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# Machine Learning-based Forest Fire Susceptibility Prediction in Semiarid Oak Forests of Western Iran

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**ABSTRACT**

**Aims:** Fire is one of the most important causes of forest degradation, especially in semiarid forest ecosystems. The increase in annual fire occurrence and the complexity of environmental factors affecting fire occurrence in the Zagros vegetation zone have increased the importance of modeling factors affecting fire occurrence in this region. Therefore, forecasting fire-prone areas and practical factors can help forest managers to prevent destructive fires. This study aims to modulate the fire-sensitive areas using machine learning methods, including support vector machine (SVM), random forest (RF), and generalized linear model (GLM).
**Materials & Methods:** Fire-effective factors were categorized into four classes (physiographic, biological, climatic, and anthropogenic factors) and 16 raster-based variables. The fire susceptibility maps were validated using the area under the curve (AUC) values extracted from the receiver operating characteristics (ROC) curve. In addition, the RF model was used to determine the relative importance of each variable.
**Findings:** Results showed that fires happened in the middle elevation (300-2000m), lower slopes (<20%), and in the west and southwest slope aspects. More fires were also in agricultural and residential areas. The validation of fire susceptibility maps showed that the RF model (AUC=0.911) has higher accuracy than the SVM (AUC=0.864) and GLM models (AUC=0.824). Based on the RF model, high and very high-risk had low areas (9.48 and 5.97%, respectively). The most effective factors on fire occurrence were anthropogenic (distance from residential, distance from agricultural lands, and distance from roads) and climatic factors (relative air humidity, wind speed, and slope aspect), and the least important factors were distance from rivers and slope aspect.
**Conclusion:** Given the role of anthropogenic factors in the occurrence of fires, it is suggested that nature-based education be increased and people's dependence on these forest ecosystems be reduced. Given the lack of sufficient information on fires and the importance of research on forest fires, it is recommended that a database of past and ongoing fires in the forests of the study area using remote sensing and geographic information systems and a history of fires in these areas be prepared to evaluate fire occurrence models in future research.

**Keywords:** Generalized Linear Model; MODIS Fire Product; Random Forest; Support Vector Machine; Zagros.

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## Introduction

Fire is one of the significant disturbances in natural terrestrial ecosystems and may increase in future years due to global warming, especially in the Middle East [1]. Fire, known as a common disturbance, occurs frequently in the semiarid oak forest of west Iran [2, 3, 4]. Awareness of the areas at risk of fire and the factors influencing them is vital in adequately managing fire risk and ecosystem management.

Fire occurrence could destroy plant and animal communities' diversity, composition, and functioning, influencing soil properties and economic, social, and security issues [5]. In addition, fires could disturb forest ecosystems, which are the largest carbon pool and have a vital role in the global carbon cycle of terrestrial ecosystems [6], accelerating global warming and increasing the potential for fires. Therefore, modeling and determining fire sensitive areas is essential in forest ecosystems.

Fire can affect forest structure [7] and soil properties [8, 9, 2]. The occurrence and distribution of fire are controlled/determined by the joint combination of ignition agents, climatic factors, vegetation characteristics, and topographical and anthropogenic factors. [10, 11, 12, 13]. Climatic factors (such as precipitation, temperature, and wind) have a strong relationship with the occurrence and intensity of forest fires [14, 15, 16]. In arid and semiarid areas, the lack of moisture dries out vegetation and the soil and increases the fire risk [17]. In addition, semiarid forest ecosystems are fire-prone due to summer droughts and the dense understory vegetation [2]. Also, human activities (land-use change, excessive presence of travelers and livestock, charcoal) influence forest fires [14, 17, 18]. As driving factors and their contribution to fire occurrence, i.e., ecological, topographical, and climatic, are not the same in different regions, by identifying and prioritizing the influencing factors and identifying the fire-prone areas, prevention of fire occurrence and management of the sensitive regions will be done with a higher efficiency [19].

Machine learning methods have recently been used to predict and identify fire-sensitive areas [20-23]. Machine learning methods and simulation models based on field studies give us a better understanding of the location and behavior of fire [24]. Using these modeling procedures, it is possible to zonate the forest regions in terms of the possibility of fire and the extent of the fire [25]. In fact, by using these models, it is possible to monitor the fire behavior (i.e., time and location of occurrence) and different environmental factors affecting the fire. Also, using these models makes it possible to determine how to allocate facilities to the fire areas [26]. Studies have been conducted in the field of modeling and predicting fire hazards. For example, Mohajane et al. (2021) used remote sensing and machine learning algorithms to map forest fires in the Mediterranean region [27]. Babu et al. (2023) used six machine-learning models to identify and predict wildfire susceptible areas in the Western Ghats using climate, topography, vegetation, and anthropogenic [28]. Sadeghi et al. (2024) investigated fire susceptibility in oak forests in Iran [29].

Zagros forests in western Iran have a high fauna and flora diversity, which makes it a valuable habitat for many endemic species [30]. These forests are composed of deciduous tree species, with the dominant species being *Quercus brantii* L., which has a significant role in the sustainability of people's lives and livelihoods [31]. Fire is the primary disturbance in these ecosystems due to the dry climate, dense herbaceous cover (as a fuel material), and high dependence of people on forest and land-use change [32]. In addition, due to the extreme topography, steep slopes, and the lack of facilities, a large area of these forests is burned yearly. Forecasting and fire management are needed





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to minimize fire frequency and prevent damage to these forests. In Ilam County, according to statistics, there were 6936 active fire spots from 1380 to 1400. To reduce the losses caused by fire, it is necessary to predict the location of the fire probability and prepare a fire risk map in the forests of Ilam County to prevent fire occurrence and manage fire. In connection with the preparation of fire maps in different regions of Zagros and the study of the effects of various factors on fire, studies have been conducted that used various machine learning models and methods for modeling, and their results have shown differences due to the nature of the process, type and number of samples. However, so far, no study has been conducted to compare the efficiency of these methods in fire modeling and introduce the optimal method with the least error, which is why the present study is new in this regard. In this study, we used different machine learning methods, including support vector machine (SVM), random forest (RF), and generalized linear model (GLM) to distinguish and determine the contribution of abiotic (physiographic, climatic) and biotic (vegetation and anthropogenic) factors in sensitivity to fire occurrence, and identify the most factor influencing the fire. Therefore, here, we try to assess the following Hypotheses including:

1) Climatic factors contribute more to fire susceptibility.

2) The RF model is more accurate than others to determine fire-sensitive areas.

## Materials & Methods

### Study Areas

The present study was done in the Zagros forest, west of Iran, Ilam County (Figure 1). Ilam County is positioned at 33° 38′ N longitude and 46° 24′ E latitude. The mean annual rainfall in Ilam city is 577.1 mm, and the mean temperature is 16.9 °C. The mean maximum relative humidity in Ilam station is in March (61%), and the minimum is in August (19%). In addition, the region's dry season starts in June and continues until October (5 months). The climate of this region is semiarid based on de Martonne's climate classification. The area is 107–2764 m above sea level, and the slope mainly varies around 20%–40%. The dominant tree species in these forests is *Quercus brantii*, a coppice form of oak sprout clumps occupying patches over the forest surface. Other tree and shrub species include *Pistacia atlantica* Desf. *and Crataegus pontica.* K. Koch*, Amygdalus scoparia* Spach. and *Acer monspessulanum* L., with a dense herbaceous understory (i.e., *Bromus tectorum*). Soil is also generally calcareous. The forests of this region are repeatedly subject to fires in mid-spring to summer [33]; due to the strong dependence of rural people on livestock grazing and firewood, land-use changes to destroy forests and develop agricultural land [34].

## Research Methodology

The first step in determining vulnerable areas to fire is determining the practical factors that influence fire occurrence. Four main factors were determined, including physiographic, biological, climatic, and anthropogenic. The raster maps of environmental factors were created with a pixel size of 30 × 30 m$^2$ in Arc GIS 10.8 software. The schematic flowchart of the study's implementation is presented in Figure 2.

### Topographic Factors

Topographic factors are one of the most critical environmental factors that directly and indirectly affect many vital functions of living organisms. Elevation, slope, and aspect are the main topographic features most well-known and studied in most studies [17, 35]. This research used the topographic map (1:25000) of the country's mapping organization and the digital elevation map extracted from the ASTER satellite images to extract elevation, slope, and aspect maps. Topographic layers were prepared using Arc GIS software.



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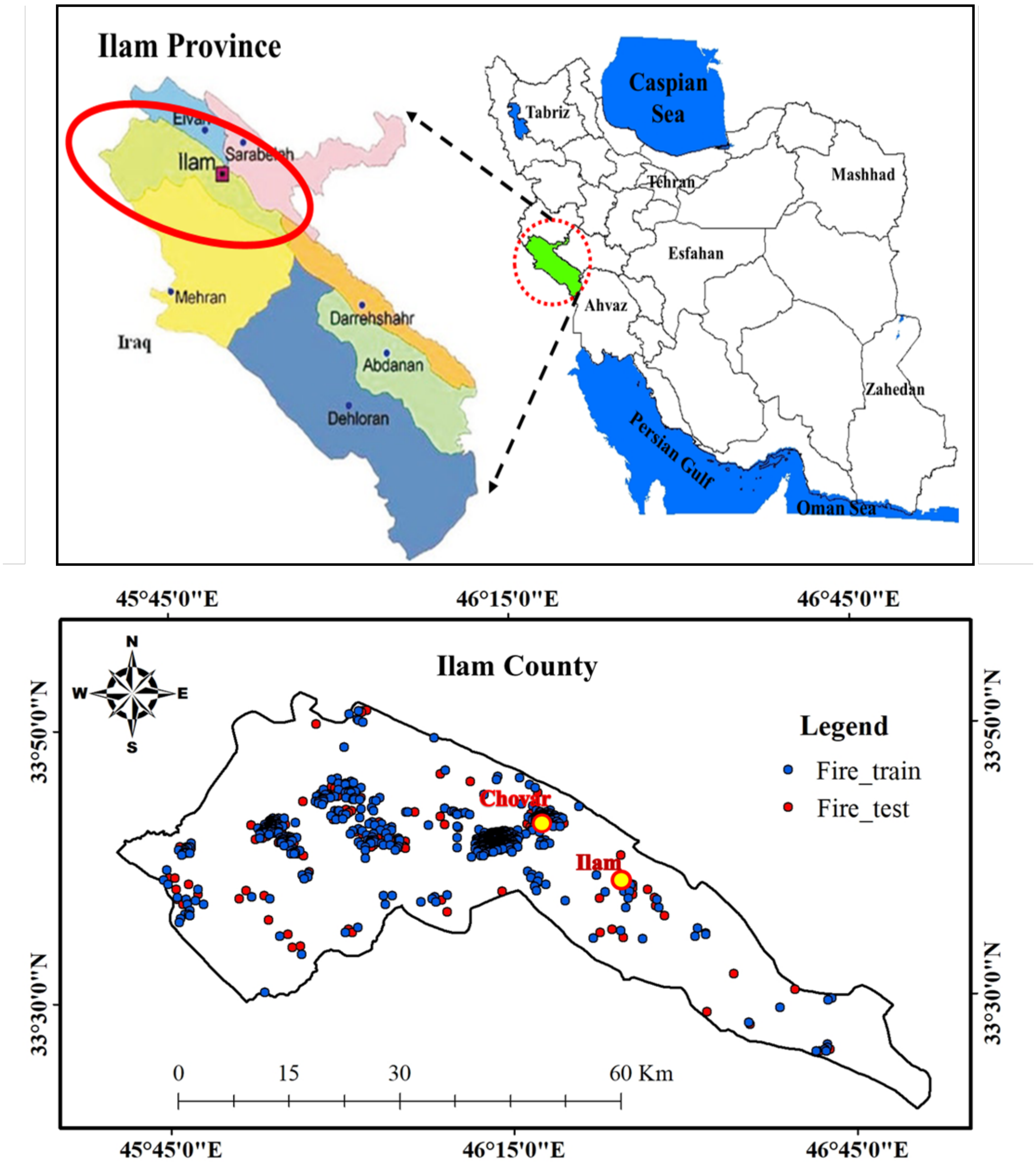


**Figure 1)** Location of the study area in the Ilam Province, western Iran.

## Biological Factors

The vegetation type could affect fire characteristics, such as ignition point, fire intensity, spread rate, and flame height [36, 37]. This study investigated vegetation type and density as biological factors [38]. Therefore, the vegetation cover, including a flammable material map, the amount of canopy cover, and the height of the forest mass, is needed. In this research, the impact of vegetation cover was assessed using the production and calculation of the NDVI vegetation index from Landsat 8 satellite image (date: 05/09/2022 and land cloud cover=0.0)

## Climatic Factors

Climatic factors directly affect fire occurrence and indirectly affect the occurrence and intensity of fire by impressing the vegetation type and density [39]. This research prepared 19 climate variables (Bio-1 to Bio-19) (Table S1). Then, using the meteorological data of all stations in Ilam province (Table 1), climatic variables were calculated for each station

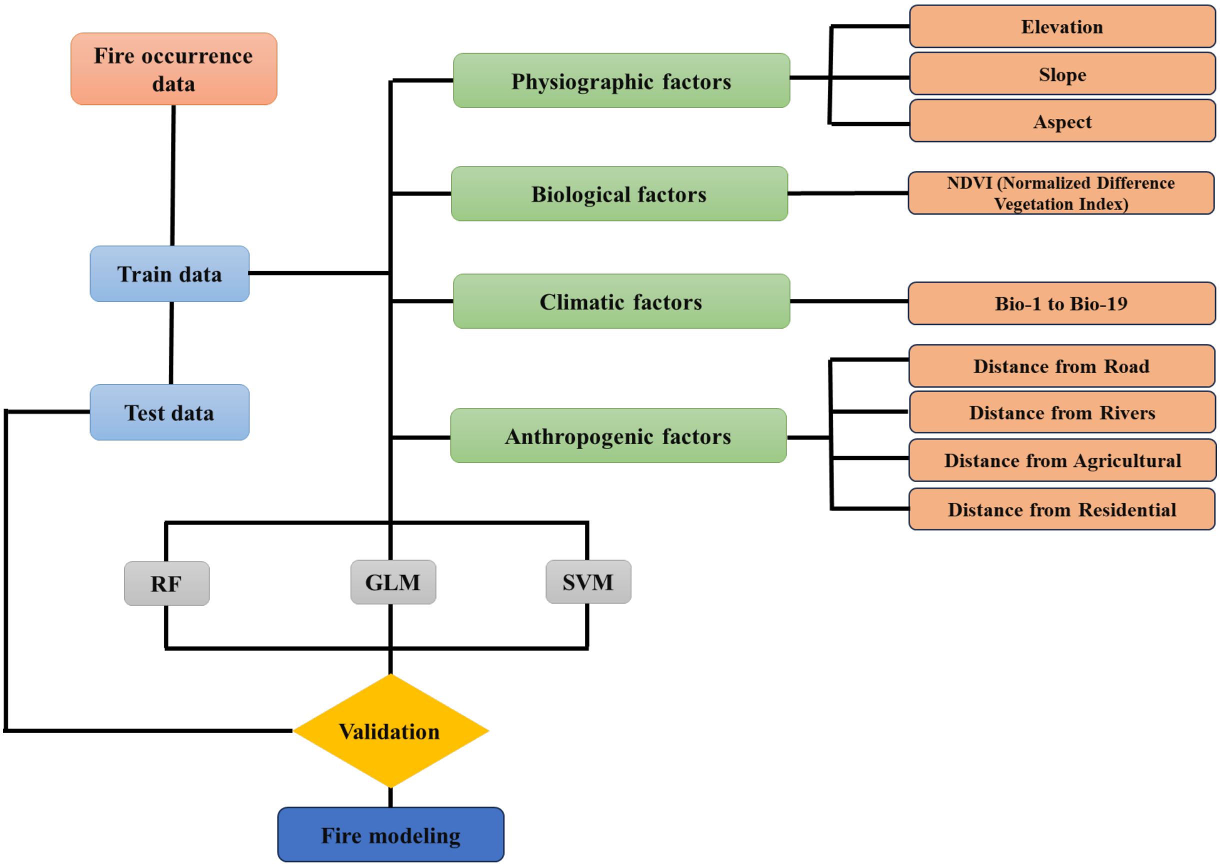


**Figure 2)** The schematic flowchart of this study.

using the "*biovars*" function in the "dismo" package in R software. Due to the large number of climate variables, using the correlation test (correlation coefficient greater than 0.7), variables with high correlation were eliminated. Finally, the Inverse distance weighted (IDW) interpolation method prepared a map of all climatic characteristics. In addition to climatic characteristics, the map of the two variables of wind speed and direction was prepared. The wind speed map and direction were prepared using the IDW interpolation method.

**Anthropogenic Factors**

Anthropogenic factors are among the most critical determining factors of fire occurrence due to their role in fire creation and management [32]. In this study, the layers of anthropogenic factors, including distance from the road, distance from residential areas, and distance from agricultural land, were created based on the land-use map of the Geological Organization of Iran. For this purpose, after determining each feature (residential areas and agricultural lands) and the road map (extracted from Google Earth software), it was entered into the ArcGIS software, and the distance map was created using the Euclidean distance method.

**Modeling and Accuracy Assessment**

All information about the fire occurrence in the last 20 years was collected from the Natural Resources and Watershed Management Organization (NRWMO) and Environmental Protection Organization (EPO), and NRWMO and EPO database, the fire product of MODIS satellite image was used. Given the need for a wide range of information to perform the modeling process and the limited information on fire areas in Iran, researchers are reluctant to use information such as the MODIS fire product. Although using these




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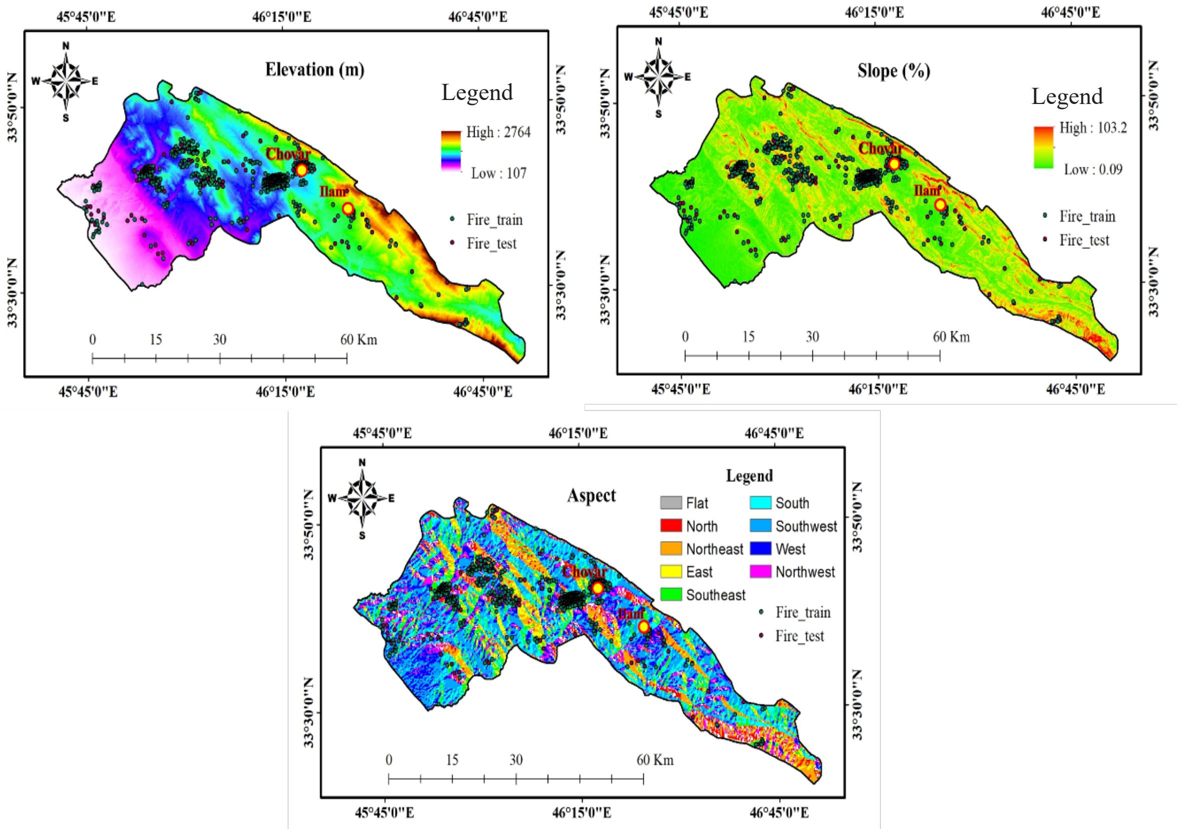


**Figure 3)** Physiographic factors map and fire distribution based on incidence data of 2001–2021.

sources is common among researchers, these satellite products also have weaknesses. This is because this satellite has temperature thresholds for recording fire points. If a fire occurs in an area and does not produce a high temperature, it may not be recorded by these satellite images. However, given the type of land-use in the area (predominance of forest and pasture), the occurrence of fires in these areas will generate much heat due to the density and type of cover, and the possibility of error in this regard is significantly reduced. After removing duplicate points, the final layer of fire points was created as a point (844 maps in total). This information was divided into two groups: points necessary for training the model (70%) and points needed for evaluating the results of the model (30%), which were utterly random [17, 20]. Three machine learning models, including support vector machine (SVM), random forest (RF), and generalized linear model (GLM), were used to modulate the areas with high sensitivity to fire occurrence. Generalized linear models (GLM) are a class of linear-based regression models developed to handle varying types of error distributions. In statistics, a generalized linear model (GLM) is a flexible generalization of ordinary linear regression. The GLM generalizes linear regression by allowing the linear model to be related to the response variable via a link function and by allowing the magnitude of the variance of each measurement to be a function of its predicted value. Random forest is a machine learning algorithm for classification, regression, and other tasks that works by creating a multitude of decision trees during training [12,13]. Random Forest, trademarked by Leo Breiman and Adele Cutler, combines the output of multiple decision trees to reach a single result. For classification tasks, the output of the random forest is the class selected by most trees [17]. For regression tasks, the output is the average of the predictions of the trees.


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A support vector machine (SVM) is a machine learning algorithm that uses supervised learning models to solve complex classification, regression, and outlier detection problems by performing optimal data transformations that determine boundaries between data points based on predefined classes, labels, or outputs [38]. RF and SVM were done in R software and "random Forest" and "e1071" packages, respectively. Also, to determine the relative importance of environmental variables, the relative importance diagram method (varImp Plot) was used in the random forest algorithm. Finally, the fire-sensitive maps were evaluated using the area under the curve (AUC) values extracted from the receiver

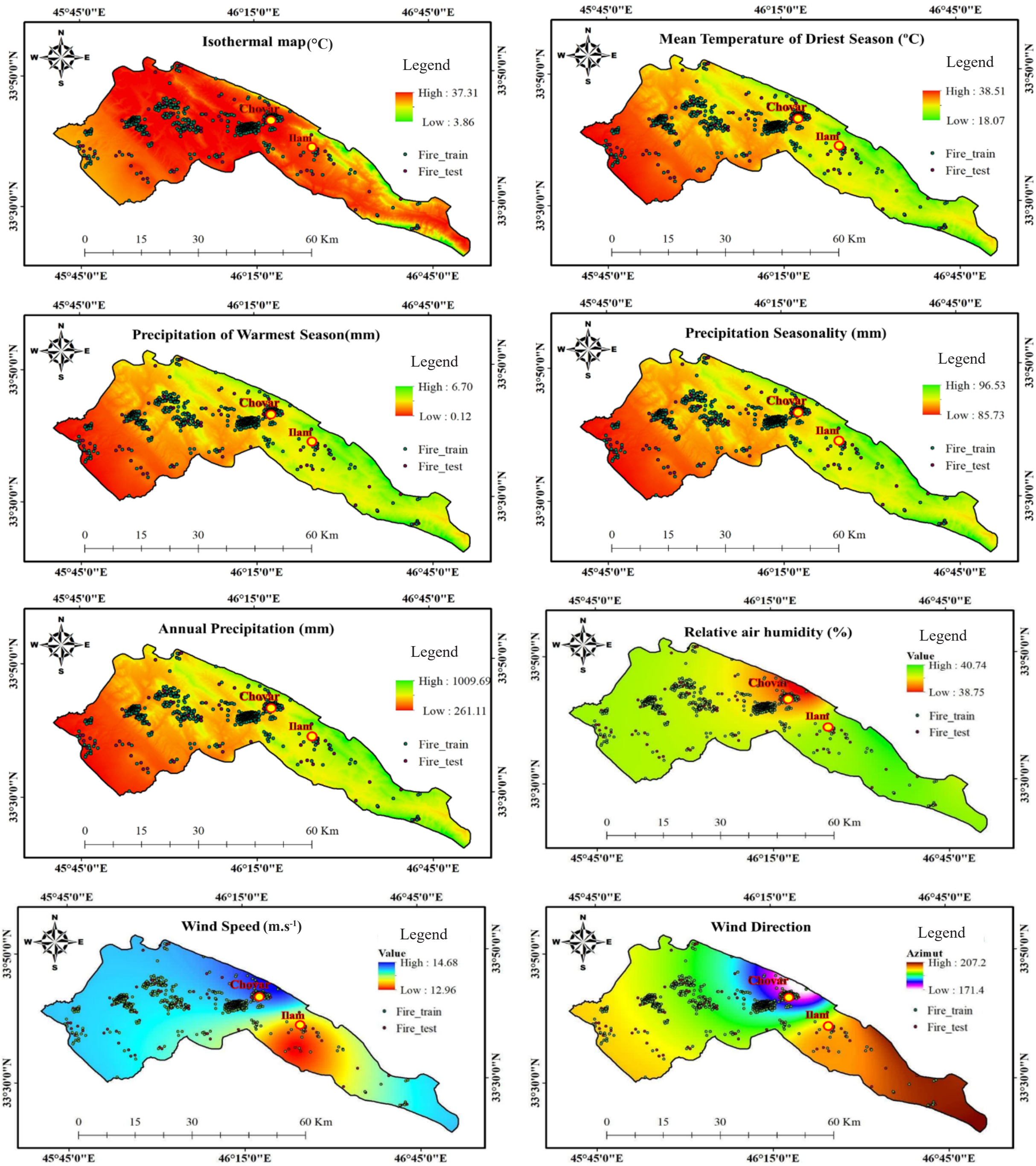


**Figure 4)** Climatic factors map and fire distribution based on incidence data of 2001–2021.

**Table 1)** Specifications of the desired synoptic stations (2000-2020).

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

operating characteristics (ROC) curve. Also, some of the most essential mutual evaluation statistics, including the correlation coefficient (r), explanation coefficient ($R^2$), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE), were used to compare the two investigated models. Also, an independent student t-test was used to compare factors influencing fire occurrence (Table S2).

## Findings

### Physiographic Factors

The results showed that the highest fire point historically occurred at an elevation of 988±349 meters, and elevations of >2000 meters and < 300 meters had low fire occurrence. The mean slope of points with a fire history was 17.99±13.51%, indicating fire occurrence in areas with low slopes (<20%). In addition, forest fires were most abundant on southwest slopes (Figure 3).

### Climatic Factors

The fire occurrence was higher in the high isothermal range. The results showed that the mean isothermal map in the fire points was 36.06±1.98 °C; increasing the temperature increased fire possibility. In addition, the frequency of fire points was higher in areas with the highest mean temperature in the dry season (Figure 4). In fire points, the mean rainfall was 512.96±99.33. In addition, the mean rainfall in the hottest season of the year in places with a fire history was 2.33±0.87 mm. The eastern and southeastern regions had the highest relative air humidity, while the central and western regions had lower relative humidity. The maximum wind speed was observed in the northern regions (14.8 m.s$^{-1}$). At the same time, the minimum wind speed occurred in the central and southern areas of Ilam city (12.96 m.s$^{-1}$). Most of the winds were from the south and southeast.

### Vegetation Cover/Density

The NDVI index of this region varied from -0.09 to 0.54. Based on the results, the mean NDVI index for areas where fire occurred was 0.122±0.035, with moderate to poor vegetation cover (Figure 5).

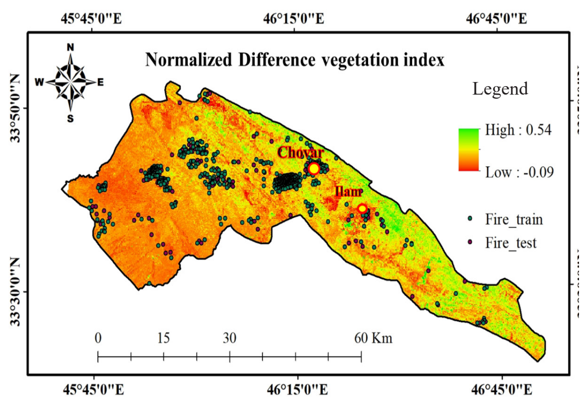


**Figure 5)** NDVI index map and fire distribution based on incidence data of 2001–2021.

**Table 2)** Classified risk classes of fire susceptibility using GLM, SVM, and RF models.

| Row | Risk Classes | GLM | | SVM | | RF | |
|---|---|---|---|---|---|---|---|
| | | Area (ha) | Area (%) | Area (ha) | Area (%) | Area (ha) | Area (%) |
| 1 | Very High | 51916.54 | 24.05 | 14750.76 | 6.83 | 12956.91 | 5.97 |
| 2 | High | 139233.29 | 64.50 | 46034.01 | 21.33 | 20568.65 | 9.48 |
| 3 | Medium | 23998.77 | 11.11 | 104002.77 | 48.19 | 60809.01 | 28.05 |
| 4 | Low | 694.91 | 0.32 | 51055.98 | 23.65 | 122502.83 | 56.50 |

**Anthropogenic-induced Factors**

The mean distance of fire points from the main road was 80.35 ± 137.74 meters. Also, the mean distance of fire occurrence from agricultural lands was 3.69±2.87 km. Considering that the maximum distance in this region is about 15 kilometers, it can be said that most of the fires occurred in areas within a short to medium distance from agricultural lands. The results also showed that more fires occurred in areas close to residential areas and that the fire occurrence potential decreased as the distance from residential areas increased. The mean distance from the rivers in the areas with a fire history was 712.89±500.65 meters (Figure 6).

**Modeling Fire Risk**

Based on GLM analysis, the sensitivity to fire occurrence was high-risk class (64.5%), very high-risk class (24.05%), medium (11.11%), and low-risk classes (0.32%), respectively. In the SVM model, medium and low-risk probability areas have occupied a large part of the study area (48.19 and 2365%, respectively). Based on the results, 14750.76, 46034.01, 104002.77, and 51055.98 hectares of these forests in the study area were in very high, high, medium, and low-risk classes, respectively (Table 2). In the RF model, the highest area was in the low-risk classes, which was 56.5% and occupied 122502.83 hectares of the study area. This was followed by the medium risk class with the highest area (28.05%). The high and very high-risk classes were 9.48% and 5.97% of the total study area. The areas in the central to southern part had the highest potential for fire occurrence, while others had a low potential for fire occurrence. (Figure 7).

**Models' Validation**

The validation results of fire susceptibility maps showed that the highest R-square value was related to the RF (0.851), and most of the existing changes are described by this model. The amount of R-square for SVM (0.733) and GLM (0.577) was lower than the RF model. Therefore, based on the R-square, the map of fire points by RF had higher accuracy than SVM and GLM (Table 3, Figure 8). Also, the root means square error (RMSE) for RF, SVM, and GLM were 0.330, 0.371, and 0.419, respectively, showing that the RF model was more accurate than others (Table 3). In addition, the normalized BIC for GLM was -1.718. Using the SVM model to prepare the fire sensitive points map, the normalized BIC was reduced to -1.962. This decrease was more severe using the RF model (-2.194). Based on the normalized BIC, the RF model is more accurate for mapping fire spots in this area.

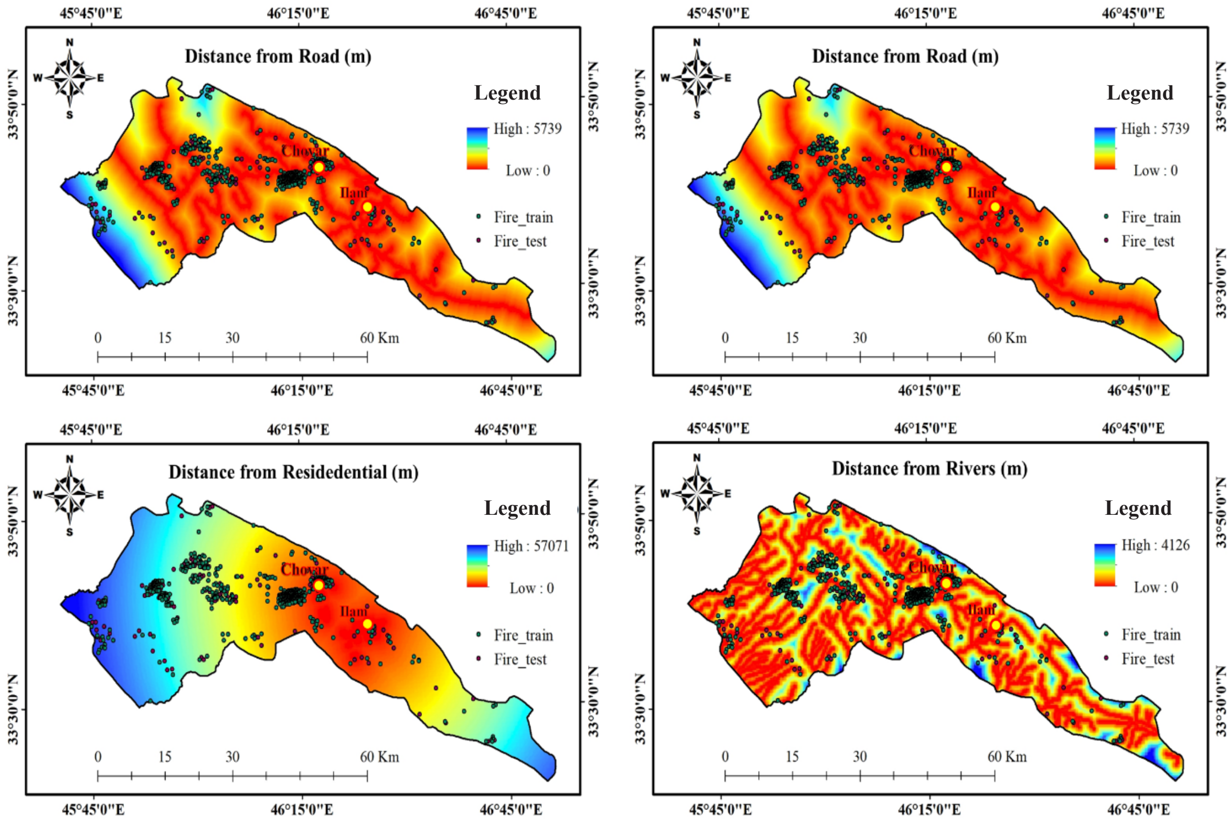


**Figure 6)** Anthropogenic-induced factors map and fire distribution based on incidence data of 2001–2021.

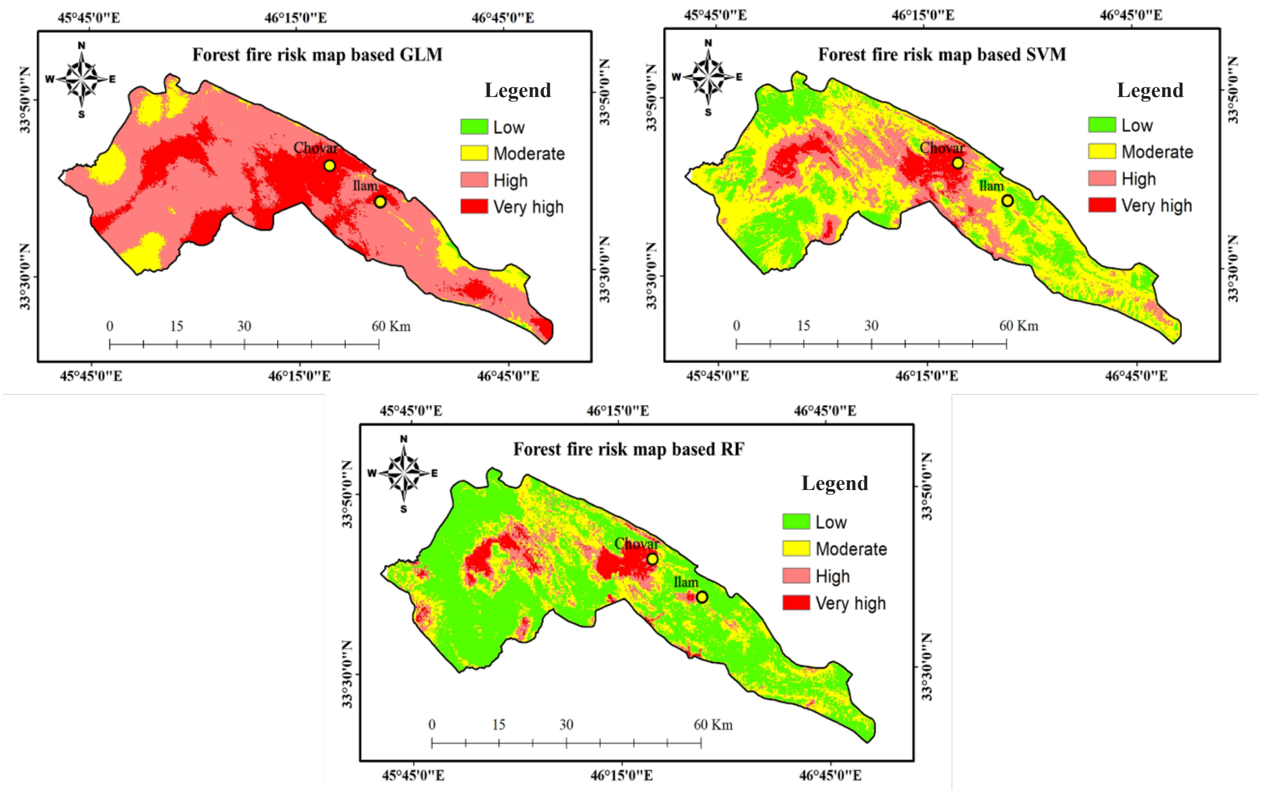


**Figure 7)** Forest fire risk map based on GLM, SVM, and RF models.





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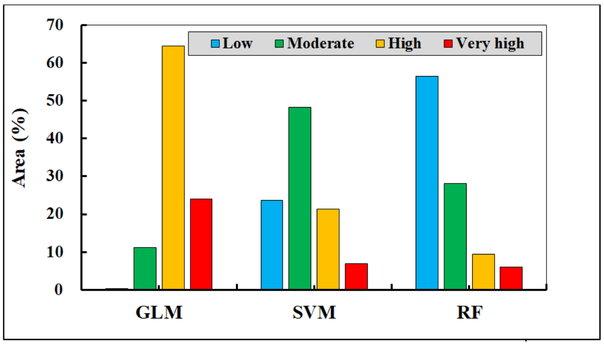


**Figure 8)** Fire susceptibility classes in different machine-learning methods.

**Table 3)** The accuracy of fire susceptibility maps.

| Statistics | GLM | SVM | RF |
|---|---|---|---|
| R-square | 0.577 | 0.733 | 0.851 |
| RMSE | 0.419 | 0.371 | 0.330 |
| MAE | 0.363 | 0.279 | 0.222 |
| Normalized BIC | -1.718 | -1.962 | -2.094 |

## Models' Accuracy

The AUC index in the ROC curve showed that the RF model (AUC = 0.911) had the highest accuracy than the SVM model (AUC = 0.864) and GLM (AUC = 0.824). Also, the RF model had the lowest error rate (E=0.013) compared to the SVM and GLM (Figure 9, Table 4).

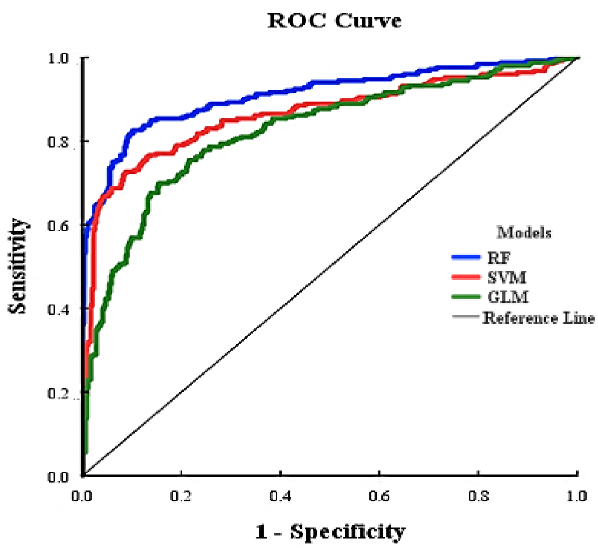


**Figure 9)** The accuracy of different machine learning methods using AUC.

**Table 4)** The accuracy evaluation of the machine learning method.

| Model | AUC | SE | Sig | Confidence Interval (95%) | |
|---|---|---|---|---|---|
| | | | | Lower Limit | Upper Limit |
| RF | 0.911 | 0.013 | 0.001< | 0.885 | 0.936 |
| SVM | 0.864 | 0.017 | 0.001< | 0.831 | 0.896 |
| GLM | 0.824 | 0.018 | 0.001< | 0.789 | 0.858 |

## The Affecting Factors on Fire Occurrence Based on the RF

The RF was introduced as a suitable model for preparing the fire map in this study area. The results showed that anthropogenic factors (including distance from residential areas, distance from agricultural land, and distance from rivers) and climatic factors (including relative air humidity, wind speed, and slope aspect) were the most influential. The distance from rivers and geographical and slope aspects were the least important factors in fire occurrence in this region. Among the physiographical factors, the elevation and slope aspects were more critical in the fire occurrence (Figure 10 and Appendix Figure S1).

## Discussion

Fire is one of the most critical factors in destroying forest ecosystems and plays a fundamental role in changing their structure and function [40]. This study prepared a fire occurrence map based on generalized linear models, support vector machines, random forest using climatic parameters, and topographic, biological, and anthropogenic factors. Topographic factors affected the occurrence of fires in the forests of the study area.

The result showed that most fires happened at elevations 300-2000 m. At low elevations, due to the higher temperature [41], the herbaceous plants (as fuel) grow earlier and are grazed earlier than in other areas by livestock;

therefore, the possibility of fire is minimized for these regions in the dry season.

The degradation and agricultural intensification create communities with discrete coverage, which can also be one of the reasons for reducing fires in this elevation [42]. On the other hand, at an elevation of> 2000 meters, due to the decrease in temperature, the growth of the ground cover of the floor as a fuel material is poor. In addition, in the high elevations of the Zagros forests, rock and stone covers increase [38], an obstacle to the spread of fire. Usually, in this forest, the highest plant coverage density is in the middle elevation [43], and due to the favorable conditions in terms of temperature and humidity, the population density is higher. Therefore, the probability of fire occurrence is higher for this region. Considering the highest density of urban and rural populations in this elevation range, land-use changes potentially increase, increasing fire occurrence.

Numerous studies suggest that a relationship exists between wildfires and topographic factors (such as elevation and slope), such as Rodriguez-Jimenez et al. (2023) [44]. This study recorded more fires in areas with a low slope (i.e., 15-35% slope). On the steeper slopes (>50%), the herbaceous cover on the ground is less dense as fuel due to the shade of the trees and the presence of rocks and stones, so fire occurrence is lower on these slopes. In addition, the heterogeneous topographical conditions of this region [45, 2, 46] can be an obstacle to fire.

Also, south and southwest-facing slopes are susceptible to fire. The slope aspect can affect forest fires by influencing the amount of sunlight, soil moisture, and floor vegetation [47]. In the drier conditions of the southern slopes, the density of tree cover is lower, and as a result, the vegetation of the forest floor, which needs less moisture, is higher, and fuel is provided for the fire. The results of our study were consistent with the results of other studies regarding the role of slope aspect in the occurrence of fire [42]. Eskandari and Miesel (2017) also mentioned that the slope and slope aspect are critical factors in the probability of fire occurrence [48].

The temperature can be among the significant factors influencing the occurrence and increasing risk of wildfires [49]. Based on the results, the potential of fire occurrence was higher in the high isothermal range. Also, the number of fires was higher in areas with the highest annual temperature, especially in the driest season. According to the results of this research, the eastern and southeastern parts had the highest relative humidity. On the other hand, relative humidity has an inverse relationship with fire occurrence. Different research results have also shown that the occurrence of fires in dry tropical ecosystems (with high temperatures) and warmer climates is higher. In many cases, temperatures have been the most important climatic factor affecting the fire regime in forest areas [50, 51]. A study conducted by Charizanos and Demirhan (2023) and Morovati and Karami (2024) revealed that dry and hot conditions can increase the potential for wildfire occurrence [52,53]. Hong et al. (2017) showed that among the climatic factors, temperature had the most significant effect on the occurrence of fire in China, which is in line with our results [39].

Floor vegetation (as a primary fuel material) is also one of the main factors affecting the occurrence of fire in different regions [54]. This study found that most fires are located in regions with moderate and weak NDVI. In areas with a high NDVI index due to the large tree cover, the forest floor vegetation is less; therefore, the fire occurrence is also less. This result is consistent with the results related to the amount of precipitation. The increase in precipitation causes more growth and density of trees in the upper story, which prevents light penetration to the forest floor and less growth and development of herbaceous plant


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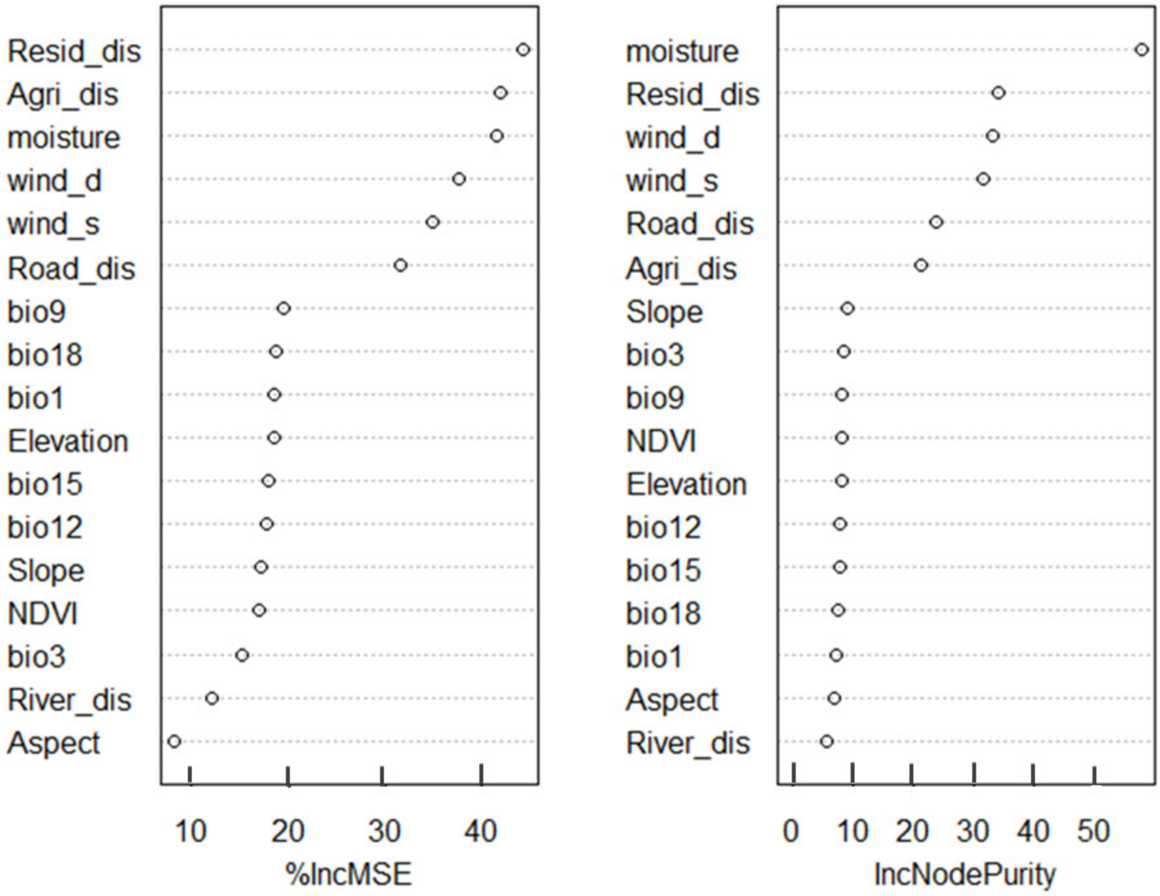


**Figure 10)** Relative importance of parameters used in random forest model.

species on the forest floor.

The distance from residential (i.e., city or villages) and agricultural land also affects fire occurrence [55]. The rural peoples in Zagros forests largely depend on the forest ecosystem to provide firewood, charcoal, livestock grazing, forest farming, and rural consumption [56]. Therefore, in addition to tourists, the role of the residents of the region in causing fires is also undeniable. According to previous studies, the occurrence of forest fires is inversely related to the distance from the village [57]. The results of the present research on the role of anthropogenic factors in the occurrence of fire in different areas of Ilam city were consistent with the results of Emami and Shahriari (2020) [58]. This study's results showed that the highest number of fires happened in the areas where human access was more. In areas with lower slopes, it is more accessible for tourists; therefore, as mentioned before, fires are more likely to occur on these slopes. Areas with a suitable slope are more accessible for people accessibility. Distance from residential areas plays a vital role in the occurrence of fire due to the increased activity of people near residential areas [59]. The results of our study were consistent with a similar survey by Mohammadi et al. (2014) [55]. Indeed, considering the anthropogenic factor as most fires, areas with high slopes have less potential for fires and land-use change due to their low suitability for agriculture.

RF is a widely used, efficient, and accurate algorithm compared to other well-known ML algorithms [60]. The result of fire susceptibility validation showed that RF had higher accuracy, which is consistent with the results of Moghim and Mehrabi (2024) [60], Eshaghi and Joybari (2016) [61], and Zhao et al. (2024)



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[62]. The RF model could predict the probability of fire occurrence better than others, with an accuracy of 85%. On the other hand, it was found that all the algorithms could classify the area well regarding the probability of fire occurrence. RF is more interpretable and has a low computational cost, which makes it suitable for handling high-dimensional datasets, and thus, it is reasonable for predictive modeling [60]. In the previous study, the RF model could predict fire risk with an accuracy of 79.5% (Holden et al. 2009) [63]. Oliveira et al. (2012) also stated that the RF algorithm has a higher ability to predict fire occurrence, consistent with our study [12]. Therefore, the fire map produced by the RF model can be used as a spatial-temporal climate warning system for the occurrence of fire in the region.

The relative importance of the factors used in the model with the highest accuracy in predicting the fire occurrence map was also determined. Anthropologic factors (including distance from settlements and agricultural land), climatic factors (including humidity and wind speed), and physiographic factors (slope aspect and elevation) were the most effective, and distance from rivers and slope aspect were the least essential parameters for forest fire occurrence in this region.

Based on the results, out of the six essential and effective factors on fire occurrence, three were human factors (distance from residential areas, agricultural areas, and road), and three were climatic factors (relative humidity, wind speed, wind direction). Considering the lack of control and the ability to make significant changes in climatic factors, we can focus on other factors to reduce fire occurrence. In other words, the best way to reduce the occurrence of fire is to increase the level of public education, increase the concentration of administrative facilities and government institutions in specified areas, and increase the promotion of public cultures of proper use and preservation of nature as the best solution to reduce the risk of fire in this area.

## Conclusion

Most fires occurred in medium altitude, low slope, and south and southwest exposure. In these areas, continuous monitoring should be possible during the dry season until the beginning of autumn when the rains begin. The parameters of anthropogenic factors (distance from residential areas, distance from agricultural lands, and distance from roads) and climatic factors (relative humidity, wind speed, and direction) are the most influential parameters in forest fires in Ilam County, which confirms hypothesis one. There were also more fires near main roads, villages, and agricultural land. One of the most critical rural problems in these areas is socioeconomic, and most of these fires are anthropogenic -induced. The forest manager/government should prevent land-use changes, excessive grazing of livestock, preparation of charcoal, and the uncontrolled presence of tourists by solving the socioeconomic problems of the people in this forest. Therefore, it has been suggested that governmental and other related national organizations did nature-based knowledge education. Considering the lack of control and the ability to significantly change climatic factors to reduce fire occurrence, we can focus on other factors. In other words, the best way to reduce the occurrence of fire is to increase the level of public education, increase the concentration of administrative facilities and government institutions in specified areas, and increase the promotion of public cultures of proper use and preservation of nature as the best solution to reduce the risk of fire in this area. Based on the results, the FR model was more accurate in fire prediction modeling than the other investigated models and is introduced as a suitable model. This result confirms the second hypothesis. The RF model results indicated that the highest area has a low risk due to heterogeneous topographical conditions. The control of fire extension is complicated, and predicting a fire before its occurrence is vital. This study offers valuable insights into the factors influencing wildfire occurrence and identifying high-risk areas. The output of this research can be utilized to mitigate forest fires effectively. It can be helpful to plan effective fire management strategies to minimize damage to the forest ecosystem. Studying the spread of fire and preparing a database of fires that have occurred and are occurring in the forests of Ilam province (including time, location, type and duration of the fire, fire-causing factors, and percentage of damage) using remote sensing and geographic information systems, as well as preparing a history of fires in the forests of these areas can be the next step to complete the results of this study.

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**Consent to participate** (All authors consent to participate in this article)

**Consent for publication** (All authors consent to publish the article in this journal)

**Availability of data and material** (Data will be made available on demand)

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## Appendix

**Table S1)** Bioclimatic variables are derived from the monthly temperature (min and max) and rainfall (mean) values.

| Abbreviation | Formula |
|---|---|
| BIO1 | Annual Mean Temperature |
| BIO2 | Mean Diurnal Range (Mean of monthly (max temp - min temp)) |
| BIO3 | Isothermality (BIO2/BIO7) (×100) |
| BIO4 | Temperature Seasonality (standard deviation ×100) |
| BIO5 | Max Temperature of Warmest Month |
| BIO6 | Min Temperature of Coldest Month |
| BIO7 | Temperature Annual Range (BIO5-BIO6) |
| BIO8 | Mean Temperature of Wettest Season |
| BIO9 | Mean Temperature of Driest Season |
| BIO10 | Mean Temperature of Warmest Season |
| BIO11 | Mean Temperature of Coldest Season |
| BIO12 | Annual Precipitation |
| BIO13 | Precipitation of Wettest Month |
| BIO14 | Precipitation of Driest Month |
| BIO15 | Precipitation Seasonality (Coefficient of Variation) |
| BIO16 | Precipitation of Wettest Season |
| BIO17 | Precipitation of Driest Season |
| BIO18 | Precipitation of Warmest Season |
| BIO19 | Precipitation of Coldest Season |

**Table S2)** Mean comparison of factors influencing fire occurrence between fire and control areas based on independent student t-test.

| Variables | t-test | | Fire point | | | Control point | | |
|---|---|---|---|---|---|---|---|---|
| | t-value | P-value | Mean | Std. Deviation | Std. Error Mean | Mean | Std. Deviation | Std. Error Mean |
| Aspect | -1.754 | 0.080 | 190.807 | 86.927 | 2.992 | 198.078 | 88.599 | 2.863 |
| Elevation (m) | 2.612 | 0.009 | 988.520 | 349.293 | 12.023 | 932.922 | 524.385 | 16.942 |
| Slope (%) | 3.359 | 0.001 | 17.993 | 13.515 | 0.465 | 15.883 | 13.120 | 0.424 |
| Agri distance (km) | 2.494 | 0.013 | 3.692 | 2.876 | 0.099 | 3.349 | 2.937 | 0.095 |
| River distance (km) | -0.868 | 0.385 | 0.713 | 0.501 | 0.017 | 0.735 | 0.591 | 0.019 |
| Road distance (km) | -13.009 | 0.000 | 80.350 | 137.740 | 0.001 | 23.293 | 1.610 | 0.001 |
| Reside distance (km) | -14.228 | 0.000 | 16.667 | 14.564 | 0.501 | 26.684 | 15.213 | 0.492 |
| NDVI | 1.980 | 0.048 | 0.122 | 0.036 | 0.001 | 0.119 | 0.041 | 0.001 |
| bio1 (C) | -2.612 | 0.009 | 20.190 | 2.445 | 0.084 | 20.580 | 3.671 | 0.119 |
| bio3 | 12.380 | 0.000 | 36.066 | 1.980 | 0.068 | 34.566 | 2.988 | 0.097 |
| bio9 (C) | -2.602 | 0.009 | 31.672 | 2.726 | 0.094 | 32.104 | 4.083 | 0.132 |
| bio12 (mm) | 2.602 | 0.009 | 512.959 | 99.326 | 3.419 | 497.235 | 148.771 | 4.807 |
| bio15 | 2.602 | 0.009 | 89.362 | 1.433 | 0.049 | 89.135 | 2.146 | 0.069 |
| bio18 (mm) | 2.602 | 0.009 | 2.332 | 0.874 | 0.030 | 2.194 | 1.309 | 0.042 |
| Moisture (%) | -22.170 | 0.000 | 39.737 | 0.334 | 0.012 | 40.030 | 0.223 | 0.007 |
| Wind speed (m/s) | 11.805 | 0.000 | 14.129 | 0.231 | 0.008 | 13.973 | 0.316 | 0.010 |
| Wind direction | -3.938 | 0.000 | 67.124 | 81.115 | 2.792 | 82.963 | 88.655 | 2.864 |


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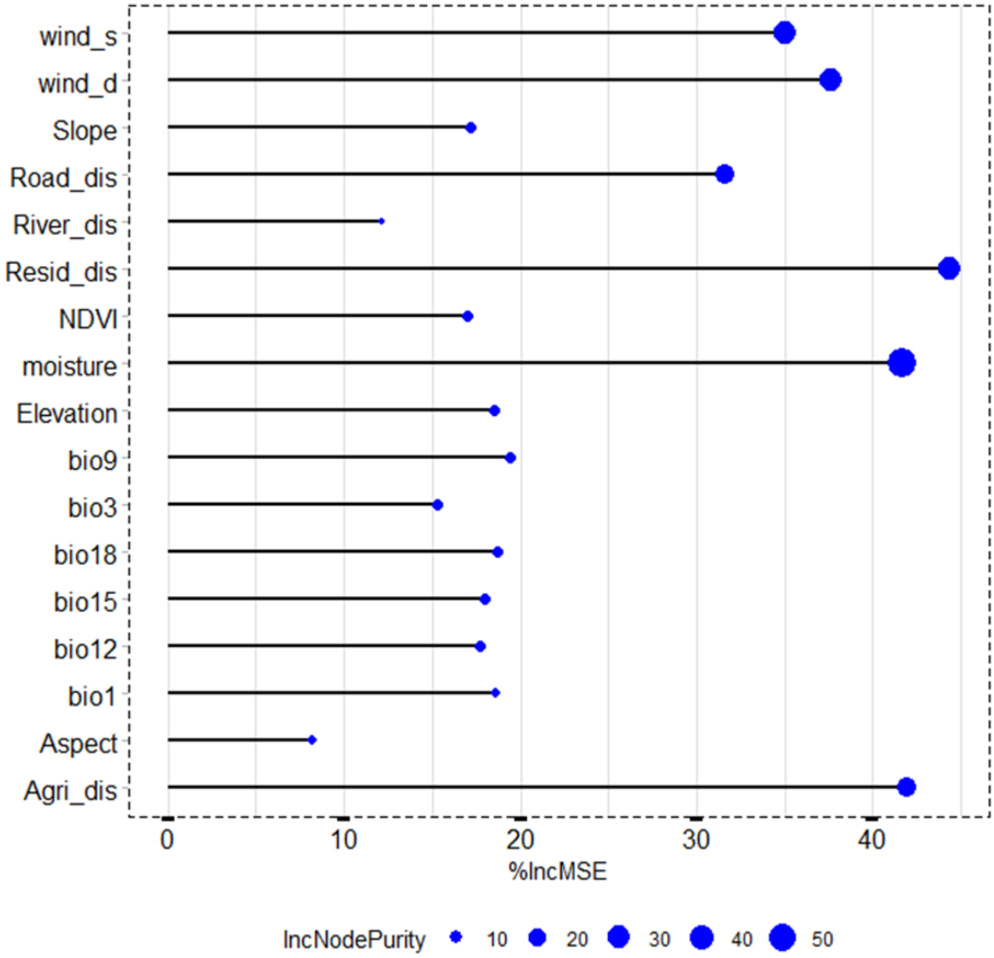
**Figure S1)** The importance of different variables used in determining fire sensitivity.



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