

# Fire Susceptibility Mapping in the Northeast Forests and Rangelands of Iran using New and Ensemble Data Mining Models

Saeedeh Eskandari (✉ [saeede.scandari@yahoo.com](mailto:saeede.scandari@yahoo.com))

Research Institute of Forests and Rangelands

Hamid Reza Pourghasemi

Shiraz University

John P. Tiefenbacher

Texas State University

---

## Research Article

**Keywords:** Fire susceptibility mapping, Data mining algorithms, Random forest, Ensemble modeling, GIS

**Posted Date:** February 19th, 2021

**DOI:** <https://doi.org/10.21203/rs.3.rs-209699/v1>

**License:**  This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

---

**Version of Record:** A version of this preprint was published at Environmental Science and Pollution Research on April 23rd, 2021. See the published version at <https://doi.org/10.1007/s11356-021-13881-y>.

# Abstract

Fires have increased in the northeastern Iran as its semiarid climate landscape is being desiccated by human activities. To combat fire outbreaks in any region, one must map fire susceptibility with accurate and efficient models. This research mapped fire susceptibility in the forests and rangelands of northeastern Iran's Golestan Province using new data mining models. Fire effective factors data describing elevation, slope angle, annual mean rainfall, annual mean temperature, wind effect, topographic wetness index (TWI), plan curvature, distance from river, distance to road, and distance to village were obtained from several sources. The relative importance of each variable was determined with a random forest algorithm. Fire susceptibility maps were produced in R 3.3.3 software using GAM, MARS, SVM algorithms and a new ensemble of the three models: GAM-MARS-SVM. Validation of the four fire susceptibility maps was performed with the area under the curve. Results show that distance from village, annual mean rainfall and elevation were of greatest importance in predicting fire susceptibility. The new GAM-MARS-SVM ensemble model achieved the highest fire susceptibility mapping precision. The fire susceptibility map produced using the GAM-MARS-SVM ensemble model best detected the high fire risk areas in Golestan Province.

## 1. Introduction

Forest fires, whether natural or human-induced, have many negative impacts on environmental, social, and economic conditions in most environments (Dimitrakopoulos and Mitsopoulos 2006). One of the solutions to prevent fires is protective management in critical fire-prone and human-occupied areas (Eskandari et al. 2015a). Therefore, to map fire susceptibility and to identify high-risk areas accurately is of utmost importance.

Iran's climates range from arid to semi-arid. Global warming, regional climate change, and human activities in Iran's natural ecosystems have caused wildfires throughout a large portion of the forests and rangelands in the northern and northeastern parts of country in the recent years (Mazandaran Natural Resources Administration 2017; Golestan Natural Resources Administration 2018). Golestan Province is one of the regions most affected by wildfires in the recent years (Golestan Natural Resources Administration 2018). This region is already prone to fire due its normal, historical climate. Based on some reports and studies, fires in Golestan Province usually occur in areas experiencing decreasing rainfall, dehydration, and leaf litter accumulation (Yousefi and Jalilvand 2010; Eskandari and Jalilvand 2017; Golestan Natural Resources Administration 2018). Rural residents are augmenting the problem by purposely and accidentally igniting fires. It has been determined that proximity to forest roads and villages is related to increased wildfire risk in natural areas of Iran (Pourghasemi 2016; Eskandari and Miesel 2017; Eskandari et al. 2020).

Many have mapped fire susceptibility in natural ecosystems around the world. Diverse models have been developed to map fire susceptibility in different regions. Analytic hierarchy process (AHP) has been applied by some (Chuvieco and Congalton 1989; Sowmya and Somashekar 2010; Atesoglu 2014;

Pourghasemi et al. 2016; Nuthammachot and Stratoulas 2019) and others have used a combination of AHP and fuzzy sets (Eskandari 2017; Vadrevu et al. 2010). Some have applied logistic regression (Rollins et al. 2004; Martinez et al. 2009; Jurdao et al. 2012; Eskandari and Chuvieco 2015; Pourghasemi 2016) and others have used artificial neural networks (ANN) (Vasconcelo et al. 2001; Alonso-Betanzos et al. 2002; Vakalis et al. 2004; Vasilakos et al. 2009; Satir et al. 2016). In the last decade, fire risk modeling by individual data mining algorithms has produced good results (Pourtaghi et al. 2016; Eskandari et al. 2020). Support vector machines (SVM) have successfully modeled fire risk (Cortez and Morais 2007; Sakr and Elhajj 2010; Eskandari et al. 2020). Random forest (RF) has also provided reliable results (Leuenberger et al. 2013; Guo et al. 2017; Song et al. 2017; Eskandari et al. 2020). Ensemble data mining algorithms have also been used successfully (Tehrany et al. 2018; Gigovic et al. 2019).

In Iran specifically, fire danger mapping has been conducted at a national scale (Eskandari and Chuvieco 2015) and at regional scales (Eskandari et al. 2015a; Pourtaghi et al. 2016; Pourghasemi et al. 2016; Eskandari et al. 2020). Despite the extensive destruction of the forests and rangelands in Golestan Province in recent years, no comprehensive study for fire susceptibility assessment has been performed at the Province scale. Highly accurate fire susceptibility maps can be very useful for guiding use and management in the zones of highest risk in the Province. The aims of this study are: (1) to map past fires in the Golestan Province; (2) to evaluate the importance of the effective factors in the prediction of fire susceptibility; (3) to map fire susceptibility using new and ensemble data mining models; and (4) to validate the fire susceptibility maps produced using AUC to identify the best modeling method for the study area.

## 2. Materials And Methods

### 2.1. Study Area

Golestan Province, Iran covers an area about 2,037,809 ha (Fig. 1). The dense forests and rangelands in this semi-arid area have long been conducive to wildfire. The Province is known to be one of the most wildfire-prone regions of Iran (Golestan Natural Resources Administration 2018).

The dominant species in forests beech (*Fagus orientalis* Lipsky), alder (*Alnus subcordata* C.A.Mey.), Caucasian oak (*Quercus castaneifolia* C.A.Mey.), eastern hornbeam (*Carpinus betulus* L.), yew tree (*Taxus baccata* L.), common juniper (*Juniperus communis* L.), cypress tree (*Cupressus sempervirens* L.), and iron wood (*Parrotia persica* (DC.) C.A.Mey.). Dominant herbaceous species include *Achillea millefolium*, *Hypericum androsaemum*, *Echium amoenum*, *Ruscushyrcanus* Woron, *Rubus* sp. and *Siclaman* sp. (Mozaffarian 2007).

### 2.2. Data

An accurate fire susceptibility map is vital for fire prevention, mitigation, and response in fire-prone areas (Tehrany et al. 2018; Eskandari et al. 2020). Selecting the factors that are most important predictors of fire susceptibility is crucial to the modeling of an accurate and reliable fire susceptibility map. In this

study, a DEM was used to determine elevations, slope angles, topographic wetness indices (TWI), plan curvatures, distances to roads, distances to villages, and distances to rivers of each of the locations of previous fires. These effective topographic and anthropogenic factors for fire susceptibility were identified in the literature (Pourtaghi et al. 2016; Pourghasemi et al. 2016; Eskandari and Miesel 2017; Eskandari et al. 2020) and based also on conditions in the study area.

To account for climatic factors, data indicating annual mean rainfall, annual mean temperature, and winds were acquired; these have been shown to influence wildfire regimes (Barbero et al. 2014; Jolly 2014; Jolly et al. 2015; Vitolo et al. 2019). It has been reported that high temperature and low precipitation generally cause an increase in fire danger (van Bellen et al. 2010; Eskandari 2015). The role of wind in promoting fire and spreading fire has also been demonstrated (Jolly 2014; Field et al. 2015; Pourghasemi et al. 2016).

The DEM of Golestan Province was generated from an ASTER-GDEM (30m- resolution) available from the USGS (<https://earthexplorer.usgs.gov>) (Fig. 2). Slope angle was calculated from the DEM. TWI is a secondary DEM feature obtained from the 30m-resolution DEM (Beven and Kirkby 1979):

$$TWI = \ln(\alpha / \tan \beta) \quad (1)$$

where,  $\alpha$  is the cumulative upslope area of drainage through a point, and  $\tan \beta$  is the slope angle at that point. TWI was expected to be an important fire-promotion factor. The wind-effect map was constructed from three variables: DEM, wind direction (degree), and wind speed (m/s) in SAGA GIS ([http://saga.sourceforge.com/documentation/2.0.7pluspdfsg2/wind\\_\\_effect\\_8cpp\\_source.html](http://saga.sourceforge.com/documentation/2.0.7pluspdfsg2/wind__effect_8cpp_source.html)) (Pourghasemi et al. 2016). A plan curvature map was a secondary DEM feature generated in ArcGIS 10.6.1.

The locations of roads, rivers, and villages in Golestan Province were extracted from 1:25,000-scale topographical maps. Distances to roads, distances to villages, and distances to rivers were then determined in ArcGIS 10.6.1. Annual mean rainfall and annual mean temperature maps were acquired from the Golestan Meteorological Administration. Maps of each of these fire susceptibility effective factors are shown in Fig. 3.

## 2.3. Methodology

### 2.3.1. Fire Occurrence Detection

For fire susceptibility modeling, actual fire data in the study area is required. All of the fires that occurred in Golestan Province from 2002 to 2017 were obtained from a MODIS fire product. The MODIS hotspots have been used by many researchers for fire occurrence mapping (Chuvienco et al. 2008; Vadrevu et al. 2010; Eskandari et al. 2015b; Eskandari and Chuvienco 2015; Jolly et al. 2019; Adelabu et al. 2020; Eskandari et al. 2020). In this study, all MODIS fire products for Golestan were obtained from NASA (<https://modis.gsfc.nasa.gov/data/>). HDFView software (<http://hdfeos.org/software/heg.php>) was used

to detect the fire pixels (HDF-EOS to GeoTIFF Conversion Tool (HEG) 2017). The fire products were imported to HDFView and the position of fire pixels were detected. A map of the pixels that represented past fires was constructed in GIS. The fire pixels were divided randomly into two groups: 70% for training and 30% for validation of the fire susceptibility modeling results (Fig. 1b).

### **2.3.2. Importance of the Effective Factors for Fire Susceptibility Mapping**

Selection of the variables that serve as the most important fire location predictors is important for the creation of reliable maps generated by proper models. In this research, the importance of effective variables on fire susceptibility mapping was determined with the random forest (RF) algorithm (Leuenberger et al. 2013; Guo et al. 2017; Song et al. 2017). A multi-collinearity test for the effective factors was used to remove the highly collinear variables (Hsiao 2014; Daoud 2017). The multi-collinearity test is frequently used to detect spatial autocorrelation among independent (predictor) variables used to model the response variable (Daoud 2017) which in this study is fire susceptibility.

### **2.3.3. Fire Susceptibility Mapping by New and Ensemble Data Mining Models**

Four individual and ensemble data mining models – GAM, MARS, SVM, and GAM-MARS-SVM – were used to map fire susceptibility. The fire susceptibility maps were created in R 3.3.3 software. The GAM-MARS-SVM is a new combined model that is being used for fire susceptibility mapping for the first time. The data mining algorithms used in this study are explained below.

**2.3.3.1. Generalized additive model (GAM):** Generalized additive model (GAM) algorithm has been used to model danger and susceptibility for different phenomena. In this study, the GAM is used as a semi-parametric extension of fire effective factors and fire occurrence (Hastie and Tibshirani 1990). As the GAM model assesses the predictor's partial response curves with a non-parametric smoothing function instead of parametric function, it provides the potential statistical relationships between fire occurrence and the effective factors and yields the spatial patterns (Pourghasemi and Rahmati 2018). In current research, the “GRASP” (Generalized Regression Analysis and Spatial Prediction) package, developed by Lehmann et al. (2002), was used to run the GAM algorithm in R 2.0.7.

**2.3.3.2. Multivariate adaptive regression spline (MARS):** MARS algorithms are used to assess the relationships between input variables (effective factors on fire) and output variables (fire susceptibility potential) (Friedman 1991). This algorithm merges three techniques to form a new algorithm: mathematical spline construction, binary recursive partitioning (BRP), and linear regression (LR) (Friedman 1991). The resulting algorithm defines the relationships of an independent variable to the effective variables as either linear or non-linear (Hastie et al. 2001; Naghibi et al. 2018). In this study, the MARS algorithm was run by the “Earth” package (Milborrow et al. 2019) in R 3.0.2.

**2.3.3.3. Support vector machine (SVM):** The SVM algorithm is a non-linear and binary classification process that aims to determine the thresholds that divide a training sample into predefined classes. The optimum separation minimizes misclassifications that usually occur during training (Mountrakis et al.

2011). Traditional machine-learning algorithms usually attempt to limit empirical training errors and tend to overfit (Vapnik and Vapnik 1998; Xie 2006). The main benefit of SVMs is their ability to convert models and solve non-linear classification problems caused by a lack of prior knowledge of the modeling conditions. For this study, fire susceptibility modeling using SVM was performed with the “Kernlab” package (Karatzoglou et al. 2004) in R 3.0.2.

**2.3.3.4. GAM-MARS-SVM:** This new ensemble machine learning/data mining technique is applied here for the first time. We have assembled three famous algorithms according to their AUC values to map fire susceptibility. This process was accomplished with R 3.5.1 statistical software.

### **2.3.4. Validation of the Fire Susceptibility Maps**

Validation of fire susceptibility maps obtained from data mining models was performed with the AUC values extracted from ROC (Receiver Operating Characteristics) curve, a technique that is widely used for accuracy assessment of the classified maps generated by algorithms (Mas et al. 2013). An area of 1 represents perfect classification; whereas an area of 0.5 or less represents a worthless result (Yesilnacar 2005).

## **3. Results**

### **3.1. Importance of Effective Factors in Fire Susceptibility Mapping**

Importance of the effective factors in fire susceptibility mapping using the RF algorithm is shown in Fig. 4.

### **3.2. Multi-collinearity Analysis**

The results of the multi-collinearity test among effective factors are shown in Table 1. As a result of this test, the aspect factor was deleted from analysis because of collinearity with other factors. There is no multi-collinearity among the other effective factors as VIF is <5 and tolerance is >0.1 (O’Brien 2007)

**Table 1** Multi-collinearity test for effective factors on fire susceptibility

Factors	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	Beta			Tolerance	VIF
DEM	0.000	0.000	-.219	-12.887	0.000**	0.505	1.980
Rainfall	0.001	0.000	0.447	17.625	0.000**	0.226	4.432
River Distance	7.757E-5	0.000	0.049	3.448	0.001**	0.722	1.385
Road Distance	-1.036E-5	0.000	-0.081	-5.045	0.000**	0.559	1.789
Slope	-3.389E-5	0.000	-0.019	-1.240	0.215	0.630	1.587
Temperature	6.730E-6	0.000	0.004	0.294	0.768	0.720	1.388
TWI	0.003	0.002	0.016	1.197	0.231	0.859	1.164
Village Distance	-1.157E-5	0.000	-0.201	-12.125	0.000**	0.531	1.883
Plan Curvature	-0.001	0.000	-0.285	-11.254	0.000**	0.227	4.403
Wind Effect	0.005	0.000	0.0045	0.589	0.000**	0.347	0.215

\*\*Significant in 99% confidence level

### 3.3. Fire Susceptibility Maps in Golestan Province using Data Mining Models

The algorithm modeled Golestan fire susceptibility maps were classified into four categories (very low, moderate, high, and very high) using natural breaks (Jenks 1967; Osaragi 2008; Lin 2013; Pappas 2013) (Fig. 5). The respective areas of the four fire susceptibility classes generated by the data mining models are shown in Table 2.

**Table 2** Area of fire susceptibility potential classes by data mining models

Area of fire susceptibility classes	GAM (%)	MARS (%)	SVM (%)	GAM-MARS-SVM (%)
Low	40.82	39.19	46.57	42.69
Moderate	19.28	21.48	15.76	17.55
High	19.64	21.41	13.86	17.70
Very High	20.26	17.91	23.82	22.06
Total	100	100	100	100

### 3.4. Validation of Fire Susceptibility Maps by the AUC

Validation results of the fire susceptibility maps from the data-mining models are shown in Fig. 6 and Table 3.

**Table 3** Validation of fire susceptibility maps produced by the four models based on AUC

Models	Area	Standard Error	Asymptotic Significant	Asymptotic 95% Confidence Interval	
				Lower Bound	Upper Bound
GAM	<b>0.825</b>	0.009	0.000	0.809	0.842
MARS	<b>0.826</b>	0.009	0.000	0.809	0.843
SVM	<b>0.808</b>	0.009	0.000	0.790	0.826
GAM-MARS-SVM	<b>0.830</b>	0.008	0.000	0.814	0.847

## 4. Discussion

Considering the problem of increasing fires in Golestan Province, this research mapped fire susceptibility using GAM, MARS, SVM and GAM-MARS-SVM data-mining models. Results of the assessment of the importance of effective factors on fire susceptibility using the RF algorithm indicate that distance from nearest village, annual mean rainfall, and elevation were the most predictive of fire susceptibility.

Human activities have already been reported as a significant cause of fire occurrence in natural areas (Stolle et al. 2003; Martinez et al. 2009; Vadrevu et al. 2010; Zumbunnen et al. 2012; Pourghasemi 2016; Eskandari and Chuvieco 2015; Bowman et al. 2018; Eskandari et al. 2020). People are the main cause of wildland fires, whether intentionally or accidentally (Flannigan et al. 2000). Rural livestock are completely dependent on forestland in northern Iran. It is logical that distance from a village is a good predictor of fire occurrence in these forests. Other studies have also shown the role of rural settlements in wildfire promulgation around the world (Martinez et al. 2009; Vadrevu et al. 2010; Zumbunnen et al. 2012;

Eskandari and Chuvieco 2015; Bowman et al. 2018). Decreasing rainfall yields dying vegetation and desiccating fuels. Decreasing rainfall has already been reported as a major factor for rising fire occurrence in the northern forests of Iran (Khorasani Nejad 1995; Yousefi and Jalilvand 2010). The role of topography (mainly elevation) in fire occurrences has also been proven (Kushla and Ripple 1997; Butler et al. 2007; van Wagner 2011; Eskandari et al. 2020). Elevation is the third most important effective factor.

Annual mean temperature, wind effects, distances to roads, and slope angle were of medium importance to fire susceptibility. Previous studies have shown that annual mean temperature has a strong relationship with the number of fires in Golestan Province (Eskandari 2015). Furthermore, the proximity to roads has also been identified as important factor in fire susceptibility potential (Martinez et al. 2009; Narayanaraj and Wimberly 2011; Rodrigues et al. 2016; Eskandari and Miesel 2017; Ricotta et al. 2018; Eskandari et al. 2020). Wind effect has also been identified as an important effective factor in fire occurrence (Tymstra et al. 2007; Jolly et al. 2015; Pourghasemi et al. 2016). TWI, distances to rivers, and plan curvature were the factors of least importance to fire susceptibility. Therefore, using them for modeling is not recommended in future studies. Aspect was collinear with the other factors and was removed from further analysis.

Based on these results, human factors (distance to villages and distance to roads), climatic factors (annual rainfall mean, annual mean temperature, and wind effect), and topographic factors (DEM and slope angle), together dictate fire susceptibility in the forests and rangelands of Golestan Province. It has been confirmed based on other studies performed about fire danger mapping in natural areas of Iran (Eskandari and Chuvieco 2015; Eskandari et al. 2020). Therefore, it seems that appropriate predictor variables have been selected.

Among the data-mining models used, the GAM-MARS-SVM (AUC = 0.830) model had the highest accuracy in predicting locations of fire. MARS (AUC = 0.826), GAM (AUC = 0.825) and SVM (AUC = 0.808) were somewhat less accurate. Thus, the new ensemble GAM-MARS-SVM model provides for a somewhat more accurate fire susceptibility map than any of the individual data-mining models (MARS, GAM and SVM). The individual data mining algorithms have demonstrated effective natural hazard prediction capacities (Pourghasemi and Rahmati 2018; Pourtaghi et al. 2016; Eskandari et al. 2020). For example, SVM has been used for fire susceptibility modeling (Cortez and Morais 2007; Sakr and Elhadj 2010; Eskandari et al. 2020) and RF has also produced reliable fire susceptibility maps (Leuenberger et al. 2013; Guo et al. 2017; Song et al. 2017; Eskandari et al. 2020). However, ensemble data-mining algorithms, such as an ensemble RF-SVM model, have shown better results for fire susceptibility mapping than the individual data mining models alone (Gigovic et al. 2019).

The ensemble GAM-MARS-SVM algorithm used for the first time in this study generated very good results for fire susceptibility mapping in the study area. At present, application of ensemble data mining algorithms for fire susceptibility mapping is new and limited. The GAM-MARS-SVM algorithm is highly recommended for future efforts to map fire susceptibility in other fire-prone areas of Iran, such as in the Hyrcanian forests of Mazandaran and Giulan Provinces, as well as in other arid and semi-arid regions of

the world. The resulting fire susceptibility maps may provide helpful information to enable better prediction of future fires in the resource-rich forests and rangelands of these Provinces.

The spatial analysis of fire susceptibility obtained from ensemble data mining algorithm (GAM-MARS-SVM model) showed that the high and very high fire-danger classes have been located in the center of Province. The individual data mining algorithms (MARS, SVM and GAM models) created different spatial pattern of fire susceptibility. The important point is that high and very high fire susceptibility locations in the results of all of the models are located in the center of Province where the village and road densities are highest. This seems to reflect the important role that humans play in causing wildfires in the Province and this has been confirmed by others (Flannigan et al. 2000; Martinez et al. 2009; Zumbunnen et al. 2012; Lasslop and Kloster 2017; Bowman et al. 2018; Eskandari et al. 2020).

Analysis of fire susceptibility based on most accurate algorithm (GAM-MARS-SVM model) demonstrated that 42.69% of Golestan Province has low fire danger, 17.55% moderate danger, 17.70% high danger, and 22.06% by very high danger. Combined, 39.76% of the study area is high or very high fire potential. These parts should, therefore, be studied and managed to mitigate and prevent ignition and augmentation of fire potential. Proactive and protective management (especially against human activities) can reduce fires in the Province.

## 5. Conclusions

Results of this study show that distance from village is the most important factor in fire susceptibility in Golestan Province. Therefore, management to prevent fires in the Province should be focused in rural areas. The high precision of the GAM-MARS-SVM ensemble model suggests that fire susceptibility mapping will be enhanced by using it to forecast areas of high fire danger. Using this ensemble model, we find that 40% of the Province has high or very high fire risk. Therefore, the Province will very likely experience many fires in the future. The fire susceptibility map that the ensemble model produced can be very useful for creating and enhancing management strategies for preventing fires, particularly in the higher risk portions of Golestan Province.

## Abbreviations

AHP: Analytic Hierarchy Process

AUC: Area Under the Curve

ANN: Artificial Neural Networks

BRP: Binary Recursive Partitioning

DEM: Digital Elevation Model

GAM: Generalized Additive Model

LR: Linear Regression

MARS: Multivariate Adaptive Regression Spline

RF: Random Forest

ROC: Receiver Operating Characteristics

SVM: Support Vector Machines

TWI: Topographic Wetness Index

## Declarations

### Ethics approval and consent to participate

All authors approve the ethics and consent to participate in this research.

### Consent for publication

All authors have consent to publish this paper.

This manuscript doesn't contain data from any individual person: "Not applicable".

### Availability of data and materials

The datasets generated and/or analysed during the current study are not publicly available due [because this data is the results of author's efforts and studies] but are available from the corresponding author on reasonable request.

### Competing interests

This manuscript doesn't have competing interests: "Not applicable".

### Funding

This research has no funding.

### Authors' contributions

**Saeedeh Eskandari** collected the required data, prepared the input maps, conducted the research, and analyzed the data. She wrote the paper, as well.

**Hamid Reza Pourghasemi** conducted the research, analyzed the data, extracted the final map, and validated the results. He edited the paper, as well.

**John P. Tiefenbacher** edited the English, grammar, and writing elements.

# References

1. - Adelabu SA, Adepoju KA, Mofokeng OD (2020) Estimation of fire potential index in mountainous protected region using remote sensing. *Geocarto Int.* 1-18.  
<https://doi.org/10.1080/10106049.2018.1499818>
2. - Alonso-Betanzos A, Fontenla-Romero O, Guijarro-Berdinas B, Hernandez-Pereira E, Canda E, Jimenez J, Luis Legido J, Muniz S, Paz-Andrade C, Paz-Andrade MI (2002) A neural network approach for forest fire risk estimation, in: Van Harmelen F. (ed.), *Proceedings of the 15th European Conference on Artificial Intelligence*; France. ECAI Publisher. p. 643-647.
3. - Atesoglu A (2014) Forest hazard identifying. Mapping using satellite imagery-Geographic Information System and Analytic Hierarchy Process: Bartin-Turkey. *J. Environ. Protect. Ecol.* 15: 715-725.
4. - Barbero R, Abatzoglou JT, Steel EA (2014) Modeling very large fire occurrences over the continental United States from weather and climate forcing. *Environ. Res Lett.* 9, <https://doi.org/10.1088/1748-9326/9/12/124009>
5. - Beven KJ, Kirkby MJ (1979) A physically based, variable contributing area model of basin hydrology/Un modèle à base physique de zone d'appel variable de l'hydrologie du bassin versant. *Hydro. Sci. J.* 24: 43-69.
6. - Bowman MJSD, Moreira-Munoz A, Kolden CA, Chavez RO, Munoz AA, Salinas F, Gonzalez-Reyes A, Rocco R, de la Barrera F, Williamson GJ, Borchers N, Cifuentes LA, Abatzoglou JT, Johnston FH (2018) Human-environmental drivers and impacts of the globally extreme 2017 Chilean fires. *Ambio.* <https://doi.org/10.1007/s13280-018-1084-1>
7. - Butler BW, Anderson WR, Catchpole EA (2007) Influence of slope on fire spread rate, in: Destin, F.L. (ed.), *The Fire Environment-innovations, Management, and Policy (Conference Proceedings)*; USA. U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. p. 26-30.
8. - Chuvieco E, Congalton RG (1989) Application of remote sensing and geographic information systems to forest fire hazard mapping. *Remote. Sens. Environ.* 29: 147-159.
9. - Chuvieco E, Giglio L, Justice CO (2008) Global characterization of fire activity: towards defining fire regimes from earth observation data. *Glob. Change. Bio.* 14: 1488-1502.
10. - Cortez PG, Morais A (2007) A data mining approach to predict forest fires using meteorological data. *Proceedings of the 13th Portuguese conference on artificial intelligence*; Portugal. p. 512-523.
11. - Daoud JI (2017) Multicollinearity and regression analysis. *J. Phys: Conf. Series*, 949: 1-6.
12. - Dimitrakopoulos AP, Mitsopoulos ID (2006) *Global Forest Resources Assessment 2005- Report on Fires in the Mediterranean Region (Fire Management Working Papers)*. Rome: Food and Agriculture Organization of the United Nations Press.
13. - Eskandari S, Chuvieco E (2015) Fire danger assessment in Iran based on geospatial information. *Inter. J. Appl. Earth. Obs. Geoinf.* 42: 57-64.

14. - Eskandari S, Jalilvand H (2017) Effect of weather changes on fire regime of Neka and Behshahr forests. *Ir. J. For. Range. Protect. Res.* 15: 30-39.
15. - Eskandari S, Miesel JR (2017) Comparison of the fuzzy AHP method, the spatial correlation method, and the Dong model to predict the fire high-risk areas in Hyrcanian forests of Iran. *Geo. Nat. Haz. Risk.* 8: 1-17.
16. - Eskandari S, Oladi J, Jalilvand H, Saradjian MR (2015a) Prediction of future forest fires using the MCDM method. *Pol. J. Environ. Stud.* 24: 2309-2314.
17. - Eskandari S, Oladi J, Jalilvand H, Saradjian MR (2015b) Evaluation of the MODIS fire-detection product in Neka-Zalemroud fire-prone forests in Northern Iran. *Pol. J. Environ. Stud.* 24: 2305-2308.
18. - Eskandari S, Pourghasemi HR, Tiefenbacher JP (2020) Relations of land cover, topography, and climate to fire occurrence in natural regions of Iran: Applying new data mining techniques for modeling and mapping fire danger. *For. Ecol. Manag.* 473: 118338.  
<https://doi.org/10.1016/j.foreco.2020.118338>
19. - Eskandari S (2015) Investigation on the relationship between climate change and fire in the forests of Golestan Province, Iran. *Ir. J. For. Range. Protect. Res.* 13: 1-10.
20. - Eskandari S (2017) A new approach for forest fire risk modeling using fuzzy AHP and GIS in Hyrcanian forests of Iran. *Arab. J. Geosci.* 10: 1-13.
21. - Field RD, Spessa AC, Aziz NA, Camia A, Cantin A, Carr R, de Groot WJ, Dowdy AJ, Flannigan MD, Manomaiphiboon K, Pappenberger F, Tanpipat V, Wang X (2015) Development of a global fire weather database. *Nat. Haz. Earth. Sys. Sci.* 15: 1407-1423.
22. - Flannigan MD, Stock BJ, Wotton BM (2000) Climate change and forest fires. *Sci. Tot. Environ.* 262: 221-229.
23. - Friedman JH (1991) Multivariate adaptive regression splines. *Annu. Statis.* 19: 1-67.
24. - Gigovic L, Pourghasemi HR, Drobnjak S, Bai Sh (2019) Testing a new ensemble model based on SVM and random forest in forest fire susceptibility assessment and its mapping in Serbia's Tara. *Forests.* 10: 408, <https://doi.org/10.3390/f10050408>
25. - Golestan Natural Resources Administration (GNRA) (2015) Forestry Plan of Golestan Forests. Gorgan: Natural Resources and Watershed Administration of Golestan Province Press.
26. - Golestan Natural Resources Administration (GNRA) (2018) Statistics and Data of Fire in Golestan Province. Gorgan: Protection Unit of GNRA Press.
27. - Guo, F., Su, Zh., Tigabu, M., Yang, X., Lin, F., Liang, H., Wang, G (2017) Spatial modelling of fire drivers in urban-forest ecosystems in China. *Forests.* 8, 1-18.
28. - Hastie T, Tibshirani R, Friedman J (2001) *The Elements of Statistical Learning: Data Mining, Inference, and Prediction.* NewYork: Springer.
29. - Hastie TJ, Tibshirani R (1990) *Generalized Additive Models.* London: Chapman & Hall.
30. - HDF-EOS to GeoTIFF Conversion Tool (HEG) (2017) HDF-EOS Tools and Information System, <http://hdfeos.org/software/heg.php>

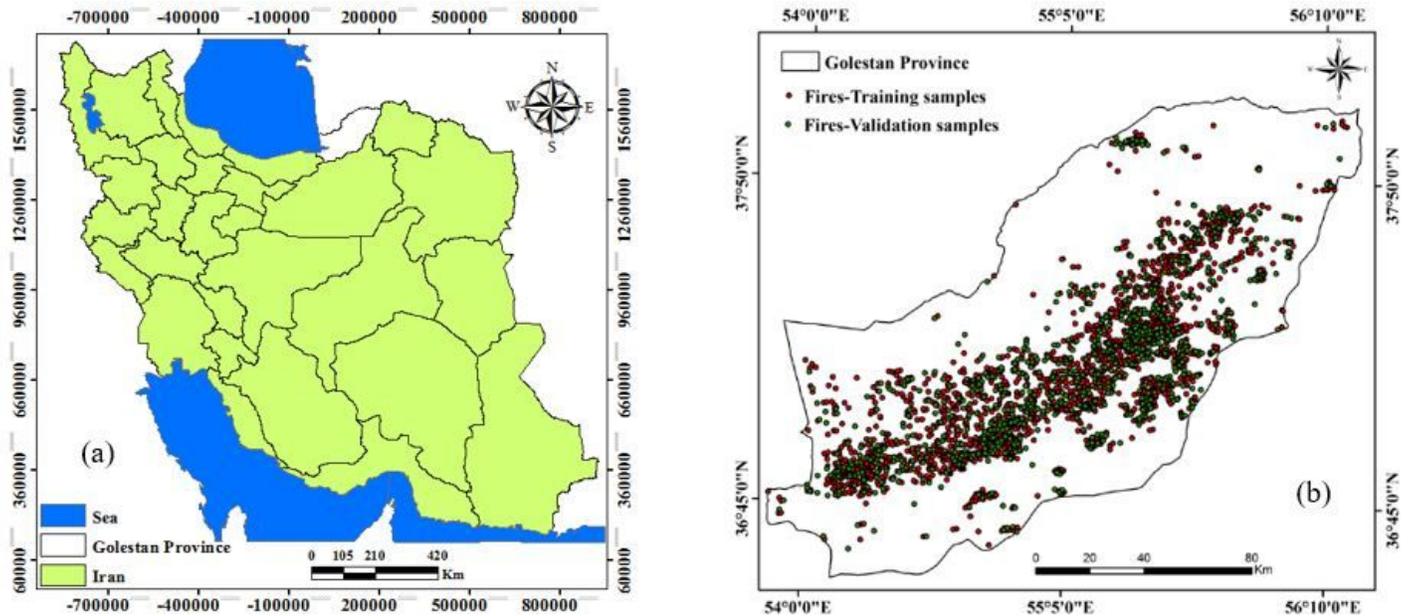
31. - Hsiao C (2014) Analysis of Panel Data. New York: Cambridge University Press.
32. - Jenks GF (1967) The data model concept in statistical mapping. *Int. Yrbook. Carto.* 7: 186-190.
33. - Jolly WM, Cochrane MA, Freeborn PH, Holden ZA, Brown TJ, Williamson GJ, Bowman DMJS (2015) Climate-induced variations in global wildfire danger from 1979 to 2013. *Nat. Commun.* 6: 1-11.
34. - Jolly WM, Freeborn PH, Page WG, Butler BW (2019) Severe Fire Danger Index: A Forecastable Metric to Inform Firefighter and Community Wildfire Risk Management. *Fire*. 2, <https://doi.org/10.3390/fire2030047>
35. - Jolly WM (2014) Assessing the Impacts of Recent Climate Change on Global Fire Danger. USDA Forest Service, Rocky Mountain Research Station, <https://www.fs.fed.us/rmrs/projects/assessing-impacts-recent-climate-change-global-fire-danger> (accessed January 2014).
36. - Jurdao S, Chuvieco E, Arevalillo JM (2012) Modelling fire ignition probability from satellite estimates of live fuel moisture content. *Fire. Ecol.* 8: 77-97.
37. - Karatzoglou A, Smola A, Hornik K, Zeileis A (2004) Kernlab: An S4 Package for Kernel Methods in R. *J. Statis. Soft.* 11: 1-20.
38. - Khorasani Nejad A (1995) Investigation of factors of fire in the Shastkalateh forest and methods of its control. Master thesis, Gorgan: Gorgan University of Agricultural Sciences and Natural Resources.
39. - Kushla JD, Ripple WJ (1997) The role of terrain in a fire mosaic of a temperate coniferous forest. *Forest. Ecol. Manag.* 95: 97-107.
40. - Lasslop G, Kloster S (2017) Human impact on wildfires varies between regions and with vegetation productivity. *Environ. Res. Lett.* 12, <https://doi.org/10.1088/1748-9326/aa8c82>
41. - Lehmann A, Overton M, Leathwick JR (2002) GRASP: generalized regression analysis and spatial prediction. *Ecol. Model.* 157: 189-207.
42. - Leuenberger M, Kanevski M, Vega Orozco CD (2013) Forest fires in a random forest. *Geophysical Research Abstracts*, Vol. 15, European Geosciences Union (EGU) General Assembly 2013; Vienna. p. 32-38.
43. - Lin Y (2013) A comparison study on natural and head/tail breaks involving digital elevation models. Bachelor thesis, Gavle, Sweden: Hogskolan I Gavle Universty, Departmnt of Indestrial Development.
44. - Martinez J, Vega-Garcia C, Chuvieco E (2009) Human-caused wildfire risk rating for prevention planning in Spain. *J. Environ. Manage.* 90: 1241-1252.
45. - Mas JF, Filho BSS, Pontius RG, Farfan M (2013) A suite of tools for ROC analysis of spatial models. *Int. J. Geo-Inf.* 2: 869-888.
46. - Mazandaran Natural Resources Administration (MNRA) (2017) Statistics and Data of Fire in Mazandaran Province. Sari: Protection Unit of MNRA Press.
47. - Milborrow S, Hastie T, Tibshirani R (2019) Package Earth: Multivariate Adaptive Regression Spline Models, version 5.1.1, License GPL 3, 51p, <http://www.milbo.users.sonic.net/earth>
48. - Mountrakis G, Im J, Ogole C (2011) Support vector machines in remote sensing: A review. *ISPRS J. Photog. Rem. Sen.* 66: 247-259.

49. - Mozaffarian V (2007) Dictionary of Iranian Plant Names Latin-English-Persian (Vol. I), 5th ed. Tehran: Moaser Publishing.
50. - Naghibi SA, Pourghasemi HR, Abbaspour K (2018) A comparison between ten advanced and soft computing models for groundwater qanat potential assessment in Iran using R and GIS. *Theat. Appl. Clim.* 131: 967-984.
51. - Narayanaraj G, Wimberly M (2011) Influences of forest roads on the spatial pattern of wildfire boundaries. *Int. J. Wild. Fire.* 20: 792-803.
52. - Nuthammachot N, Stratoulas D (2019) A GIS- and AHP-based approach to map fire risk: a case study of Kuan Kreng peat swamp forest, Thailand. *Geocarto Int.* 1-14.  
<https://doi.org/10.1080/10106049.2019.1611946>
53. - O'Brien RM (2007) A caution regarding rules of thumb for variance inflation factors. *Qual. Quant.* 41: 673-690
54. - Osaragi T (2008) Classification methods for spatial data representation. Research paper, University College London, Centre for Advanced Spatial Analysis, 20p.
55. - Pappas V (2013) Data classification methods in GIS, the most common methods. Research paper, University of Thessaly, Department of Planning and Regional Development, 10p.
56. - Pourghasemi HM, Beheshtirad M, Pradhan B (2016) A comparative assessment of prediction capabilities of modified analytical hierarchy process (M-AHP) and Mamdani fuzzy logic models using Netcad-GIS for forest fire susceptibility mapping. *Geo. Nat. Haz. Risk.* 7: 861-885.
57. - Pourghasemi HR, Rahmati O (2018) Prediction of the landslide susceptibility: which algorithm, which precision. *Caten.* 162: 177-192.
58. - Pourghasemi HR (2016) GIS-based forest fire susceptibility mapping in Iran: A comparison between evidential belief function and binary logistic regression models. *Scand. J. For. Res.* 31(1): 80-98.
59. - Pourtaghi ZS, Pourghasemi HR, Aretano R, Semeraro T (2016) [Investigation of general indicators influencing](#) on forest fire and its susceptibility modeling using different data mining techniques. *Ecol. Indic.* 64: 72-84.
60. - Ricotta C, Bajocco S, Guglietta D, Conedera M (2018) Assessing the influence of roads on fire ignition: does land cover matter? *Fire.* 1, <https://doi.org/10.3390/fire1020024>
61. - Rodrigues M, Jimenez A, de la Riva J (2016) Analysis of recent spatial-temporal evolution of human driving factors of wildfires in Spain. *Nat. Haz.* 84: 2049-2070.
62. - Rollins MG, Keane RE, Parsons RA (2004) Mapping fuels and fire regimes using remote sensing, ecosystem simulation and gradient modeling. *Ecol. Appl.* 14: 75-95.
63. - Sakr GE, Elhadj IH (2010) Artificial intelligence for forest fire prediction: a comparative study. *Proceedings of the Sixth International Conference on Forest Fire Research; Coimbra.* p. 653-661.
64. - Satir O, Berberoglu S, Donmez C (2016) Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem. *Geo. Nat. Haz. Risk.* 7: 1645-1658.

65. - Song Ch, Kwan M, Song W, Zhu J (2017) A Comparison between spatial econometric models and random forest for modeling fire occurrence. *Suscep.* 9: 1-21.
66. - Sowmya SV, Somashekar RK (2010) Application of remote sensing and geographical information system in mapping forest fire risk zone at Bhadra wildlife sanctuary, India. *J. Environ. Bio.* 31: 969-974.
67. - Stolle F, Chomitz KM, Lambin EF, Tomich TP (2003) Land use and vegetation fires in Jambi Province, Sumatra, Indonesia. *For. Ecol. Manage.* 179: 277-292.
68. - Tehrany MSh, Jones S, Shabani F, Martínez-Álvarez F, Bui DT (2018) A novel ensemble modeling approach for the spatial prediction of tropical forest fire susceptibility using LogitBoost machine learning classifier and multi-source geospatial data. *Theo. Appl. Clim.*  
<https://doi.org/10.1007/s00704-018-2628-9>
69. - Tymstra C, Flannigan MD, Armitage OB, Logan K (2007) Impact of climate change on area burned in Alberta's boreal forest. *Int. J. Wild. Fire.* 16: 153-160.
70. - Vadrevu KP, Eaturu A, Badarinath KVS (2010) Fire risk evaluation using multicriteria analysis, a case study. *J. Environ. Monit. Assess.* 166: 223-239.
71. - Vakalis D, Sarimveis H, Kiranoudis CT, Alexandridis A, Bafas GV (2004) A GIS based operational system for wildland fire crisis management, I. Mathematical modelling and simulation. *Appl. Math. Model.* 28: 389-410.
72. - van Bellen S, Garneau M, Bergeron Y (2010) Impact of climate change on forest fire severity and consequences for carbon stocks in boreal Quebec, Canada: a synthesis. *Fire. Ecol.* 6: 16-44.
73. - Van Wagner CE (2011) Effect of slope on fires spreading downhill. *Can. J. For. Res.* 18: 820-822.
74. - Vapnik VN, Vapnik V (1998) *Statistical Learning Theory*. New York: Wiley.
75. - Vasconcelo MJ, Silva S, Tome M, Alvim M, Perelra JMC (2001) Spatial prediction of fire ignition probabilities: comparing logistic regression and neural networks. *Photog. Eng. Rem. Sen.* 67: 73-81.
76. - Vasilakos C, Kalabokidis K, Hatzopoulos J, Matsinos I (2009) Identifying wildland fire ignition factors through sensitivity analysis of a neural network. *Nat. Haz.* 50: 125-143.
77. - Vitolo C, Giuseppe FD, Krzeminski B, San-Miguel-Ayanz J (2019) A 1980-2018 global fire danger re-analysis dataset for the Canadian Fire Weather Indices. *Scient. Data.* 6: 190032.
78. - Xie C (2006) *Support Vector Machines for Land Use Change Modeling*. Calgary: University of Calgary Press.
79. - Yesilnacar EK (2005) The application of computational intelligence to landslide susceptibility mapping in Turkey. Ph.D. thesis, Melbourne: University of Melbourne, Department of Geomatics.
80. - Yousefi A, Jalilvand H (2010) Investigation of fire situation in forest and pasture areas of Mazandaran Province (Basin of Sari Natural Resources Administration) from 2004 to 2007. *Proceedings of the Second International Conference on Climate Change and Tree Chronology; Gorgan.* p. 1-15.

81. - Zumbrunnen Th, Menendez P, Bugmann H, Conedera M, Gimmi U, Bürgi M (2012) Human impacts on fire occurrence: a case study of hundred years of forest fires in a dry alpine valley in Switzerland. *Reg. Environ. Change.* 12: 935-949.

## Figures



**Figure 1**

Locations of (a) Golestan Province in Iran and (b) past fires in Golestan Province for training and validation samples Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

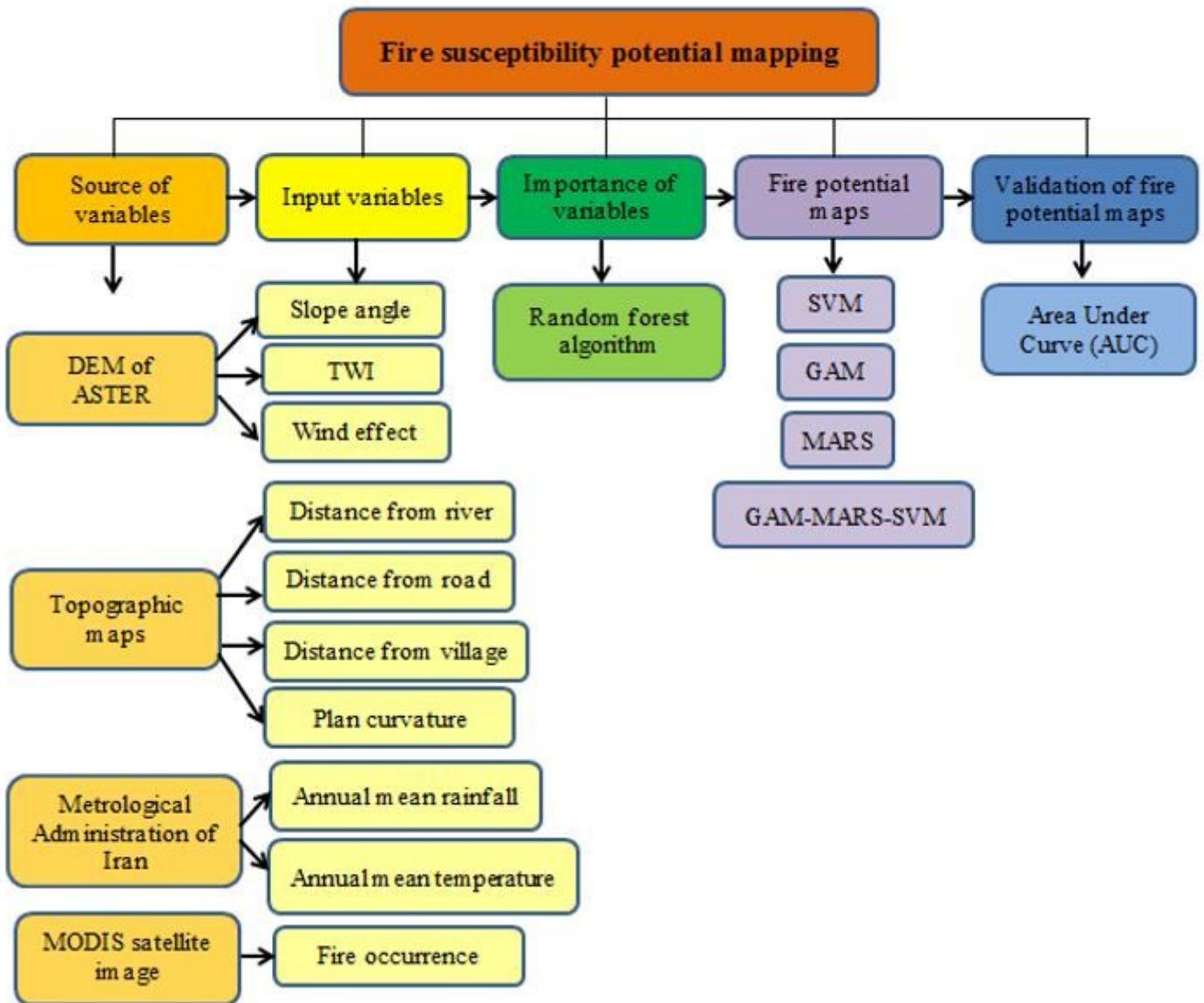
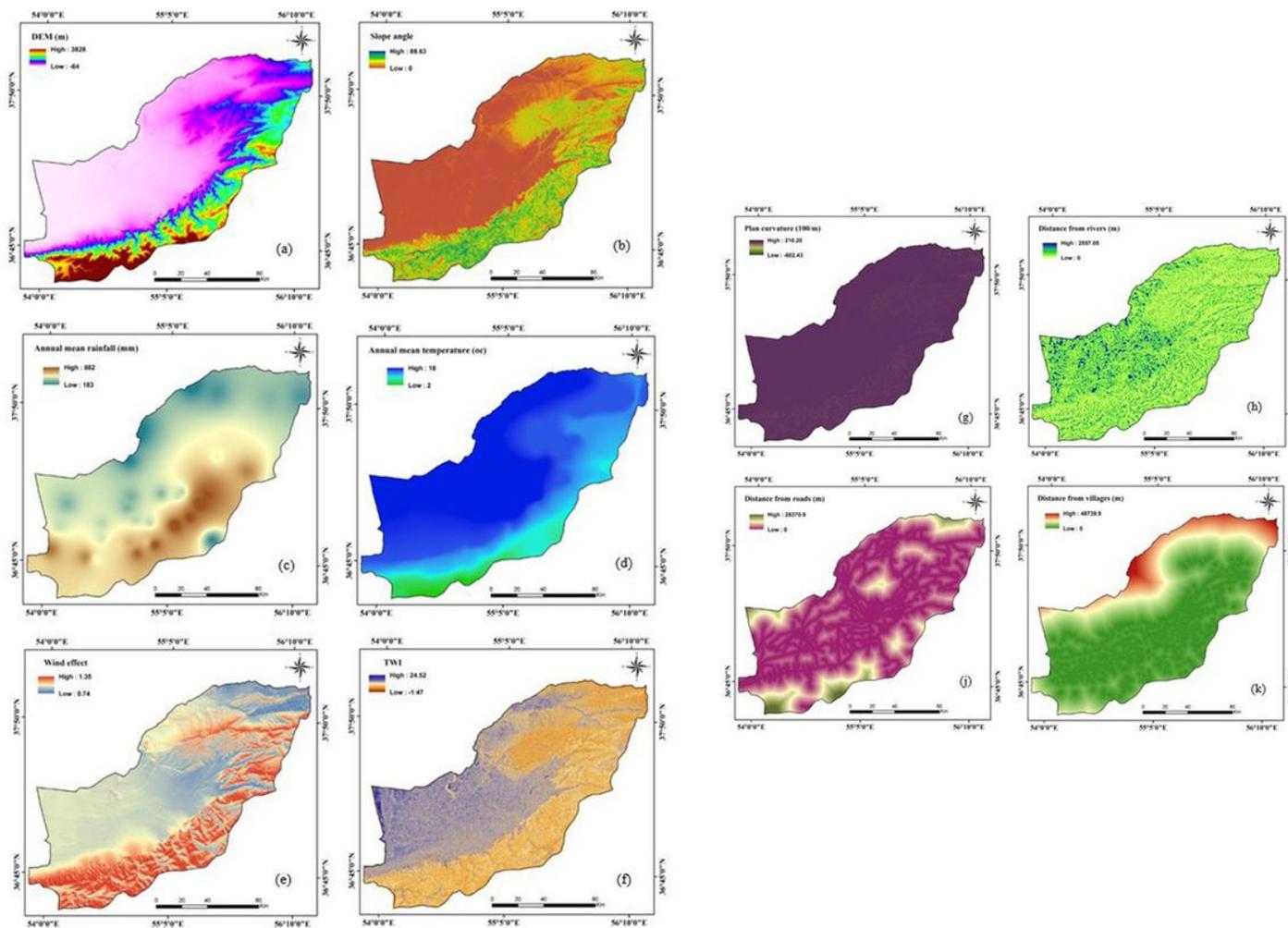


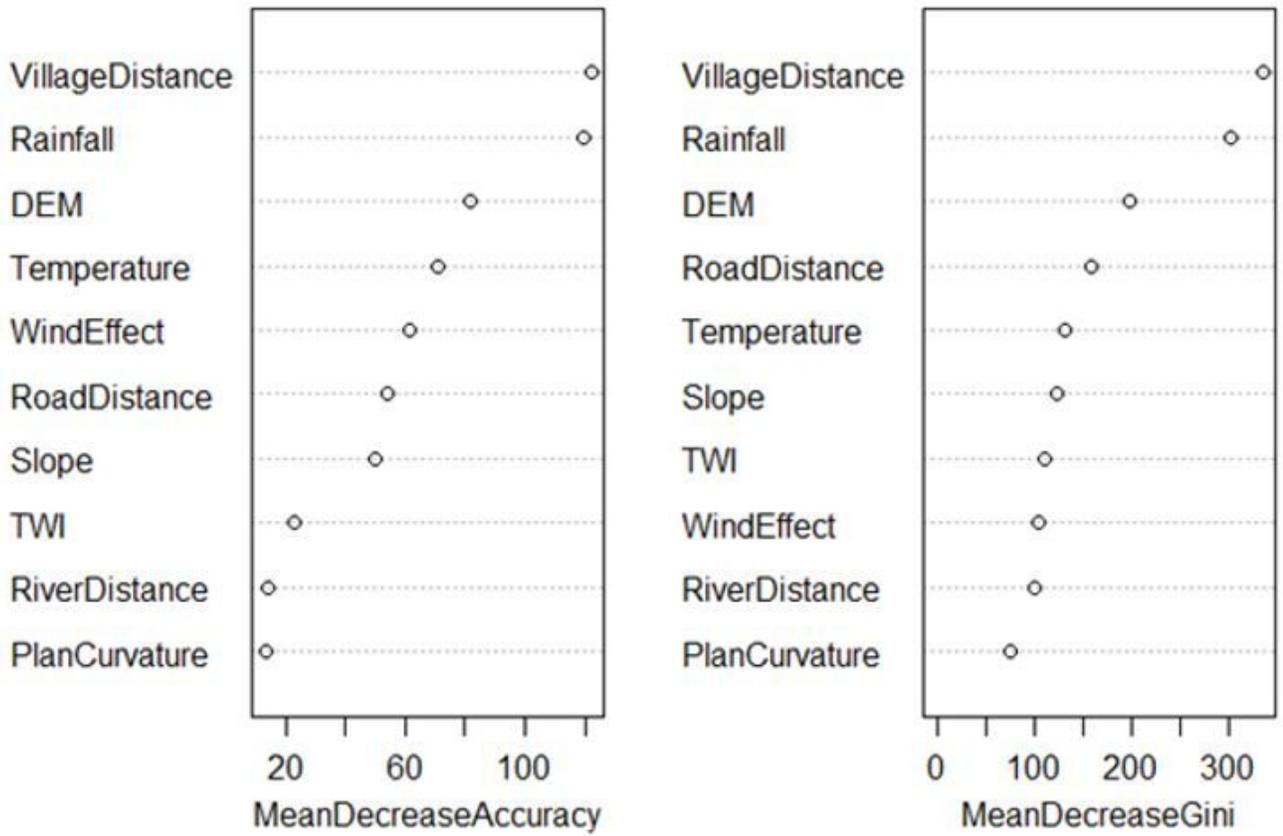
Figure 2

Flowchart of the current research



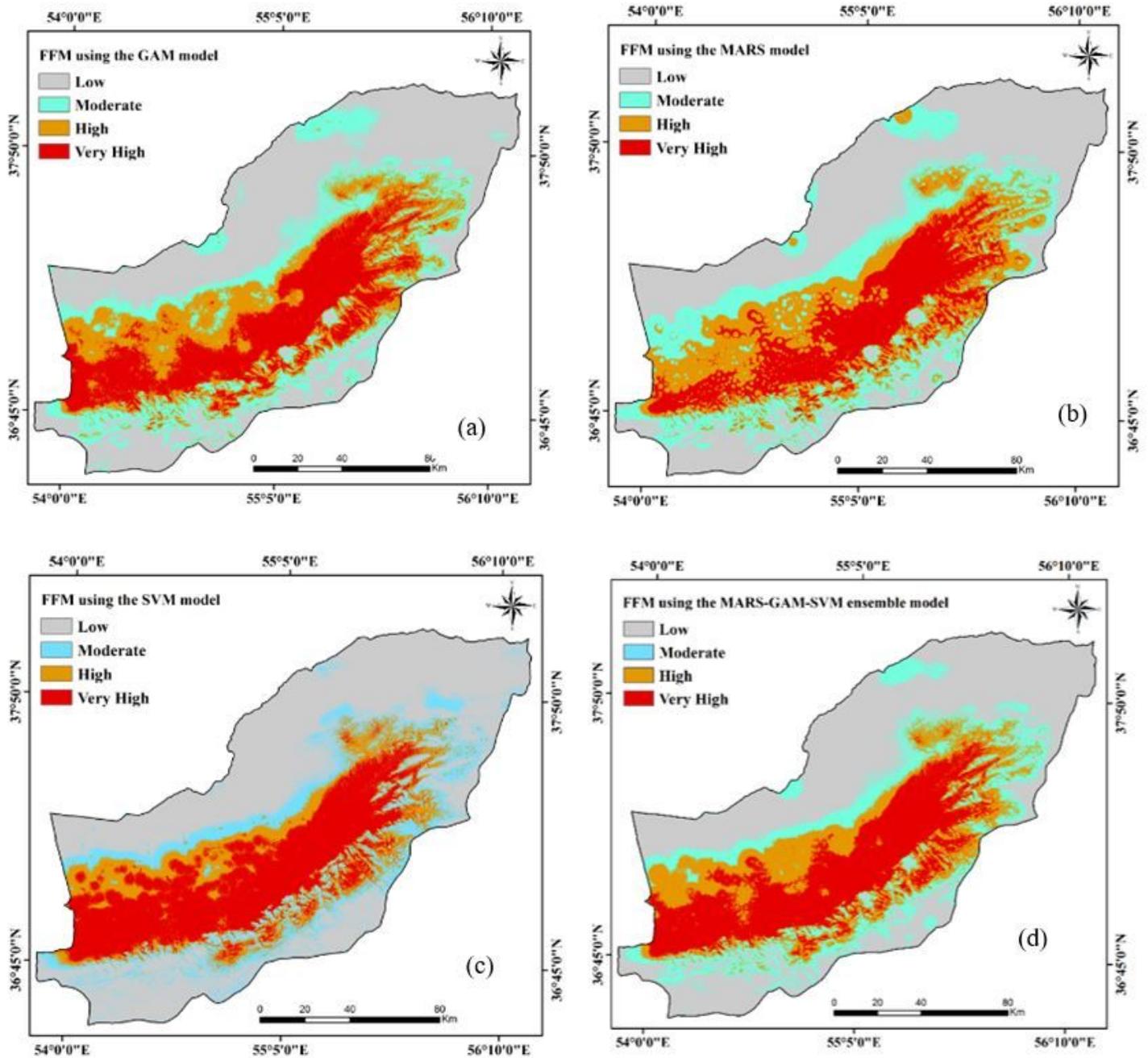
**Figure 3**

Maps of effective factors on fire susceptibility: a) Elevation, b) Slope angle, c) Annual mean rainfall, d) Annual mean temperature, e) Wind effect, f) TWI, g) Plan curvature, h) Distance to river, j) Distance to road, and k) Distance to village Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.



**Figure 4**

Importance of the effective factors in fire susceptibility mapping using RF algorithm



**Figure 5**

The fire susceptibility maps in Golestan Province using data mining models: a) GAM, b) MARS, c) SVM, and d) GAM-MARS-SVM. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

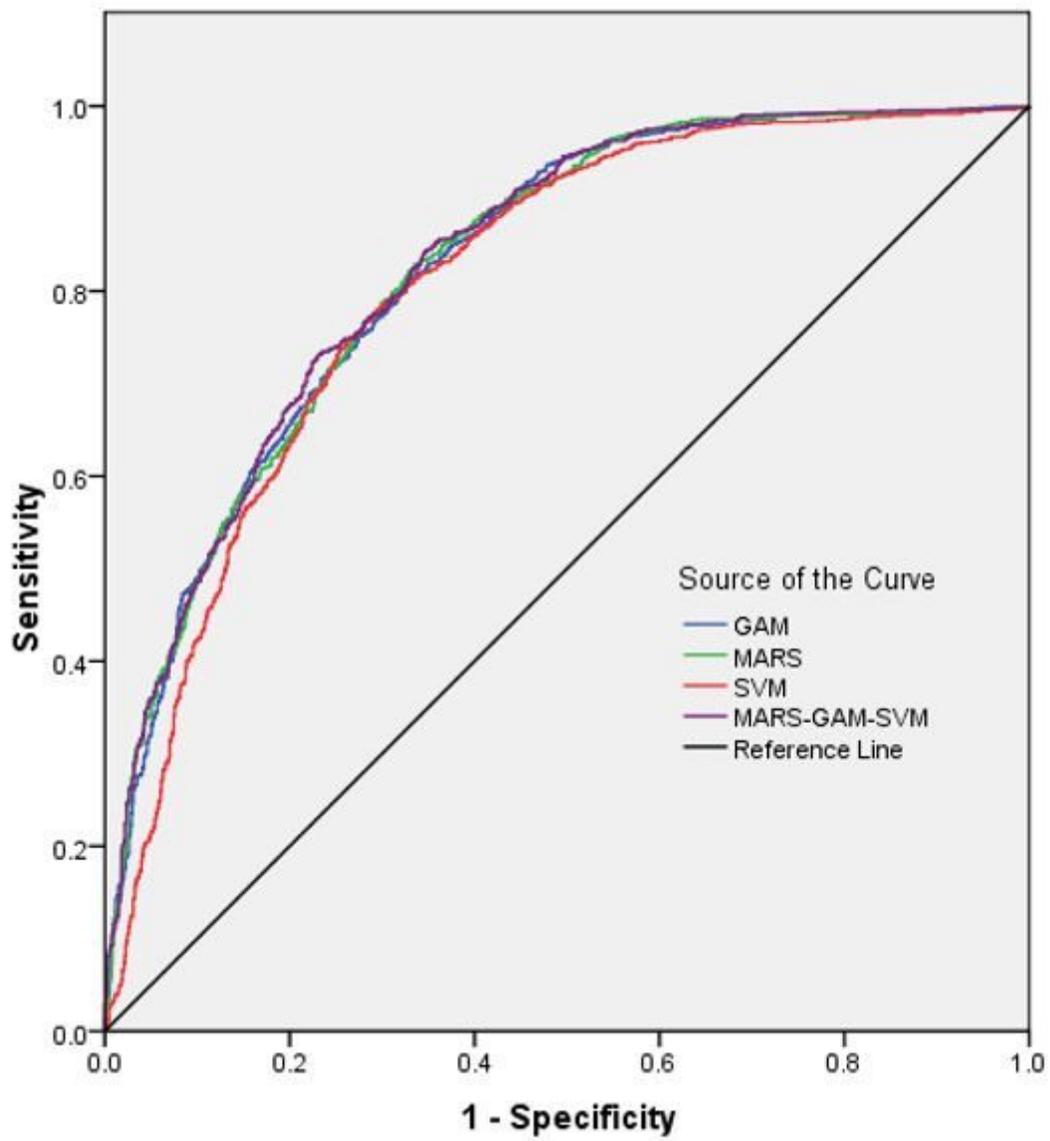


Figure 6

The ROC curve and the AUC values of four data mining models