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GIS-BASED FOREST FIRE SUSCEPTIBILITY ASSESSMENT BY RANDOM FOREST, ARTIFICIAL NEURAL NETWORK AND LOGISTIC REGRESSION METHODS

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The knowledge and prediction of spatial distribution of forest fire is essential for improving fire prevention strategies in forest areas. Forest fire susceptibility maps of the Babolrood Watershed in the Mazandaran Province of Iran were obtained from random forest, artificial neural network and logistic regression models. The important factors identified to affect forest fires include first and secondary topography, climate, vegetation cover and related human activities. Forest fire susceptibility maps were prepared using three models and the accuracy of the results was evaluated using validation datasets, kappa coefficient (K) and area under the receiver operating characteristic curve (AUC). All three methods produced forest fire susceptibility maps of reasonable accuracy; artificial neural network model with K = 0.61 and AUC = 0.88; random forest model with K = 0.64 and AUC = 0.93 and logistic regression model with K = 0.52 and AUC = 0.79. These results showed that the accuracy of forest fire susceptibility map obtained from the random forest method was slightly higher. According to the random forest results, 6.18% and 16.08% of the study area had very high and high potential for fire occurrence respectively. In general, the aforementioned methods can be applied for forest fire susceptibility mapping in forest areas with similar conditions.

Keyword: Ignition points, data mining, secondary topographic variables, accuracy assessment

INTRODUCTION

Fire plays an important role in natural lands especially in vegetation succession and landscape deformation (Hong et al. 2018). However, wildfires are one of the most devastating natural resource crises that endanger human life, damage forest resources and biodiversity, the atmosphere, financial resources and other environmental and recreational values. Forest fire has had widespread impacts in many countries around the world such as Indonesia, Brazil, Mexico, Canada, United States, France, Turkey, Spanish, Greece and Italy (Kanga et al. 2014, Astiani et al. 2018).

It was predicted that due to the continual occurrence of climate change the risk of forest fire will increase (Brown et al. 2017). Due to the multitude of forest fires, fire hazard zoning is an essential component in planning for the protection of forested areas (Chuvieco et al. 2014). The ability to predict the spatial distribution of fire is essential for improving fire prevention strategies and tactics. Recently, the spatial prediction of forest fire hazards became increasingly important to protect forest resources and fire management at different scales (You et al. 2017). It is important to develop appropriate and reliable forest fire susceptibility prediction models for forest management, the deployment of necessary facilities and a more appropriate fire prevention and response. Despite many progresses, it is still difficult to develop accurate prediction models for forest fires (Pettinari & Chuvieco 2017) because forest fire is a nonlinear and complex process influenced by many parameters. The occurrence of fire not only caused by combustion factors and biomass fuels, but also by weather and topography. Geographical Information System (GIS)-based forest fire susceptibility assessment could be used to develop forest fire hazard zoning maps that linked environmental factors to areas with the potential for forest fires, thereby enabling hazard potential mapping in different ecosystems (Helfenstein & Kienast 2014). Different regression models were proposed to predict the risk of forest fires such as geographically-weighted regression (Koutsias et al. 2010), logistic regression (Arndt et al. 2013), and linear regression (Oliveira et al. 2012). In recent years, machine learning algorithms such as neural networks (Satir et al. 2016) and random forests (Oliveira et al. 2012) have been considered for forest fire susceptibility assessment. However, the best method or technique for forest fire modelling is still debatable. Therefore, the comparison of methods and techniques to obtain appropriate conclusions for forest fire prediction is important and essential. Various studies had shown that vegetation, topography and climatic factors, and the use of fire history data were the most important variables in the modeling of forest fire susceptibility (Brown et al. 2017, Hong et al. 2018).

Literature review on forest fire research indicated that artificial neural network, random forest and logistic regression methods were used in many studies to map forest fire susceptibility. The main objective of this study was to apply these methods for the development of a conceptual scheme for the preparation of the forest fire susceptibility and fire progress potential map for Babolrood watershed in Mazandaran Province of Iran. The variables affecting forest fire susceptibility and fire progress potential were identified and their importance were evaluated using the three predictive models and compared for accuracy.

MATERIALS AND METHODS

Study area

Babolrood watershed (36° 02′–36° 22′ N and 52° 38′–52° 55′ E) with an area of 51725 ha is located in Mazandaran Province, a northern region of Iran (Figure 1). It has a mean annual temperature and rainfall of 14.1 °C and 782 mm, respectively and the climate type is semi-humid based on the Amberge climatic method. The study focused on the fire season from June to September between 2012 to 2019 when the mean monthly rainfall was 43.3 mm and mean temperature was 21.9 °C. The meteorological data were obtained from the Meteorology Office of Mazandran Province.

About 80% of the study area was covered by forests up to 2800 m above sea level. The forest consisted of temperate deciduous broadleaf with uneven-aged seed-borne structures. The dense forests covered up to about 1800 m above sea level. Plant species richness were high and includes alder, boxwood, hornbeam, sateplum, spruce, walnut, oak, elm and beech. At higher altitudes the lower quality beech forest was replaced by oak species. Data records were obtained from the Resource Management Center of Babolrood Watershed.

Data collection and preprocessing

Forest fire database

Figure 2 shows the study methodology within a framework. The forest fire inventory map of the study area was compiled using documentation from Natural Resources Office of Mazandaran Province, national reports and Moderate-Resolution Imaging Spectro Radiometer satellite images (http://earthdata.nasa.gov/firms). Multiple field surveys and screening processes were conducted to remove records with inaccurate locations. Detailed data showed that between 2012–2019, 297 notable forest fires represented in the ignition fire points vector format were recorded in the study area. The fire occurred during the dry season from late May to middle of October. According to Department of Natural Resources and Watershed Management data, 95% of the fires were human-caused factor. Forest fire locations were randomly divided into two datasets. Out of the 297 forest fire locations, 207 (70%) were used to prepare and operate the models and the remaining 90 (30%) were used to evaluate the accuracy of the models (Jaafari et al. 2017).

Fire ignition factors

Forest fires strongly depend on fire ignition factors such as topography (i.e. slope and aspect), fuel (i.e. vegetation or normalised difference vegetation index) and climate (i.e. temperature and rainfall) (Pourtaghi et al. 2016, Tien Bui et al. 2017). In the study, 22 factors were selected as study parameters. These independent variables were slope, slope aspect, elevation, plan curvature, profile curvature, effective air flow height, heat loading index, topographic position

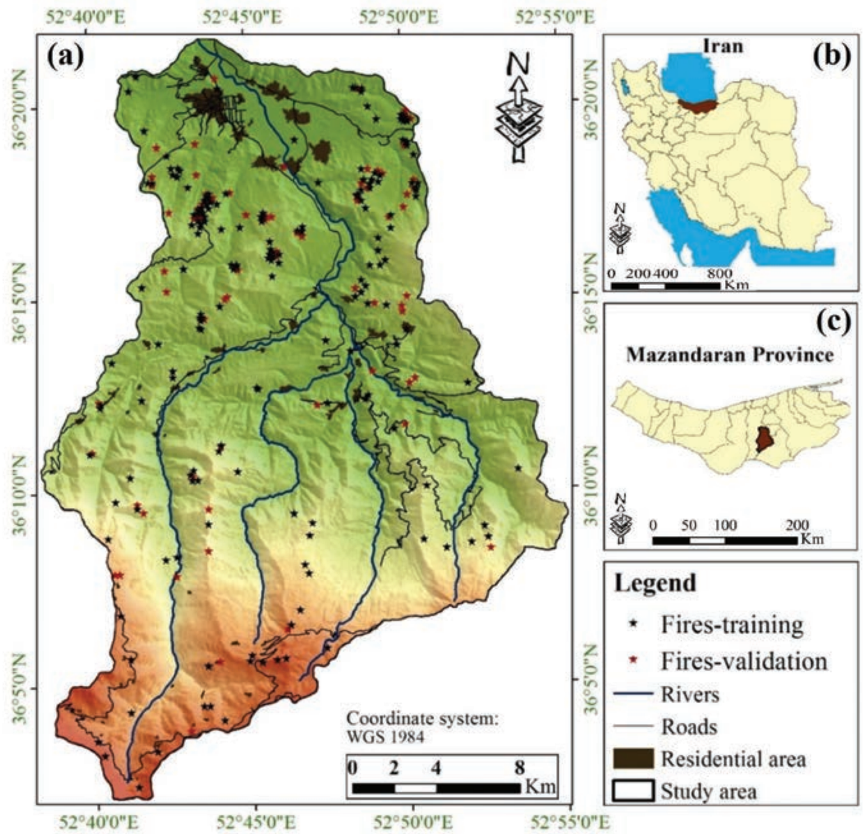


Figure 1 Maps of (a) Babolrood watershed for the case study (b) location of Mazandaran Province (shaded) in the northern region of Iran and (c) Mazandaran Province, with the watershed (shaded)

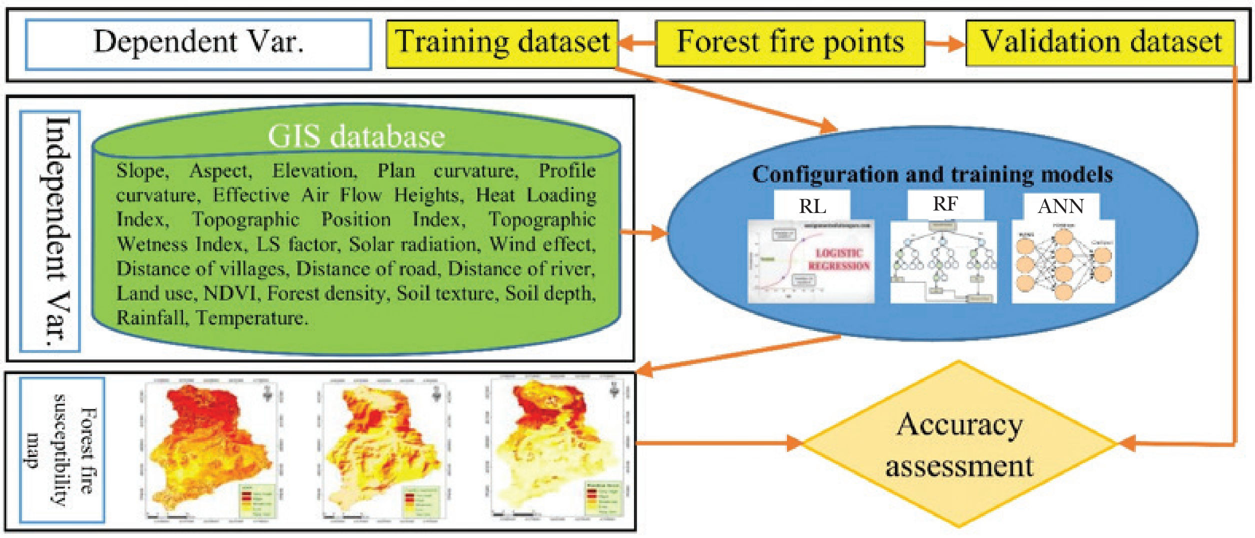


Figure 2 Methodological framework adopted for forest fire susceptibility mapping
LS = slope length and steepness, NDVI = normalized difference vegetation index, LR = logistic regression, RF = Random Forest, ANN = artificial neural network

index, topographic wetness index, slope length and steepness factor, solar radiation, wind effect, distance to villages, roads, and rivers, landuse/cover type, normalised difference vegetation index, forest density, soil texture, soil depth, rainfall and temperature.

Slope, aspect, elevation, plan curvature, profile curvature (Costa-Cabral & Burges 1994), heat loading index (McCune & Keon 2002), topographic position index (Guisan et al. 1999), effective air flow height, topographic wetness index, slope length and steepness factor, solar radiation and wind effect (Boehner & Antonic 2009) maps were extracted from a digital elevation model (DEM) with a 20 m^2 pixel size. The source of the DEM was from the digital contour data (10 m contour spacing) prepared by the National Cartographic Center using SAGA-GIS software. The normalised difference vegetation index (NDVI) is one of the indicators of vegetation conditions in each region and is calculated based on equation 1.

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{IR}) / (\mathrm{NIR} + \mathrm{IR}) \qquad (1)$$

where IR = reflectance measured in the visible region and NIR = reflectance measured in near-infrared region (Tien Bui et al. 2017).

The landuse/cover and normalised difference vegetation index maps were extracted from Landsat OLI satellite images of 7^{th} May 2018 of the United States Geological Survey archive (http://earthexplorer.usgs.gov). The initial satellite images were preprocessed through geometric and atmospheric corrections while the landuse/cover map of the study area were later prepared by classification process using the neural network classification method in IDRISI Selva software with an overall accuracy of 78.6%. Forest density and soil maps were collected from the Resource Management Center of Babolrood Watershed (2008).

For this study, the annual rainfall and temperature maps were prepared using the inverse distance weighted interpolation method in GIS (Hong et al. 2018) based on data from 16 meteorological stations in 1997–2016 from the Meteorology Office of Mazandaran Province. Road networks and villages were extracted from Google Earth and the proximity maps were produced by buffering villages and road segments using ArcGIS software. River networks were extracted from the digital elevation model and the map of proximity to rivers was produced by buffering river sections. Figure 3 shows maps of the independent variables. The average temperature of the study area ranged from 10.6–17.5 °C and average annual rainfall ranged from 555.0–1081.9 mm.

In order to better understand fire behaviour affected by the variables in the study, the descriptive statistics of the independent variables (Table 1) were examined in relation to fire location. In locations where fires occurred, the average elevation was about 710.21 m above sea level with a slope of 25.44%. Fires usually occurred further from the river and closer to villages and roads. Also in these areas, heat loading index, normalised difference vegetation index, wind effect index and temperature were higher while rainfall was lower.

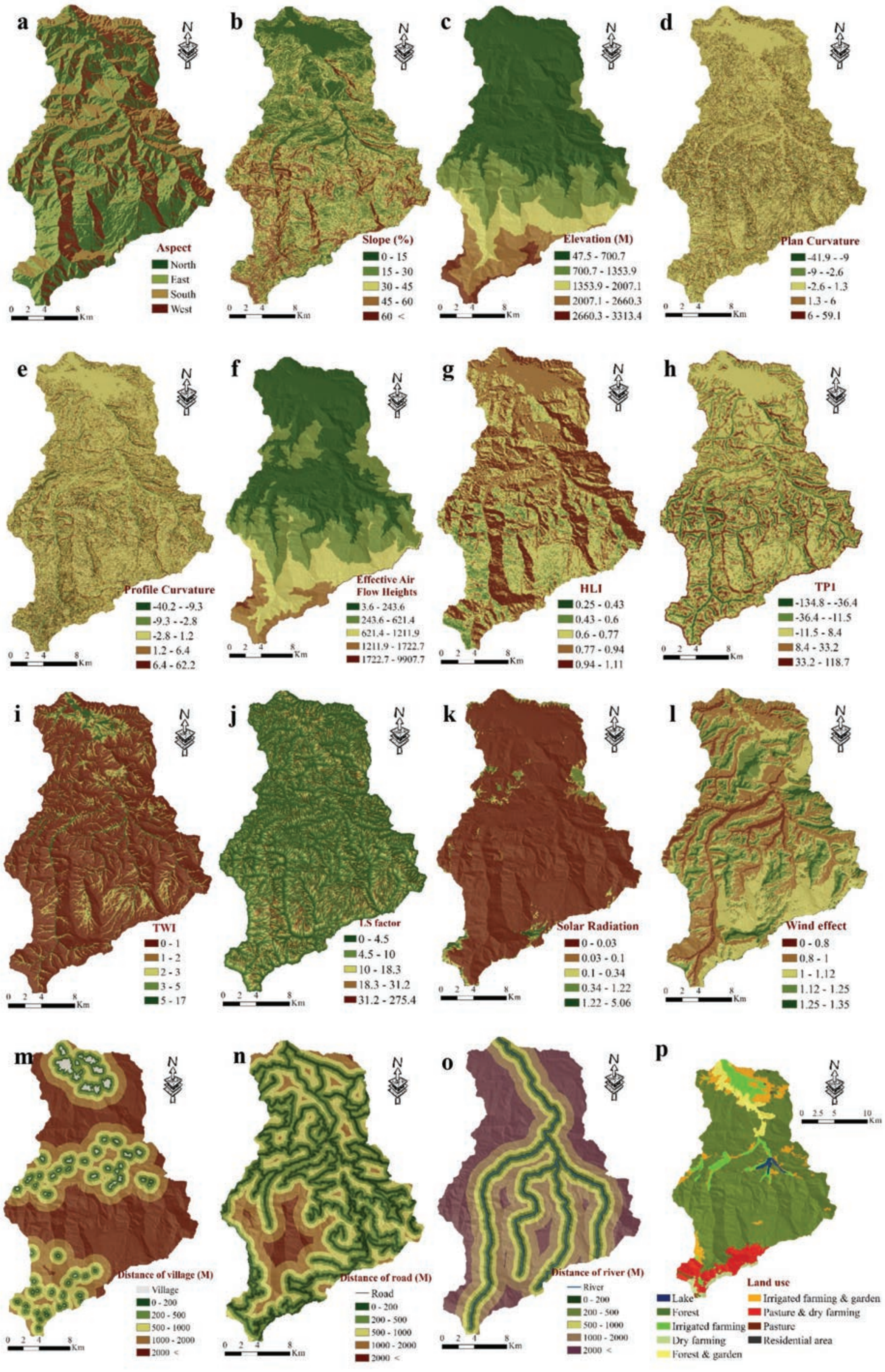
Method and models

In the artificial neural network method, the multilayer perceptron neural network (MLP-Net) structure was chosen to be utilised (Satir et al. 2016). Each MLP-Net consisted of input, hidden, and output layers, with an activation function connecting the input and hidden layers and a linear function connecting the hidden and output layers (Haykin 1998). The back-propagation algorithm was used because it was proven to work in complex real-world problems. The nonlinear sigmoid activation function was likewise chosen, with the number of neurons set at 22, learning rate of 0.2 and 1000 training iterations (Tien Bui et al. 2016).

Random forest is an ensemble learning technique which required two parameters for implementation based on the number of trees and the number of variables. It was suggested to pick a large number of trees and the square root of the dimensionality of the input space for the number of variables (Micheletti et al. 2014). For forest fire modelling, bootstrap subsets were generated from the training dataset, each subset was used to build an individual decision tree. In addition, 100 trees were used to ensure a stable result as suggested by Ghimire et al. (2012) and Stevens et al. (2015). The size of the decision tree was four including the root node and 11 nodes. Finally, the random forest model was formed by combining all decision tree classifiers.

In the logistic regression model, numbers close to 0 indicated a lower probability of occurrence and numbers near 1 indicated a higher probability of occurrence. The dependent variable (Y) was calculated using the following equation 2.

$$Y = \mathrm{Logit}\ (p) = \mathrm{Ln}\ (p / (1 - p)) = C_o + (C_1X_1) + (C_2X_2) + \ldots + (C_nX_n) \qquad (2)$$



a
Aspect
North
East
South
West
b
Slope (%)
0 - 15
15 - 30
30 - 45
45 - 60
60 <
c
Elevation (M)
47.5 - 700.7
700.7 - 1353.9
1353.9 - 2007.1
2007.1 - 2660.3
2660.3 - 3313.4
d
Plan Curvature
-41.9 - -9
-9 - -2.6
-2.6 - 1.3
1.3 - 6
6 - 59.1
e
Profile Curvature
-40.2 - -9.3
-9.3 - -2.8
-2.8 - 1.2
1.2 - 6.4
6.4 - 62.2
f
Effective Air Flow Heights
3.6 - 243.6
243.6 - 621.4
621.4 - 1211.9
1211.9 - 1722.7
1722.7 - 9907.7
g
HLI
0.25 - 0.43
0.43 - 0.6
0.6 - 0.77
0.77 - 0.94
0.94 - 1.11
h
TPI
-134.8 - -36.4
-36.4 - -11.5
-11.5 - 8.4
8.4 - 33.2
33.2 - 118.7
i
TWI
0 - 1
1 - 2
2 - 3
3 - 5
5 - 17
j
LS factor
0 - 4.5
4.5 - 10
10 - 18.3
18.3 - 31.2
31.2 - 275.4
k
Solar Radiation
0 - 0.03
0.03 - 0.1
0.1 - 0.34
0.34 - 1.22
1.22 - 5.06
l
Wind effect
0 - 0.8
0.8 - 1
1 - 1.12
1.12 - 1.25
1.25 - 1.35
m
Distance of village (M)
Village
0 - 200
200 - 500
500 - 1000
1000 - 2000
2000 <
n
Distance of road (M)
Road
0 - 200
200 - 500
500 - 1000
1000 - 2000
2000 <
o
Distance of river (M)
River
0 - 200
200 - 500
500 - 1000
1000 - 2000
2000 <
p
Land use
Lake
Forest
Irrigated farming
Dry farming
Forest & garden
Irrigated farming & garden
Pasture & dry farming
Pasture
Residential area
0 2 4 8 Km
0 2.5 5 10 Km
N

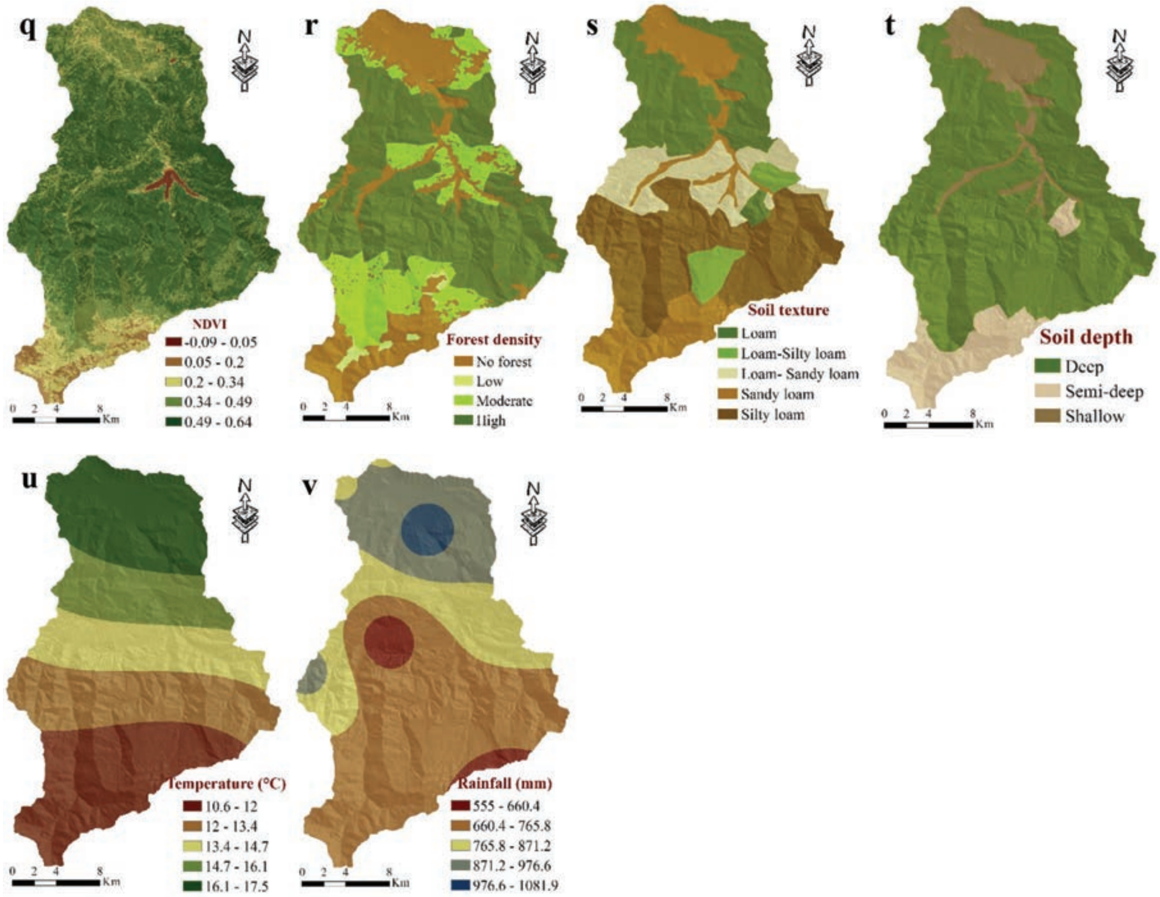


Figure 3 Forest fire variables: (a) aspect, (b) slope, (c) elevation, (d) plan curvature, (e) profile curvature, (f) effective air flow height (EAFH), (g) heat loading index (HLI), (h) topographic position index (TPI), (i) topographic wetness index (TWI), (j) slope length and steepness factor (LS factor), (k) solar radiation, (l) wind effect, (m) distance of villages (n) distance of roads (o) distance of rivers (p) land use, (q) normalized difference vegetation index (NDVI), (r) forest density, (s) soil texture, (t) soil depth, (u) temperature, (v) rainfall

Table 1 Descriptive statistics for the independent variables at fire location points

Variables	Average	Minimum	Maximum	Standard deviation
Aspect (°)	187.11	1.13	359.65	117.31
Distance to river (m)	6747.97	250.00	10000.00	4051.05
Distance to road (m)	859.49	25.00	1800.00	1603.86
Distance to village (m)	13902.52	48.00	2200.00	8814.21
Effective air flow height	318.34	6.36	1704.58	346.26
Elevation (m)	710.21	74.81	3011.40	663.06
Forest density	2.30	0.00	3.00	1.03
Heat loading index	0.82	0.41	1.10	0.12
Land use/cover type	2.80	2.00	5.00	0.94
Slope length and steepness factor	5.80	0.00	39.56	6.07
Normalized ifference vegetation index	0.51	0.27	0.58	0.06
Plan curvature	-0.30	-9.43	13.99	3.34
Profile curvature	-0.35	-14.43	13.35	3.72
Rainfall (mm)	842.78	635.77	1072.99	91.04
Slope (%)	25.44	1.30	84.74	14.68
Soil depth	1.12	1.00	3.00	0.38
Soil texture	1.66	1.00	4.00	1.02
Solar radiation	0.04	0.00	4.62	0.31
Temperature (°C)	16.16	11.71	18.43	2.00
Topographic position index	0.35	-64.39	91.11	22.55
Topographic wetness index	0.16	-3.12	9.38	1.77
Wind effect	1.09	0.74	1.34	0.15

where p = probability of the dependent variable, $(p/(1 - p))$ = odds ratio or probability, C_o = constant value or intercept, $(C_1, C_2, ..., C_n)$ = coefficients of the independent variables which represented the contribution of each independent variable to the probability value p, $(X_1, X_2, ..., X_n)$ = independent variables, e.g., slope, aspect, elevation. The importance of the variables $(C_1, C_2, ..., C_n)$ was determined by the training sample values entered into the regression model.

Pixel values of raster maps of the independent variables were extracted using Spatial Analyst Tools in ArcGIS 10.8 software and entered into Statistica 10 software along with the training data. The probability of fire occurrence was modeled using artificial neural network and random forest algorithms and the results were converted into a raster map in the GIS environment. Independent variables were entered into R software version 3.5.0 along with the training data to generate the logistic regression model of fire susceptibility and the modelling result was converted into a raster map. Finally, the results of the three methods were reclassified into 5 classes using the Jenks natural breaks method.

In machine learning, comparison of models should take into account the cost of error, thus the use of kappa coefficients (K) is recommended. Performances of forest fire prediction models were considered to be more realistic if their K values were closer to 1 (Thach et al. 2018). The area under the ROC curve was used to determine the accuracy of forest fire susceptibility mapping models (Sahana & Ganaie 2017). The area under the ROC curve values approaching 1 indicated an increasingly accurate model. In addition, the Wilcox and Pearson correlation tests were used to compare and quantify differences with regard to the spatial distribution of fire risk classes in forest fire susceptibility maps obtained from different methods.

RESULTS

Artificial neural network

Based on the forest fire susceptibility map obtained from the artificial neural network model (Figure 4 (a)), About 9.21% of the study area showed very high risk of fire occurrence and 10.11% of the study area showed very low risk of fire occurrence (Figure 5). Figure 4 (b) showed the root mean square error (RMSE) values in 1000 training iterations. The root mean square error decrased from iteration 14 to the lowest value at iteration 600, after which it remained unchanged.

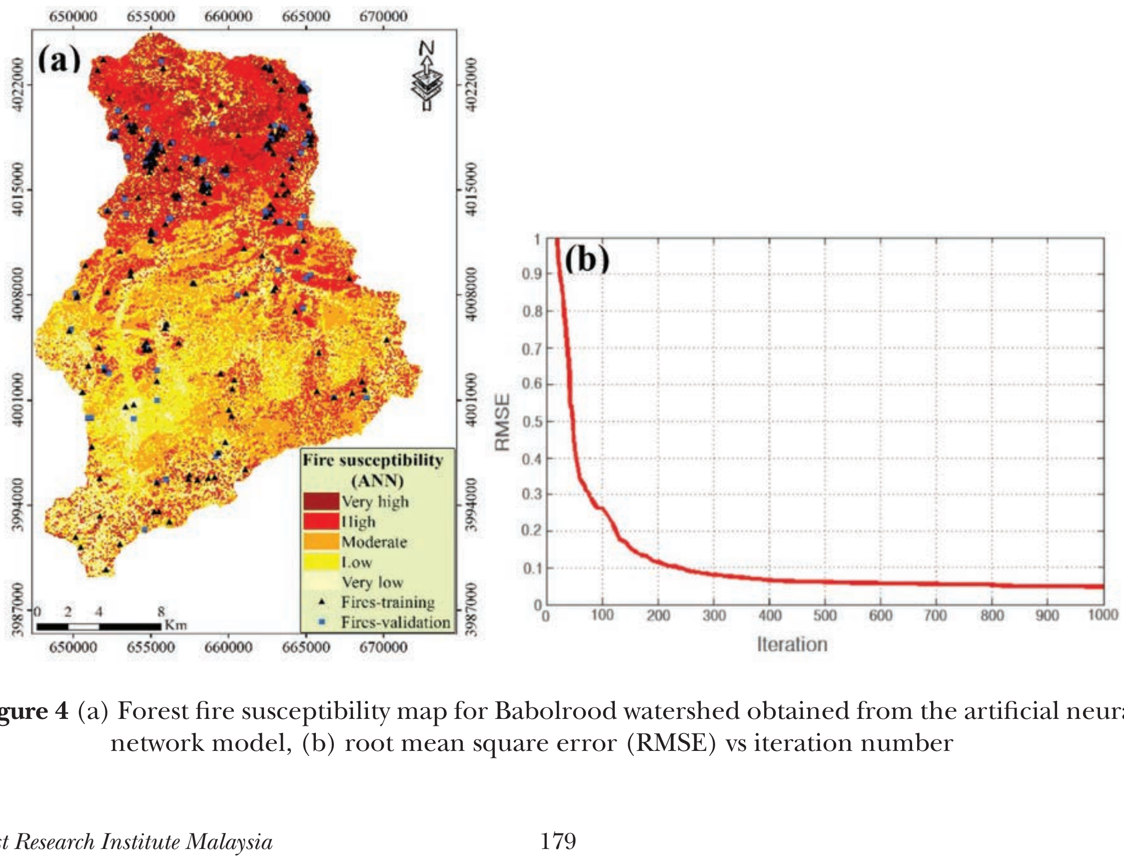


Figure 4 (a) Forest fire susceptibility map for Babolrood watershed obtained from the artificial neural network model, (b) root mean square error (RMSE) vs iteration number

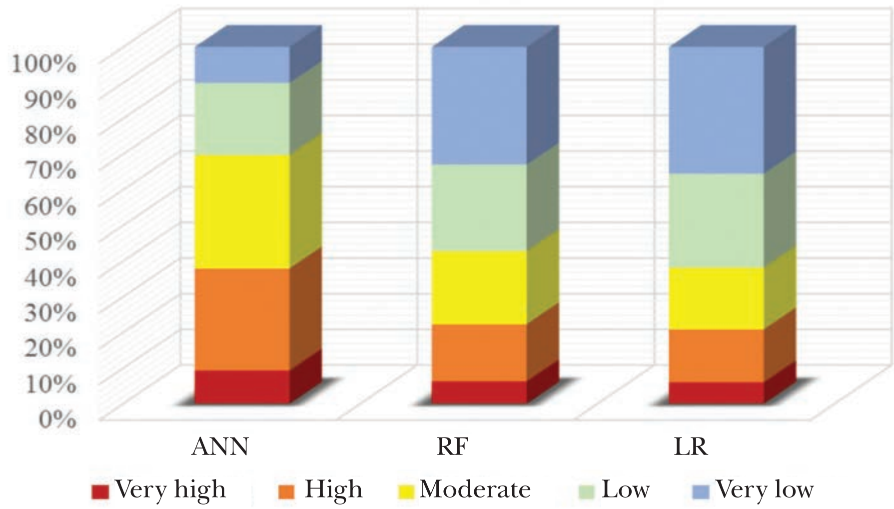


Figure 5 Spatial prediction of fire occurrence in relation to risk classification for three models ANN = artificial neural network, RF = random forest, LR = logistic regression

Random forest

Figure 6 showed the forest fire susceptibility map obtained from the random forest model. Based on the results, 6.18% of the study area showed very high fire potential and about 16.08% of the study area showed high potential (Figure 5).

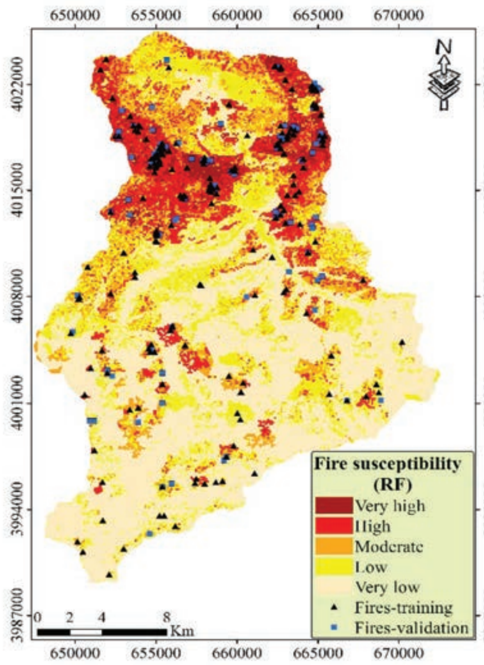


Figure 6 Forest fire susceptibility map for Babolrood Watershed obtained from the random forest model

Logistic regression

Temperature, heat loading index, topographic wetness index, rainfall and solar radiation, respectively, were the most important variables (Figure 8). The results of forest fire susceptibility map based on linear regression (Figure 7) showed that 5.92% of the study area had very high risk of fire occurrence and 14.90% of the study area had high risk (Figure 5).

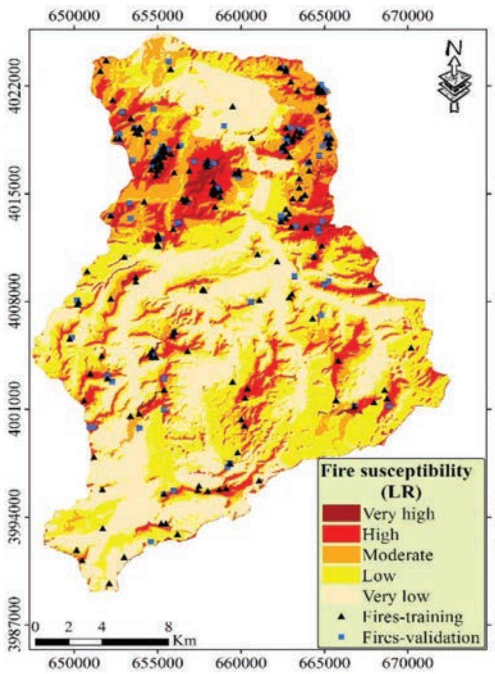


Figure 7 Forest fire susceptibility map for Babolrood Watershed obtained from the logistic regression model

Comparison of different models for fire susceptibility mapping

While the three models involved different internal algorithms for determining the importance of the independent variables, the models shared several same variables most important in mapping fire susceptibility (Figure 8).

In the random forest model, rainfall, temperature, landuse or cover, solar radiation and distance from villages were the most important variables in mapping fire risk. In the artificial neural network model, temperature, rainfall, distance from villages, heat loading index and landuse or cover were the most important variables while in the logistic regression model, the most important variables were temperature, heat loading index, solar radiation, topographic wetness index and rainfall. The positive or negative effects of these variables on fire occurrence were similar across the models.

In the artificial neural network model, a larger area was classified under very high and high risk of fire occurrence while the logistic regression model gave the smallest area under very high and high risk of fire occurrence (Figure 5). There was significant difference between forest fire susceptibility maps in the spatial distribution of fire risk classes (p = 0.001 for all three pairwise comparisons using Wilcox test). Correlation analysis between the three forest fire susceptibility maps showed significant correlation at the 0.01 level (Table 2). The map obtained from the random forest model was more than 59 and 43% similar with the maps obtained from the artificial neural network and logistic regression models respectively. The similarity of artificial neural network model

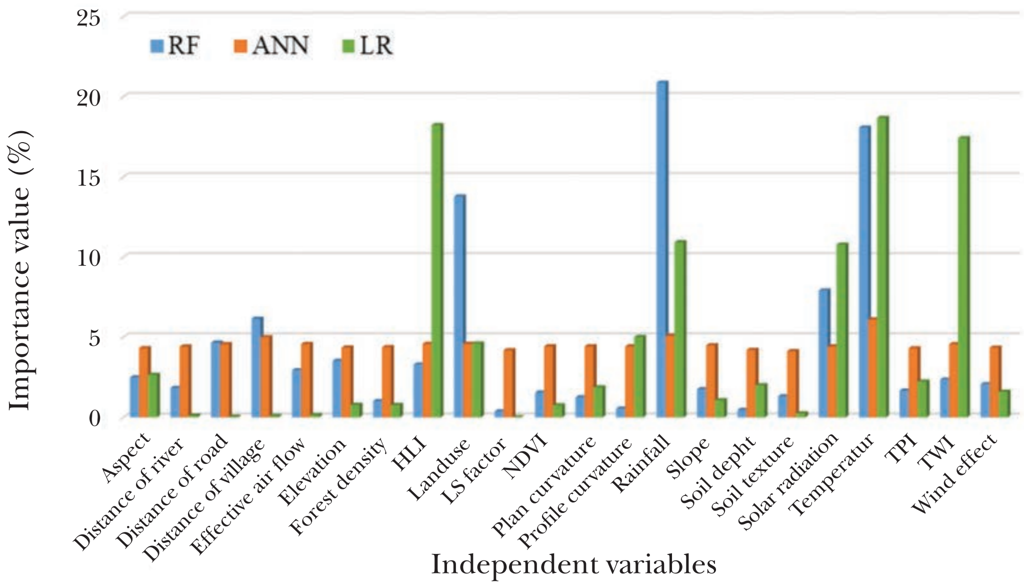


Figure 8 The importance of different variables in the three models of forest fire susceptibility mapping
RF = random forest, ANN = artificial neural network, LR = logistic regression

Table 2 Pearson correlations between forest fire susceptibility maps obtained from the random forest (RF), artificial neural network (ANN) and logistic regression (LR) models

	RF	ANN	LR
RF	1	0.594**	0.432**
		0.000	0.000
AN	0.594**	1	0.241**
N	0.000		0.000

** Correlation is significant at the 0.01 level (2-tailed).

results with logistic regression model results was 24%.

All the models had good predictive ability (Table 3), with the best being the random forest model (AUC = 0.93). Furthermore, the K value at 0.64 indicated a substantial agreement between observed and predicted fires. The artificial neural network model was second best in predictive ability (AUC = 0.88, K = 0.88) while the logistic regression model had fair predictive ability (AUC = 0.79, K = 0.52).

Table 3 The area under the ROC curve (AUC) and kappa coefficient for the three forest fire susceptibility models on the validation dataset

Model	Kappa coefficient	AUC
ANN	0.61	0.88
RF	0.64	0.93
LR	0.52	0.79

ANN = artificial neural network, RF = random forest, LR = logistic regression

DISCUSSION

The work involved comparative study of three data mining approaches, i.e. artificial neural network, random forest and logistic regression respectively for forest fire susceptibility and progress potential of fire mapping. One of the most important parts of this study was to determine the best variables for modelling fire occurrence. As reported by Randerson et al. (2006), temperature was one of the most important factors affecting fire occurrence. High temperatures increased evapotranspiration and humidity and thus increased the probability of fire occurrence (Gao et al. 2015). Rainfall conversely reduced the probability of fire occurrence by adjusting the amount of atmospheric and soil moisture. In the present study, the maximum risk of fire occurrence was found in areas with high temperature and low rainfall, which concured with findings from previous studies (Pourtaghi et al. 2016, Tien Bui et al. 2016, Tien Bui et al. 2017). High fire susceptibility could be attributed to environmental conditions such as high fuel loads and other fuel hazards that predisposed severe wildfires. The impact of human factors could be linked to the economic and social challanges faced by Iran's natural areas, including extreme dependence of the dwellers on these areas and population growth. Distance to roads and villages were also important forest fire susceptibility factors as deliberate fire were more likely to occur near roads and villages (Hong et al. 2017). Proximity to rivers and the resulting increase in tourist traffic increased forest fire susceptibility in other studies (Semeraro et al. 2016, Pourtaghi et al. 2016) but our regional surveys ruled out this factor for Babolrood Watershed. Conversely, increasing proximity to river could increase relative humidity, soil moisture, fuel moisture content and evapotranspiration thus reducing the probability of fire occurrence (Hong et al. 2018). Vegetative cover became fuel material for fire in dry and dense conditions. The normalised difference vegetation index and forest density as major factors in the fire regime related to tree cover contributed to fuel load variability (Holsinger et al. 2016). Topography affects fire behaviour (Adab et al. 2013, Pourtaghi et al. 2016). The positive correlation between slope and the probability of a fire occurrence in our study was in line with findings by Hong et al. (2018) and could be attributed to the greater fuel load higher up the slopes of the study area. Aspect factor was an important explanatory variable for fire occurrence in the Deccan Plateau in India where the drier, hotter and vegetation-sparse southern area was predicted to be at high risk (Prasad et al. 2008). Of the climatic, anthropogenic, vegetation and topographic factors influencing forest fire susceptibility, important secondary topographic variables had been identified and used (Pourtaghi et al. 2016, Hong et al. 2018, Sahana & Ganaie 2017). The findings from this study showed that heat loading index, solar radiation, topographic wetness index and wind effect were very important variables in all three models. The topographic wetness index had an impact on hydrological conditions and area fire susceptibility (Tien Bui et al. 2016). Heat loading index and solar radiation were indexes that expressed surface temperature as influenced by solar radiation (Hong et al. 2018).

Different testing models revealed some advantages and disadvantages that caused errors in the results. In these models, input data types, scales and local conditions might cause prediction errors. Therefore, comparing and using different data and new models would improve the efficiency of fire prediction and reduce uncertainties. The results of the forest fire susceptibility mapping were compared with the forest fire validation dataset to assess the spatiality of forest fires among the risk classes. While all the three methods produced forest fire susceptibility maps with acceptable accuracy the forest fire susceptibility map derived from the random forest method was more accurate than other methods. The good performance of the random forest model could be due to the fewer parameters required and easy determination of the parameters (Pal 2005). In addition, the algorithm used was a flexible method and could be improved by changing the number of trees and nodes to improve the result. The random forest model had many advantages over other multivariate regression or classification methods. There was no requirement for assumptions about the distribution of explanatory variables. It allowed the use of categorical and numerical variables briefly without reusing index variables, and showed interaction and nonlinearity between variables. Another advantage of the random forest algorithm was the determination of the significance for the input variables.

More than 22% of the study area was classified under high and very high risk of wildfires. It was evident that areas close to villages and roads with dense forest cover and the south and west slope aspect were more susceptible to fire. The forest fire susceptibility map prepared could be used by fire managers, forestry officials and emergency departments for designating and locating potential fire-susceptible area planning and allocation purposes, watch tower site selection and construction, firebreaks construction, resource allocation, fire control and management-related work.

CONCLUSIONS

The results of this study provided significant contribution to forest fire literature. The proposed conceptual scheme could be prescribed for other climate types, forest species, tree composition and percentage of crown cover throughout the world by selecting classification parameters and variables reflected in the local environment.

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