices are developed just for certain areas, and we cannot use the same weights and variables at other regions because forest fire in each part of the earth has its own characteristics. Therefore, fire risk indices should be modified according to the needs of each region. The results of this study show that remote sensing and GIS technologies that make use of spatial data integrated with appropriate algorithms or models, can provide a set of information that can be used to determine the forest fire risk. This information is essential not only to save the many resources provided by forest but also to preserve loss of human lives.

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