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Forest fire spatial modelling using ordered weighted averaging multi-criteria evaluation

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Abstract: Forest fires are a major environmental issue because they are increasing as a consequence of climate change and global warming. The present study was aimed to model forest fire hazard using the ordered weighted averaging (OWA) multi-criteria evaluation algorithm and to determine the role of human, climatic, and environmental factors in forest fire occurrence within the Golestan National Park (GNP), Iran. The database used for the present study was created according to daily classification of climate changes, environmental basic maps, and human-made influential forest fire factors. In the study area, the forest fires were registered using GPS. Expert opinions were applied through the analytic hierarchy process (AHP) to determine the importance of effective factors. Fuzzy membership functions were used to standardize the thematic layers. The fire risk maps were prepared using different OWA scenarios for man-made, climatic, and environment factors. The findings revealed that roads (weight = 0.288), rainfalls (weight = 0.288), and aspects (weight = 0.255) are the major factors that contribute to the occurrence of forest fire in the study area. The forest fire maps prepared from different scenarios were validated using the relative operating characteristic (ROC) curve. Values of forest fire maps acquired from scenarios of human, environment, climate factors and their combination were 0.87, 0.731, 0.773 and 0.819, respectively.

Keywords: agents fire, ordered weighted averaging; fuzzification; analytic hierarchy process; Golestan National Park

Natural or anthropogenic forest fire is a ponderous threat with irreversible damage and deep ecological and socio-economic impacts, especially in tropical forests, and its negative impacts could sometimes last more than one decade (Alexandridis et al. 2008; Artés et al. 2014; Rahman et al. 2018). Forest fires seriously threaten the sustainability and environmental services of these ecosystems (Hong et al. 2018), profoundly change the structure of vegetation and biodiversity (Bengtsson et al. 2000; Gandhi et al. 2001), increase absolute carbon storage (Healey et al. 2014), and endanger species composition (Moretti et al. 2004). It has been estimated that about 20% of CO_2 emission into the atmosphere is caused by forest fires (Kuhrt et al. 2001), and the possibility of fire in the future could be attributed to climate change conditions (Holsten et al. 2013). Therefore, analysis of factors affecting the occurrence and spread of fire as well as understanding its dynamic behaviour is necessary to minimize the occurrence of forest fires (Kandya et al. 1998).

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It is of great importance to determine the fire severity and frequency and develop effective strategies for forest-fire management (Miller et al. 2016). Modelling natural processes enhances understanding of the natural environment as well as the relationships and dynamics of its interacting parts. By presenting a simplified or an abstract representation of the world, models can provide insight into the past, define the present or predict the future state of natural phenomena (Smyth 1998). According to the inventory of forest fires and geographical and meteorological data, a large number of methodologies and probabilistic models have been developed and frequently applied to predict forest fires. Such models include, but not limited to, hybrid machine learning methods and GIS-based spatial prediction models (Bui et al. 2018), overlap indices and inference algorithm (Garcia-Jimenez et al. 2017), optimal combination using genetic algorithms (Hong et al. 2018), ground-based data of forest fires (Ying et al. 2018), fuzzy inference system (Lin et al. 2018), design and application of fuzzy logic-based fire monitoring (Sarwar et al. 2018), and fire susceptibility using data mining techniques (Pourtaghi et al. 2016).

In parallel to the above-mentioned methods, multi-criteria evaluation (MCE) as decision support systems-based models have been applied for forest fire crisis management (Srivastava et al. 2019). Over the past years, MCE has become more common to identify conservation priorities and threats as well as to develop and evaluate alternative plans which facilitate a compromise between interested parties (Malczewski 1999; Karnatak et al. 2007; Wood, Dragicevic 2007; Geneletti, Van Duren 2008). MCE simplifies complex decisions with multiple criteria and helps identify areas of good planning and success in environmental protection areas. MCE consists of three main procedures including Boolean overlay, weighted linear combination (WLC), and ordered weighted averaging (OWA). OWA can be applied in the natural sciences to improve decision-making (Mokarram, Hojati 2017).

The Golestan National Park (GNP) in the north of Iran is one of the oldest reservoirs of the biosphere and biome mountain complex systems with complicated zoning in Odwardy's classification outstanding and distinct characteristics of Hyrcanian Province. This national park is the only sample of the above-mentioned biome in the world network of biosphere reserves and is an important touristic area (Ghoddousi et al. 2018). It has been estimated that one-eighth of plants, one-third of bird species, and over 50 percent of mammalian species of Iran live in the above-mentioned park. Due to being exposed to wet and dry winds and, in turn, being susceptible to fire (Shokri et al. 2002), in this park there burned about 3 000 ha in September 2013, 250 ha in September 2014, 1 400 ha in July 2015, and 300 ha in July 2018. Therefore, the present study applied GIS-based MCE with a focus on the analytic hierarchy process (AHP) algorithm and OWA to identify areas vulnerable to fire risk based on human, environment, and climate factors and also to assess their accuracy in the study area.

MATERIAL AND METHOD

Study area. The GNP with the area of 91 895 ha is located in the northeast of Iran, from 37°16'34''to 37°31'00''N and 55°43'00'' to 56°17'45''E (Figure 1). It occupies a transitional position between the subhumid south Caspian region and the semi-arid parts of central and east-central Iranian plateau. The presence of several relatively high mountains blocks the wet air masses from the Caspian Sea, creating particular microclimatic conditions with precipitation varying from 150 mm·year^{-1} in the SE to more than 750 mm·year^{-1} in some central parts of the park. The park possesses a diverse mosaic of vegetation units, including the Hyrcanian low- to high-altitude mesophytic forests, shrub lands, open and closed scrubs, sometimes mixed with C4 grasslands, Juniperus woodlands, mountain steppes and meadows, Artemisia and Artemisia–Stipa steppes and different transitional and halophilous communities (Akhani 1998; Akhani, Ziegler 2002).

Method. The research was conducted in four steps including (1) creation of a spatial database, (2) preparation of criteria, (3) normalization of factors, and (4) application of the multi-criteria evaluation using the ordered weighted average scenarios and analytic hierarchy process (Figure 2). All of the steps were conducted in the IDRISI Taiga and ArcGIS (Ver. 10.4, 2019) software. Firstly, the factors influencing the fire were identified and the data were obtained through field surveys in the study area and from government organs. The factors were classified into climatic, human, and environmental factors, and their fuzzy state was estimated according to their influencing way.

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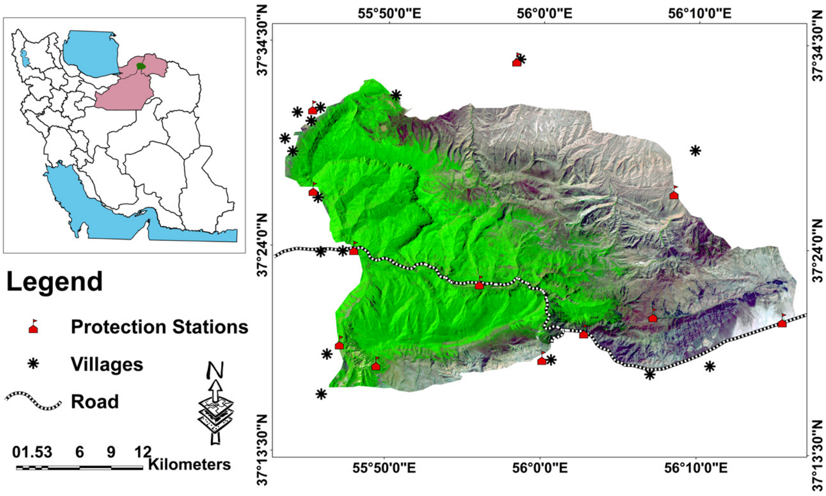

Figure 1. Map of the Golestan National Park (GNP) in the northeast of Iran with the location of sampling sites and nearby villages

Modelling was performed using six scenarios of OWA and weights obtained from the participatory technique AHP. The models were evaluated on the basis of the map obtained from the fires that occurred in the area as well as the characteristics of the relative factor.

Forest fire effective factors. The factors affecting fire were divided into three categories (Table 1): anthropogenic factors, in which humans play an essential role; climate factors, prepared by meteorological data during the last 10 years; and environmental factors, dealing with local conditions.

Analytic hierarchy process. The participatory technique which involves opinions of experts in various areas related to a specific subject was used to define factors and constraints as well as weight of each criterion (Eastman 1999). AHP is one of the most popular multi-criteria decision-making techniques that allows to formulate a problem in a hierarchical manner and to consider the possibility of different quantitative and qualitative criteria about the problem. One of the important advantages of this process in group decision-making is the decision combination of the group members so that the optimal decision will be computed based on the votes of all members. Therefore, in this part of the study, the factors related to climatic, human, and environmental agents were assessed using AHP and weights were obtained for the factors and agents. For this purpose, questionnaires were filled by ten specialists and the mean weight was determined.

Fuzzy logic. Fuzzy theory (Zadeh 1965) was raised against classical logic theory, a powerful tool to address the requirements of complex systems which are dependent on human reasoning, deci-

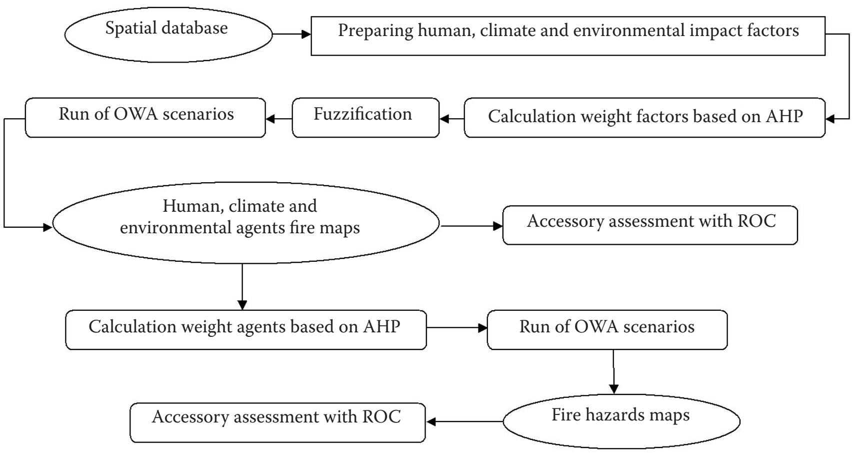

Figure 2. Flow chart of the major processes conducted for forest fire hazard mapping
OWA – ordered weighted averaging; AHP – analytic hierarchy process; ROC – relative operating characteristic

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Table 1. Forest fire effective factors and their categorization

Agents	Factors (scale)	Source factors	Description
Climate	rainfall-plant (mm)	April to November is the growing season of the plants in the park. We obtained the average monthly rainfall during these months, and the map was prepared using the inverse distance weighted (IDW) interpolation method	Precipitation during the growing season will increase due to rising fuel fires (Chapin et al. 2003).
	rainfall (mm) moisture (%) pressure (mbar) temperature (cc)	maps of temperature, rainfall, pressure, and moisture were prepared from meteorological data using the IDW interpolation method	Increasing precipitation and moisture reduce the risk of fire (Tanskanen et al. 2005). Temperature, pressure, and wind are factors which increase the fire risk (Keeley, Keeley 1988; Whelan 1995; Balzter et al. 2005).
	wind (m/s)	wind maps were obtained according to wind speed and direction at the weather stations in four parts of the park, wind rose plots at the stations were plotted in the WRPLOT View software	
Environmental	elevation (m)	DEM was obtained from a topographic map at 1 : 30 000-scale	Topographic factors explain variation in local climate and indirectly influence factors, and fire risk is reduced with increasing elevation (Whelan 1995).
	slope (%)	slope map was prepared from the built DEM	Slope produces a direct physical effect on active fire fronts (Bui et al. 2017).
	aspect	aspect map was obtained from the built DEM	Fires would be more in the parts that get more sunlight intensity (Franklin et al. 2000).
	landuse	land use map with resolution of 300 meters was prepared in the Environment Department for 2017	Landuse maps have impact on the fire risk based on users (Cantarello et al. 2011).
	spring (m)	distance map of springs was obtained in the study area with GPS	Springs attract tourists in the study area.
	NDVI	NDVI map was obtained from 2017 Landsat 8 satellite images	NDVI data for dynamically assessing the potential fire risk (Gonzalez-Alonso et al. 1997; Burgan et al. 1998; Zipoli et al. 2000).
Human	main road (m)	distance map of the transit road across the park	Forests located near roads are more sensible to fire (Jaiswal et al. 2002).
	side roads (m)	distance map of the roads around boundaries and roads in the park for the access of guards	
	village (m)	distance map of the villages around the park	Housing developments and human population density will increase fire forest (Glickman, Babbitt 2001; Rundel, King 2001).
	camping (m)	distance map of camping areas	Since tourists increase the probability of forest fires (Sunlu 2003).
	hunters (m) shepherds (m)	distance map of the arrest shepherds and hunters information recorded by the central office park	Shepherds and hunters cause intentional and unintentional forest fires (Faramarzi et al. 2014).

NDVI – normalized difference vegetation index; DEM – digital elevation model

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sion making and inference. In this study, in order to standardize the GIS data layers for subsequent integration, the factor maps were fuzzified according to their nature using different membership functions. The membership functions were specified as monotonically increasing or decreasing functions which are controlled by breakpoints ordered from low to high on the measurement scale, as specified in Table 2. Regarding monotonically increasing functions, the first point indicates the location where the membership function begins to rise above 0, and the second one shows the point of unity (i.e., 100 percent class membership). The output was scaled from 0 (zero class membership) to 255 (100 percent class membership) for each layer (Mokarram, Hojati 2017).

OWA. OWA is a weighted average-based method, except that the amount of pre-multiplying the vector weight is ordered. This type of sorting is the special feature of the approach and leads to nonlinear models (Wu 2018). With different sets of ordered weights, one can generate a wide range of OWA operators, including the three special cases of the WLC, Boolean overlay combination AND (non-risk), and OR (risk-taking) (Malczewski 2006). The WLC method is an intermediate measure with full compensation between two functions of AND and OR, whereas the OWA method is an intermediate one with different compensation between these two functions.

OWA method combines common functions and provides a continuous fuzzy compensation between the feed (AND) and union (OR) through integrating the weight-degree average (Eastmam 1997). The degree of dispersion of the weights is controlled by the level of TRADEOFF using two ANDness and ORness characteristics which indicate the size of the compensation (Valente, Vettorazzi 2008).

This method leads to continuous grading of scenarios between the operators subscription and community, and this continuous grading is done by the local and global weights. To control the level of compensation, the global weight is added gradually based on expert opinion and through a paired comparison, and the local weight is added gradually and removal criteria and leverage provide to control the level of uncertainty and risk-taking (Malczewski 1999; Jiang, Eastman 2000), thereby providing a full range of risk scenarios between the two operators subscription (AND) and union (OR) as follows (Gorsevski et al. 2012):

Table 2. Standardization method for effective factors according to fuzzy logic

Agents	Factors	Membership function type	Membership function shape	Control points	
				a, c	b, d
Climate	temperature	linear	increasing	12	17
	rainfall-plant	linear	increasing	50	250
	pressure	linear	increasing	877	951
	rainfall	linear	decreasing	190	615
	moisture	linear	decreasing	61	68
	wind	linear	decreasing	1	8
Environmental	elevation	linear	decreasing	500	2 200
	NDVI	linear	decreasing	0.2	0.8
	slope	linear	decreasing	10	60
	land use	linear	decreasing	1	10
	aspect	linear	increasing	1	9
	springs	J-shaped	increasing	1 000	10 000
Human	road side	J-shaped	decreasing	1 000	15 000
	road main	J-shaped	decreasing	1 000	12 000
	village	J-shaped	decreasing	5 000	15 000
	farmer	J-shaped	decreasing	2 000	6 000
	camping	J-shaped	decreasing	1 000	7 000
	hunter	linear	decreasing	3 000	20 000

NDVI – normalized difference vegetation index

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(*i*) Average risk and full TRADEOFF; this scenario provides the same result as the WLC, and the risk is at the midpoint of AND-OR functions and the TRADEOFF is full. That is, sequential weight is distributed evenly between all invoices, irrespective of their position in the ranking order of the minimum to the maximum (i.e., AND and OR function, respectively) at any position. This distribution demonstrates no deviation towards the two functions and the results are placed in intermediate risk, like the WLC method.

(*ii*) Low-risk and no TRADEOFF; this scenario makes results for low risk (i.e., use of a logic close to the AND logic) which assigns all weight to the first order rank. In this way, therefore, weighting makes no compensation possible.

(*iii*) Low-risk and a small amount of TRADEOFF scenario; this method distributes the weights between the factors, and the first factor has the highest weight and then the weights are decreased. It has a middle range function between the end-AND function and intermediate-risk WLC situations.

(*iv*) High-risk and a few TRADEOFFS; like the low-risk and a few TRADEOFFS scenarios, weight is distributed between factors, but the first factor in the ranked order has the lowest weight and then the weights are increased in the order. This scenario has a central function in the intermediate risk range OR WLC's position.

(*v*) Average risk and no TRADEOFF; the factor or factors account for all the centre order weights. This scenario is the average risk, like the WLC method, but there is no TRADEOFF.

(*vi*) High-risk and no TRADEOFF; in this scenario high-risk conclusion [use of a logic close to the logic OR (maximum risk sequence)] is created and all weight is allocated to the last rank sequence, and thus weighting will make no compensation.

In the ordered weighted average, the method diagonally arranges relative weights and the risk level associated with AND-OR can be obtained from integration between AND and OR from the equations in OWA (Equations (1) to (4)) (Jiang, Eastman 2000; Rinner, Malczewski 2002; Valente, Vettorazzi 2008).

$$\text{ANDness} = (1/(n-1))\ \Sigma((n-i)\ W_{\text{orderi}}) \tag{1}$$

$$\text{ORness} = 1 - \text{ANDness} \tag{2}$$

$$\text{TRADEOFF} = 1 - \sqrt{\frac{n(\Sigma W_{\text{orderi}} - 1/n)^2}{n-1}} \tag{3}$$

$$\text{RISK} = \left(\frac{1}{n-1}\right)\Sigma[(n-i)\,W_{\text{orderi}}] \tag{4}$$

where:

n – the number of variables;

W_{orderi} – the weight of variable.

The sequence weights and above equations for each of the scenarios of OWA were determined for human, climate, and environmental factors and combined agents (Table 3 and 4).

Accessory assessment with relative operating characteristic. the relative operating characteristic (ROC) module can be used to compare the image of a probabilistic model versus a real picture (Hong et al. 2018); that is, ROC is an index used to measure the accuracy of a probability prediction compared to the observed land use change. ROC curves are drawn using true-positive and false-positive proportions (Figure 3).

The ROC statistic (i.e., area under the curve) is calculated using Equation (5).

$$\text{AreaUnderCurve} = \Sigma^{\text{n}}_{i=1}[x_{i+1} + 1 - x_i] \times \times [_{\text{yi}} + (y_{i+1} - y_i)/2] \tag{5}$$

where:

x_i, y_i – false and true pixel percentages for scenario I, respectively;

n – the number of scenarios (Pontius, Schneider 2001).

The ROC graph for three input images; the diagonal dark line was derived from the input image where the positions were assigned the actual values randomly, and two lines were of different models. The model shown in thin line with a hollow square has a lower implementation proportion dark line model.

After OWA, the values of ROC for each of these maps to Boolean map were obtained according to fire occurrence in the study area. The forest fire locations were identified according to field surveys, MODEIS satellite images, and the historical fires recorded by the park authority during 1981–2018. A total of 70 fires were recorded and used in this study.

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Table 3. Different ordered weighted averaging (OWA) procedures for six factors

OWA operator	Order weights	ANDness	ORness	TRADEOFF
Average risk and full TRADEOFF	0.16, 0.16, 0.16, 0.16, 0.16, 0.16	0.48	0.52	0.993
Low risk and no TRADEOFF	1, 0, 0, 0, 0, 0	1	0	0
Low risk and a few TRADEOFF	0.5, 0.3, 0.125, 0.05, 0.025, 0	0.84	0.16	0.804
High risk and a few TRADEOFF	0, 0.025, 0.05, 0.125, 0.3, 0.5	0.16	0.84	0.804
Average risk and no TRADEOFF	0, 0, 0.5, 0.5, 0, 0	0.5	0.5	1
High risk and no TRADEOFF	0, 0, 0, 0, 0, 1	0	1	0

Table 4. Different ordered weighted averaging (OWA) procedures for three agents

OWA operator	Order weights	ANDness	ORness	TRADEOFF
Average risk and full TRADEOFF	0.33, 0.33, 0.33	0.495	0.505	0.996
Low risk and no TRADEOFF	1, 0, 0,	1	0	0
Low risk and a few TRADEOFF	0.5, 0.35, 0.15	0.675	0.325	0.824
High risk and a few TRADEOFF	0.15, 0.35, 0.5	0.325	0.675	0.824
Average risk and no TRADEOFF	0, 1, 0	0.5	0.5	1
High risk and no TRADEOFF	0, 0, 1	0	1	0

RESULTS

Figure 4 demonstrates the weights of human, climate, and environmental agents and their importance in the occurrence of forest fires in the study area which was calculated using AHP.

According to the opinions of the experts, the main important factors related to humans, climate and environment are roads, rainfall, plant, and land use, respectively, where the human agent is the most important. Factors related to hunters, farmers, and tourists exhibited average weights, yet the ones related to villagers and side roads did the lowest. Climate factors including temperature, annual rainfall, humidity, and wind showed almost equal weights, but air pressure had the lowest weight. Weights of normalized difference vegetation index (NDVI) and elevation factors were medium, whereas slope and spring distance obtained low weights.

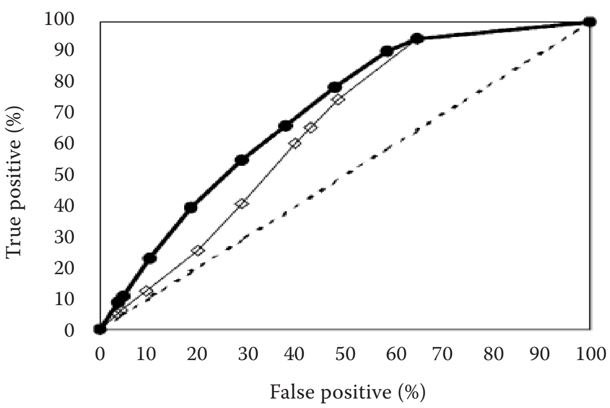

Figure 3. Relative Operating Characteristic (ROC) graph

Risk maps for human, environmental, and climatic agents were provided by OWA scenarios (Figure 5). These maps were compared with the real fire map and the area under the curve (AUC) was calculated for all of the scenarios. In all scenarios, the map of human agent displayed the highest AUC; indeed, the implementation model of human agent appeared to be more suitable or stronger. The best scenario maps for the desired factors were as follows: human agent, average risk and no TRADE-OFF; climate agent, low-risk and low TRADEOFF; environmental agent, low-risk and no TRADEOFF; and combined agent, average risk and no TRADE-OFF. These scenarios showed the highest AUC amounts.

According to the obtained ROC for each of the scenarios, the human agent map showed higher usability than the others (Table 5). In all scenarios, the maps obtained from the combined agents demonstrated high accuracy except the high-risk and no TRADEOFF scenario, which is a poor performance scenario. Scenarios with low-risk and low TRADEOFF as well as with suitable amount of ROC showed the best performance. Moreover, the

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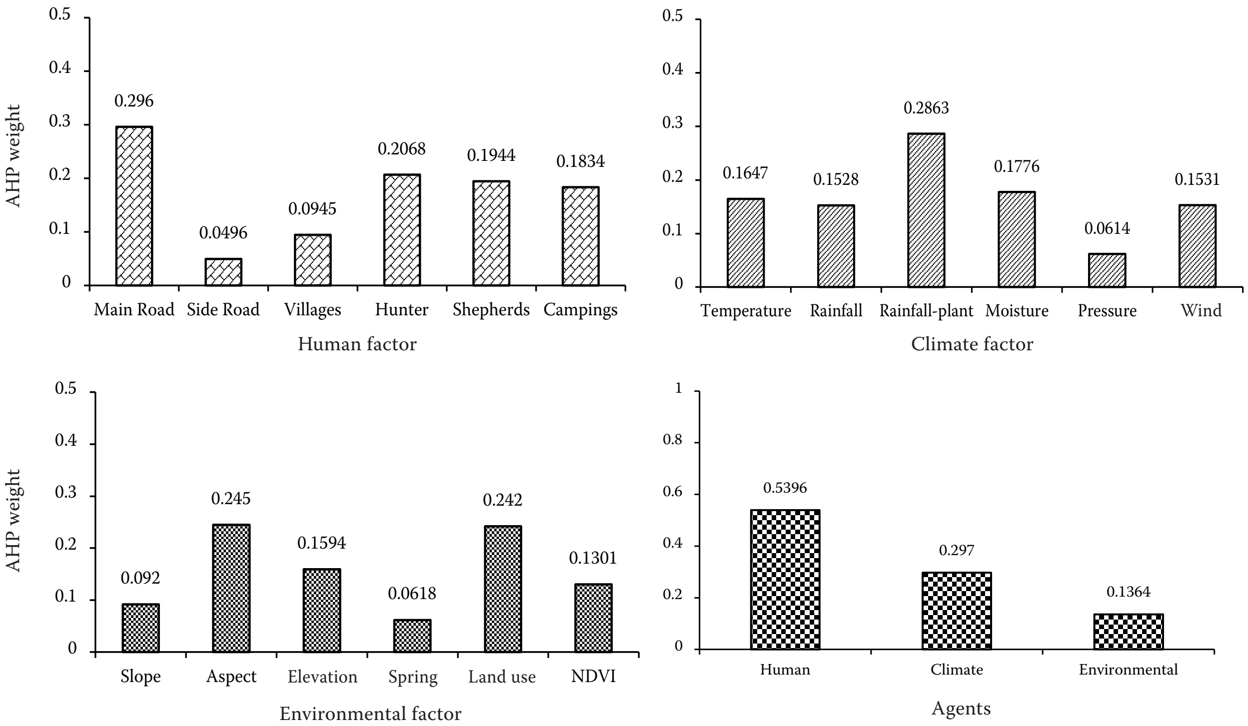

Figure 4. Diagram of analytic hierarchy process (AHP) weight

low-risk and no TRADEOFF scenario with the value greater than 0.7 demonstrated acceptable performances for all agents.

Finally, the fire risk maps were obtained from the best OWA scenarios: human agent of average risk and low TRADEOFF (Figure 6A), climate agent of low risk and a few TRADEOFFS (Figure 6B), environmental agent of low risk and no TRADEOFF (Figure 6C), and agents of low risk and a few TRADEOFFS (Figure 6D). In addition, the respective lower and higher membership classes were as follows: in the map of human agent, 3 and 245; in the climate agent map, 0 and 144; in the environmental factor map, 0 and 129; in the combined agent map, 5 and 92.

DISCUSSION

The development of GIS and decision support systems (DSS) have introduced a toolset which efficiently integrates many different GIS data layers to be used in hazard maps for conservation planning and assessment (Karnatak et al. 2007; Wood, Dragicevic 2007; Geneletti, Van Duren 2008). The present study introduced a tool for preventing and examining the accordance of wild fire in the GNP. Validated threat maps were generated using MCE, and the approach was developed in our study to decide on protection policies for the study area against fire risk and for strategic planning in management. In particular, our analysis involved a series of MCE approach tests on the fire hazards and provided conservation planners with new spatial information which could guide the future allocation of financial resources for conservation. Despite the important role of human factors in forest fire and fire spreading, we notify and educate individuals to reduce the risk of fire.

To compare and calculate the weight of factors, they should be in the same group and the same direction (Kahraman 2008); in this study, three classified agents including human, environmental, and climate factors were in one direction.

According to the opinions of the experts about human factors, this study also demonstrated that the transit road through the park has been the most important factor in forest fire, and the lowest weight obtained between human factors is related to the side road. Faramarzi et al. (2014) evaluated GNP fires and showed that 46% of fires in the area is directly associated with transit road. High frequency of fires around the roads is influenced by the num-

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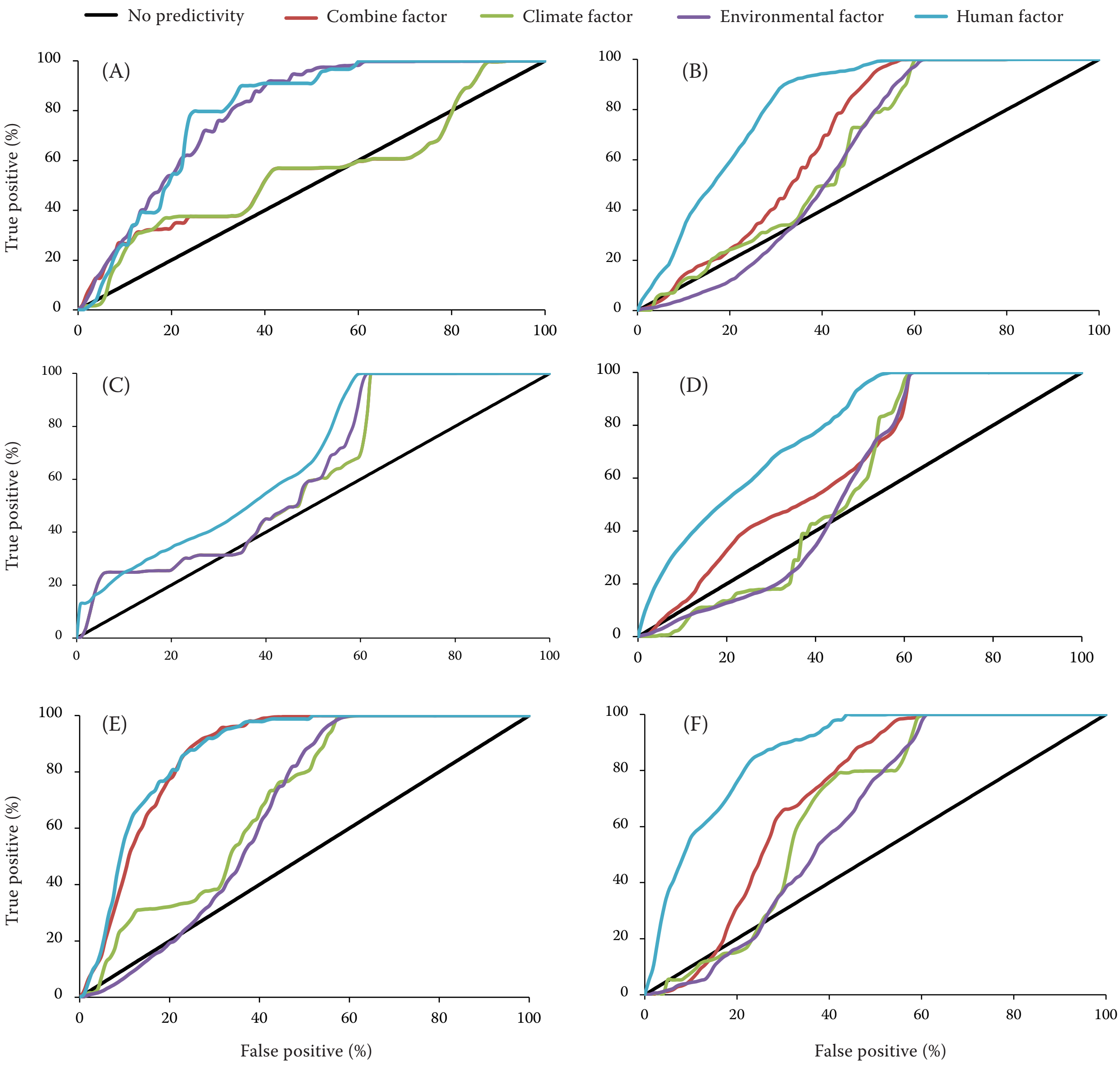

Figure 5. Relative operating characteristic (ROC) graph for ordered weighted averaging (OWA) scenarios: (A) low risk and no TRADEOFF, (B) average risk and full TRADEOFF, (C) high risk and no TRADEOFF, (D) high risk and a few TRADEOFFS, (E) low risk and a few TRADEOFFS, and (F) average risk and no TRADEOFF

ber of tourists and passengers passing through the roads; however, high-frequency roads can have a positive impact on roadside facilities to reduce and timely control fires. Due to the main road crossing through the park, heavy traffic of travellers and tourists is the most important factor in initiating fire. Thus, the protective agencies around the roads play an important role in fire control.

The results of AHP showed that hunter, farmer, and tourist factors play important roles in fire occurrence. Generally, parks with landscape and diverse wildlife attract tourists and hunters. In addition, farmers living in the park or villages in the vicinity influence the plant biota through grazing. In the same study Murthy et al. (2019) stated that anthropogenic variables including distance to villages and roads influenced fire incidences while about 3 km from villages and roads are high-risk areas in terms of susceptibility to fire.

Among the climatic factors, rainfall in the growing season of plants exhibited the maximum weight. Precipitation in the growing season causes

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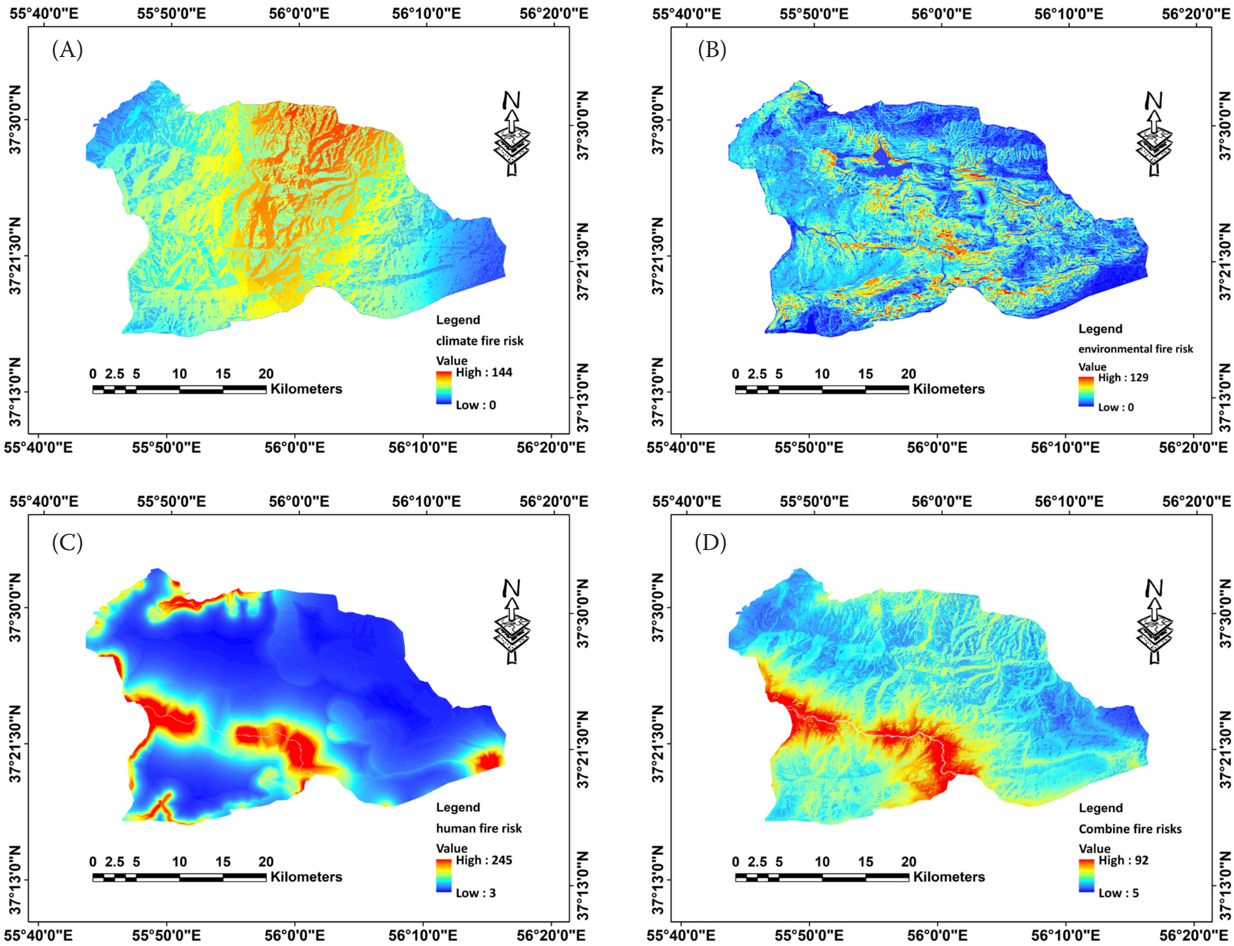

Figure 6. Fire risk maps of best ordered weighted averaging scenarios: (A) climate agent of low risk and a few TRADEOFFS, (B) environmental agent of low risk and no TRADEOFF, (C) human agent of average risk and no TRADEOFF, and (D) combined agents of low risk and a few TRADEOFFS

a dense coverage of annual plants, whose drying in autumn, in turn, increases the risk of fire hazard. In addition, among the environmental factors the maximum weight has been allocated to landuse because the different directions of a land vary in terms of light, coverage, and moisture capacity (Saklani 2008). In the studied area, the highest frequency of fires has occurred in the southern and southwestern regions because of exposure to sun light and thus being hotter.

Land use factor determines the type of vegetation in the park, and given that the aggregation of vegetation determines and causes more fire, increasing thorns and chips can be considered among the most important factors in the fire management plan of the parks. The MCE models work according to the decision maker assumptions which are based on the ascending or descending weights. In this study, some of the features of the model were solved based on OWA space and the results were compared with each other. The results demonstrated that the position of the model in different strategic spaces leads to different outputs in fire hazard modelling, and the ROC value obtained from different scenarios of OWA represented the issue when compared with the fires that occurred in the area. In multi-criteria decision making, in general, the weight of each criterion is calculated based on the decision maker›s approximation and estimates, though accompanied by error. Therefore, considering different spaces and evaluating them could increase the accuracy of the model. The ROC charts exhibit the status of AUC when compared to the fires that occurred in the area, and in all scenarios the AUC value for the human factor model was higher than in the other models.

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Considering ROC values, the results of the human agent model indicated good overall performance. The area under the curve (AUC) with values between 0.5–0.7, 0.7–0.9 and > 0.9 indicates low accuracy, useful application and high accuracy, respectively (Swets 1988), albeit the main cause of fire is the human factor. Despite the amount of low accuracy, ROC for climate factors derived from the model showed an important role of forest fire when compared to the climate factors, especially in drought years.

The maps obtained from human, climatic and environmental factors revealed good AUC values and combination of these three maps can be used in fire management procedures in the study area. Concerning the selection of a membership function, previous researchers applied linear functions on different factors, including elevation and slope as well as distance to rivers, location of fires, and villages and constructions (Fuller et al. 2010). In this study, the membership functions were selected in two forms (linear and J-shaped) due to the relation between each factor and the fire occurrence. That is, where the effect of factors on fire is centralized and decentralized in a region, the J-shaped and linear membership function has been used, respectively.

Table 5. Relative operating characteristic (ROC) value for factors and agents for ordered weighted averaging (OWA) scenarios

OWA operator	Risk map	ROC value
Average risk and full TRADEOFF	human factors	0.821
	climate factors	0.67
	environmental factors	0.638
	agents	0.794
Low risk and no TRADEOFF	human factors	0.795
	climate factors	0.706
	environmental factors	0.773
	agents	0.797
Low risk and a few TRADEOFF	human factors	0.85
	climate factors	0.731
	environmental factors	0.704
	agents	0.819
High risk and a few TRADEOFF	human factors	0.771
	climate factors	0.611
	environmental factors	0.622
	agents	0.719
Average risk and no TRADEOFF	human factors	0.87
	climate factors	0.621
	environmental factors	0.693
	agents	0.791
High risk and no TRADEOFF	human factors	0.681
	climate factors	0.644
	environmental factors	0.629
	agents	0.674

Both “low-risk and no TRADEOFF” and “low-risk and low TRADEOFF” scenarios show the best results with high ROC values, and the combination maps could be introduced as the best performance in mapping fire hazards. In this scenario, pixels with the lowest rank (i.e. value) are assigned as the highest weight. That is, pixels with a minimum role in the result of this model displayed the highest weight, leading to high accuracy of the final map. Moreover, the results showed the output maps with different class membership.

Indeed, a higher number of influential factors in some areas and the distance between the minimum and maximum pixels in the factors associated with the human agent would increase the value of membership class. However, there is no significant difference in the value of pixels in environmental and climate factors, and thus the classes are not important in these factors. Roads which are divided into smaller parts in natural areas can be used as firebreak to prevent the spread of fire (Eker, Oguz Coban 2010). Risk fire maps, therefore, can be used as a guide for creating firebreak during the preparation of new roads (Demir et al. 2009). Studies conducted in Southern California demonstrated that the road is an important factor and useful strategy to prevent or control fire in forests.

CONCLUSION

This article presents an applied research which was carried out using the multi-criteria evaluation method, when the human, climatic, and environmental factors were considered to determine the areas with potential fire hazard in the Golestan National Park. The results highlighted the importance of human factors in the occurrence of fires in the study area, among which the transit road that passes through the park has the most significant impact on wildfires in the region that greatly increase the importance of clearing the road from the park. Low risk and a few TRADEOFFS scenarios show, on average, the best performance among OWA

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scenarios, which indicates the importance of the interaction of all variables in the incidence of fires. According to the fire risk mapping and assessment review, the results demonstrated that the accuracy of each method, despite the practical and usable maps, could be used in fire crisis management. To determine the fire risk maps using human, climatic, and environmental factors, each map can be used in special cases. For example, prevention and management programs using warning tools could be considered in areas where human factors are more prominent than the other ones. Moreover, making natural cut fire and cultivation of fire-resistant species as well as preparing maps of wind patterns and high-temperature days could be useful strategies in forest fire management programs. A reasonable management approach to tackle this issue in the park could be suggested to design water tanks or to build helicopter pads in high fire risk areas to fight fire as quickly as possible.

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