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Research Article

Modeling and predicting forest fire susceptibility using machine learning methods in a semi-arid oak forest

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Abstract

Fire is one of the most pervasive factors destroying forest ecosystems, with ecological, economic, and social consequences. Therefore, analyzing changes in the situation of the region in terms of fire occurrence danger and also the parameters affecting it will be very useful in the field of fire risk management and control approaches. This is especially true in semi-arid oak forests. The current study was conducted in several stages. First, thirteen parameters, including topographical, climatic, biological, anthropogenic, and soil surface moisture as effective factors in forest fire risk, were assessed and modulated using machine learning methods. Raster-based maps for these criteria were generated using integrated geographic information systems (GIS) and remote sensing. Subsequently, fire risk maps were developed using historical fire occurrence data. Model's accuracy assessment revealed that the Random Forest (RF) model outperformed both Generalized Linear Models (GLM) and Support Vector Machine (SVM) models in fire risk detection. According to the RF model results, 33.95 and 18.84% of the studied areas were classified as low and high fire risk classes, respectively. The investigation of the factors affecting the occurrence of fire showed that anthropogenic factors (distance from residential areas, distance from agricultural lands), climatic factors (temperature, wind speed, relative humidity), and topographical factors (elevation) played a more important role in places with a history of fire. Therefore, to mitigate fire frequency and associated damages, it is essential to address the causes and motivations of fire ignition while minimizing fire-prone conditions through preventive measures

Keywords: Forest fire modeling, Random Forest, Support Vector Machine, Semi-arid oak forest

Introduction

Forests are among the main terrestrial ecosystems that sequester carbon dioxide (Sun & Liu, 2020; Mo et al., 2023), and are exposed to various types of disturbances such as fires, and storms (including windthrow), as well as disease, and insect outbreaks. Although these disturbances are part of the natural dynamics of the forest and play a vital role in succession processes, they may lead to a temporary reduction or elimination of the protective effects of the forest (Mackey et al., 2020). Additionally, they may impair forest ecosystem functions and services (Bullock & Woodcock, 2021; Bentsi-Enchill et al., 2021). Fire is often mentioned as a factor that destroys vegetation. This can have positive or negative effects on the components of forest ecosystems, depending on the type and intensity of the fire, the time of occurrence, and the type of vegetation (Chamandeh et al), 2017). Among the negative effects of fire on different forest characteristics are the reduction of vegetation cover, such as perennial grasses and broadleaves in the understory (Chamandeh et al., 2017), adverse effects on the soil seed bank and future vegetation composition (Heydari and Faramarzi, 2015), increased soil erosion (Girona-Garca et al., 2021), the loss of forest capital (Hemmatboland et al., 2010), and the reduction of soil fertility in the long term (Sadeghifar et al., 2016). In addition, the destruction of forest ecosystems by fire has many environmental and socio-economic effects and causes a perturbation in the ecological balance of these ecosystems (Amiri et al., 2017). On the other hand, recent droughts, lack of proper planning, lack of awareness, and the ineffectiveness of society in dealing with natural disturbances have caused the spread of fire occurrences, both in terms of burned surfaces and the number of times they occur (Aleemahmoodi Sarab et al., 2014). Also, fire increases soil temperature and damages the underground plant organs (Decastro et al., 1998). If fire is associated with the loss of organic matter, nitrogen, and sulfur after excessive grazing, it will be the most important factor in the destruction of natural ecosystems (Liedloff et al., 2001). In addition, fire, by burning the vegetation, causes a significant reduction in herbaceous, woody, and bushy plants and provides a favorable environment for the emergence and spread of invasive and poisonous plants (Wienk et al., 2004).

Forest protection management is based on ensuring the continuity of forest protection effects. This goal is to modify the stand capacity to remain in the event of disturbances (Ammann et al., 2009; Seidl et al., 2016). On the other hand, as climate change intensifies (i.e., warming air and decreasing rainfall) in areas such as the Middle East (Abedi et al., 2022; Zittis et al., 2022), the potential for fire occurrence (i.e., intensity and number of fire) in natural ecosystems will increase, especially in semi-arid oak forests. Natural disturbances such as fire are unpredictable and uncontrollable natural events that threaten people's lives and activities (Cencerrado et al., 2012). In this context, forest fire is one of the disturbances that causes a lot of damage/negative effects in the world every year (De Angeli et al., 2022; Kalogiannidiset al., 2023). This phenomenon has serious negative effects on the quality of forests and public safety (Brun et al., 2013). For instance, fire occurrence may accelerate deforestation and desertification due to the destruction of vegetation (Cochrane, 2003), increase carbon dioxide, which intensifies global warming (Singh, 2022), and reduce the delivery of forest services (Agbeshie et al., 2022; Moghli et al., 2022). Therefore, forest fire is considered one of the main natural disturbances (Adab et al., 2013), and it has attracted the attention of many researchers (Pham et al., 2020; Sivrikaya et al., 2022; Mirzaei et al., 2023; Noroozi et al., 2024).

Due to the location of Iran in the dry belt of the world and the high-pressure area of the subtropical region, the necessary weather conditions for the occurrence of fires in forest ecosystems are present (Ghanbari Motlagh et al., 2022; Foroutan & Islamzadeh, 2023). On the other hand, human factors, such as the carelessness of travelers or deliberate fires set to convert forest lands to agricultural use, have caused fires in the forest areas of Iran (Sarkargar Ardakani, 2007). The proximity of forest land to residential areas, and on the other hand, road development in forest ecosystems, also increases human access to the forest and the probability of fires (Giglo, 2010). In addition, drought periods, characterized by dry and hot winds during the day in dry continental areas, lead to an increase in heat and dryness, resulting in plant destruction (Jaafari et al., 2022). Indeed, these factors strengthen the atmospheric conditions for lightning storms, which are the source of many fires (Janbazghobadi, 2019).

Generally, research shows that descriptive-analytical research has been done less frequently or not at all in Iran. The summary of research done in other regions of the world indicates that vegetation type, slope angle and aspect, and distance from the residential areas, roads, agricultural lands, and forest edge are among the most effective factors in modeling fire occurrence (Jahdi and Arabic, 2020; Eskandari, 2017). On the other hand, Eskandari et al. (2020) emphasized the importance of climatic factors (i.e., average annual precipitation) in fire occurrences in the northeast of Iran. According to reports published by the FAO, every year about 0.06% of Iran's forests (14 million ha) are destroyed by fire annually (Ardakani et al., 2010; Motazeh et al., 2013). In addition, according to the Iranian Natural Resources and Watershed Management Organization, Iran's natural resources (rangeland and forest) cover about 61.82% of the country's area (Shariatnejad, 2008), and more than 90% of fires occur in these areas (Eskandari et al., 2020). In this regard, the most effective way to reduce the damage caused by forest fires is to quickly find the high-risk fire occurrence areas and respond comprehensively with all protective measures (Ali Mahmoudi, 2013). The Zagros Forest ecosystem in western Iran, with an area of 5 million hectares (Heidarlou et al.,2019; Mahdavi et al., 2019; Moradi & Shabanian, 2023), is one of the oldest forests in the world and plays an important role in the economic, social, and livelihoods of its inhabitants (Khosravi et al., 2016; Mahmoudi et al., 2023). The mountainous nature of this area, along with the rainfall suitable for rain-fed agriculture, has made these areas prime candidates for land use conversion and fire occurrence (Heidarlou et al., 2020). Also, the presence of damaged and destroyed grass cover, which is sensitive to the occurrence of fire, has greatly increased fire occurrence during the hot season (i.e., summer).

Modeling and preparing forest fire risk maps will be greatly helpful in controlling and preventing fire, aiding proper management of these areas. The results of such research provide appropriate information for more efficient management and allocation of personnel and facilities during the fire season in high-risk areas. additionally, by identifying high-risk areas and implementing parallel measures, executive and educational activities can help reduce fire risk. these include creating fire breaks, raising awareness among local people, training them in fire extinguishing, as well as determining immediate access routes to fire sites for effective fire response. Various factors contribute to these fires, and if they are identified and controlled, the fire risk in these forests can be significantly managed. Therefore, this research aims to assess fire occurrence potential in different areas in Malekshahi County and identify the most important contributing factors. Furthermore, the capability of different machine learning methods will be evaluated.

Wildfire hazard in Ilam Province, Malekshahi County, is assessed and managed using fire modeling due to the susceptibility of the area to fire caused by high vegetation cover, extended drought periods, and climatic factors that are suitable for fire transmission (Yaghobi et al., 2019; Azizi et al., 2025). Hence, the incorporation of advanced models of fire behavior prediction allows for mapping of hazard zones, thus identifying areas for mitigation measures such as fuel load reduction, controlled burning, and firebreak construction. Since the Malekshahi county relies on agro-pastoral activities and is characterized by high biodiversity, integrating geospatial fire modeling into land-use planning is critical for sustainable land use and climate change adaptation to increasing wildfire risk.

Martial and methods

Study area

Malekshahi County, with an area of 160030.35 h, is located in Ilam province, where more than 95% of its surface is covered by forest and rangeland (Omidipour et al., 2013). It lies within the geographical coordinates of 46º 16′ to 46º 52′ east longitude and 32º 5′ to 33º 30′ north latitude (Figure 1). The Malekshahi forest ecosystem is part of the dry and semi-dry forests of Zagros

Mountain (Azizi et al., 2025). These forests have been shaped by climatic factors, uneven topography, unique geology, and - most significantly - human interference and overexploitation, resulting in a distinctive vegetation composition. The dominant cover is the oak species (*Quercus brantii* Lindl.), which comprises approximately 90% of the forest cover, while wild pistachio (*Pistacia atlantica*) accounts for about 6%. Other woody plants in the area include *Amygdalus orientalis*, *Am*. *elaeagnifolia*, *Celtis australis*, *Acer monspessulanum*, and *Crataegus pontica*.

The oak forest community in this region grows at elevations between 450 and, 2600 meters above sea level. At low elevation, forest distribution is limited by agricultural expansion and human exploitation pressures. At high elevation, climatic constraints and fuelwood by nomadic communities restrict the forests primarily to elevations between of 900–2100 meters. Forest cover density typically ranges from 5-25%, though in some areas (such as the Bivareh region), it exceeds 50%

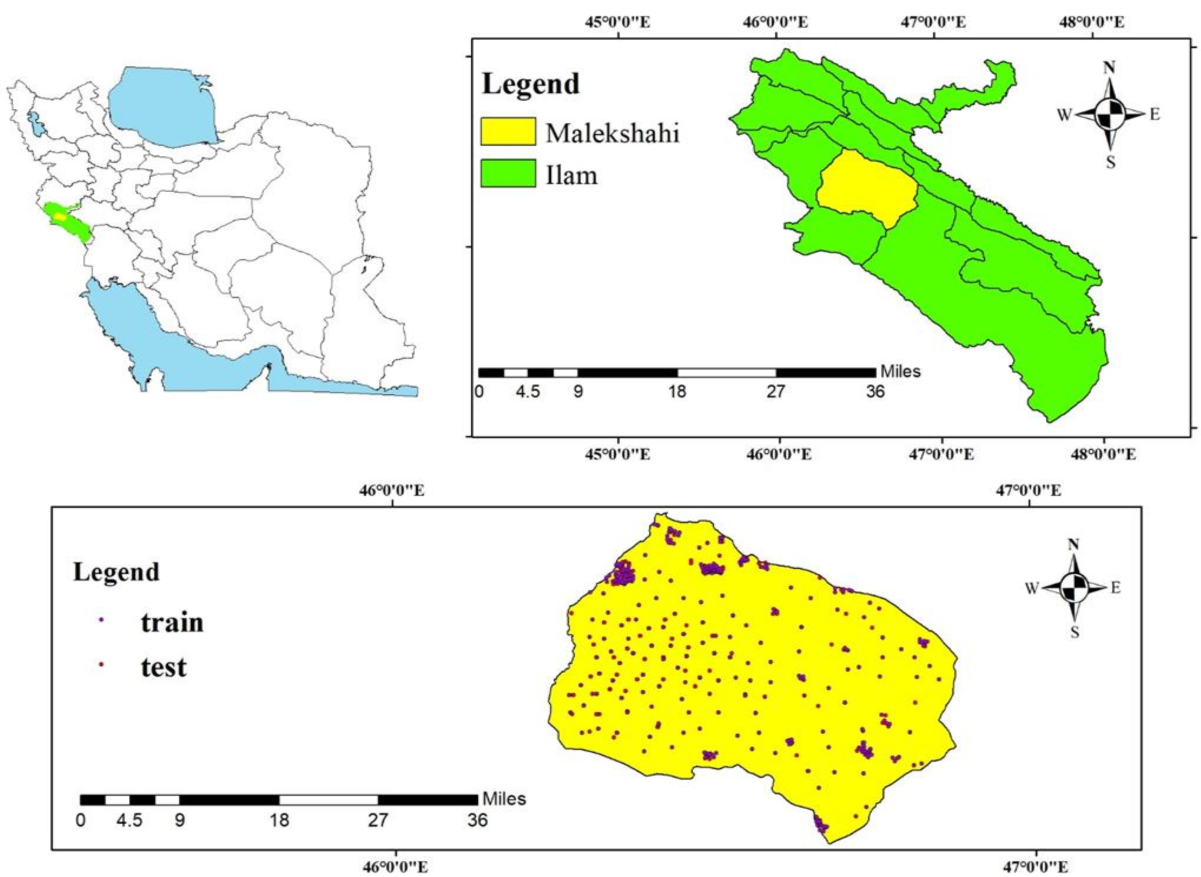

Figure 1. Geographical location of Malekshahi county in Ilam province, western Iran

This study flowchart is categorized into 5 important steps: (1) determining and mapping the effective factors in fire occurrence risk, (2) preparing the fire occurrence history and mapping the fire occurrence map, (3) identifying the importance of factors affecting fire occurrence risk, (4) integrating the effective factors and mapping of fire occurrence risk, and (5) validation of the accuracy of different algorithms used in modeling fire occurrence risk maps.

Factors affecting fire occurrence

To prepare the fire risk zoning map, the factors influencing the fire occurrence in the region were first identified (Figure 2). As fire occurrence may result from natural or human-caused activities, the factors affecting each are different (Eskandari et al., 2020). However, considering human activities as the main reason for fires in western Iran's forests (accounting for more than 90% of occurred fires) (Eskandari et al., 2020), the following four categories were selected. (1) topographical parameters, including elevation, slope, and slope aspect; (2) biological parameters including the normalized difference vegetation index (NDVI) and soil moisture (the normalized difference water index (NDWI) and the land surface water index (LSWI)); (3) climatic parameters, including temperature, precipitation, relative humidity, wind speed and wind direction; and (4) human-based parameters, including distance from roads, distance from agricultural lands, distance from forest areas and distance from residential areas.

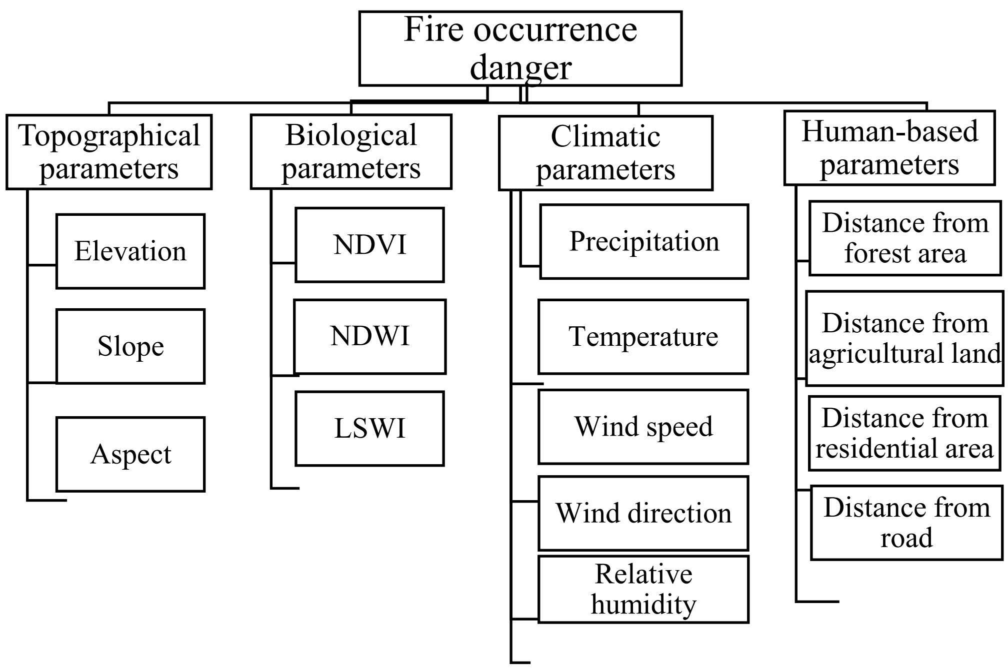

Figure 2. Hierarchical structure for forest fire occurrence danger

Topographical variables

Topographical variables (elevation, slope, and aspect) were extracted from a Digital Elevation Map (DEM) obtained from the ASTER Global DEM (30 m spatial resolution) via EarthExplorer (USGS) (https://earthexplorer.usgs.gov) (Fig. 3).

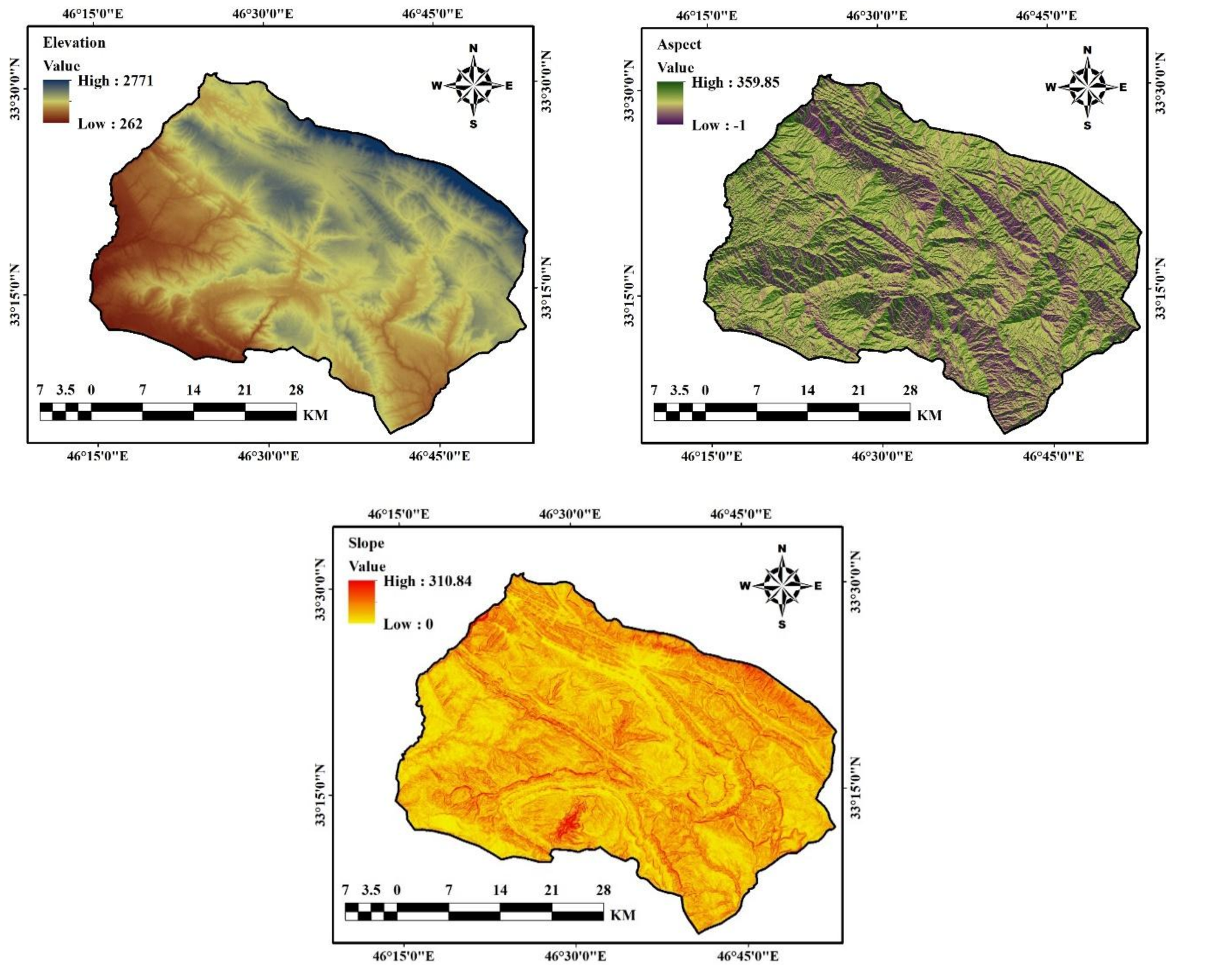

Figure 3. Map of topography parameters including elevation, slope direction, and slope respectively

Biological variables

Biological variables included NDVI and soil moisture indices (NDWI and LSWI). NDVI values are directly related to vegetation cover/density, which is potentially correlated with fire risk(Digavinti & Manikiam, 2021). Thus, incorporating NDVI data could improve fire risk predictability (Michael et al., 2021). On the other hand, soil moisture exhibited a negative relationship with fire occurrence potential (Sazib et al., 2021; Krueger et al., 2022). In this study, NDVI, NDWI, and LSWI maps were derived from Operational Land Imager (OLI) Landsat imagery (acquired on: 12 May 2023; land cloud cover=0.11%) (Fig. 4) using the following equations (1-3):

Eq. (1): NDVI = (NIR-RED)/(NIR+RED)

Eq. (2): NDWI = (NIR-SWIR2)/(NIR+SWIR2)

Eq. (3): LSWI = (NIR-SWIR1)/(NIR+SWIR1)

Where NIR is the near infrared band, RED is the red band, and SWIR1-2 are the shortwave infrared1-2 bands.

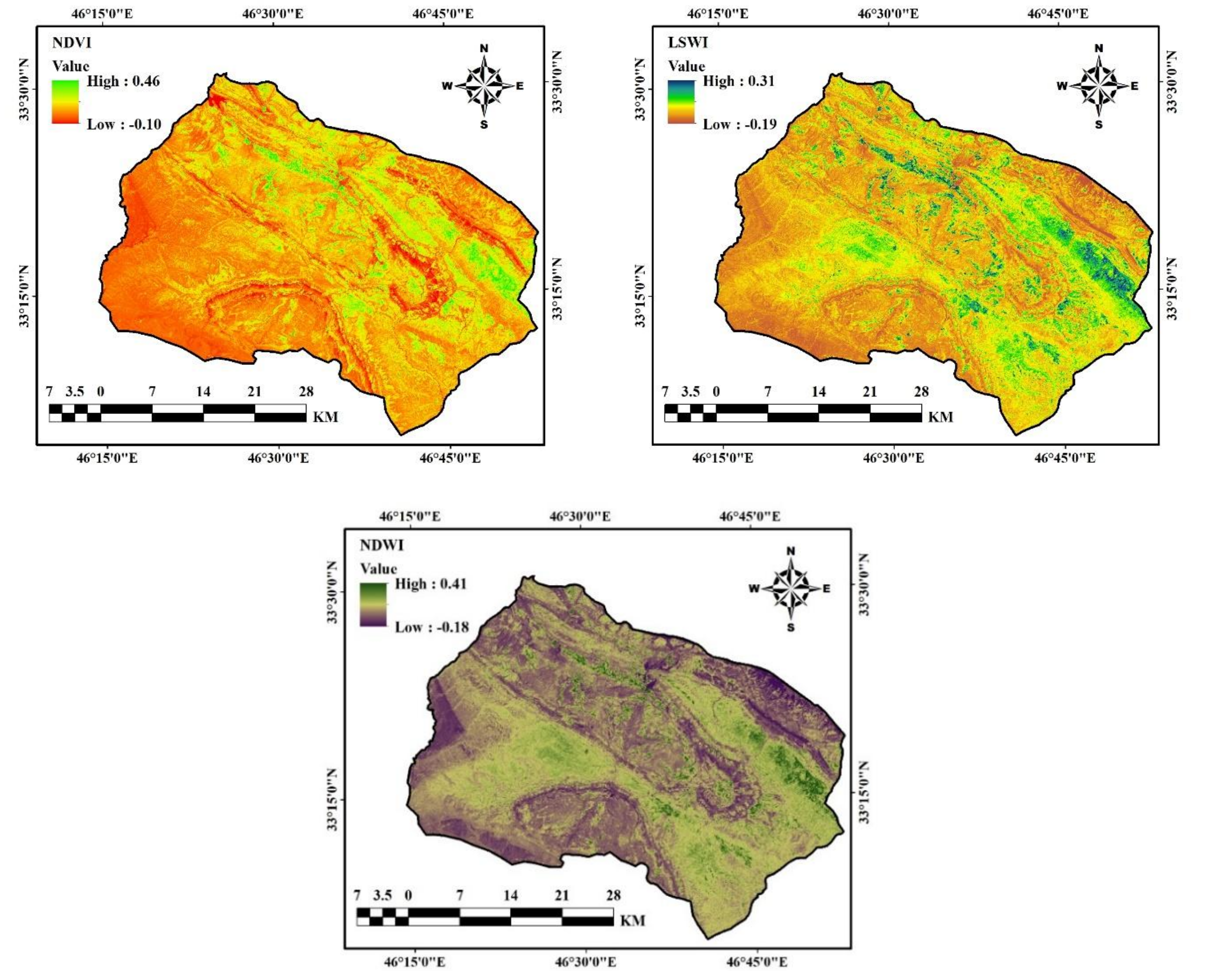

Figure 4. Map of biological parameters according to NDVI and soil moisture (including LSWI and NDWI)

Climatic parameters

To assess the effects of climatic parameters on fire risk, five key climatic variables (temperature, precipitation, relative humidity, wind speed, and wind direction) were considered as the most effective climatic variables affecting fire susceptibility. These parameters were produced by interpolation of climatic data from seven local synoptic meteorological stations (Table 1) in Ilam Province (Fig. 5). Considering the existence of extreme (rough) topography in our studied area (Henareh Khalyani et al., 2012; Safari et al., 2022), large-scale satellite-derived climatic datasets (e.g., NASA Earth Observatory) were deemed unsuitable due to their low accuracy and limited spatial differentiation. Therefore, the climatic data (2000-2023) was obtained from the National Meteorological Organization of Iran. As recommended in previous studies (Raziei & Pereira, 2013; Ibrahim & Nasser, 2017), the inverse distance weighting (IDW) interpolation method was employed due to the limited number of stations. IDW interpolation method assigns weight to each measurement based on its distance from the unknown (predicted) location (Singh & Verma, 2019). Then these weights are adjusted by a predefined weighing power.

Table 1. The location and some characteristics of the used weather stations

Station name	Longitude	latitude	Elevation (m)	Mean annual rainfall (mm)
Ilam	E" 824'24°46	N" 383'37°33	1364	572.4
Ivan	E" 43'18°46	N" 14'49°33	1184	679.4
Sarablah	E" 809'33°46	N" 190'46°33	1028	550
Dehloran	E" 873'16°47	N" 880'40°32	211	284.8
Darehshahr	E" 283'23°47	N" 022'09°33	645	290
Abdadanan	E" 354'25°47	N" 870'59°32	928	507
Mehran	E" 525'10°46	N" 110'06°33	155	295

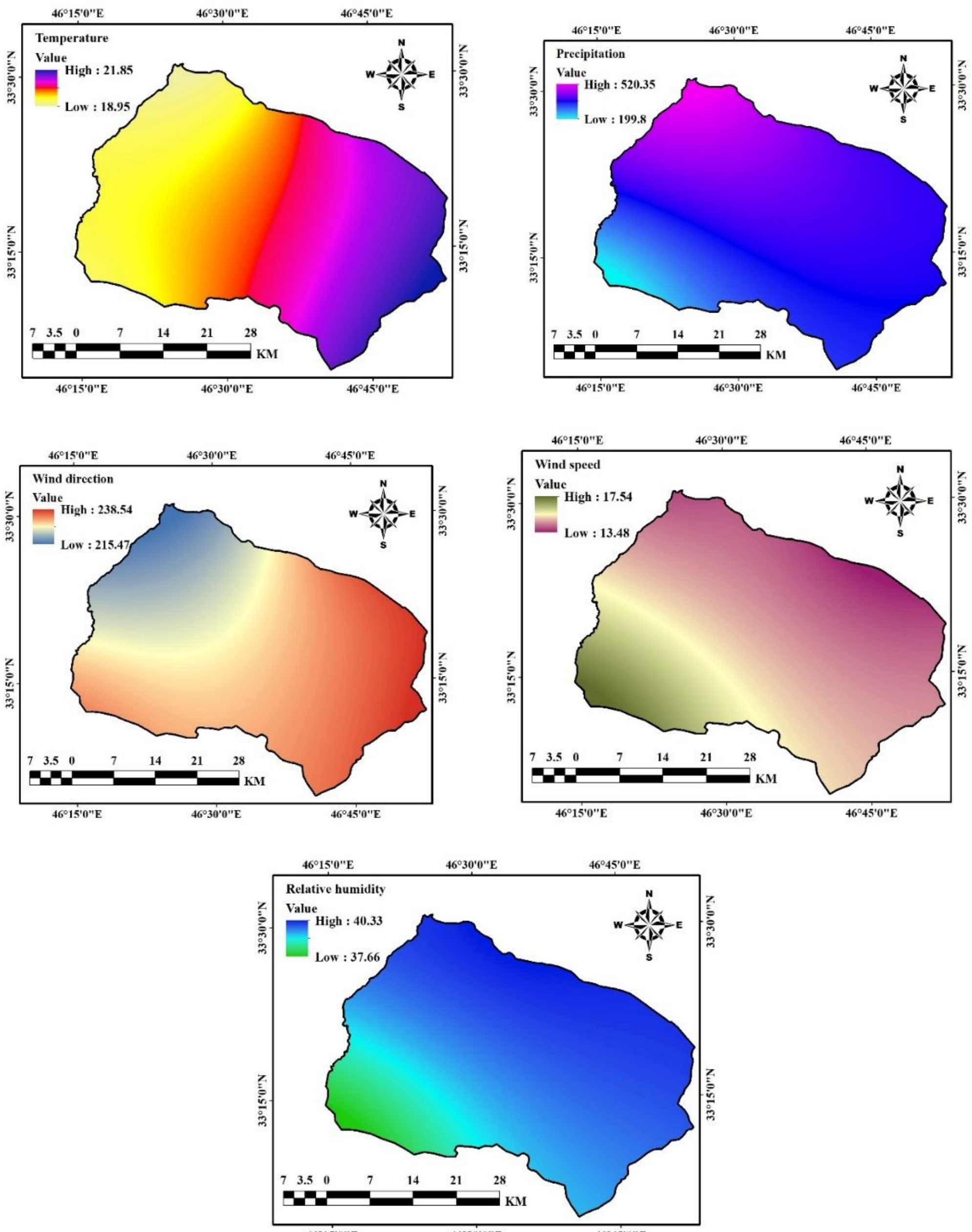

Figure 5. Map of climatic parameters (ordered as): temperature, precipitation, wind speed, wind direction, relative humidity

Anthropogenic parameters

Finally, the human-related parameters were generated using Euclidean distance analysis in ArcGIS version 10.8 software (https://www.esri.com/en-us/home), based on Shapefile layers of each feature. In this research, initial maps of agricultural land, forest area, and residential areas were extracted from a land use classification map produced from an OLI Landsat image (acquired on 12 May 2023; land cloud cover =0.11%) using a maximum likelihood algorithm in TerrSet var. 19 (overall accuracy =0.89 and Kappa coefficient =0.84). additionally, the road network map was extracted from 1:25,000-scale topographic maps (Fig.6).

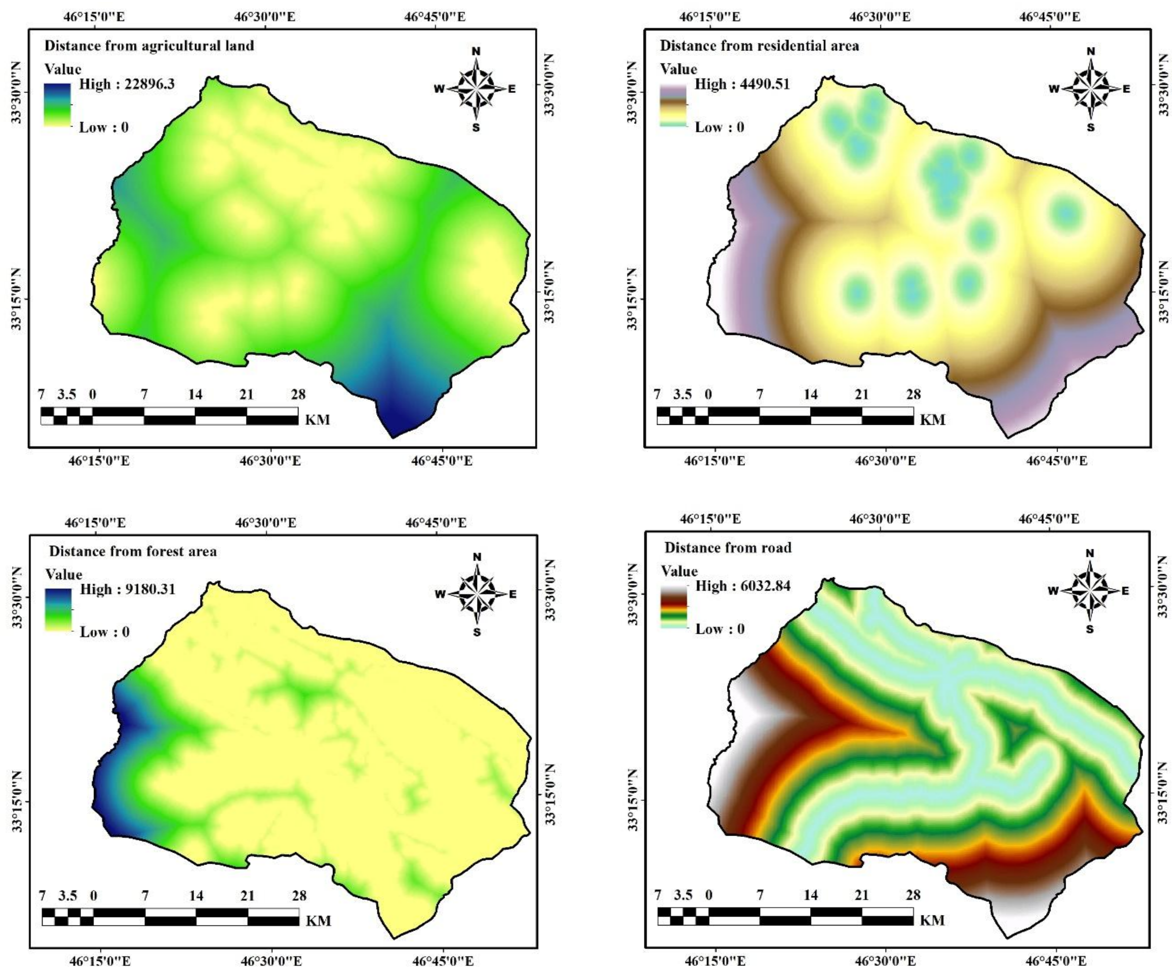

Figure 6. Map of human parameters (Ordered as): distance from agricultural lands, distance from residential areas, distance from forest, and distance from roads

Constructing the fire occurrence map

An accurate fire risk map requires reliable fire occurrence data (Dickson et al., 2006; Chang et al., 2013; Eskandari et al., 2020). In the current research, we utilized fire events data recorded by the Natural Resources and Watershed Management Administration of Ilam province, supplemented with MODIS fire products (2000-2022) obtained from NASA (https://modis.gsfc.nasa.gov/data). MODIS data (i.e., fire products), have been widely used in fire risk mapping studies (Hawbaker et al., 2008; Ardakani et al., 2010; Chen et al., 2017; Albar et al., 2018; Parajuli et al., 2020; Bolaño-Díaz et al., 2022). Then, all fire location data was integrated in a GIS environment (using the Merge function) to produce a comprehensive fire occurrence map for Malekshahi County. In total, 330 fires occurred in the study area from 2000 to 2022. After conversion of the fire point to a 30×30 m raster grid, fire pixels were randomly divided into two groups of training (70%, 231 points) and validation (30%, 99 points) of the fire danger models development and evaluation (Fig. 1).

Relative importance of the effective factors for fire occurrence danger

The relative importance of predictor variables for fire risk mapping was assessed using the Random-Forest (RF) algorithm (Grömping, 2009; Gregorutti et al., 2017). Variable importance was computed and visualized through the varImpPlot function in the "randomForest" package in R software. In addition, to exclude variables with high collinearity, a multicollinearity test was performed using two parameters: tolerance (T) less than 0.01 and a variance inflation factor (VIF) less than 5 (Dormann et al., 2013; Kim, 2019). Subsequently, we used a stepwise procedure to obtain the best collection of effective variables. specifically, after each model run, a variable with the highest VIF (<5) was removed, and the multicollinearity test was run again. This procedure continued until all variables showed no collinearity.

Integration of the effective factors and mapping of the fire occurrence danger

In this research, we employed three widely-used machine-learning algorithms to model fire risk potential, including RF, SVM, and GLM, in R software and "randomForest" and "e1071" packages. Each algorithm generated a continuous fire risk prediction, which we subsequently classified into four danger levels: low, moderate, high, and very high. Finally, these fire danger maps with continuous values were imported into ArcGIS. Then, we used the equal intervals to classify the fire danger maps into four risk classes, including low, moderate, high, and very high danger classes (0-25%, 25-50%, 50-75%, and 75-100 %, respectively).

Random forest (RF)

The Random Forest (RF) algorithm is a versatile non-parametric machine-learning technique known for its simplicity and flexibility (Cheng et al., 2022; Souaissi et al., 2023). This algorithm builds multiple decision trees using random subsets of feature observations and combines the trees in the forest, increasing the prediction accuracy (Oliveira et al., 2012; Collins et al., 2018). The RF advantage is its dual capability to perform both classification and regression processes (Svetnik et al., 2003; Lagomarsino et al., 2017). The RF algorithm was performed using the "randomForest" package (RColorBrewer & Liaw, 2018) in R software for model development.

Support Vector Machine (SVM)

The Support Vector Machine (SVM) algorithm is a powerful supervised learning method that creates optimal non-linear decision boundaries to separate data into predefined classes (Nie et al., 2020; Singh et al., 2021). In this procedure, the optimum separation criterion minimizes misclassifications during the training phase (Mountrakis et al., 2011). The primary advantage of the SVM model is its ability to handle non-linear classification problems even with prior knowledge of the modeling conditions (Ghorbanzadeh et al., 2019). For this study, fire risk modeling using SVM was performed with the "e1071" package (Dimitriadou et al., 2009) in R software.

Generalized linear model (GLM)

The Generalized linear model (GLM) algorithm is a flexible extension of a linear-based regression model developed to handle non-normal error distributions (Park et al., 2018). This model generalizes ordinary linear regressions, which allow error distributions rather than normal distributions for output variables (Zuur et al., 2009; Warton et al., 2016). The GLM models the relationships between a dependent (response) variable and independent (predictor) variables (Ozdemir & Altural, 2013).

Accuracy assessment

Fire risk maps derived from data-mining models were validated by 30% of historical fire data (validation set), which was not considered in the training. The first method used in this research was the area under the curve (AUC) values extracted from the receiver operating characteristic (ROC) curve. This index ranges from 0 to 1 in which the value of 1 indicates perfect classification (Gonçalves et al., 2014). Also, cross-validation was performed based on some of the most important mutual evaluation statistics, including correlation coefficient (r), explanation coefficient (R2), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE) were used to compare the two investigated models.

Results

Relative importance of variables affecting the fire occurrence danger

Multi-collinearity tests for effective factors indicate that there was collinearity among input variables (Table 2). Based on the results, three layers, including LSWI (VIF= 14.74, Tolerance=0.068); mean annual precipitation (MAP) (VIF= 10.55, Tolerance= 0.095), and distance from forest area (ForestDis) (VIF= 6.987, Tolerance= 0.143) had the highest collinearity and were excluded from the final modeling.

Table 2. Multicollinearity test for effective factors on fire occurrence danger

Variables	Unstandardized coefficients		Standardized coefficients	t-value	*P*-value	Collinearity statistics	
	B	Std. Error	Beta			Tolerance	VIF
Aspect	0.007	0.062	0.004	0.107	0.915	0.942	1.062
Elevation	0.578	0.126	0.224	4.585	< 0.001	0.439	2.278
Slope	1.859	0.310	0.211	5.997	< 0.001	0.844	1.185
NDVI	-1.039	0.543	-0.179	-1.911	0.057	0.896	1.116
NDWI	-1.923	0.257	-0.331	-7.484	< 0.001	0.537	1.861
WindSP	1.304	0.159	0.444	8.212	< 0.001	0.359	2.786
WindDI	1.253	0.289	0.143	4.335	< 0.001	0.766	1.306
MAT	-1.319	0.137	-0.506	-9.665	< 0.001	0.382	2.618
Humidity	-0.693	2.274	-0.249	-4.305	< 0.001	0.237	4.222
ResidDis	-0.00013	0.000	-0.017	-.518	0.605	0.921	1.086
RoadDis	0.062	0.095	0.028	0.645	0.519	0.548	1.824
AgriDis	2.878	0.340	0.458	8.470	< 0.001	0.359	2.785

The results showed that climatic variables (temperature (MAT), wind speed (WindSP) and direction (WindDI), relative humidity), man-made factors (distance from agricultural lands, distance from residential areas), and environmental factors (elevation) were the most important factors affecting the occurrence of fire (Fig. 7). In contrast, soil surface moisture (NDWI), distance from the forest areas, slope, and slope aspect were the least effective factors.

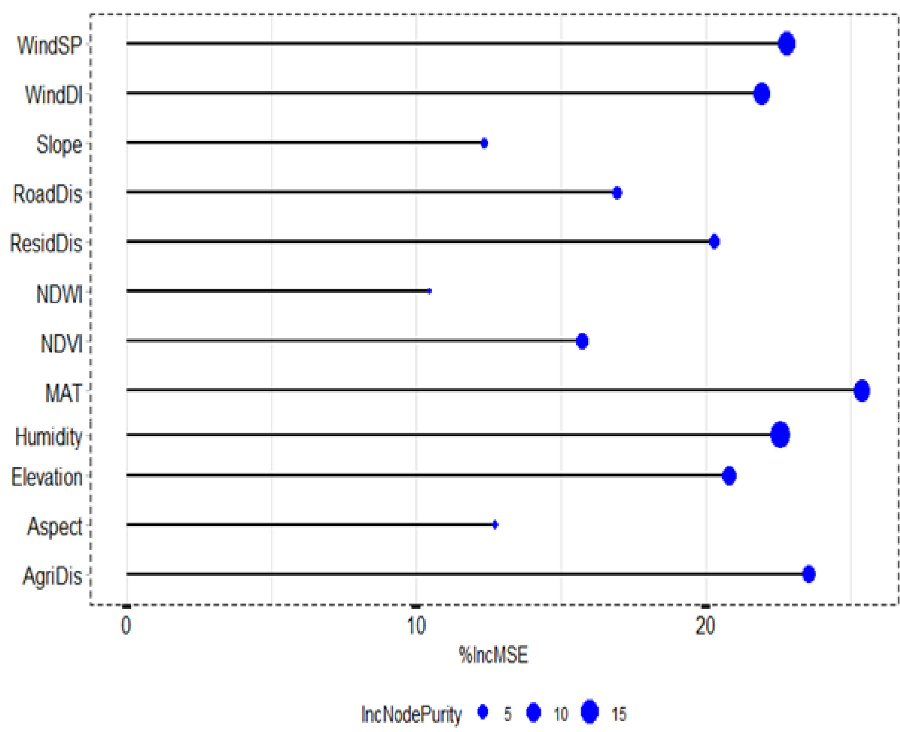

Figure 7. The most important factors affecting fire occurrence risk based on the random forest model

After preparing a map of environmental factors using extracted information for 70% of the fire points, modeling was performed using three models: RF, GLM, and SVM. Based on the results of all models, the northern and southeastern regions had the highest potential for fire occurrence, while the central and western regions had the lowest potential for fire occurrence (Figure 8).

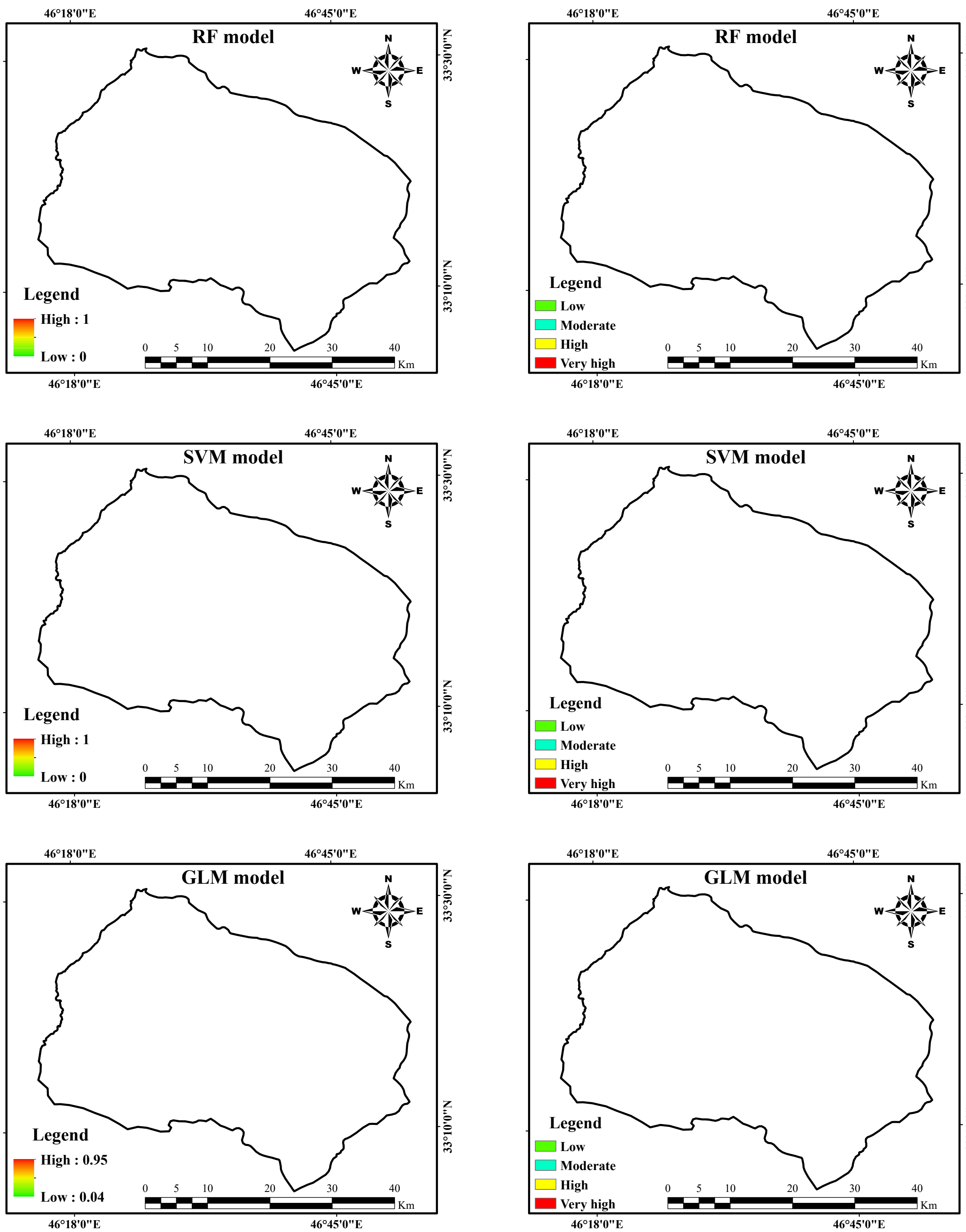

Figure 8. Fire risk potential map derived from the GLM, SVM, and RF models

Analysis of fire potential areas showed that across all three models, the smallest area corresponded to the very high potential class. According to the results of the RF model, the class of low fire susceptibility had the largest area (33.95%), while in the GLM and SVM models, moderate fire susceptibility areas were most extensive (39.22% and 33.06 %, respectively) (Table 3).

Table 3. Area of fire susceptibility classes based on the GLM, RF, and SVM models

Fire class	SVM		GLM		RF	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
1	42994.02	24.72	30372.15	17.46	59042.87	33.95
2	57502.34	33.06	68221.69	39.22	42969.89	24.71
3	52526.8	30.20	53882.3	30.98	40351.39	23.20
4	20907.75	12.02	21454.78	12.34	32773.44	18.84

Models' accuracy assessment

The accuracy assessment of the models, evaluated using 30% of fire data (99 fire points and 101 fire points) showed that all three models achieved very high accuracy (Figure 9 and Table 4). Based on the obtained results, the RF model had the highest performance with an area under the curve (AUC) of 0.994, followed by the GLM (AUC = 0.983) and SVM (AUC = 0.971) models.

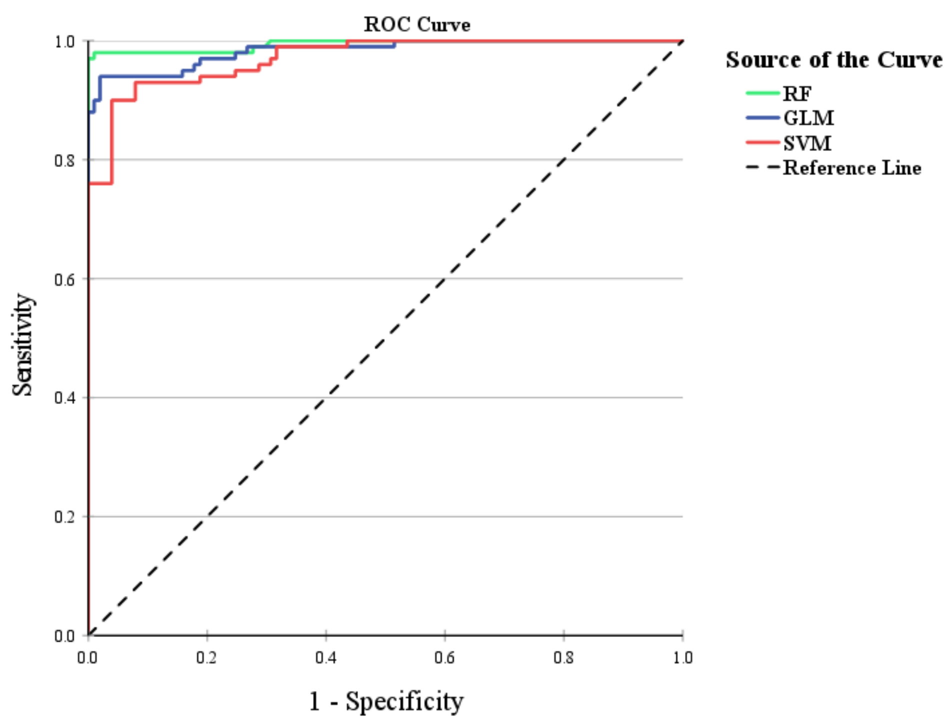

Figure 9. The AUC value for validation of the models used for the fire susceptibility map.

Table 4. Validation of fire accuracy maps produced using the studied models based on AUC

Models	Area under the curve	Std. Error	P-value	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
RF	.994	.004	< 0.001	.986	1.000
GLM	.983	.007	< 0.001	.969	.998
SVM	.971	.010	< 0.001	.952	.990

Cross-validation

The comparative evaluation of the studied models showed that the highest determination coefficient was related to the RF model (R^2= 0.877), followed by SVM (R^2= 0.733) (Table 5). In addition, based on the RMSE and MAE statistics, the RF (RMSE= 0.308; MAE= 0.239) and SVM (RMSE= 0.260; MAE= 0.171) models had the highest accuracy, and the lowest accuracy was related to the GLM model (Table 5).

Table 5. The Cross-validation accuracy of fire susceptibility maps. r: correlation coefficient; R^2: explanation coefficient: RMSE: Root Mean Squared; MAE: Mean Absolute Error

Statistics	GLM	SVM	RF
r	0.79	0.86	0.94
R^2	0.625	0.733	0.877
RMSE	0.177	0.260	0.308
MAE	0.110	0.171	0.239

Mapping the sensitive areas to fire based on three models

Examining the accuracy of the three investigated models based on fire points showed that the RF model correctly classified 82% of the fire points in the class of highly sensitive areas. The GLM and SVM models classified 72% and 53% of fire points in areas with high sensitivity to fire (Table 6). Also, the evaluation of the accuracy of the investigated models based on the points without a history of fire showed that the RF model placed 92% of the points without a history of fire (control points) in the class of low fire susceptibility. The GLM and SVM models placed 87% and 57% of the points with no history of fire in areas with low susceptibility to fire (Table 6).

Table 6. Evaluation of the accuracy of the investigated models based on points with a history of fire occurrence and control

Test data category	Fire class	SVM		GLM		RF	
		N.	%	N.	%	N.	%
Fire Point	1	2	2.02	1	1.01	1	1.01
	2	7	7.07	7	7.07	4	4.04
	3	38	38.38	20	20.20	13	13.13
	4	52	52.53	71	71.72	81	81.82
Non-Fire Point (Control)	1	56	56.57	86	86.87	91	91.92
	2	45	45.45	14	14.14	10	10.10
	3	0	0.00	1	1.01	0	0.00
	4	0	0.00	0	0.00	0	0.00

Discussion

Forests are among the most important components of terrestrial ecosystems (covering 31% of the total land area), known as the largest carbon pool (Zhao et al., 2019; Sun & Liu, 2020). It's estimated that over 86% of the global vegetation carbon storage and over 73% of the global soil carbon pool are deposited in forest ecosystems (Sun & Liu, 2020). Consequently, any destruction of forest ecosystems will intensify climate change and global warming. Fire is one of the most significant natural/human-based factors that impacts Earth's forests (Clarke et al., 2022). The semi-arid oak forest in Western Iran is one of the most essential ecosystems affected by annual fire (Ardakani et al., 2010; Motazeh et al., 2013). On the other hand, the widespread destruction of forest ecosystems in western Iran, there is a pressing need to develop and analyze the quantitative and spatial relationships between fire-promoting factors and fire occurrence danger (Eskandari et al., 2022). Therefore, this study tries to assess the contribution of different factors affecting fire occurrence danger and predict the areas with high fire occurrence danger in the semi-arid oak Zagros Forest in Western Iran.

According to the evaluation of the accuracy of the models, although all the models had high accuracy, the RF model indicates higher accuracy than the other models (GLM and SVM). This result is consistent with the findings from previous studies(Eskandari et al., 2020; Milanović et al., 2021; Gao et al., 2024; Noroozi et al., 2024). Based on the results, the RF model identified 18.84%, of the area as high fire risk, compared to SVM and GLM models' estimates of 12.34% and 12.02%, respectively. Therefore, it can be concluded that both models, support vector machine and GLM, underestimate high fire risk areas.

The results indicate that climatic factors were the main effective factors in fire risk. The climatic parameters used in forming the final model demonstrated sufficient capability to predict the risk of this phenomenon. This is in line with the results of Maeda et al. (2009) and Cortez and Morais (2007), who reported that climatic parameters such as temperature and relative humidity significantly influence the occurrence of fire. In detail, our results indicate that temperature, wind speed and direction, and relative humidity were the main climatic factors that caused forest fires in the semi-arid oak Zagros Forest in Western Iran. Generally, an increase in temperature leads to the drying out of fuel and a decrease in relative humidity (Hong et al., 2017; Clarke et al., 2022), increasing fire risk. Zumbrunnen et al. (2011) concluded that temperature is the most important climatic factor influencing the fire regime in forest ecosystems, with higher fire frequency. Clarke et al. (2022) argued that an increase in temperature allows fire to spread into rainforests and other fire-sensitive forest communities. In addition, the wind speed intensifies fire spread and severity (Flannigan et al., 2013). On the other hand, increased wind speed contributes to the drying of live and dead fuels and decreases the relative humidity (Keeley & Syphard, 2019). In this regard, Wu et al. (2018) reported that fire spread increases with decreasing relative humidity and increasing wind speed. Therefore, we conclude that a mixture of climatic factors, including higher temperature and wind speed combined with lower relative humidity, drives forest fire in the semi-arid oak Zagros Forest.

After climatic factors, man-made factors- particularly proximity to agricultural lands and distance from residential areas- played a vital role in the occurrence of fire. Generally, human activities have already been reported as an important cause of fires in natural areas such as forest ecosystems (Zumbrunnen et al., 2012; Eskandari & Chuvieco, 2015; Bowman et al., 2018; Eskandari et al., 2022), and proximity to residential areas is a significant factor on fire ignition (Romero-Calcerrada et al., 2008; Syphard et al., 2008; Syphard & Keeley, 2015; Elia et al., 2020; Eskandari et al., 2022; Barati Jozan et al., 2024; Noroozi et al., 2024; Wang et al., 2024). In our study area, distance from agricultural areas was the main man-made factor that has played a vital role in the occurrence of fires in the forests of our studied region. These results were in line with the fact that human-made fires are used as a tool to clean forest areas and the development of agricultural lands (Jahdi et al., 2020). The results of other studies have also shown that in the case of small agricultural lands, fire may be used to develop agricultural land, clear previous crops, or burn agricultural residues (Stolle et al., 2003). In this regard, Eskandari et al. (2022) reported that fires occurred primarily along roads, near residential areas, and within agricultural lands in Central Koohdasht, Lorestan Province, Western Iran. Additionally, the use of forest areas as tourist camps by the people of these areas, being close to residential areas will increase the potential for fire occurrence danger. Finally, for many ranchers, fire is an essential tool to convert shrubland (dominated by species such as Astragalus) and forests into pastures dominated by herbaceous plants. This action will increase the quantity and quality of forage used by livestock in the short term (Dufek et al., 2014; Thapa et al., 2022; Wanchuk et al., 2024). Based on the results, the northern and southeastern areas had a higher potential for fire occurrence, while the central and western regions had a lower potential for fire occurrence. This occurrence potential had a high overlap with the elevation and vegetation map (NDVI). In other words, in higher-elevation areas with dense vegetation, the potential for fire occurrence was increased (Argañaraz et al., 2020). In line with this result, many studies have reported a positive relationship between increased elevation and fire occurrence potential (Hawbaker et al., 2013; Schwartz et al., 2015; Estes et al., 2017; D'Este et al., 2020). Generally, as altitude increases, access to burned areas for fire management and control decreases, explaining why mountainous areas have a higher likelihood of large fires than plains (Laschi et al., 2019). Our results also indicate that the northern regions had the highest distance from the road. On the other hand, greater vegetation cover/biomass has a direct relationship with the increase in fire occurrence potential (Novo et al., 2020; Abatzoglou et al., 2021; Abdollahi & Yebra, 2023). Therefore, high-risk areas in this study are characterized by dense vegetation cover, high elevation, and poor road access. Subsequently, an expanding road network could reduce fire risk in these areas.

Conclusion

The increase in industrial activities, along with the expanding human impact, has intensified the rise in carbon dioxide emissions and accelerated global warming. Forest ecosystems, as one of the most important carbon sinks, play a vital role in mitigating these effects. meanwhile, fire remains one of the most significant threats to natural ecosystems like semi-arid forests. Therefore, investigating and modeling the influence of various environmental factors on fire occurrence is of great importance. In this study, we examined the contribution of multiple environmental factors to fire occurrence and modeled fire-prone areas in the semi-arid oak Zagros Forest in Western Iran. Our results indicate that various machine learning methods achieved high accuracy in modeling fire-prone areas, with the random forest model showing the best performance among the methods evaluated. According to the results, human-made factors and climatic factors contributed most significantly to fire occurrence in the studied area. Given the impossibility of controlling climatic factors, focusing on human factors through public education, along with promoting eco-friendly practices, could substantially reduce fire risk.

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