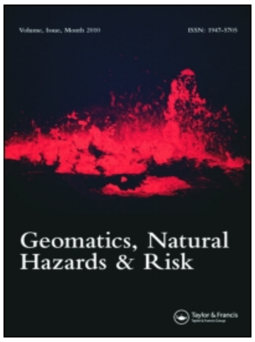

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Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem

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ABSTRACT

Forest fires are one of the most important factors in environmental risk assessment and it is the main cause of forest destruction in the Mediterranean region. Forestlands have a number of known benefits such as decreasing soil erosion, containing wild life habitats, etc. Additionally, forests are also important player in carbon cycle and decreasing the climate change impacts. This paper discusses forest fire probability mapping of a Mediterranean forestland using a multiple data assessment technique. An artificial neural network (ANN) method was used to map forest fire probability in Upper Seyhan Basin (USB) in Turkey. Multi-layer perceptron (MLP) approach based on back propagation algorithm was applied in respect to physical, anthropogenic, climate and fire occurrence datasets. Result was validated using relative operating characteristic (ROC) analysis. Coefficient of accuracy of the MLP was 0.83. Landscape features input to the model were assessed statistically to identify the most descriptive factors on forest fire probability mapping using the Pearson correlation coefficient. Landscape features like elevation ($R = -0.43$), tree cover ($R = 0.93$) and temperature ($R = 0.42$) were strongly correlated with forest fire probability in the USB region.

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KEYWORDS
Forest fire probability and hazard; landscape feature; weighting; artificial neural network; Mediterranean region; fire weather index

1. Introduction

Forest fires are one of the most detrimental environmental issues in the Mediterranean. Approximately 434,927 ha area was burnt in the Mediterranean region only in 2009 (JRC 2009). The loss of terrestrial vegetation implies a reduction in carbon fixation. Soil erosion increases, due to both loss of vegetation cover, which attenuates rainfalls and facilitates water percolation in the soil, and to the physicochemical alteration of the soil surface. For these reasons, prevention activities have become a major concern for policy makers, and in this context fire risk mapping is considered to be an important tool (Maffei et al. 2007).

Each annual fire-fighting season incurs significant costs, measurable principally in terms of loss of human life, investment in fire-fighting resources, damage to the environment and the cost of recuperating the affected areas. However, the costs and complications of fire fighting make it impractical to simultaneously maintain active fire-fighting units in various parts of a country. Recent years, therefore, have seen a number of technical developments in the field, aimed at improving communications networks, detection systems and fire prediction systems design. However, the diversity of

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environmental factors (vegetation type, climate, soil composition, topography, etc.) has limited adaptation of general solutions for specific regions or countries (Betanzos et al. 2003).

In the US fire community—the National Fire Danger Rating System (NFDRS), the occurrence of a spreading fire, or fire incidence, is literally termed "fire risk". Additionally, the NFDRS classifies two sources of fire risk: (1) lightning risk (LR) and (2) man-caused risk (MCR) (Hardy 2005).

In Eastern Mediterranean Region of Turkey, MCR is very important to assess the forest fire probability; on the other hand, it is not as important as sparsely populated regions of the world such as Amazon, Middle African or some part of the Australian forest lands. Each region must be evaluated separately according to the causes of fire, vegetation dynamics, climate conditions and physical environment structures for the accurate fire risk mapping.

Challenges in the study of fire probability estimation may not be amenable to conventional parametric statistical modelling. Fire weather indexes are commonly used by the scientists to define actual, seasonal and long-time forest fire hazard (McArthur 1966; Fosberk 1978). Fire weather indexes (FWI) are run by weather data (dry bulb temperature, humidity and wind speed, etc.) to calculate fire danger rating and fuel moisture content. Additionally, remotely sensed data such as normalized difference vegetation index (NDVI) time series and normalized difference water index (NDWI) were used to retrieve vegetation variables to evaluate fire hazard (Gabban et al. 2008; Maffei et al. 2007). Even if such techniques have good results, only climate or vegetation variables are not enough for forest fire hazard description alone in the regional scale. Multi-criteria evaluation techniques using GIS tools might be useful in multiple data assessment. However, weighting the inputs is major problem in such kinds of techniques because of subjective ranking (Jaiswal et al. 2002). Weight of evidence analyses can be used for weighting the input variables according to fire occurrence and location to solve this problem (Dickson et al. 2006). This analysis needs categorical inputs to determine the weights for each category. Limitation of this method is subjective to categorization such as how many categories are ideal for road density factor. Artificial neural networks provide a different alternative because these learning machines can act as universal approximators of complex functions. MLP networks can capture linear or nonlinear relationships between predictors and responses and learn about functional forms in an adaptive manner. Therefore, there are several studies performed on forest fire prediction systems using forest fire databases based on non-parametric models. These models can utilize machine learning approaches such as artificial neural network, support vector machine and fuzzy techniques to predict burnt area size (Ozbayoglu & Bozer 2011; Cortez & Morais 2007) and these techniques are very useful to define forest fire probability especially for simulating the fire behavior prediction using only meteorological data. Considering the literature MLP technique may be successful to predict forest fire probability using climate, physical and anthropogenic data together in the regional scale.

In this study, we investigated the performance of MLP architectures using back propogation algorithm. Similar techniques can be run using non-categorical input data and, the neural networks are fitted to data in the training set, with the connection strengths and biases modified iteratively. All input factors were selected according to fire causes, physical structure, vegetation cover and climate conditions of Upper Seyhan Basin (USB) in the Eastern Mediterranean Region of Turkey using spatial fire history data (fire locations and fire magnitude).

The objectives of this research were to: (1) produce a reliable forest fire hazard map in the regional scale with a high spatial resolution (30 m) using remote sensing and GIS techniques; (2) to evaluate the predictive ability of fully connected MLP neural network in terms of mapping the forest fire hazard; (3) detect the relationships between forest fire risk and landscape features; (4) create a layout to assess environmental risks on USB for decision makers.

2. Study area and data

Upper Seyhan Basin is located on the Taurus Mountain chain in the Eastern Mediterranean Region of Turkey (Figure 1).

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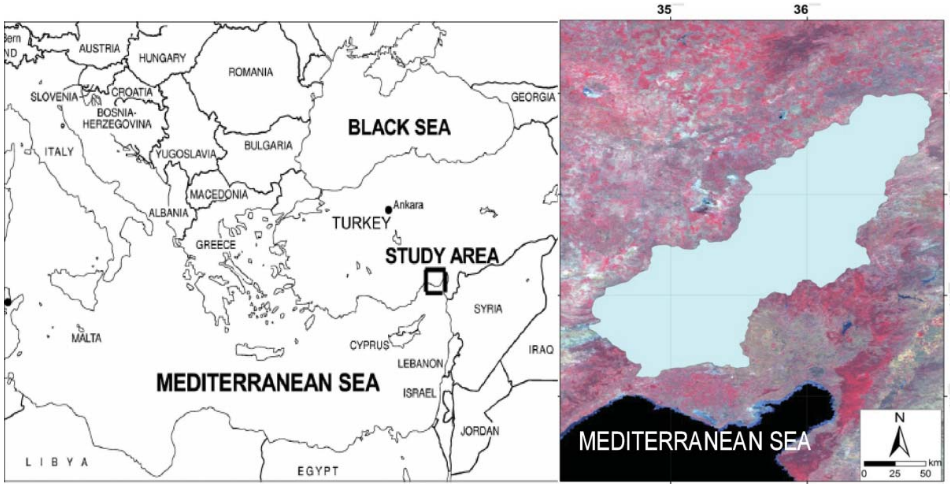

Figure 1. Study area location.

The region covers approximately an area of 21,641.69 km^2 and comprises pure and mixed conifer forests. These forests are recognized as a Mediterranean evergreen cover type (Koppen 1931) and estimated to be approximately 100 yr old from tree cores. Dominant tree species are Crimean pine (*Pinusnigra*), Lebanese cedar (*Cedruslibani*), Taurus fir (*Abiescilicica*), Turkish pine (*Pinusbrutia*) and juniper (*Juniperusexcelsa*) (Davis 1965; Berberoglu & Satir 2008). The prevailing climate is Mediterranean, characterized by mild and rainy winters, hot and dry summers. The total annual rainfall is approximately 800 mm. Rainfall is variable in amount and timing in that 75% of rainfalls mainly during the autumn and winter. The mean annual temperature between 1990 and 2005 was 19 °C, with mean minimum and maximum temperatures of 8 °C in January and 30 °C in July, respectively (TSMS 2005). The dominant soils of the forest stands are classified as Lithic Xerorthent of Entisol and developed on fluvial and lacustrine materials during the Oligocene Epoch (Soil Survey Staff 1998).

Five major data types were used in this study: (1) fire history (location and magnitude of forest fires), (2) climate data (humidity, dry bulb temperature, and wind speed), (3) anthropogenic data (roads, settlements and farmlands), (4) digital elevation model (DEM) and (5) percent tree cover (Table 1).

Table 1. Modeling dataset characteristics.

Data	Source	Method	Output
Climate Relative Humidity (%) Temperature (°C) Wind speed (km/h)	State Meteorological Works (45 climate stations)	Kriging interpolation method with 30 m resolution	*F* index (Fire Weather Index)
Anthropogenic Road maps Settlement locations	Regional Directorate of Forestry (Vector format)	Euclidian Distance	Distance from roads Distance from settlements Distance from farmlands
Farmlands	Berberoglu et. al. (2009)		
Topographic Data DEM	Aster GDEM 30 m		Digital Elevation Map of USB
Vegetation Data Tree cover	Landsat ETM and Ikonos	Regression tree	Percent Tree canopy
Fire Data Fire locations Fire magnitudes	Regional Directorate of Forestry	GIS mapping	Training and testing dataset for fire risk assessment

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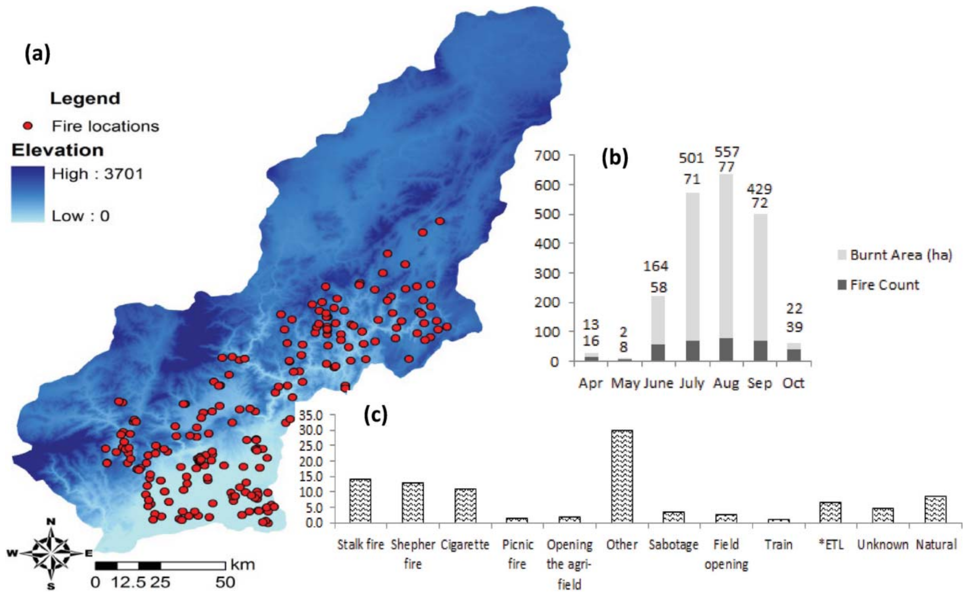

Figure 2. (a) Fire locations used for testing and training, (b) seasonal fire count and total burnt area, and (c) percentage of the fire reasons vs. fire count.

2.1. Fire history data

Five year (2004–2009) fire information and history dataset was received from Government Regional Forest Directorate (GRFD). This dataset contains fire geographical location, fire magnitude and monthly total fire occurrence at each fire season and yearly forest fire causes (Figure 2). This dataset was used for training and testing. Fire occurrence number, causes and locations were evaluated with landscape features.

2.2. Climate data

Long-term time series climate data from 1975 to 2010 were used. Dry bulb temperature, relative humidity and maximum wind speed of fire season (April to October) were obtained from 45 Government Meteorological Works stations (GMWS), which were located in and around the study area. Climate data were interpolated using the kriging method. Fire Index (*F* index) was derived from this dataset.

2.3. Anthropogenic data

One of the major effects on forest fire is the human activities such as picnic fire, stalk fire, cigarette, electric transportation lines (ETL), etc. (Figure 2). Roads, farmlands and settlements are the essential factors to evaluate man-caused risk (MCR). Detailed road (main roads, village roads, forest roads) and settlement location maps were provided by the GRFW. However, farmland locations were derived from previous works for the study area by Berberoglu, Gultekin, et. al. (2009a) with a 30 m spatial resolution.

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Distance measures the Euclidean, as the crow flies, distance between each cell and the nearest set of target features. Euclidean distance from roads, settlements and farmlands were produced as inputs to assess anthropogenic effects.

2.4. Elevation and tree cover data

Aster GDEM data were used as elevation data. The highest altitude is 3701 m, at the same time this in the study area and also in the Taurus mountain range. Weather conditions, forest cover and type, human population density and oxygen level are based on elevation.

Tree cover data produced using multi-temporal Landsat ETM (30 m spatial resolution) and Ikonos (1 m spatial resolution) images using the regression tree (RT) method. Testing and training pixels were selected from high-resolution Ikonos image and Landsat ETM data were used to derive percent tree cover using the RT method.

3. Methods

In this study, the method consisted of three main stages; (1) deriving input features, (2) mapping forest fire hazard using MLP, and (3) relative operating characteristic (ROC) analyses for accuracy assessment.

3.1. F (fire weather index)

Fire danger index introduced by Sharples et al. (2009a) is a combination of information on wind speed and fuel moisture content, where the latter is derived through consideration of temperature and relative humidity. Intuitively, fire danger decreases as fuel moisture content increases, whereas increases as wind speed increases.

Sharples et al. (2009a) compared three popular fire weather index (FWI) in the literature and produced a simple FWI which has advantages over others called *F index*. Additionally, Sharples et al. (2009b) introduced a dimensionless fuel moisture index (FMI), which was compared to several existing models for determining the moisture content of fine, dead fuels. The results suggested that FMI provides a measure of fuel moisture content that is equivalent to that produced by the complex models. The FMI is given by the simple expression;

$$\mathrm{FMI} = 10 - 0.25(T - H) \tag{1}$$

where T is the dry bulb temperature (°C) and H is the relative humidity (%). *F index* calculated by the following equation;

$$F = \max(U)/\mathrm{FMI}, \tag{2}$$

U is the wind speed (km h^{-1}) and FMI fuel moisture index defined in Equation (1).

Dry bulb temperature, maximum wind speed and humidity values were interpolated by ordinary kriging using 45 meteorological stations.

Kriging is a statistical estimation technique for spatial interpolation of random quantities. The kriging method allows obtaining the quantity value at an unobserved location from observations of its value at nearby locations, being the unknown value obtained by a weighted mean of the available data (Deutsch & Journel 1992; Bayraktar & Turalioglu 2005).

The aim of kriging is to estimate the value of an unknown real-valued function, f, at a point, x^*, given the values of the function at some other points, $x_1 \ldots\ldots x_n$. A kriging estimator is said to be linear because the predicted value $\hat{f}(x^*)$ is a linear combination that may be written as

$$\hat{f}(x^*) = \sum_{i=1}^{n} \lambda_i(x^*) f(x_i). \tag{3}$$

The weights λ_i are solutions of a system of linear equations which is obtained by assuming that f is a sample-path of a random process F(x), and that ε(x) the error of prediction is to be minimized in some sense.

$$\varepsilon(x) = F(x) - \sum_{i=1}^{n} \lambda_i(x) F(x_i) \tag{4}$$

3.2. Percentage tree cover estimation using regression tree (RT) method

The RT method has in recent years become a common alternative to conventional soft classification approaches, particularly with MODIS data (Hansen et al. 2005). The basic concept of a decision tree is to split a complex decision into several simpler decisions that can lead to a solution easier to interpret. When the target variable is discrete (e.g., class attribute in a land cover classification), the procedure is known as decision tree classification. By contrast, when the target variable is continuous, it is known as decision tree regression. In an RT, the target variable is a continuous numeric field such as percentage tree cover. RT models can account for nonlinear relationships between predictor and target variables and allow both continuous and discrete variables as input. The accuracy and predictability of RT models have been found to be potentially greater than those of simple linear regression models (De'Ath & Fabricius 2000; Huang & Townshend 2003; Pal & Mather 2003) linear mixture model and artificial neural network model (Berberoglu, Satir, Atkinson 2009). The RT algorithm takes the form:

$$D = D_s - D_t - D_u \tag{5}$$

where D is the deviance as measured by the corrected sum of squares for a split, s represents the parent node, and t and u are the splits from s. The deviance for nodes is calculated from the equation:

$$D_i = \Sigma_{(\text{cases } j)} (yi - uj) \tag{6}$$

for all j cases of y and the mean value of those cases, u (Hansen et al. 2005).

3.3. Multi-layer perceptron (MLP)

The multilayer perceptron described by Rumelhart et al. (1986) is the most commonly encountered Artificial neural network (ANN) model in data analysis and remote sensing (because of its generalization capability) and this model is used in the current study.

Forest fire hazard mapping using an ANN consists of three stages: training, allocation and testing. In training, grid values are presented to the neural network, together (batch learning) with known fire point values in each input layer. The aim of network training is to build a model of the data generating process so that the network in the testing stage can generalize and predict outputs from inputs it has not seen before. There are different types of learning algorithms for training the network. The most commonly used algorithm in spatial data analyses is backpropagation, using the generalized delta rule (Rumelhart et al. 1986). Network weights are adjusted to minimize an error based on a measure of the difference between the desired and

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the actual feedforward network output. This process is repeated iteratively until: (1) the maximum number of pre-specified iteration was reached, (2) performance had met a suitable level, and (3) the gradient was below a suitable target. This threshold, which must be determined experimentally, controls the generalization capability and total training time. In this paper, the basic feedforward, back-propagation ANN described above is used as a regression model to estimate fire probability based on input features that include the climate, anthropogenic and physical data.

3.4. Relative operating characteristic

The Relative Operating Characteristic (ROC) is an excellent method to assess the validity of a model that predicts the location of the occurrence of a class by comparing a suitability or probability image depicting the likelihood of that class occurring and a Boolean image showing where that class actually exists. For example, the ROC could be used to compare an image of modelled probability for deforestation against an image of actual deforestation (Pontius & Schneider 2001).

The ROC answers one important question "How well is the category of interest concentrated at the locations of relatively high fire risk probability for that category?" The answer to this question allows the scientist to answer the general question, "How well do the pair of maps agree in terms of the location of cells in a category?" while not being forced to answer the question "How well do the pair of maps agree in terms of the quantity of cells in each category?" Thus, the ROC analysis is useful for cases in which the scientist wants to see how well the probability map portrays the location of a particular category but does not have an estimate of the quantity of the category.

4. Results

F index, percent tree cover, DEM, distance from roads (DFR), distance from settlements (DFS) distance from farmlands (DFF) fire history and magnitude variables used to produce forest fire probability maps in 30 m spatial resolution using MLP approach. ROC analysis used to validate result based on ROC coefficient. Landscape features that are used in this study and fire locations compared each other to define impact of the inputs on forest fire hazard.

4.1. Modelling inputs

In FWI calculation, maximum wind speed, dry bulb temperature and relative humidity data used from 45 climate stations and spatially distributed using the ordinary kriging method. Prediction map errors were calculated with equation (4). These errors were acceptable for forest fire hazard mapping (table 2).

F index is a new and effective FWI to assess the climate factors on forest fire hazard mapping. *F* index map created based on wind speed, relative humidity and dry bulb temperature given in equation (2) (Figure 3).

Table 2. Spatially distributed climate data and prediction parameters in fire season.

Prediction Map	Min. Value	Max. Value	Mean Value	Average Std. Error
Max. Wind speed (km/h)	5.01	21.25	10.36	2.7
Humidity (%)	39.8	75.83	51.2	7.64
Temperature (°C)	13.15	23.95	18.13	2.18

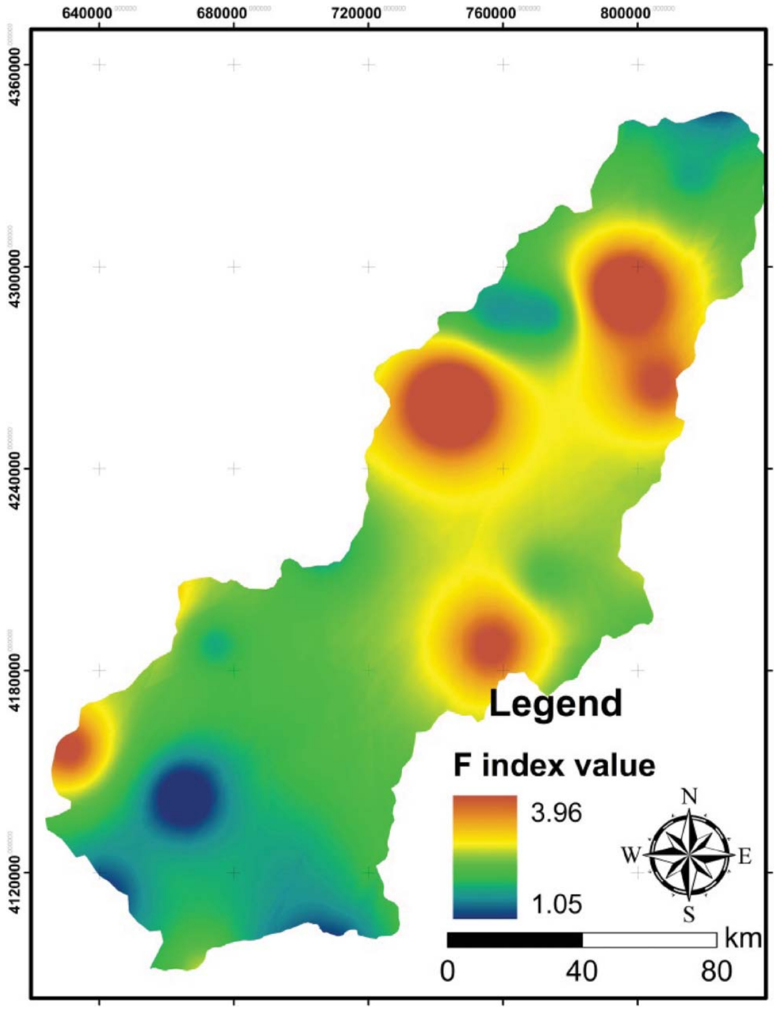

Figure 3. *F* index image.

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FWI indices use only climate dataset such as *F* index. The highest value refers low humidity, high temperature and high wind speed. This condition is the ideal for forest fire occurrence.

Prediction tree canopy cover with the RT analysis was accomplished through a recursive binary partitioning of training data, sampled from the IKONOS imagery, so that values are representative of the entire dataset. These samples are then used in the production of rule sets. The relevant variables were determined by SLR for estimating percent tree cover. The 23 variables were selected among 35 for the analysis of the LANDSAT bands. The brightness values of pixels in these wavebands are the predictor variables and the known tree cover proportions of a pixel are the target variable of the regression tree. The RT model was initialized with 0.81 correlation and 12% RMSE (figure 4).

Distance from roads, settlements and farmlands maps was produced to evaluate anthropogenic effects on forest fire probability. Euclidian distance of each variable mapped within a GIS environment (figure 5).

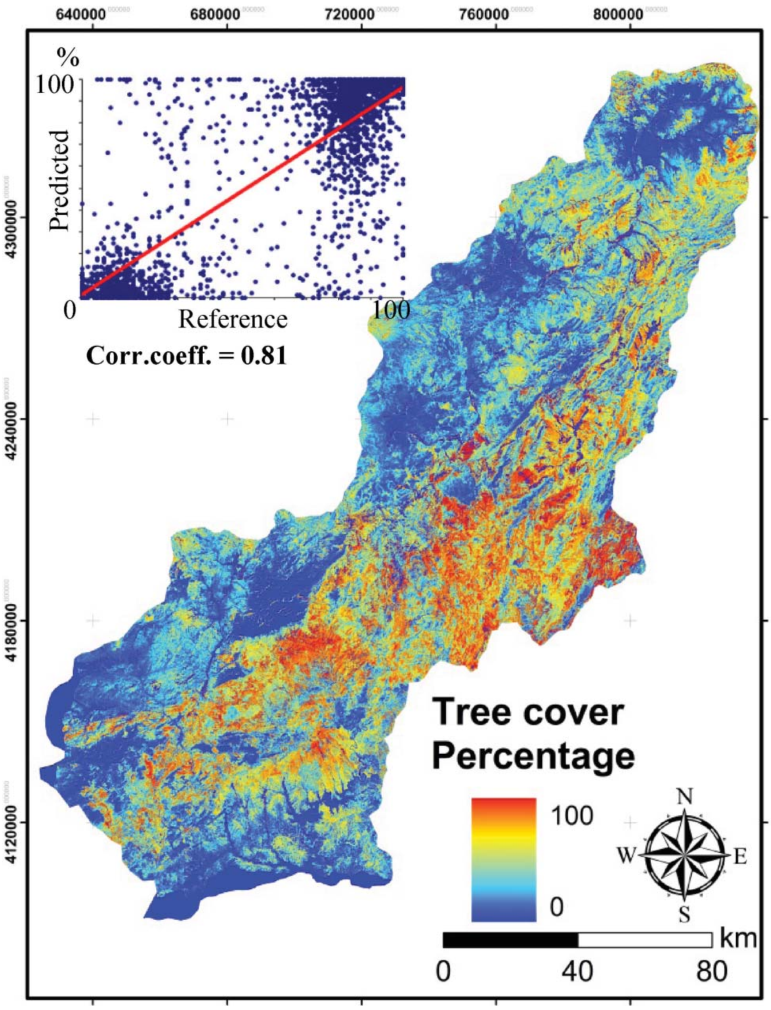

Figure 4. Tree canopy cover percentage from Landsat TM/ETM dataset.

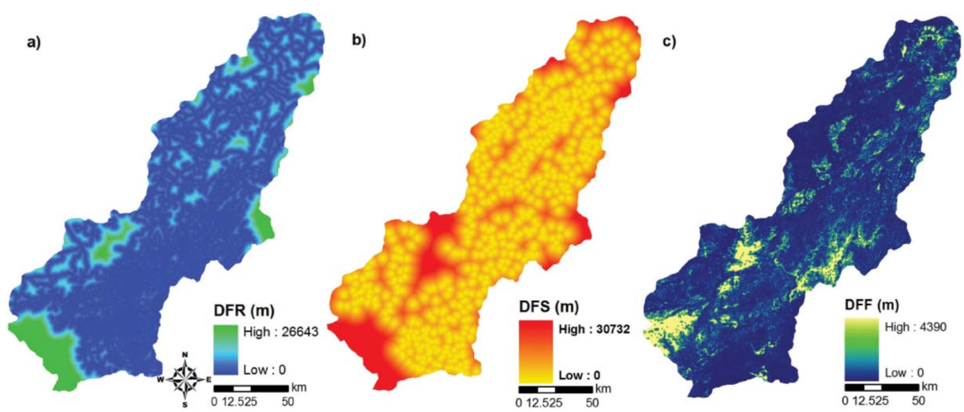

Figure 5. (a) Distance from roads, (b) distance from settlements and (c) distance from farmlands maps.

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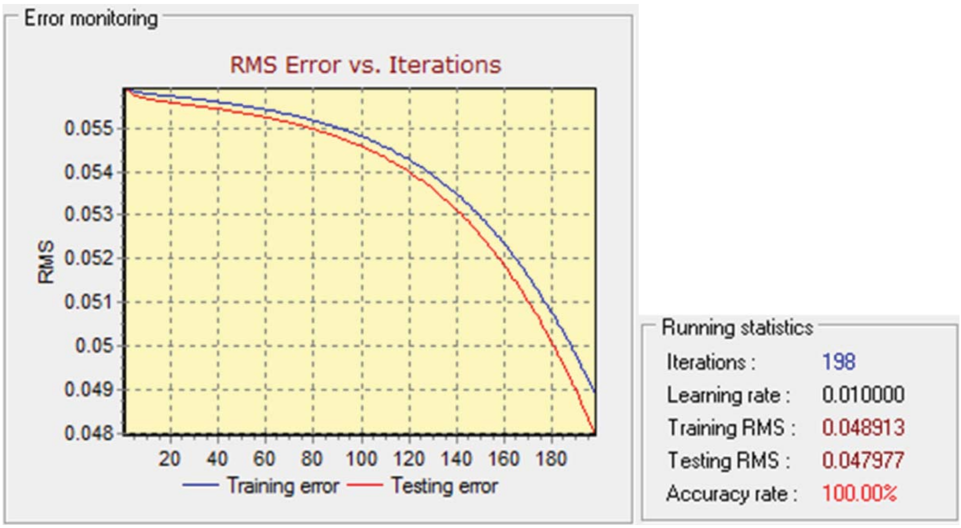

Figure 6. MLP training error monitor.

4.2. Forest fire probability mapping using MLP

The accuracy of an MLP is affected primarily by five variables: (1) the size of the training set, (2) the network architecture, (3) the learning rate, (4) the learning momentum, and (5) the number of training cycles.

(1) *Size of training dataset*. Totally 232 fire has been recorded between 2004 and 2008 by the GRFW. 51 of them used as training data because these fires were larger than 2 ha and location of the fires considered as hottest spots for fire probability assessment. Other 181 fire points described were smaller than 2 ha fire locations and used for testing the fire probability in ROC stage. So that the best subset were used for training.

(2) *Network architecture*. The number of input units was six including percent tree cover, elevation, *F* index, distance from road, distance from settlement and distance from farmlands which were described in Table 1. The neural network architecture that results in the most accurate output in MLP neural network architecture can only be determined experimentally and this can be a lengthy process for large classification tasks. This often seen as a limitation of MLP. However, some geometrical arguments can be used to derive heuristics to set an approximate network size (Paola & Schowengerdt 1997). In the majority of cases, a single hidden layer is sufficient. The dominant factor is the number of the units within the hidden layers, as the number of hidden layers has a secondary effect. Ideally, the first hidden layer of a network should contain two to three times the number of input layer units. In the present case, the network architecture consisted of a single hidden layer with 13 nodes.

(3) *Learning rate*. The learning rate determines the portion of the calculated weight change that will be used for weight adjustment. This acts like a low-pass filter, allowing the network to ignore small features in the error surface. Its value ranges between 0 and 0.99. The smaller the learning rate, the smaller the changes in the weights of the network at each cycle. The optimum value of the learning rate depends on the characteristics of the error surface. The network was trained with a learning rate of 0.1 as this resulted in the most accurate classification. However, this rate requires more training cycles than a larger learning rate.

(4) *Learning momentum*. Momentum is added to the learning rate to incorporate the previous changes in weight with the current direction of movement in the weight space. It is an additional correction to the learning rate to adjust the weights and ranges between 0.1 and 0.9. The network was trained with a back-propagation learning algorithm and a learning momentum value of 0.5.

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(5) *Number of training cycles.* The network was trained until the root mean square (RMS) error reduced to a constant value that was considered acceptable (lower than 0.05). This is one of the most important issues in the design of an MLP as it is easy to overtrain, thus reducing the generalization capability of the network. The network was trained with 198 cycles. Training dataset divided two parts as training and testing in training stage. When the accuracy rate becomes optimum, training was stopped in 198 cycles. Training dataset divided two parts in each iteration and accuracy of the training calculated for each iteration. When the RMS error was lower than 0.05, training progress was stopped to avoid system overtraining and memorization (Figure 6).

The output generated by the MLP was coded as hazardous and non-hazardous areas, where the output nodes range between 0 and 1 and it was rescaled to 0 and 100 (figure 7).

ROC coefficient of MLP for hazardous areas was detected as 0.83. A ROC value of 1 indicates that there is perfect spatial agreement between the class map (reference image) and the probability map. A ROC value of 0.5 is the agreement that would be expected due to chance. The ROC value showed that MLP technique can be used for mapping forest fire hazard.

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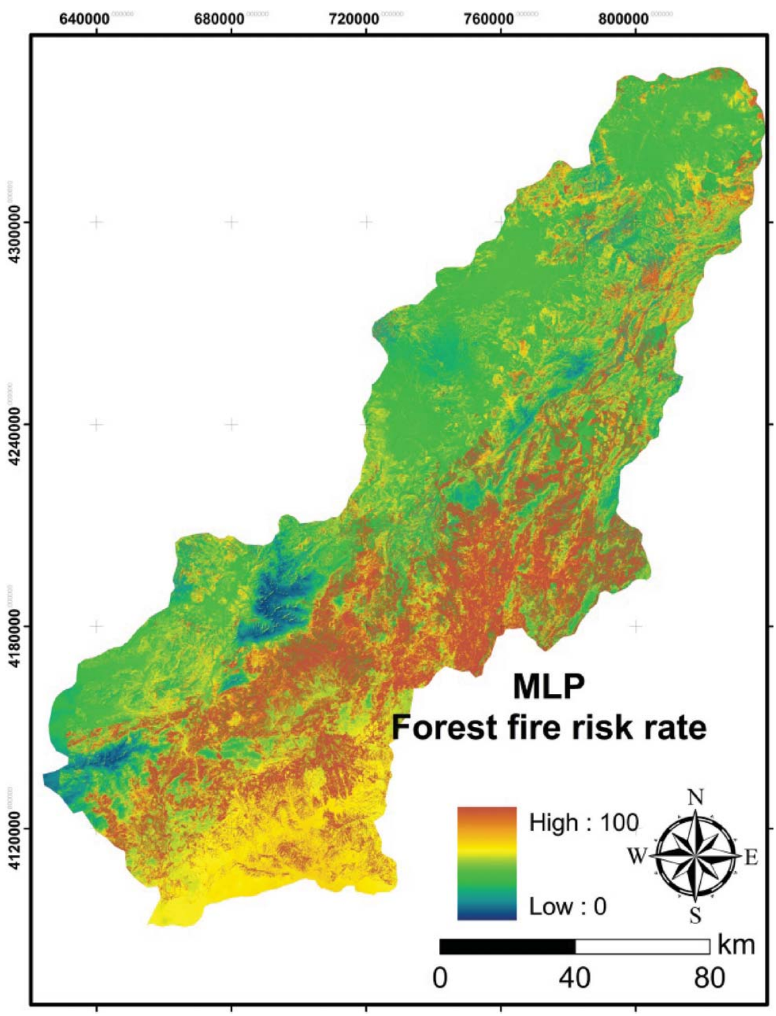

Figure 7. Forest fire probability map using MLP method.

Table 3. Relationship of landscape features and forest fire risk (R values).

	Tree cover	DEM	Temperature	Humidity	Wind speed	DFR	DFS	DFF
MLP forest fire probability	0.93^{***}	-0.43^{**}	0.42^{*}	0.17^{*}	0.1^{NS}	-0.11^{NS}	-0.05^{NS}	-0.08^{NS}
Normalized Weighting constant	0.41	0.18	0.17	0.07	0.043	0.048	0.021	0.04

*, **, ***: significant at $P < 0.05$, $P < 0.01$, $P < 0.001$, respectively. NS: non-significant.

4.3. Evaluation of relationship between landscape features and forest fire risk

Eight different landscape features have been compared with the MLP result to evaluate which factors are dominant for mapping forest fire probability in the USP region. Simple regression analyze was used and relationship rate was evaluated based on correlation coefficiencies (R) (Table 3).

The most descriptive features were tree canopy cover, DEM and temperature. However, relationship of wind speed, anthropogenic factors and forest fire risk were non-significant in our study area.

5. Discussion and conclusions

One of the most popular non-parametric data-dependent techniques was evaluated for forest fire probability mapping presented for the Mediterranean Region. Fire location data were used as dependent whereas independent variables were selected according to the regional fire factors. In this context, percent tree cover, elevation, temperature, wind speed, air moisture, distance from road, distance from settlement and distance from farmland were defined spatially. Several approaches were discussed in the literature on forest fire hazard mapping. Most of them were applied multilayer evaluation system provided from different data sources such as remote sensing, climate stations and pre-designed maps (road, settlement, land use) (Jaiswal et al. 2002; Adab et al. 2013). In a multilayer assessment system, weighting the each layer is the most important issue. Essentially, there are three different ways to solve this problem; literature review, expert knowledge and for the ideal points or areas for weighting. This study differs from the others as the all input layers were assessed non-categorically and all weights were defined based on regional forest fire aspects. Because each region has own landscape characteristic and using the literature for weighting the each layer may not be suitable to map regional forest fire probability.

Additionally, there are some studies that focused on the both vegetation parameters derived from remotely sensed data and climate data or only one of them for detecting the forest fire probability (Maffei et al. 2007; Gabban et al. 2008; Sharples et al. 2009). Although the results were acceptable, human effects were ignored due to study areas were located in rural places mainly. Oppositely, some papers were evaluated only human effects and study results were useful too because of study area was located nearby the big city (Calcerrada et al. 2008). Many researches showed that forest fire probability approaches and data must be match with landscape structure for a reasonable result. Although USB region was mainly a rural area, human factor could have been important effect on forest fire probability according to the fire reasons. However, our results were shown that tree cover, temperature, elevation and humidity were significant effect on regional forest fire probability in different trust levels where as anthropogenic effects were not as significant as these factors. Tree cover showed a linear relationship with forest fire risk positively. Because forestlands with high density are *Pinus brutia* (Turkish pine), formation and it is located under the 700 m elevation. Turkish pine is too sensitive against forest fire (Akkas et al. 2008). Second important landscape feature was elevation. Oxygen level and temperature are depends on elevation directly.

Weights of each layer were defined automatically without using any parametric technique in artificial neural network system. Commonly applied back propagation neural network architecture in the literature was evaluated in the MLP technique. When the training dataset is sufficient enough, some parametric techniques such as logistic regression might be more successful than MLP. However, only

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51 fire location data were used in this study and size of the dataset was insufficient to define weights for such a large geographic coverage. ANN techniques were more capable than linear and parametric techniques using small training data (Berberoglu 1999; Şatır 2012).

In conclusion, MLP can be used to map forest fire hazard successfully. All predictors must be selected according to regional variability and fire reasons. Anthropogenic effects were not a significant impact on forest fire hazard alone. Because the best predictors for the Eastern Mediterranean of Turkey were tree cover, DEM and mean temperature. When these three factors were available for the forest fire occurrence, anthropogenic effect on forest fire is raised in the region.

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