



Detection of high fire risk areas in Zagros Oak forests using geospatial methods with GIS techniques

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Abstract

Every year, fires, as natural crises, destroy forests as an important part of the environment. Identifying the effective factors in the occurrence of fires and identifying high-risk areas is the primary measure to address fires. In this study, high-risk areas in Zagros forests in Kohgiluyeh and Boyer-Ahmad Province in western Iran were zoned based on three GIS methods (ANP and fuzzy, Dong model, and CFRISK model). Biological, physiographic, climatic, and socio-economic criteria in the form of 11 sub-criteria were ranked as effective parameters in the occurrence of fire by ANP method. The results showed that the parameters of distance from farmlands, residential areas, and land use were the main factors affecting the occurrence of fires in forest ecosystems of the region. Multi-criteria decision analysis with more parameters and higher accuracy based on validation has performed better than the other two methods. The map of high-risk areas with this method can play an important role in assessing the sensitivity of forest areas and making the right management decisions in fire prevention and extinguishing in these valuable resources.

Keywords ANP · Dong · Fire · Zagros · Iran

Introduction

The Zagros vegetation area in western Iran, with a history of more than 5500 years and an area of about 6 million hectares, is the habitat of Iranian oak forests, which is extended in 11 provinces and covers about 20% of the country (Ghanbari Motlagh et al. 2020). The forests of this area are important ecological resources and a central natural forest

ecosystems in Iran, which guarantee water and soil sustainability as a valuable natural resource (Rasooli and Bonyad 2019; Ahmadi Ardakani et al. 2015). In recent years, these forests have been greatly degraded due to environmental stresses such as droughts, dust, and soil erosion, protruding agricultural land, pests, and fires (Mahdavi et al. 2012; Jafarzadeh et al. 2017; Ghanbari Motlagh et al. 2020). Also, in recent years, there have been concerning reports of frequent and widespread fires in these forests (Aleemahmoodi Sarab et al. 2015; Rasooli and Bonyad 2019). The growing spread of forest fires in recent decades has made it a pervasive crisis and a major destructive factor of natural ecosystems. (Valizadeh Kamran et al. 2014; Adab et al. 2013; Gigović et al. 2018; Pandey and Ghosh 2018; Suryabhadgavan et al. 2016; Vadrevu et al. 2010; Abedi Gheshlaghi 2019). As a potential threat, fire is considered a destructive factor of forests which are home to essential organisms and species (Ajin et al. 2016; Pourghasemi et al. 2014; Gerdzheva 2014; Pourtaghi et al. 2015). As a factor in disturbing forest ecosystems, it has led to the extinction of plant and animal species, reducing habitat quality and changing the ecology of the region, disrupting the structure and composition of forests, destroying forest regeneration, affecting species health and vitality, degradation of forest biomass pattern hence soil

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erosion, changes in physical and chemical properties of soil and microclimate, loss of nutrients in the underground parts of the ecosystem due to the burning of vegetation and litter, and fueling greenhouse emissions (Abdi et al. 2018; Mehta et al. 2018; Ghorbanzadeh and Blaschke 2018; Mirdeylami et al. 2014; Vidamanesh et al. 2018). According to FAO statistics, about 6% of Iran's forests are destroyed annually by fire (Eskandari et al. 2013). This statistic has been increasing in recent years for various reasons and is not even reliable in Iran (Mahdavi et al. 2012; Eskandari and Chuvieco 2015; Ahmadi Ardakani et al. 2015). Meanwhile, Iran, with 0.2 hectares of forest per capita, is one of the poorest countries in terms of forest resources (Abedi Gheshlaghi et al. 2019).

In general, the causes of forest fires are natural and human factors (Ajin et al. 2016). Natural forest fires are usually caused by lightning, global warming and climate change, lack of rainfall and insufficient moisture, hot winds, accumulation of litter, and friction between dry litter (Rasooli and Bonyad 2019; Adab et al. 2013; Dong et al. 2005; Rajabi et al. 2013). On the other hand, fires are formed by the interplay of ecological (physical, biological) and socio-economic (human) factors (Eskandari 2017; Vasilakos et al. 2009). Environmental or ecological factors include climatic criteria, vegetation, and topography, which, along with human factors, provide the basis for forest fires (Pourtaghi et al. 2015; Mirdeylami et al. 2014; Mosa Beigi and Mirza Beigi 2017). Studies have shown that Iran's location in the dry belt of the Earth and the subtropical high-pressure zone and the phenomenon of drought due to climate change and, changes in rainfall and climate patterns, especially in recent years have been regarded as principal factors that increase forest fires (Pourghasemi et al. 2014; Jaafari and Mafi Gholami 2017; Jafarzadeh et al. 2017). In addition, human carelessness, and the presence of travelers or deliberate fires to convert forest lands to agriculture and orchards for their possession have increased the frequency and extent of fires in Iran's forest areas (Eskandari et al. 2013; Vadrevu et al. 2010; Ahmadi Ardakani et al. 2015).

Controlling forest fires requires thorough and continuous monitoring conducted by field studies at local scales (Jaafari and Mafi Gholami 2017). In the process of fire crisis management, identifying fire-prone areas and identifying critical points or high-risk areas for initial preparedness and preventing deforestation are some strategies that have always been considered (Eskandari et al. 2013; Güngöroğlu 2017; Pourghasemi et al. 2014; Gerdzheva 2014; Dong et al. 2005; Mirdeylami et al. 2014; Jaafari and Mafi Gholami 2017). By preparing a map of fire risk areas and planning for these areas, the risks and, consequently, the costs can be greatly reduced (Rajabi et al. 2013; Rasooli and Bonyad 2019; Adab et al. 2013; Erten et al. 2004; Mohammadi et al. 2014).

Advances in remote sensing (RS) and geographic information systems (GIS) in recent decades have provided

researchers with more accurate facilities and tools to study forest fires, trends, and causes from a variety of perspectives (Valizadeh Kamran et al. 2014; Abedi Gheshlaghi 2019; Gigović et al. 2018; Kayet et al. 2018). Using different methods of spatial modeling and preparing forest fire risk maps through modeling in spatial information and remote sensing software can help monitor, prevent, and manage the issue. The combination of these techniques is one of the most comprehensive systems designed for decision making that allows the problem to be formulated spatially and allows the consideration of various quantitative and qualitative criteria affecting the problem (Eskandari 2017; Ajin et al. 2016; Pourghasemi et al. 2014; Gerdzheva 2014; Jafari Goldarag et al. 2016). This has been addressed with a wide range of methods including regression and correlation methods, Dong model, fuzzy method, AHP, ANP, and other multi-criteria evaluation methods such as linear-weight combination, artificial neural network method, and other new non-parametric methods such as machine learning (Abdi et al. 2018; Rasooli and Bonyad 2019; Abedi Gheshlaghi et al. 2019).

Eskandari and Miesel (2017) study for predicting fire risk areas in Hyrcanian forests of northern Iran showed that the spatial correlation model (accuracy 0.92) has the strongest ability to predict fire risk areas compared to two models of fuzzy AHP (accuracy 0.8) and Dong model (accuracy of 0.51). The results of the study of Dong model in determining the fire vulnerability of Zarivar Lake forests in Iran by Rasooli and Bonyad (2019) showed that 74% of the region is located in the three categories of highly vulnerable, vulnerable, and moderate vulnerability. In the forests of Nevesinje, Bosnia, and Herzegovina, Gigović et al. (2018), from 8 criteria by AHP method, classified the final forest fire hazard map into 5 categories of very low to very high risk. The results showed that 13.2% of the forest area is in the area of high fire risk. Kayet et al. (2018) in Melghat Tiger Reserve forests of India, FFR and multi-criteria AHP models were compared for comparative analysis of forest fire risk mapping. The results showed similar trends from the two models FFR and AHP. The FFR model had significantly higher accuracy than the AHP. Research by Suryabhadgavan et al. (2016) in the Harena forests of Ethiopia with multi-criteria decision technique showed that 3.4% of the forest cover of the region is at high risk and 24% at high fire risk. The map obtained from the forest fire risk zoning using the AHP method in the forests of Paveh in western Iran in 5 floors was consistent with the burned areas and 90% of the burned areas were located in high-risk areas (Mohammadi et al. 2014). Results of ROC comparing the capability of two methods of logistic regression and neural network in zoning fire sensitivity of forest and rangeland areas of Mazandaran Province by Vidamanesh et al. (2018) showed that both methods have high accuracy but the neural network method is more accurate.

The correlation coefficient between the two methods showed that 0.97 sensitivity zones are the same in both methods and 21.6% of the total area of the province is located in high and very high sensitivity zones of forest and rangeland fires.

The mentioned methods have capabilities and limitations and, in many cases and places, they may not be efficient enough for accurate prediction and zoning of the risk of fire. Examining the capability of these methods and using them in different regions can help in concluding to choose the best and most effective method (Valizadeh Kamran et al. 2014; Güngöroğlu 2017; Suryabhadgavan et al. 2016; Vadrevu et al. 2010; Pourtaghi et al. 2015). Based on this, various methods based on spatial modeling in this study regarding the determination of high-risk regions and factors affecting fire in the Zagros forests of Kohgiluyeh and Boyer-Ahmad Province in western Iran were studied. This region has experienced many fires in recent years, mostly as intentional and unintentional fires. In this study, with multi-criteria evaluation methods (ANP and fuzzy), Dong and CFRISK models, the map of high fire risk areas in the forests of this province was studied and their validity was compared with the real map of fires in the forests of the province.

Materials and methods

Study area

The study area is the forests of Kohgilouyeh and Boyer-Ahmad Province in southwestern Iran. This province with an area of about 15504km² and the center of Shahrekord county is located in the foothills of the Zagros Mountains (Fig. 1). The highest point of the province is Dena Peak with a height of 4283 m and its lowest point at 115 m in Gachsaran. This province has a variety of vegetation due to its high altitudes, heavy rainfall, and suitable temperature. Due to the geographical conditions of the province, along the Zagros Mountains from northeast to southwest, the amount of rainfall and humidity is significantly reduced. This natural condition has created dual climatic characteristics and has divided the province into cold and tropical regions. In this area, most precipitation falls in winter. The ambrothermic curve of the region indicates a relatively long dry period from mid-May to mid-October. The average relative humidity of the region is 46.4%. This province has 16% of the Zagros forests and 7% of the total forests of Iran,

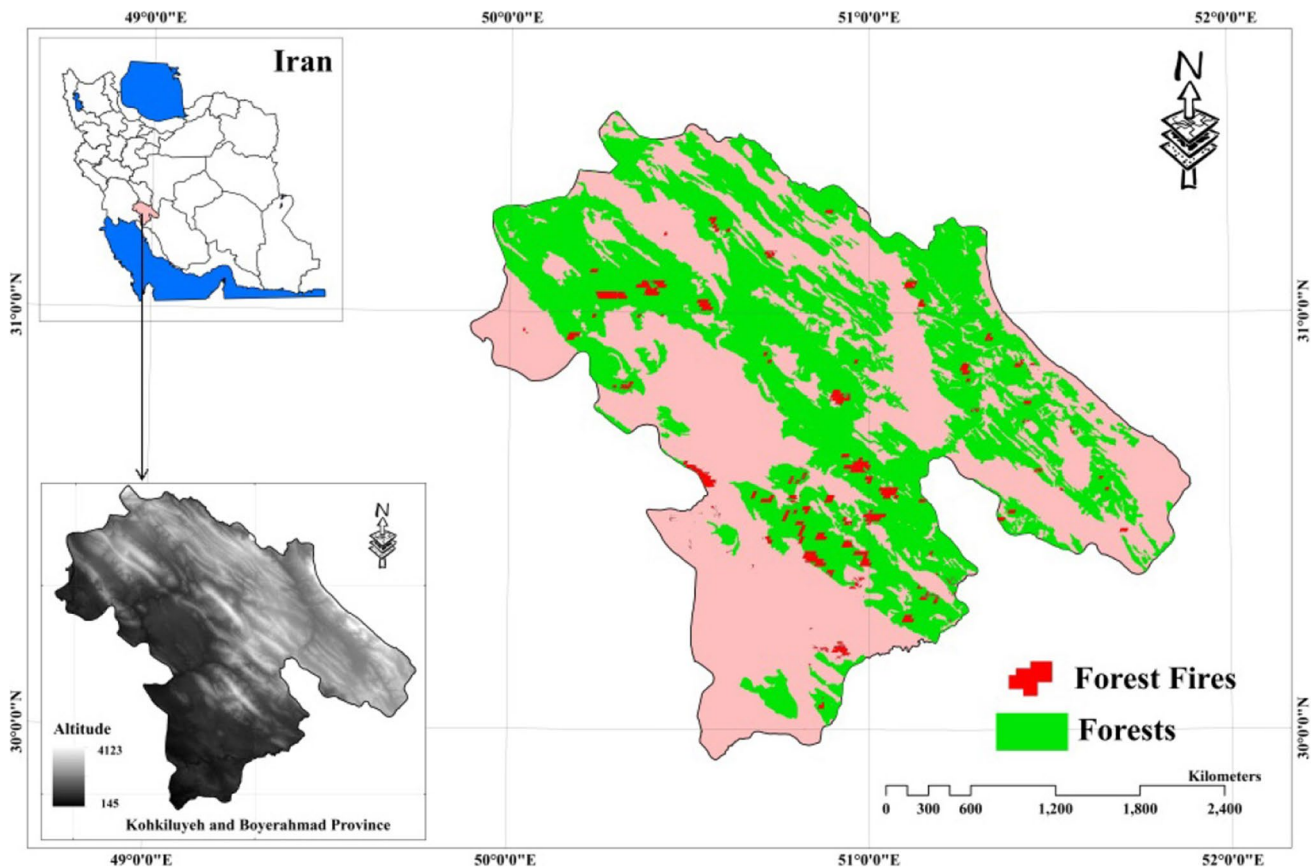


Fig. 1 Location of Kohgiluyeh and Boyer-Ahmad Provinces and its forests in Iran

which is one of the densest forests in the Zagros vegetation region. Persian oak (*Quercus brantii* Lindl.) is the largest forest formation in the province (Kohgiluyeh and Boyer-Ahmad Province Land use planning 2015).

Data collection

Fire data

In this study, fire locations in the forests of the province related to the statistical period 2010 to 2020 were determined and extracted from the data of MODIS products, and compared with the reports of fires recorded by the General Department of Natural Resources of Kohgiluyeh and Boyer-Ahmad and review fields. These areas were identified to verify the validity of the final maps as well as the distribution and general knowledge of the sensitive areas in which a fire has already occurred (Ghorbanzadeh and Blaschke 2018; Kayet et al. 2018; Pourtaghi et al. 2015; Abedi Gheshlaghi 2019).

Data related to criteria affecting fire

Methods of collecting information, preparing and constructing maps related to these criteria and sub-criteria (11 sub-criteria in the form of 4 main biological, physiographic, climatic, and socio-economic criteria) are given in the next steps (Table 1 and Fig. 2).

Climatic criteria.

Climatic conditions, in addition to directly affecting the occurrence and severity of fires, indirectly affect the type and

density of vegetation as a fuel. In areas with higher temperatures, the risk of fire increases. With increasing rainfall and humidity, the risk of fire decreases in frequency and severity (Vadrevu et al. 2010; Rasooli and Bonyad 2019; Güngöroğlu 2017; Jaafari and Mafi Gholami 2017; Ahmadi Ardakani et al. 2015). In this study, two sub-criteria of mean annual temperature (°C) and total annual precipitation (mm), which play an important role, were considered climatic criteria.

Physiographic criteria.

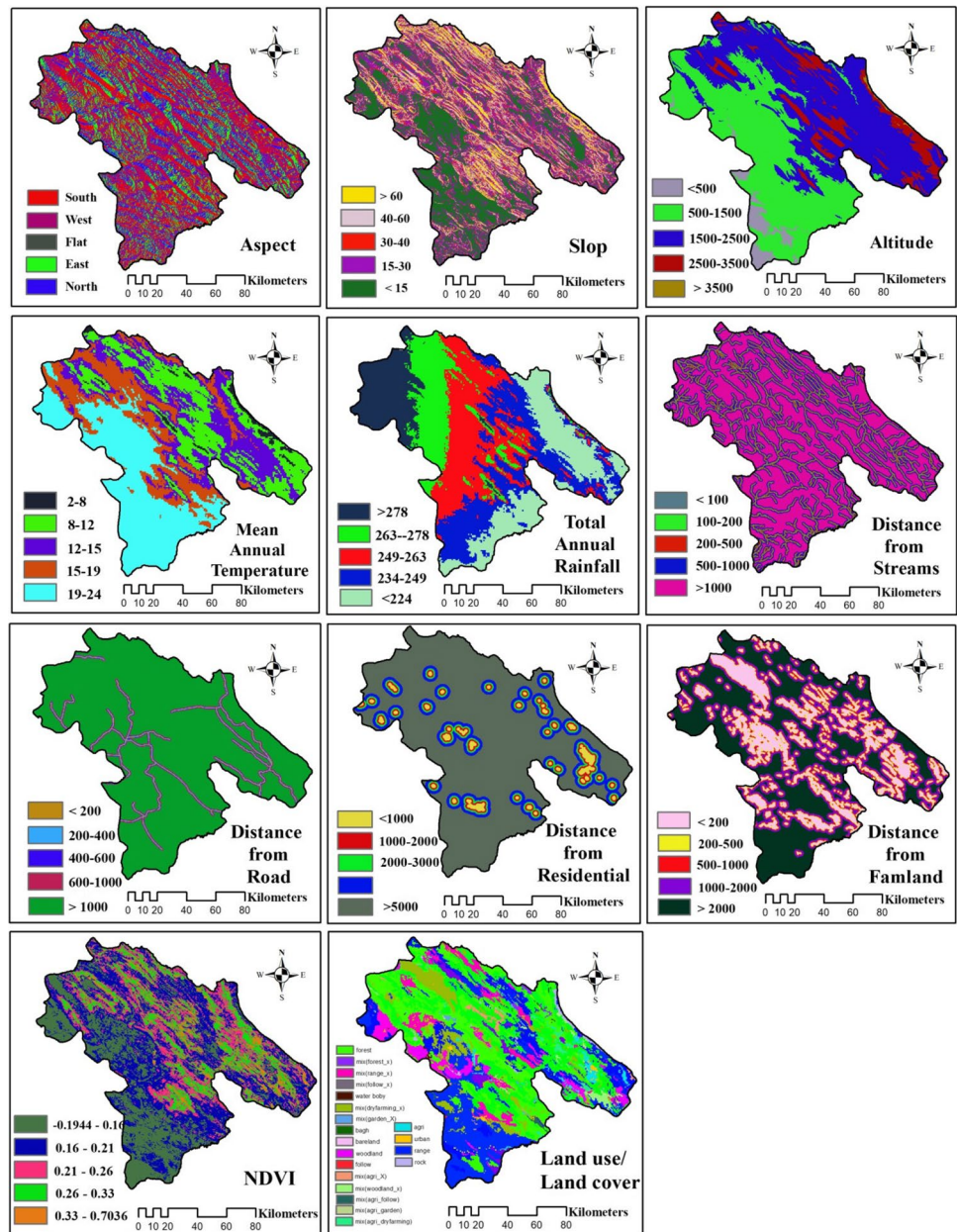
Physiographic features are essential in studying the patterns of fire and the factors affecting it (Mohammadi et al. 2014; Eskandari and Chuvieco 2015). At higher altitudes, the probability of a fire event decreases, as they have high humidity and low temperature. The amount of vegetation is less and there are faster winds. It is also more difficult for humans to reach these areas. Therefore, the probability of fire is inversely related to the altitude (Mosa Beigi and Mirza Beigi 2017). In the lower to middle altitudes of an area, due to relatively high temperatures, lower humidity, and ease of human access, fires are much more likely to occur than at higher altitudes. (Jaafari and Mafi Gholami 2017). In addition, the slope has an immediate effect on the speed and manner of fire spread in forest areas (Vadrevu et al. 2010; Jafari Goldarag et al. 2016; Abedi Gheshlaghi et al. 2019). According to studies, there is more destruction and damage in steeper slopes, because fire travels faster in steeper slopes.

The amount of light energy that an area receives from the sun depends on its slope as the direction of the slope is related to the dryness of the plants in the area. Plants in the south and west are drier and more exposed to combustion with more light and temperature. After that, the eastern,

Table 1 Selected criteria and sub-criteria and their information resources for determining the high fire risk areas

Criteria	Sub-criteria	Resource	Functions, computational methods, and formulas
Physiographic	Altitude	STRM-DEM elevation model	
	Slop	STRM-DEM elevation model	
	Aspect	STRM-DEM elevation model	
	Distance from streams	Iran Water Resources Management Company	Surface water layer of the area
Socio-economic	Distance from roads	Forests, Rangelands and Watershed Management Organization of Iran	Roads layer of the area
	Distance from farmlands	Forests, Rangelands and Watershed Management Organization of Iran	Farmlands layer of the area
	Distance from residential	Iran National Cartographic Center	Residential layer of the area
	Land use/land cover	Iran National Cartographic Center, Google Earth	Land cover/Land cover layer of the area
Climatic	Mean annual Temperature	Data from Meteorological stations in the area (Meteorological Organization of Iran)	Ordinary Kriging Interpolation Model in GIS
	Total annual rainfall	Data from Meteorological stations in the area (Meteorological Organization of Iran)	Ordinary Kriging Interpolation Model in GIS
Biological	Vegetation density	NDVI, MOD13Q1 product of the MODIS sensor	$NDVI = \left(\frac{NIR-RED}{NIR+RED} \right)$

Fig. 2 Basic maps of study criteria



northern, and plain areas receive lesser radiation, respectively (Mosa Beigi and Mirza Beigi 2017; Vadrevu et al. 2010). The physiographic criteria studied in this study are altitude (m), slope percentage (%), slope direction, and distance from surface waters (rivers) (m). The relevant sources of information layer construction are listed in Table 1.

Biological criteria.

Biological criteria, including vegetation as the main fuel, play a critical role in the occurrence and spread of forest fires (Eskandari et al. 2013). Vegetation is a major factor in forest fires and its spread in Zagros forests. Vegetation density also indicates the amount and availability of fuels in each fire and affects the intensity and distribution of fire and plays the role of fuel (Vadrevu et al. 2010; Rasooli and Bonyad

2019). In this study, the NDVI index of the MODIS product MOD13Q1 was used as an information layer of regional forest density, in order to investigate the relationship between fire and regional forests.

Socio-economic criteria.

Socio-economic factors or human causes play a major role in forest fires, especially in developing countries (Vasilakos et al. 2009; Aleemahmoodi Sarab et al. 2015; Mohammadi et al. 2014).

Due to population growth in recent decades in Iran, the invasion of forest areas for livelihood, fuel supply, and agriculture has increased. Also, the inhabitants of the settlements around or inside the forest areas are dependent on the forest. Proximity to residential areas for forest fires is an

effective and destructive factor, because residents depend on the forest and its land to meet their needs, and in this regard, even intentional fires in the forest. Therefore, the expansion of residential areas increases the likelihood of fires (Mosa Beigi and Mirza Beigi 2017). Areas close to communication routes are also at greater risk of fire, because access to these areas is easier. Furthermore, human factors, e.g. carelessness of travelers or tourists, increase the probability of fire (Jaafari and Mafi Gholami 2017; Jafari Goldarag et al. 2016; Vidamanesh et al. 2018). For this purpose, 4 sub-criteria of distance from agricultural lands (m), distance from roads (m), distance from residential (m), and land use were used as socio-economic criteria affecting forest fires in the region. These maps are updated with Google earth images and ground control.

Methods of making a map of high-risk areas in the study area

In this research, in order to facilitate the comprehension of the process of calculations and operations to prepare and build these maps and modeling, three methods ANP and fuzzy, Dong method, and CFRISK method were employed.

Multi-criteria evaluation method

Among the various methods that have been used to map fire critical points, multi-criteria assessment (MCDM) methods have been widely used in fire studies (Ghorbanzadeh and Blaschke 2018; Güngöroğlu 2017; Sharma et al. 2012; Vadrevu et al. 2010). GIS-based multi-criteria analysis includes a series of methods in which different and varied effective, and sometimes, contradictory indicators and criteria are scored on an issue, and then, available options are ranked. The purpose of multi-criteria evaluation is to select the best and most suitable place

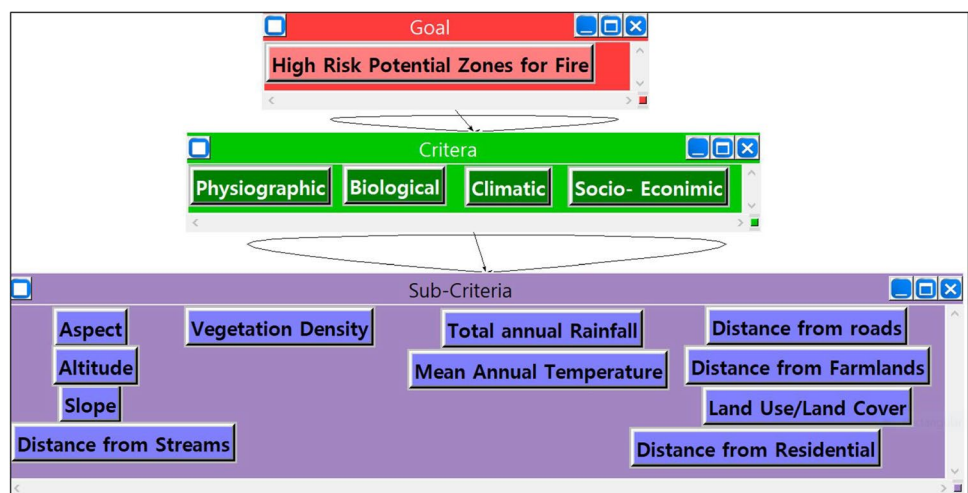
for the intended purpose by evaluating the main criteria (Pourghasemi et al. 2014; Abedi Gheshlaghi et al. 2019; Jafari Goldarag et al. 2016). In this study, ANP and fuzzy methods were used to determine the most effective criteria and produce a map of high-risk points.

Determining the weight of criteria and sub-criteria in modeling high-risk areas of forest fires using ANP method.

Network analysis process (ANP) method was used to determine the importance and weight of factors affecting fire risk in the study area. This method has been introduced in order to solve the drawbacks of AHP method, in solving complex problems with non-class structure and internal interdependencies and interdependencies between criteria and indicators and decision system options based on supermatrix technique (Saaty 2002). In this model, the subject is placed in a network of criteria and options that are effective and relevant to the subject, which is possible in a flexible context of feedback and confrontation between them (external and internal dependencies) (Ghorbanzadeh and Blaschke 2018; Abedi Gheshlaghi et al. 2019). The model network structure was formed in the Super Decisions software (Fig. 3).

Binary comparisons were consulted to score the criteria. The relative importance of the elements was measured using a 1–9 Saaty scale (Saaty and Vargas 2006). Then, the local priority vector was used to indicate the relative importance of the elements. The accuracy of the pairwise comparison matrix was determined based on the consistency ratio (CR) (Eqs. 1 and 2). In Eq. 1, the CI (consistency index) is the compatibility index and n is the matrix dimension. In Eq. 2, the RI (random index) is a random index or random matrix incompatibility coefficient that depends on the number of elements being compared. A pairwise comparison will be acceptable when the CR is less than 0.1 (Saaty 2002).

Fig. 3 Network structure of effective criteria for determining high-risk areas of fire



$$CI = \frac{(\lambda_{max} - 1)}{(n - 1)} \tag{1}$$

$$CR = CI/RI \tag{2}$$

The next steps include the formation of the initial supramatrix (unweighted supermatrix), the weighted supermatrix (weighted supermatrix), and the formation of the limit supermatrix (limit supermatrix) and the calculation of the general weight vector (Saaty 2002). In the final stage, the weight of each of the effective criteria in the Super Decisions software environment was obtained. These weights were later multiplied by the layers of fire criteria in the GIS environment.

Standardization of sub-criteria layers based on fuzzy logic model.

To analyze and evaluate multiple criteria, the measurement scale in the criteria layer maps must be consistent with each other. An important step in fuzzy logic is to define the fuzzy membership value for each criterion. In this model, the membership of a parameter in a set is defined by a value in the range 1 to 0 (Valizadeh Kamran et al. 2014). For this purpose, first, the base map of each sub-criterion was reclassified to a raster format with a code of 1 to 5 based on fire risk. Buffer command was used for linear and polygonal layers. Standardization was then performed using the “fuzzy membership” command in GIS. Higher values of membership in standardized maps of criteria show a higher probability of fire in the forests of the province (Table 2).

Production of the final map.

At this stage, each criterion and sub-criteria layer was multiplied by the weight obtained by ANP method and weighted layers were obtained. This was carried out by applying the “Raster Calculator” option in GIS. The final map of high-risk areas with the overlap of weighted fuzzy maps of each sub-criterion and criterion was made in five categories of very low, low, moderate, high, and very high.

Dong model

Dong model was adopted as one of the most practical models to map high-risk areas of fire in this study (Erten et al. 2004; Eskandari et al. 2013; Rasooli and Bonyad 2019; Dong et al. 2005). This model is designed and presented based on the most important research sources for evaluating the numerical index of fire potential (R_c) and various factors that affect the occurrence of fire. It is also based on trial and error and the performance of mathematical operations in GIS environment by Dong (Dong et al. 2005). The mentioned model is in the form of Eq. (3):

$$R_c(V_t + V_d) + 3(D_r + D_f + D_s) + 5(S + A + E) \tag{3}$$

where in.

- R_c : numerical index of fire potential.
- V_t : type of vegetation (land use/land cover).
- V_d : vegetation density.
- S : slope.
- E : altitude.
- A : aspect.
- D_r : distance from the road.
- D_f : distance from agricultural lands.
- D_s : distance from residential areas.

By weighting all 8 maps and giving specific weight to each factor based on the model using the Raster Calculator command in GIS environment, a fire risk potential map of the area was prepared in five classes.

CFRISK (cumulative fire risk index model)

Occurrence of fire in a forest area depends on several factors; the effectiveness of each of these factors varies according to the specific natural and socio-economic conditions of each region. In this respect, the impact of environmental factors on their occurrence and spread is undeniable. CFRISK is a cumulative fire risk index first calculated by Huyen and Tuna (2008). In the present study, spatial modeling has been performed to obtain the cumulative effect of the study criteria. The relation used for forest fire risk zoning is presented in Eq. 4:

$$CFRISK = 4 \times FUI + 2 \times SLI + 3 \times ASI + 1 \times SI + 1 \times ELI + 1 \times RI \tag{4}$$

- $CFRISK$: cumulative forest fire risk index value (FFRZ).
- ELI : elevation.
- SLI : slope.
- ASI : aspect.
- RI : proximity to the road.
- SI : proximity to settlements.
- And FUI : fuel type (Sharma et al. 2012).

Evaluating the validity of the models used in preparing the map of high-risk areas of fire

In order to evaluate the accuracy or validity of the generated maps, the digital layer of real fire areas was used based on MODIS sensor data and on the recorded fire data that were digitized in GIS environment and closed as polygons in the area. The accuracy of the models used in the study and the actual map of past fires in the region were validated to examine the extent of overlap with areas with high fire potential (high-risk and very high-risk areas) with the actual fire map of the region.

In order to validate, the ROC (receiver operating characteristic) method and the area under curve (AUC) were used.

Table 2 Defined classes, fire hazard ranking, and weight obtained by ANP method for criteria and sub-criteria used and sources used

References	ANP weight	Fire risk rating	Classes	Sub-criteria
Abedi Gheshlaghi et al. 2019; Mohammadi et al. 2014; Mosa Beigi and Mirza Beigi 2017; Mirdeylami et al. 2014; Ahmadi Ardakani et al. 2015; Jafarzadeh et al. 2017; Aleemahmoodi Sarab et al. 2015	0.056	5	< 500	Altitude
		4	500–1500	
		3	1500–2500	
		2	2500–3500	
		1	> 3500	
Mehta et al. 2018; Erten et al. 2004; Eskandari 2017; Ghorbanzadeh and Blaschke 2018; Gigović et al. 2018; Kayet et al. 2018; Mahdavi et al. 2012; Abedi Gheshlaghi et al. 2019	0.040	1	< 15	Slop
		2	15–30	
		3	30–40	
		4	40–60	
		5	> 60	
Dong et al. 2005; Eskandari 2017; Ghorbanzadeh and Blaschke 2018; Güngöroğlu 2017; Kayet et al. 2018; Mahdavi et al. 2012; Pourghasemi et al. 2014; Pandey and Ghosh 2018; Jafari Goldarag et al. 2016	0.032	3	Flat	Aspect
		1	North	
		2	East	
		5	South	
		4	West	
Eskandari and Miesel 2017; Mahdavi et al. 2012; Pourghasemi et al. 2014; Rasooli and Bonyad 2019; Sharma et al. 2012; Jafarzadeh et al. 2017; Gerdzheva 2014; Abedi Gheshlaghi et al. 2019; Mohammadi et al. 2014;; Jafarzadeh et al. 2017	0.116	1	Rock, urban, water body, wetland, bareland	Land cover/land cover
		2	Agriculture, mix (Agri-x), poor range	
		3	Woodland, very low forest, garden, mix (forest-x)	
		4	Low forest, moderate range, grassland, plantation	
		5	Dense forest, moderate forest, good range	
Ghorbanzadeh and Blaschke 2018; Pourghasemi et al. 2014; Abedi Gheshlaghi 2019; Gerdzheva 2014; Abedi Gheshlaghi et al. 2019; Jafari Goldarag et al. 2016	0.055	1	– 0.19 to 0.16	Vegetation density (NDVI)
		2	0.16–0.25	
		3	0.25–0.30	
		4	0.30–0.5	
		5	0.5–0.70	
Eskandari 2017; Pandey and Ghosh 2018; Rajabi et al. 2013; Jafarzadeh et al. 2017; Mohammadi et al. 2014; Mohammadi et al. 2014	0.109	1	< 100	Distance from streams
		2	100–200	
		3	200–500	
		4	500–1000	
		5	> 1000	
Ghorbanzadeh and Blaschke 2018; Gigović et al. 2018; Güngöroğlu 2017; Mahdavi et al. 2012; Pandey and Ghosh 2018; Rajabi et al. 2013; Rasooli and Bonyad 2019; Sharma et al. 2012; Valizadeh Kamran et al. 2014; Abedi Gheshlaghi 2019; Gerdzheva 2014	0.082	5	< 200	Distance from roads
		4	200–400	
		3	400–600	
		2	600–1000	
		1	> 1000	
Dong et al. 2005; Eskandari and Miesel 2017; Eskandari 2017; Rasooli and Bonyad 2019; Jafarzadeh et al. 2017; Mohammadi et al. 2014; Mirdeylami et al. 2014; Jafarzadeh et al. 2017	0.232	5	< 200	Distance from farmlands
		4	200–500	
		3	500–1000	
		2	1000–2000	
		1	> 2000	
Ajin et al. 2016; Eskandari and Miesel 2017; Pandey and Ghosh 2018; Rajabi et al. 2013; Rasooli and Bonyad 2019; Sharma et al. 2012; Suryabhagavan et al. 2016; Abdi et al. 2018; Abedi Gheshlaghi et al. 2019; Jafari Goldarag et al. 2016	0.164	5	< 1000	Distance from residential
		4	1000–2000	
		3	2000–3000	
		2	3000–5000	
		1	> 5000	

Table 2 (continued)

References	ANP weight	Fire risk rating	Classes	Sub-criteria
Ghorbanzadeh and Blaschke 2018; Gigović et al. 2018; Güngöroğlu 2017; Kayet et al. 2018; Pourghasemi et al. 2014; Mosa Beigi and Mirza Beigi 2017; Mird-eylami et al. 2014	0.039	1	< 8	Average annual temperature
		2	8–12	
		3	12–15	
		4	15–19	
		5	> 24	
Eskandari and Miesel 2017; Gigović et al. 2018; Güngöroğlu 2017; Rajabi et al. 2013; Vadrevu et al. 2010; Abdi et al. 2018; Pourtaghi et al. 2015; Mohammadi et al. 2014; Jafarzadeh et al. 2017; Aleemahmoodi Sarab et al. 2015	0.077	5	< 220	Total annual rainfall
		4	220–240	
		3	240–270	
		2	270–300	
		1	> 300	

This is one of the most common methods for evaluating modeling performance (Adab et al. 2013; Ghorbanzadeh and Blaschke 2018). The ROC method is a graphical representation of the balance between the first type error rate (false positive) and the second type error (false negative) for each possible value (Jafari Goldarag et al. 2016). The area under the ROC curve, i.e. AUC, is calculated based on the two curves of success rate and forecast rate. These curves represent the performance of the model using training data and validation, respectively (Mohammadi et al. 2014). The AUC value varies between zero and 1. AUC between 0.8 and 1 indicates very good performance, 0.7 to 0.8 good performance, 0.6 to 0.7 moderate performance, and 0.5 to 0.6 poor performance of the model (Ghanbari Motlagh et al. 2020). Evaluation of the obtained models was evaluated using ROC statistics and the comparison with the reality map of forest fires in the province.

Results

The results of fires in the region

Analysis of fire data results showed that the highest number of fires and the highest area of fires occurred in the last two years (2020 and 2019) (Fig. 4a and b). Most fires occurred in June and May and the largest area of fires was in the same months and August (Fig. 4c and d). The location of the burned areas is shown in Fig. 1.

Determining the weight of criteria and preparing a map of high-risk areas of fire

After preparing the combined matrix, the weight comparison of the sub-criteria was obtained (Table 2). The results

of ANP method in the Super Decisions software showed that the most important factors on the occurrence of fires in the region were distance from agricultural land, distance from residential areas, and land use, as well as general socio-economic factors. Aspect and temperature criteria were the least important. After producing the fuzzy criteria map, these maps were combined and the final map of potential high-risk fire areas on the 5 categories was made (Fig. 5). According to ANP-fuzzy map, about 5.87% and 38.75% of the forest area are located in the classes of very high and high risk of fire, respectively. According to the map, 30.26% of forest lands are in the medium-risk potential classes and 25.09% in the low- and very-low fire risk classes (Table 3).

The potential mapping of high-risk fire areas based on the Dong method and the CFRISK model is also shown in Fig. 5. According to Dong model, 14.83% and 27.24% of the forest area of the region have very high and high fire risk potential, 24.32% have moderate, and 21.96% and 11.63% have low and very low fire risk potential. The final map based on CFRISK method showed that 31.50 and 9.38% of forest lands were in high and very high-risk potential classes, 22.94 and 1.20% fell in low and very low classes, and the average class share was 34.96 (Table 3).

Validation of the maps of high-risk areas of fire

The accuracy of the maps was evaluated by ROC method. Real fire data in the province were used for comparison. The results showed the ROC index for multi-criteria evaluation models, Dong method and CFRISK method, at 0.815, 0.617, and 0.690, respectively, based on which the multi-criteria evaluation model had the highest accuracy (Fig. 6).

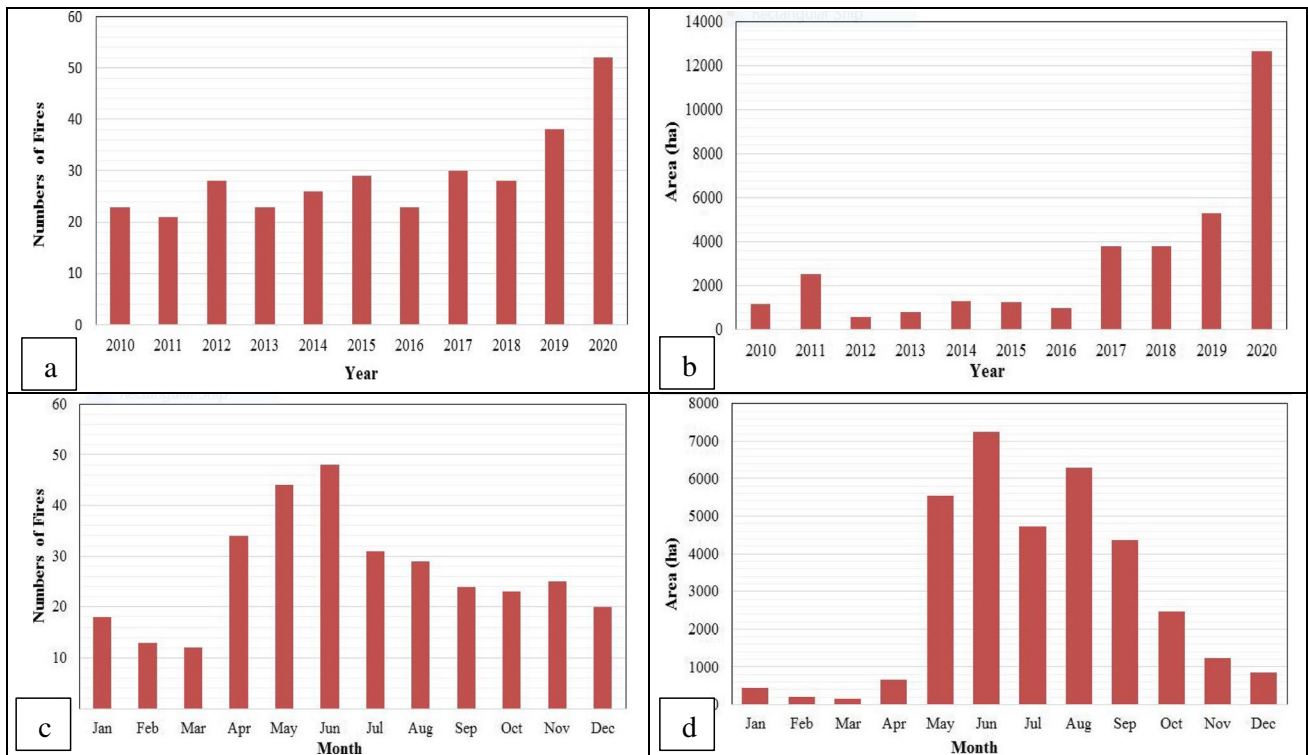


Fig. 4 Analysis of fire data results

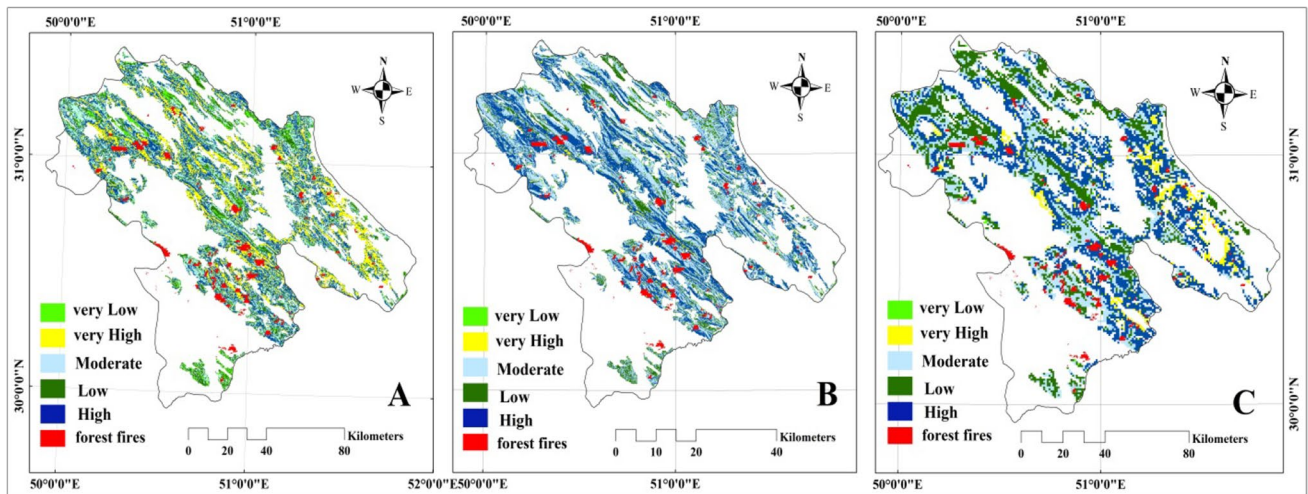


Fig. 5 Potential maps of high-risk fire areas based on different methods (A Dong model, B CFRISK, C fuzzy-ANP)

Table 3 Percentage of forest fire risk potential classes in the study area based on different models

	Fire risk potential class %					Model
	Very low	Low	Moderate	High	Very high	
	0.235497363	24.86372522	30.26777596	38.75636479	5.876636661	Fuzzy-ANP
	11.63005893	21.96672952	24.32530213	27.24568813	14.8322213	Dong
	1.20445804	22.946643	34.9635249	31.500277	9.38509712	CFRISK

Discussion

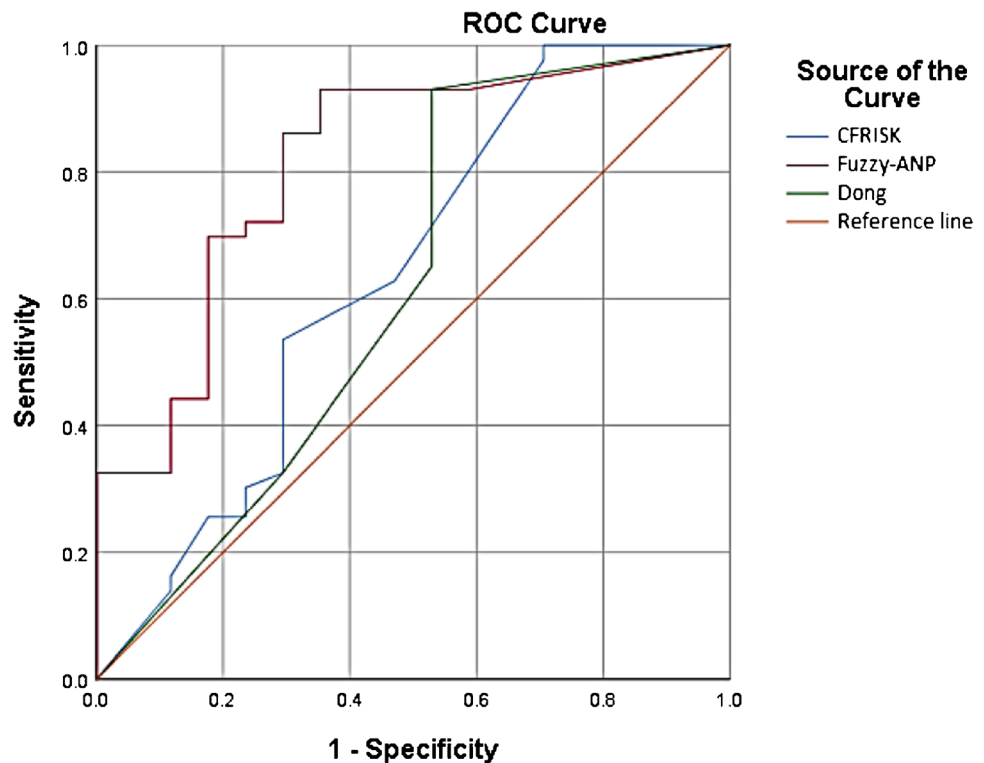
In recent years, alarming frequent and widespread fires have been reported in the Zagros forests of West and southwest Iran. Annually, an average of about 10,000 hectares of natural resources in Iran are burned, with most fires in natural resources in the Zagros (Pourtaghi et al. 2015). In general, the zoning map of the potential of high-risk fire areas based on three methods showed that in total, more than 40% of the forests in the area are prone to high and very high fire, and on average, about 30% have a medium potential. The highest area of high-risk areas and the lowest area of low-risk areas were obtained in the multi-criteria assessment method. This method also had the highest spatial overlap with previously burned areas.

The results of various multi-criteria assessment methods in Iran and other parts of the world have also shown the high efficiency of this method in assessing and zoning high-risk areas of fire. Jafari Goldarag et al. (2016) state that in the forests of northern Iran, the AHP method has increased accuracy. Mohammadi et al. (2014) in Zagros forests in Ilam Province in western Iran have obtained 90% validity for their results by AHP method. Ahmadi Ardakani et al. (2015) found higher accuracy for AHP-OWA method than fuzzy gamma for fire risk zoning method in Zagros forests in Kermanshah. The study of Mosa Beigi

and Mirza Beigi (2017) in western Iran by ANP method, while confirming the high efficiency of this method, showed that 30.4% of the region’s forests in Manesht and Qalarang protected areas in Ilam Province have a high and very high fire risk. Abedi Gheshlaghi (2019) obtained a 64% kappa coefficient for the ANP and fuzzy methods in the forests of Nowshahr in northern Iran. Eskandari (2017) obtained 80% accuracy in FAHP method in the forests of northern Iran. Pourghasemi et al. (2014) have introduced a successful method with M-AHP method and Mamdani fuzzy in the same forests. Gigović et al. (2018) in the forests of Sarajevo, the AHP method has been described as a successful method. Also, Güngöroğlu (2017) studies with FAHP method in Turkish forests, Suryabagavan et al. (2016) with AHP method in Ethiopia, and Vadrevu et al. (2010) with FAHP method in India presented successful results.

The problem of forest fires in the study area includes various criteria including climatic (2 sub-criteria), physiographic (4 sub-criteria), biology (1 sub-criteria), and socio-economic (4 sub-criteria). Each of these criteria has spatial dimensions that have been used in the multi-criteria decision-making method (MCDM) in the spatial field, a suitable framework for assessing forest fire risk. This method provides a suitable context for examining the effect of the criteria involved in the fire phenomenon. Combining these multiple criteria using multi-criteria decision-making methods in a common

Fig. 6 Validation results of the methods used based on the ROC method



Diagonal segments are produced by ties.

framework can provide good results (Valizadeh Kamran et al. 2014). Also, the threshold of each of the studied criteria has been determined using data and expertise, from which high-risk areas are identified with high accuracy, as confirmed by the high validity results of this method in this study.

Dong model is one of the most common methods used to determine high-risk forest areas in various studies, but it is designed for Chinese forests (Rasooli and Bonyad 2019). For the Zagros forests of Iran, this study has shown a moderate efficiency (0.617) to identify high-risk areas for fire. In addition, climatic parameters are not involved. This is also true for the CFRISK method ($ROC = 0.690$). The results of the study of Sharma et al. (2012) in India have been satisfactory. Eskandari et al. (2013) obtained more than 80% validity for the Dong method in the forests of northern Iran. Mehta et al. (2018) estimated the CFRISK method to be highly accurate in Indian forests.

The high accuracy of the generated map showed that the coefficients obtained from the multi-criteria decision analysis (ANP) have satisfactory results in modeling fire risk and identifying areas with high fire potential. In fact, multi-criteria decision-making considers the conditions related to the fire event using the available data and expert knowledge and uses them to determine the threshold related to the fire conditions (Jafari Goldarag et al. 2016). On the other hand, the results of ANP method showed that in a general view, socio-economic criteria had the highest effect on forest fires in the region. This is because the conditions of the Zagros region have provided more access to forest areas for recreation, livestock grazing, agriculture, and other uses (Ahmadi Ardakani et al. 2015). The movement of humans, vehicles, and animals on roads near the forest creates opportunities for fires. Lighting fire and carelessness are effective factors in creating a fire. Proximity to habitats is a devastating factor for forest fires as the residents depend on the forest and its land to meet their needs, and in this regard, they even start a deliberate fire in the forest. Also, the carelessness of shepherds, drivers, and hunters are among the major causes of fires in these forests (Mirdeylami et al. 2014; Jaafari and Mafi Gholami 2017; Vidamanesh et al. 2018). Fire statistics show that the highest frequency of fires was almost from mid-spring to summer, which can be attributed to rising temperatures and decreasing relative humidity and dry vegetation in the region. Density of annual wheat has resulted in increased vegetation density and supply of fuels effective in surface fires. Considering the increase in temperature and dryness of surface vegetation in summer and the subsequent impact of human activities has intensified the fire in the region (Aleemahmoodi Sarab et al. 2015; Vidamanesh et al. 2018).

Mohammadi et al. (2014) and Mosa Beigi and Mirza Beigi (2017) studied the parameters of vegetation type

and density, Jaafari and Mafi Gholami (2017) and Aleemahmoodi Sarab et al. (2015) probed into the land use parameter, Mahdavi et al. (2012) investigated the factor of human factors, and Rasooli and Bonyad (2019) identified the land use factor in different parts of the Zagros forests with the highest weight. In the study of Mehta et al. (2018), vegetation type, aspect, and agricultural workers, and the study of Kayet et al. (2018) have stated that LST, wind speed, and NDVI are the most important parameters affecting forest fires in different states of India. Güngöroğlu (2017) stated that socio-economic factors are the most important factors influencing the probability of fires in the forests of Antalya in Turkey.

The map obtained from this study helps fire management in the study area, fire prevention, and finally its rapid extinction. Based on this research and the results obtained from it, appropriate facilities can be used to deal with fire in dangerous and very dangerous areas before the start of the fire season. However, in general, to use each model to prepare a fire risk map in each area of the vast forest areas of western Iran, it is necessary to first modify and localize these models according to the conditions of these forests considering a larger number of local factors affecting the occurrence of fire, and then to increase their accuracy with real data in each region.

Conclusion

A wide range of techniques using GIS capabilities can facilitate zoning and modeling of the occurrence and risk of fire. In addition, various factors are involved in modeling forest fire risk and preparing risk potential maps. These issues complicate the modeling of forest fire risk. The aim of this study was to investigate the effectiveness of three multi-criteria evaluation methods (fuzzy-ANP), Dong model, and CFRISK model in mapping high fire risk areas in Zagros forests in Kohgiluyeh and Boyer-Ahmad Province. The results showed that socio-economic criteria are the most important factors determining the high risk of fire in these forests. The map based on multi-criteria evaluation method showed the highest accuracy compared to real fire data where more than 40% of forests have a high and very high risk of fire. Differences in the number and nature of variables used in a variety of methods and models also render different results. The map of high-risk areas made with this method can play an important role in assessing the sensitivity of forest areas and making the right management decisions in fire prevention and extinguishing in these valuable resources.

Data availability The datasets used and/or analyzed during this study are available from the corresponding author. The datasets supporting the conclusions of this article are included within the article.

Declarations

Conflict of interest The authors declare no competing interests.

References

- Abdi O, Kamkar B, Shirvani Z, Teixeira da Silva JA, Buchroithner MF (2018) Spatial-statistical analysis of factors determining forest fires: a case study from Golestan, Northeast Iran. *Geomat Nat Haz Risk* 9(1):267–280
- AbediGheshlaghi H (2019) Using GIS to develop a model for forest fire risk mapping. *J Indian Soc Remote Sens* 47(7):1173–1185
- Abedi Gheshlaghi H, Feizizadeh B, Blaschke T (2019) GIS-based forest fire risk mapping using the analytical network process and fuzzy logic. *J Environ Plan Manage* 63(3):481–499
- Adab H, Kanniah KD, Solaimani K (2013) Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. *Nat Hazards* 65(3):1723–1743
- Ahmadi Ardakani M, Rajabi M, Ardakani A (2015) Forest wildfire potential zoning using multi-criteria decision making methods. *Geogr Environ Plan* 7(15):49–66 ((In Persian))
- Ajin RS, Loghini AM, Jacob MK, Vinod PG, Krishnamurthy RR (2016) The risk assessment study of potential forest fire in Idukki Wildlife Sanctuary using RS and GIS techniques. *Int J Adv Earth Sci Eng* 5(1):308–318
- Aleemahmoodi Sarab S, Feghhi J, Danehkar A, Atarod P (2015) Spatial indicators effects on the forest fire potential in Zagros region. *Iran J For Poplar Res* 23(3):425–438 ((In Persian))
- Dong XU, Li-min D, Guo-fan S, Lei T, Hui W (2005) Forest fire risk zone mapping from satellite images and GIS for Baihe Forestry Bureau, Jilin. *China J For Res* 16(3):169–174
- Erten E, Kurgun V, Musaoglu N (2004) Forest fire risk zone mapping from satellite imagery and GIS: a case study. XXth Congress of the International Society for Photogrammetry and Remote Sensing. Istanbul, Turkey, pp 222–230
- Eskandari S (2017) A new approach for forest fire risk modeling using fuzzy AHP and GIS in Hyrcanian forests of Iran. *Arab J Geosci* 10(8):190
- Eskandari S, Chuvieco E (2015) Fire danger assessment in Iran based on geospatial information. *Int J Appl Earth Obs Geoinf* 42:57–64
- Eskandari S, Miesel JR (2017) Comparison of the fuzzy AHP method, the spatial correlation method, and the Dong model to predict the fire high-risk areas in Hyrcanian forests of Iran. *Geomat Nat Haz Risk* 8(2):933–949
- Eskandari S, Ghadikolaei JO, Jalilvand H, Saradjian MR (2013) Detection of fire high-risk areas in northern forests of Iran using Dong model. *World Appl Sci J* 27(6):770–773
- Gerdzheva AA (2014) A comparative analysis of different wildfire risk assessment models (a case study for Smolyan District Bulgaria). *Eur J Geogr* 5(3):22–36
- Ghanbari Motlagh M, Amraei B, Halimi M (2020) Evaluating the hazardous potential of the dieback of the Zagros Oak forests using the multi-criteria decision-making methods. *Arab J Geosci* 13(995):1–11
- Ghorbanzadeh O, Blaschke T (2018) Wildfire susceptibility evaluation by integrating an analytical network process approach into GIS-based analyses. In *Proceedings of ISERD International Conference*, 11–12 July. Tehran, Iran, p 6
- Gigović L, Jakovljević G, Sekulović D, Regodić M (2018) GIS multi-criteria analysis for identifying and mapping forest fire hazard: Nevesinje. *Bosnia Herzegovina Tehnički Vjesnik* 25(3):891–897
- Güngöröglü C (2017) Determination of forest fire risk with fuzzy analytic hierarchy process and its mapping with the application of GIS: the case of Turkey/Çakırlar. *Hum Ecol Risk Assess Int J* 23(2):388–406
- Huyen DT, Tuan VA (2008) Applying GIS and multi criteria evaluation in forest fire risk zoning in son la province, Vietnam. *International Conference on Geoinformation Spatial-Infrastructure Development in Earth and Allied Sciences*. Hanoi, Vietnam, pp. 9–11
- Jaafari A, MafiGholami D (2017) Wildfire hazard mapping using an ensemble method of frequency ratio with Shannon's entropy. *Iran J For Poplar Res* 25(2):232–243 ((In Persian))
- Jafari Goldarag Y, Mohammadzadeh A, Ardakani AS (2016) Fire risk assessment using neural network and logistic regression. *J Indian Soc Remote Sens* 44(6):885–894
- Jafarzadeh AA, Mahdavi A, Jafarzadeh H (2017) Evaluation of forest fire risk using the Apriori algorithm and fuzzy c-means clustering. *Journal of Forest Science* 63(8):370–380. <https://doi.org/10.17221/7/2017-JFS>
- Kayet N, Chakrabarty A, Pathak K, Sahoo S, Dutta T, Hatai BK (2018) Comparative analysis of multi-criteria probabilistic FR and AHP models for forest fire risk (FFR) mapping in Melghat Tiger Reserve (MTR) forest. *J For Res* 31(2):565–579. <https://doi.org/10.1007/s11676-018-0826-z>
- Kohgiluyeh, Boyerahmad Province Land use planning (2015) Analysis of the status of the Province. Natural Resources and Environment, Sabz Andish Payesh Consulting Engineers Company (SAP). pp 205 ((In Persian))
- Mahdavi A, Shamsi SF, Nazari R (2012) Forests and rangelands' wildfire risk zoning using GIS and AHP techniques. *Caspian J Env Sci* 10(1):43–52
- Mehta D, Kaur Baweja P, Aggarwal RK (2018) Forest fire risk assessment using fuzzy analytic hierarchy process. *Curr World Environ* 13(3):307–316
- Mirdeylami T, Shataee Sh, Kavousi MR (2014) Forest fire risk zone mapping in the Golestan national park using weighted linear combination (WLC) method. *Iran J For* 5(4):337–390 ((In Persian))
- Mohammadi F, Bavaghar MP, Shabaniyan N (2014) Forest fire risk zone modeling using logistic regression and GIS: an Iranian case study. *Small-Scale For* 13(1):117–125
- MosaBeigi M, Mirza Beigi F (2017) Zoning forest fire risk in the Manesht and Qalarang Protected Area using a network analysis model and geographic information system. *Environ Sci* 14(4):175–188 ((In Persian))
- Pandey K, Ghosh SK (2018) Modelling of parameters for forest fire risk zone mapping. The international archives of the photogrammetry, remote sensing and spatial information sciences. 20–23 November 2018. ISPRS TC V Mid-term Symposium “Geospatial Technology – Pixel to People”, Vol XLII-5. Dehradun, India. pp 299–304
- Pourghasemi HR, Beheshtirad M, Pradhan B (2014) A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping. *Geomat Nat Haz Risk* 7(2):861–885
- Pourtaghi ZS, Pourghasemi HR, Rossi M (2015) Forest fire susceptibility mapping in the Minudasht forests, Golestan province. *Iran Environ Earth Sci* 73(4):1515–1533
- Rajabi M, Alesheikh A, Chehreghan A, Gazmeh H (2013) An innovative method for forest fire risk zoning map using fuzzy inference system and GIS. *Int J Sci Technol Res* 2(12):57–64
- Rasooli SB, Bonyad AE (2019) Evaluating the efficiency of the Dong model in determining fire vulnerability in Iran's Zagros forests. *J For Res* 30(4):1447–1458. <https://doi.org/10.1007/s11676-018-0765-8>
- Saaty RW (2002) Decision making in complex environments: the analytic network process (ANP) for dependence and feedback; A Manual for the ANP Software SuperDecisions. Creat Decis Foundation, Pittsburgh, PA 15213, p 199

- Saaty TL, Vargas LG (2006) Decision making with the analytic network process. Economic, political, social and technological applications with benefits, opportunities, costs and risks. Springer Science+ Business Media, LLC, Berlin, Germany, p 282
- Sharma LK, Kanga S, Nathawat MS, Sinha S, Pandey PC (2012) Fuzzy AHP for forest fire risk modeling. *Disaster Prev Manag* 21(2):160–171
- Suryabhadgavan KV, Alemu M, Balakrishnan M (2016) GIS-based multi-criteria decision analysis for forest fire susceptibility mapping: a case study in Harenna forest, southwestern Ethiopia. *Trop Ecol* 57(1):33–43
- Vadrevu KP, Eaturu A, Badarinath K (2010) Fire risk evaluation using multicriteria analysis—a case study. *Environ Monit Assess* 166(1–4):223–239. <https://doi.org/10.1007/s10661-009-0997-3>
- Valizadeh Kamran K, Omrani K, Khosroshahi SS (2014) Forest fire risk assessment using multi-criteria analysis: A case study Kaleybar forest. Proceedings of the International Conference on Agriculture, Environment and Biological Sciences, (ICFAE' 14) June 4–5, 2014. Antalya, Turkey, pp 30–33
- Vasilakos C, Kalabokidis K, Hatzopoulos J, Matsinos I (2009) Identifying wildland fire ignition factors through sensitivity analysis of a neural network. *Nat Hazards* 50(1):125–143
- Vidamanesh A, Adab H, Atabati A (2018) Comparison of the applicability of two methods of logistic regression and neural network in zoning fire sensitivity of forest and rangeland areas of Mazandaran province. *J Nat Environ* 71(4):549–563 (**In Persian**)