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

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ABSTRACT
This study was done to evaluate the efficiency of three methods to predict the high-risk areas for fire in District Three of Neka Zalemroud forests located in Mazandaran Province, Iran. The fuzzy analytic hierarchy process (fuzzy AHP) and the spatial correlation method were used to model fire risk in the study area. The Dong model was used to provide the fire risk map. Following the construction of fire risk maps using three methods, the map of actual fires was overlaid to validate the used methods. Then the area of the high-risk and very high-risk classes of each fire risk map within the perimeters of actual fires was calculated. Results showed that the high-risk areas in the fire risk map prepared by the fuzzy AHP and spatial correlation methods closely follow the actual fires. On the other hand, the high-risk areas in the fire risk map prepared by the Dong model showed only a moderate agreement with actual fire areas. The final results showed that the fuzzy AHP model (accuracy 0.8) and the spatial correlation model (accuracy 0.92) have the strongest ability to predict the fire high-risk areas in Hyrcanian forests of Iran, relative to the Dong model (accuracy 0.51).

KEYWORDS
Fire; fuzzy analytic hierarchy process (fuzzy AHP); spatial correlation method; Dong model; Hyrcanian forests of Iran

1. Introduction
Wildland fires have increased in the forests and rangelands of arid and semi-arid areas in recent years (Eskandari & Chuvieco 2015). Wildland fire is a global phenomenon, and a result of interactions between climate-weather, fuels and people (Flannigan et al. 2009). Fire can have many negative impacts on forest ecosystems and human communities, especially when fire occurs at a frequency or severity for which the ecosystem is not adapted. In these situations, fire can result in damage to ecosystem properties or forest resources. Thus, prediction of potential future fire occurrence and recognition of high-risk areas in the forests through selection of the best method or model can be help to conserve these valuable ecosystems.

So far, several different methods and models have been used to evaluate forest fire risk in different areas and at various scales, each with different efficiency across the various areas and range of conditions. For example, some studies have used Dong models to predict fire high-risk areas in the forests (Dong et al. 2005; Erten et al. 2005; Eskandari et al. 2013a), whereas other researchers have applied analytic hierarchy process (AHP) or fuzzy sets to model forest fire risk (Chuvieco & Congalton 1989; Vadrevu et al. 2009; Sowmya & Somashekar 2010; Mahdavi et al. 2012; Zarekar et al. ...
2013; Atesoglu, 2014; Eskandari et al. 2015). Logistic regression has been used to model fire ignition probability (Vasconcelo et al. 2001; Rollins et al. 2004; Martinez et al. 2009; Jurdao et al. 2012; Sitanggang et al. 2013; Eskandari & Chuvieco 2015), and the artificial neural network has been used to predict fire regimes (Alonso-Betanzos et al. 2002; Vakalis et al. 2004, Vasilakos et al. 2009; Satir et al. 2016). Finally, the support vector machine approach has also been proposed for fire risk modelling (Cortez & Morais 2007; Sakr & Elhajj 2010).

However, no study has been done to compare the accuracy of the different weighting models for fire risk modelling in the temperate deciduous forests (Hyrcanian forests) of Northern Iran, even though large areas of these forests have been burned by wildland fires in recent years (Mazandaran Natural Resources Administration (MNRA) 2014; Eskandari 2016). Thus, it is essential to use the best model to predict fire occurrence in these forests. The novelty of this research is the use of spatial correlation method to model forest fire risk in Hyrcanian forests for the first time. This method may have good efficiency to weight the effective factors in forest fire risk; however, no study conducted to date has considered this method for modelling forest fire risk. In addition, the comparison of the efficiency of the different weighting methods for fire risk modelling has not been done in the fire-prone Hyrcanian forests of Iran; however, selection of the best model for fire risk modelling in these forests can help forest managers to reduce future fires by identifying areas of greatest risk. Thus, the aim of this study is to comparison the efficiencies of the fuzzy AHP method, the spatial correlation method and the Dong model to predict high-risk areas for fire in Hyrcanian forests of Iran.

In the first step of the research, AHP along with fuzzy sets was used to rank and weigh the effective factors in forest fire, and to model fire risk and provide a fire risk potential map. In the second step, spatial correlation method between fire effective factors and actual fires was used to rank and weigh the effective factors in forest fire, and to model fire risk and provide a fire risk potential map. In the third step, the Dong model was used to provide the fire risk potential map. Finally, the accuracy of the three weighting methods was tested against a map of actual fire occurrence to find out the best method for fire risk assessment in Hyrcanian forests of Iran.

2. Material and methods

2.1. Study area

The study area is a part of the temperate deciduous forests (Hyrcanian forests) of Northern Iran. These forests are District Three of Neka Zalemroud (DTNZ) forests located between 36°30’ to 36°40’ N latitude and 53°15’ to 53°26’ E longitude in South of Neka and Behshahr counties of Mazandaran Province in Northern Iran. The study area covers an area of 153 km². The minimum and maximum altitudes from sea level are 90 and 820 m, respectively. DTNZ forests have 103 km of forest roads, 27 km of rural roads and 21 km of asphalt roads (Figure 1).

Forests in this study area have an uneven-aged structure with mixed species. Vegetation composition includes several species of trees (Fagus orientalis, Carpinus betulus, Quercus castaneifolia, Alnus subcordata, Parrotia persica, Zelcoa carpinifolia, Acer sp., etc.), shrubs (Buxus hyrcanus, Mespilus germanica, Crataegus pentagyna, Prunus caspica, etc.) and herbaceous plants (Asperula odorata, Ruscus hyrcanus, Siclaman sp., Carex sp., Rubus sp., etc.) (MNRA 2010). DTNZ forests have high potential for fire ignition as 1039.5 ha of these forests have been burned by fires in recent years. The past fires mostly caused by human ignitions based on some reports (MNRA 2014).

2.2. Data collection

In this study, the required data for modelling fire risk potential using fuzzy AHP and spatial correlation methods included four major criteria and seventeen sub-criteria (Figure 2). The influencing level of these criteria and sub-criteria may vary based on different study areas and conditions. In
Figure 1. Study area map.

Figure 2. Diagram showing the major criteria (level one) and sub-criteria (level two) used for fire risk modelling.
In this research, different weighting methods (fuzzy AHP, spatial correlation and Dong model) were evaluated for ranking these criteria and sub-criteria.

The maps of the major criteria and sub-criteria were prepared in Geographic Information System (GIS). The major criteria included the topographic, biologic, climatic and human parameters. The preparation methods of the major criteria and sub-criteria maps in the study area are described below.

2.2.1. Topographic criteria
The effect of terrain attributes on forest wildfire has been assessed by Kushla and Ripple (1997) and others. We used four topographic sub-criteria as the causing factors in fire occurrence: elevation (m), slope (%), aspect and distance from river (m). The elevation, slope and aspect maps were derived from the Digital Elevation Model of the ASTER sensor (with 25 m pixel size). In addition, the route of only river in the study area (Mehranboud River) was provided from MNRA. Then the river buffer map (in five classes based on potential of the classes for fire ignition) was developed in GIS. Finally, all topographic sub-criteria maps were classified into some defined classes based on potential of the classes for fire ignition.

2.2.2. Biologic criteria
Biologic criteria have important influences on forest fire occurrence. For example, forest fires have had significant relationships with plant species diversity in the tropical dry deciduous forests (Kodandapani et al. 2008). Vegetation must be considered in fire risk assessment because some vegetation types are more flammable than others, thereby increasing the fire hazard (Rothermel 1983). Vegetation cover has also been an important factor in forest fire ignition and spread in western Iran (Biranvand et al. 2011). In this study, six biologic parameters were used as the causing factors of fire occurrence: vegetation type, vegetation density (m³/ha), leaf litter depth (cm) and leaf litter moisture (%). We included two types of soil properties in the biologic criteria: soil texture (sand, silt, clay, sandy loam, clay loam, etc.) and soil moisture (%). The maps of these parameters were provided from MNRA and were digitized in GIS. Then, each map was classified into some defined classes based on potential of the classes for fire ignition.

2.2.3. Climatic criteria
Fire occurrence, frequency, and intensity are primarily dependent on climate through weather conditions, which influence fuel moisture and likelihood of ignition (Vadrevu et al. 2009). In addition, the role of temperature in fire occurrence in Neka and Behshahr forests (Northern Iran) has already been confirmed in other studies (Eskandari 2015). In this study, we considered the annual mean temperature (°C), annual mean relative humidity (%), annual mean wind velocity (m/s) and annual mean precipitation (mm) as the effective climatic parameters contributing to forest fire ignition in the study area. These climatic data (between 1998 and 2014) were provided from the local meteorological records at Mazandaran Meteorological Administration. The data for mean annual temperature, mean annual relative humidity, mean annual wind velocity and for mean annual precipitation from five climatology stations around the study area were used for this purpose. These data of climatology stations were used to provide the climatic sub-criteria maps using inverse distance weighting (IDW) interpolation in GIS. Then, each climatic map was classified into some defined classes based on potential of the classes for fire ignition.

2.2.4. Human criteria
The role of human causes in forest fire ignition is very important. Regional surveys have shown that 90% of forest fires have been reported as human-caused in the USA and Europe (Holbrook 1943; California Division of Forestry 1953; FAO 2001). It has also been reported that 90% of all forest fires in Siberia (Zhukov 1976) and 97% of the fires in Mexico (Stolzenburg 2001) are human-caused.
Similarly, 95% of forest fires in Iran are also human-caused (Eskandari et al. 2013b; MNRA 2014). In this study, we considered distance from roads (m), distance from settlements (m) and distance from farmlands (m) as the effective human criteria on fire occurrence risk. The human sub-criteria maps were obtained from MNRA and were digitized in GIS. Then the buffer maps of the human sub-criteria were provided in GIS. Finally each map was classified into some defined classes based on potential of the classes for fire ignition.

2.2.5. The actual fire map
The map of actual fires that occurred in DTNZ forests between 1998 and 2014 was provided from MNRA and was digitized in GIS (Figure 3). The total area burned by the actual fires in these years was 1039.5 ha.

2.3. Methods of modelling fire risk
A great range of techniques have been used to model fire risk, from pure crisp mathematical models (usually based on the Rothermel’s (1983) equations), to computational intelligence techniques (Allgower et al. 2003). Additionally, various factors are involved to model forest fire risk and to provide fire risk potential maps. These issues complicate the modelling of fire risk. The more complex fire models require spatial information that is furnished by remote sensing and GIS (Bonazountas et al. 2005). Thus, integration of Multi Criteria Decision Making (MCDM) methods in the spatial domain provides a proper framework for fire risk assessment. The forest fire problem in the study area is spatially diverse in nature and involves both biophysical and anthropogenic parameters, providing an ideal scenario to test MCDM methodologies. Also, each of the biophysical (topography, vegetation, climate) and anthropogenic parameters have spatial dimension (they vary across the district). Therefore, combining these multiple parameters using decision-making methods in a collaborative framework may yield good results (Saaty 1994; Malczewski 2002).
In this study, three weighting methods were used to model forest fire risk and to provide fire risk maps: the fuzzy AHP method, the spatial correlation method and the Dong model.

In the fuzzy AHP model, a combination of AHP and fuzzy sets is used to weight the effective contributing factors in forest fire, and to model fire risk. This modelling method uses expert ideas to express the importance and priority of each of the effective factors that contribute to forest fire. In this method, the fuzzy sets enter into the modelling process to express uncertainty, and to get more accurate results than the AHP method (Vadrevu et al. 2009). After obtaining the weights of all effective factors in fire occurrence, all digital maps of effective factors should be adjusted to fuzzy format based on fuzzy membership functions in GIS. Thus, the statistics and spatial analysis would be more robust than other modelling methods. However, the complexity of the required calculations and more analysis on digital maps complicate the use of this method. On the other hand, the high reliability and accuracy of the fuzzy AHP method demonstrated by previous studies is one of the benefits of this method (Vadrevu et al. 2009; Zarekar et al. 2013; Eskandari et al. 2015).

In the spatial correlation method, the accordance of environmental and anthropogenic factors with the actual fires is used to rank the effective factors in forest fire and to model the fire risk. The prerequisite for this method is accessibility to the exact data of past actual fires, and of the environmental and anthropogenic factors in the study area. In this method, the extent of very high and high-risk classes of each criterion map (in terms of potential for fire ignition) should be calculated within the perimeters of past actual fires to find out the importance (weight) of each criterion in fire risk. The advantage of this method is that it may produce a desirable accuracy, but accessibility to exact data of past actual fires and environmental and anthropogenic factors can limit the use of this method.

The Dong model (2005) is the usual model for provision of fire risk potential map and has been used previously in published studies (Dong et al. 2005; Erten et al. 2005; Eskandari et al. 2013a). This model can be considered as an efficient model in fire risk assessment because the most important effective factors in fire occurrence have been considered in this model. In addition, the simplicity of use of this model is another advantage. Although there is high efficiency of this model for areas with similar conditions to those for which the model was developed, there has been limited use of this model in other areas.

These mentioned methods are relevant together technically. Preparation of criteria maps, determination of criteria weights, assignment of weights to criteria in GIS and weighted overlays of criteria maps to construct the fire risk potential map shows the technical relationships among these methods. Thus, the basis of all these methods is allocation of proper weight to different effective factors in forest fire risk. In addition, modelling of fire risk is done in a MCDM framework in all these methods. Furthermore, spatial analysis is the common aspect of these different methods.

The reputation of fuzzy AHP and Dong models has been proven in previous studies, and these methods have been used previously for modelling forest fire risk. However, fire risk modelling based on the spatial correlation method has been used in this research for the first time. Therefore, the reason for the use of the fuzzy AHP method is its accuracy based on previous research (Vadrevu et al. 2009; Zarekar et al. 2013; Eskandari et al. 2015), the reason for the use of the spatial correlation method is its novelty, and the reason for the use of the Dong model is the commonality of its use in fire risk assessment researches (Dong et al. 2005; Erten et al. 2005; Eskandari et al. 2013a). The modelling of forest fire risk based on these methods (models) has been described in detail in the sections below.

2.3.1. Fuzzy AHP method

Of the several algorithms, since fuzzy linguistic models permit the translation of verbal expressions into numerical values, MCDM methods based on fuzzy relations have been used quite successfully (Malczewski 2002; Kahraman et al. 2003). Thus, in the first method, Saaty’s (2000) AHP, a MCDM
methodology in conjunction with fuzzy logic, was used to rank and prioritize the causative factors of fire risk in the study area.

2.3.1.1. Determination of criteria and sub-criteria weights and modelling of forest fire risk using fuzzy AHP. For the fuzzy AHP method, the topographic, biologic, climatic and human parameters were used to evaluate the fire risk potential in the study area. The hierarchical structure for quantifying fire risk has been given in Figure 2. For estimating the importance (weight) of the effective factors in forest fire risk based on fuzzy AHP, 30 expert questionnaires (30 expert judgments) were distributed among the scientific and operating experts of forest fires to express the importance and priority of effective factors in forest fire. Each questionnaire included five pairwise comparison matrices (topographic sub-criteria comparison matrix, biologic sub-criteria comparison matrix, climatic sub-criteria comparison matrix, human sub-criteria comparison matrix and major criteria comparison matrix). In each questionnaire, the fuzzy triangular numbers along with linguistic variables (Table 1) were used to express the relative importance of sub-criteria and major criteria in five pairwise comparison matrices.

After collecting 30 questionnaires completed by experts, the mean questionnaire was obtained by calculating the average of 30 questionnaires. The mean questionnaire (including five mean pairwise comparison matrices) was analysed based on fuzzy extent analysis (Chang 1996) to get the fuzzy weights of major criteria and sub-criteria. Fuzzy extent analysis (Chang 1996) was performed for five mean pairwise comparison matrices (topographic sub-criteria comparison matrix, biologic sub-criteria comparison matrix, climatic sub-criteria comparison matrix, human sub-criteria comparison matrix and major criteria comparison matrix). Each mean fuzzy comparison matrix was considered as a matrix $A$. The steps of Chang’s fuzzy extent analysis can be summarized as follows (Chang 1996):

First, sum of each row of the fuzzy comparison matrix $A$ was calculated. Then the row sums (obtaining their fuzzy synthetic extent) was normalized by the fuzzy arithmetic operation:

$$
\tilde{S}_i = \sum_{j=1}^{n} \tilde{a}_{ij} \otimes \left[ \sum_{k=1}^{n} \sum_{j=1}^{n} \tilde{a}_{kj} \right]^{-1}
$$

$$
= \left( \frac{\sum_{j=1}^{n} l_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} u_{kj}}, \frac{\sum_{j=1}^{n} m_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} m_{kj}}, \frac{\sum_{j=1}^{n} u_{ij}}{\sum_{k=1}^{n} \sum_{j=1}^{n} l_{kj}} \right)
$$

$$
i = 1, \ldots, n.
$$

where $\otimes$ denotes the extended multiplication of two fuzzy numbers. These fuzzy triangular numbers were known as the relative weights for each alternative under a given criterion and were also used to represent the weight of each criterion with respect to the total objective. A weighted summation was used to obtain the overall performance of each alternative.

Second, the degree of possibility for $\tilde{S}_i \geq \tilde{S}_j$ was computed by the following equation:

$$
V(\tilde{S}_i \geq \tilde{S}_j) = \sup_{y \geq x} \left[ \min(\tilde{S}_i(x), \tilde{S}_i(y)) \right].
$$

| Table 1. Linguistic values and corresponding fuzzy numbers (Chang 1996). |
|---------------------------------------------------------------|
| Linguistic variable for importance expression | Fuzzy sets |
| Just equal | $(1, 1, 1)$ |
| Equally important | $(\frac{1}{2}, 1, \frac{3}{2})$ |
| Weakly more important | $(1, \frac{3}{2}, 2)$ |
| Strongly more important | $(\frac{3}{2}, 2, 3)$ |
| Very strongly more important | $(2, \frac{5}{2}, 3)$ |
| Absolutely more important | $(\frac{5}{2}, 3, 3)$ |
This formula can be equivalently expressed as

\[
V(\tilde{S}_i \geq \tilde{S}_j) = \begin{cases} 
1 & m_i \geq m_j \\
\frac{u_i-l_j}{(u_i-m_i) + (m_j-l_j)} & l_j \leq u_i, \quad i, j = 1, \ldots, n; j \neq i \\
0 & \text{otherwise}
\end{cases}
\]  

(3)

where \( \tilde{S}_i = (l_i, m_i, u_i) \) and \( \tilde{S}_j = (l_j, m_j, u_j) \).

Finally, the priority vector \( W = (w_1, \ldots, w_n) \) of the fuzzy comparison matrix \( \tilde{A} \) was estimated as follows:

\[
w_i = \frac{\sum_{k=1}^{n} V(\tilde{S}_k \geq \tilde{S}_j | j = 1, \ldots, n; j \neq i)}{\sum_{j=1}^{n} V(\tilde{S}_i \geq \tilde{S}_j | j = 1, \ldots, n; j \neq k)}, \quad i = 1, \ldots, n
\]  

(4)

where \( w_i \) is fuzzy weight of each criterion or sub-criterion. After obtaining the fuzzy weights of all criteria and sub-criteria, the consistency ratio (CR) was calculated to evaluate the accuracy of the obtained fuzzy weights (equations (5)–(8)):

\[
\tilde{A}W = \lambda_{\text{max}}w
\]  

(5)

\[
\lambda_{\text{max}} = \frac{\lambda_{\text{max}_1} + \lambda_{\text{max}_2} + \cdots + \lambda_{\text{max}_n}}{n}
\]  

(6)

where \( \lambda_{\text{max}} \) is the largest eigenvalue of the matrix \( \tilde{A} \) (maximum eigen value) and \( w \) is the corresponding eigenvector of the matrix \( \tilde{A} \) which it contains only positive entries. \( \lambda_{\text{max}} \) is average of \( \lambda_{\text{max}_i} \) and \( n \) is number of criteria in matrix \( A \). Then consistency index (CI) was calculated as below

\[
\text{CI} = \frac{\lambda_{\text{max}} - n}{n - 1}
\]  

(7)

The logical consistency of comparison matrix \( \tilde{A} \) was evaluated using the CR, which is defined as

\[
\text{CR} = \frac{\text{CI}}{\text{RI}}
\]  

(8)

where RI is the random index (Saaty & Vargas 1993). The mean RI table has been given in Saaty (1980). This table has been obtained by averaging of CIs of many randomly generated pairwise comparison matrices. RI was extracted from the mean RI table (Saaty 1980) based on number of criteria \( n \) in pairwise comparison matrix (matrix \( A \)). The CR was computed for each pairwise comparison matrix and only those with \( \text{CR} \leq 0.1 \) were included in a combined matrix. In general, \( \text{CR} \leq 0.1 \) was considered to be tolerable (Saaty & Vargas 1993). The detailed equations involved in AHP calculation have been provided in Saaty (2000) and also in Wang et al. (2006), Wu et al. (2007) and Ying et al. (2008).

Finally, the model (Index) of each major criterion was obtained based on fuzzy weights of its sub-criteria. For instance, for topographic criterion model (Index), the fuzzy weights of elevation, slope, aspect and distance from river were considered as the coefficients of these sub-criteria in topographic criterion model. All the major criteria models (topographic, biologic, climatic and human models) were provided based on this process. Finally, the fire risk model was obtained based on fuzzy weights of major criteria. As the fuzzy weights of topographic, biologic, climatic and human criteria were considered as the coefficients of these criteria in fire risk model.
2.3.1.2. Assignment of weights to sub-criteria and construction of fuzzy maps in GIS. At the level-two hierarchy (Figure 2), each sub-criterion was prepared in the form of a GIS map. The detailed procedures for generating the fuzzy criteria maps and weights using the linguistic variables and corresponding fuzzy membership functions have been given in Malczewski (1999). First, maps of each sub-criterion at the level-two hierarchy were converted to raster format. The range of values in each sub-criterion raster map was assigned from ‘very low’ (0) to ‘very high’ (10) (Tables 2–5). Then, the fuzzy membership function from Chen and Hwang (1992) was used to standardize all the sub-criteria maps of each major criterion in GIS (for example, elevation, slope, aspect and distance from river for topography major criterion, and so on). The fuzzy map of each sub-criterion was provided based on this function.

2.3.1.3. Combination of fuzzy sub-criteria maps and fuzzy major criteria maps to construct the fire risk potential map. The fuzzy map of each major criterion (topographic, biologic, climatic and human criteria) was obtained by weighting the overlay of its sub-criteria fuzzy maps in GIS. Finally, the fuzzy map of fire risk potential was obtained by weighting the overlay of major criteria fuzzy maps in GIS. This map was classified to five fire potential classes from very low risk to very high risk.

2.3.2. Spatial correlation method

In the second method of this research, a spatial correlation method in conjunction with GIS was used to rank and prioritize the causing factors of fire risk in the study area. For the spatial correlation method, 17 parameters (sub-criteria) were used to evaluate the fire risk potential in the study area (Figure 2).

After preparation of all factors maps (17 sub-criteria; Figure 2), each map was classified from ‘very low’ to ‘very high’ in terms of potential for fire risk (Tables 2–5). Then the map of actual fires was overlaid on each factor map. After overlaying, the area of the very high and high-risk classes of each factor map located within the actual fires was calculated to investigate the accordance of the very high and high-risk classes in each factor map with the actual fires. Then the spatial correlation between each factor with actual fires was obtained from the relationship of the area of very high and high-risk classes of each factor map in the actual fires to the total area of the actual fires. Finally, the

| Sub-criterion | Classes | Fire risk potential | In-layer weight (value) |
|---------------|---------|---------------------|------------------------|
| Slope (%)     | > 40    | Very high           | 10                     |
|               | 30–40   | High                | 8                      |
|               | 20–30   | Medium              | 6                      |
|               | 10–20   | Low                 | 2                      |
|               | 0–10    | Very low            | 0                      |
| Aspect        | South   | Very high           | 10                     |
|               | West    | High                | 8                      |
|               | Flat    | Medium              | 6                      |
|               | East    | Low                 | 2                      |
|               | North   | Very low            | 0                      |
| Elevation (m) | 11–150  | Very high           | 10                     |
|               | 150–300 | High                | 8                      |
|               | 300–450 | Medium              | 6                      |
|               | 450–600 | Low                 | 2                      |
|               | > 600   | Very low            | 0                      |
| Distance from river (m) | > 800  | Very high           | 10                     |
|               | 600–800 | High                | 8                      |
|               | 400–600 | Medium              | 6                      |
|               | 200–400 | Low                 | 2                      |
|               | 0–200   | Very low            | 0                      |
### Table 3. The weight assignments to classes of biologic sub-criteria maps in GIS.

| Sub-criterion                          | Classes                                      | Fire risk potential | In-layer weight (value) |
|----------------------------------------|----------------------------------------------|--------------------|------------------------|
| Vegetation type                        | Protected area                               | Very high          | 10                     |
|                                        | *Carpinus–Fagus, Fagus–Carpinus*             | Very high          | 10                     |
|                                        | *Carpinus*, shrubbery                        | High               | 8                      |
|                                        | *Carpinus–Parrotia*                          | High               | 8                      |
|                                        | *Parrotia–Carpinus*                          | Medium             | 6                      |
|                                        | Plantation                                   | Medium             | 4                      |
|                                        | *Quercus*                                    | Low                | 2                      |
|                                        | *Zelkova–Quercus*                            | Low                | 2                      |
|                                        | Mixture                                      | Very low           | 0                      |
| Vegetation density (m³/ha)             | Protected area                               | Very high          | 10                     |
|                                        | > 350                                        | Very high          | 10                     |
|                                        | 200–350                                      | High               | 8                      |
|                                        | 100–200                                      | Medium             | 6                      |
|                                        | < 100                                        | Low                | 2                      |
|                                        | Plantation                                   | Very low           | 0                      |
| Leaf litter moisture (%)               | 2–5                                          | Very high          | 10                     |
|                                        | 5–10                                         | High               | 8                      |
|                                        | 10–15                                        | Medium             | 6                      |
|                                        | 15–20                                        | Medium             | 4                      |
|                                        | 20–25                                        | Low                | 2                      |
|                                        | 25–<                                         | Very low           | 0                      |
| Leaf litter depth (cm)                 | 8–<                                          | Very high          | 10                     |
|                                        | 6–8                                          | High               | 8                      |
|                                        | 4–6                                          | Medium             | 6                      |
|                                        | 2–4                                          | Low                | 2                      |
|                                        | 0–2                                          | Very low           | 0                      |
| Soil moisture (%)                      | 9–15                                         | Very high          | 10                     |
|                                        | 15–20                                        | High               | 8                      |
|                                        | 20–25                                        | Medium             | 6                      |
|                                        | 25–30                                        | Medium             | 4                      |
|                                        | 30–35                                        | Low                | 2                      |
|                                        | 35–<                                         | Very low           | 0                      |
| Soil texture                           | Sandy loam                                   | Very high          | 10                     |
|                                        | Sandy loam–loam                              | High               | 8                      |
|                                        | Loam sandy                                   | Medium             | 4                      |
|                                        | Loam                                         | Low                | 2                      |
|                                        | Wasteland                                    | Very low           | 0                      |

### Table 4. The weight assignments to classes of climatic sub-criteria maps in GIS.

| Sub-criterion                        | Classes                      | Fire risk potential | In-layer weight (value) |
|--------------------------------------|------------------------------|--------------------|------------------------|
| Annual temperature average (°C)     | 19–<                         | Very high          | 10                     |
|                                      | 18–19                        | High               | 8                      |
|                                      | 17–18                        | Medium             | 6                      |
|                                      | 16–17                        | Low                | 4                      |
|                                      | 15–16                        | Very low           | 0                      |
| Annual relative humidity average (%)| 57–60                        | Very high          | 10                     |
|                                      | 60–65                        | High               | 8                      |
|                                      | 65–70                        | Medium             | 6                      |
|                                      | 70–75                        | Low                | 4                      |
|                                      | 75–<                         | Very low           | 0                      |
| Annual precipitation average (mm)    | 602–605                      | Very high          | 10                     |
|                                      | 605–609                      | High               | 8                      |
|                                      | 609–613                      | Medium             | 6                      |
|                                      | 613–617                      | Low                | 4                      |
|                                      | 617–621                      | Very low           | 0                      |
| Annual wind velocity average (m/s)   | 11–<                         | Very high          | 10                     |
|                                      | 9.5–11                       | High               | 8                      |
|                                      | 8–9.5                        | Medium             | 6                      |
|                                      | 6.5–8                        | Low                | 4                      |
|                                      | 5–6.5                        | Very low           | 0                      |
spatial correlation value of each factor with fire occurrence was obtained, to obtain values between 0 and 1 which were considered as the spatial weight (coefficient) of each factor in the fire risk model. Finally, the forest fire risk map was constructed by weighting the overlays of all 17 factor maps using raster calculator in GIS, and classifying to five classes from very low to very high for fire risk potential.

2.3.3. Dong model

In the third method, the Dong model (Dong et al. 2005) was used to evaluate fire risk in the study area, because this model includes the most effective factors in forest fire occurrence. The Dong model is

\[ Rc = 7(V_t + V_d) + 5(S + A + E) + 3(D_r + D_s + D_f) \]  

In equation 9, \( Rc \) is the numerical index of forest fire risk where \( V_t \) and \( V_d \) indicate the vegetation type and density, respectively, \( S \) indicates the slope, \( A \) indicates the aspect and \( E \) indicates the elevation. \( D_r, D_s \) and \( D_f \) indicate the distance from roads, settlements and farmlands, respectively.

Therefore, in the case of the Dong model approach, the data used included the maps of eight factors (vegetation type and density, slope, aspect, elevation, distance from roads, settlements and farmlands). Each factor map was classified from ‘very low’ to ‘very high’ in terms of potential for fire risk. The fire risk map was obtained by weighting the overlays of eight factor maps based on the coefficient of each factor in the Dong model in GIS, followed by classification to five classes from very low to very high fire risk potential.

2.4. Evaluation of accuracy of three methods

In this study, the accuracy of the three fire risk potential maps obtained from the three different methods was tested against the map of actual fires in DTNZ forests (Figure 3). This map was overlaid on the fire risk potential maps to validate the fire risk potential maps and to assess the overall accuracy of fire risk models based on the fuzzy AHP method, the spatial correlation method and the Dong model for the study area. For this purpose, the area of the very high and high-risk classes of each fire risk potential map within the perimeters of the actual fires was calculated.

| Sub-criterion | Classes | Fire risk potential | In-layer weight (value) |
|---------------|---------|---------------------|------------------------|
| Distance from road (m) | 0–200 | Very high | 10 |
| 200–400 | High | 8 |
| 400–600 | Medium | 6 |
| 600–800 | Low | 4 |
| >800 | Very low | 0 |
| Distance from settlement (m) | 0–1000 | Very high | 10 |
| 1000–2000 | High | 8 |
| 2000–3000 | Medium | 6 |
| 3000–4000 | Low | 4 |
| >4000 | Very low | 0 |
| Distance from farmland (m) | 0–1000 | Very high | 10 |
| 1000–2000 | High | 8 |
| 2000–3000 | Medium | 6 |
| 3000–4000 | Low | 4 |
| >4000 | Very low | 0 |
3. Results

3.1. The fuzzy weights of sub-criteria and criteria based on fuzzy AHP method

The fuzzy weights of sub-criteria and criteria based on fuzzy AHP method have been shown in Tables 6 and 7.

The major criteria indexes (models) and the fire risk model have been presented based on obtained fuzzy weights (equations (10)–(14)):

Topographic criterion index = 0.2517 (slope) + 0.3056 (aspect) + 0.2177 (elevation) + 0.225 (distance from river)  
(10)

Biologic criterion index = 0.1839 (vegetation type) + 0.1762 (vegetation density) + 0.1839 (leaf litter depth) + 0.1839 (leaf litter moisture) + 0.1306 (soil texture) + 0.1415 (soil moisture)  
(11)

Climatic criterion index = 0.2652 (temperature) + 0.2257 (precipitation) + 0.2381 (relative humidity) + 0.271 (wind velocity)  
(12)

Human criterion index = 0.3736 (distance from road) + 0.3227 (distance from settlement) + 0.3037 (distance from farmland)  
(13)

Fire risk model = 0.208 (Topographic index) + 0.2595 (Biologic index) + 0.2315 (Climatic index) + 0.301 (Human index)  
(14)

Table 6. The fuzzy weights of sub-criteria.

| Criterion     | Sub-criterion     | Fuzzy weight |
|---------------|-------------------|--------------|
| Topographic   | Slope             | 0.2517       |
|               | Aspect            | 0.3056       |
|               | Elevation         | 0.2177       |
|               | Distance from river| 0.225      |
| Climatic      | Annual mean temperature | 0.2652    |
|               | Annual mean precipitation | 0.2257    |
|               | Annual mean relative humidity | 0.2381    |
|               | Annual mean wind velocity | 0.271      |
| Biologic      | Vegetation type   | 0.1839       |
|               | Vegetation density| 0.1762       |
|               | Leaf litter depth | 0.1839       |
|               | Leaf litter moisture| 0.1839     |
|               | Soil texture      | 0.1306       |
|               | Soil moisture     | 0.1415       |
| Human         | Distance from road| 0.3736       |
|               | Distance from settlement | 0.3227  |
|               | Distance from farmland | 0.3037    |

Table 7. The fuzzy weights of major criteria.

| Criterion     | Fuzzy weight |
|---------------|--------------|
| Topographic   | 0.208        |
| Biologic      | 0.2595       |
| Climatic      | 0.2315       |
| Human         | 0.301        |
3.2. The spatial correlation between each effective factor (sub-criterion) and actual fires

The spatial correlation values between each effective factor (sub-criterion) and actual fires have been shown in Table 8.

| Criterion         | Sub-criterion                        | Very high and high risk classes | Area of very high and high risk classes of each sub-criterion in the actual fires (ha) | Spatial correlation value |
|-------------------|--------------------------------------|---------------------------------|--------------------------------------------------------------------------------------|--------------------------|
| Topographic       | Slope (%)                            | 30%–40%, >40%                  | 359.39                                                                                | 0.3                      |
| criterion         |                                       |                                 |                                        |                          |
|                    | Aspect                               | South, West                     | 518.28                                                                               | 0.5                      |
|                    | Elevation (m)                        | 11–150 and 150–300 m           | 551.0                                                                                | 0.5                      |
|                    | Distance from river (m)              | 600–800 and >800 m             | 975.31                                                                               | 0.9                      |
| Biologic criterion| Vegetation type                      | *Carpinus–Fagus, Fagus–Carpinus,*| 702.59                                                                               | 0.7                      |
|                    |                                      | *Carpinus–Parrotia, Carpinus,*  |                                        |                          |
|                    |                                      | shrubbery, protected area      |                                        |                          |
|                    | Vegetation density (m³/ha)           | 200–350 and >350 m³/ha,        | 762.40                                                                               | 0.7                      |
|                    |                                       | protected area                 |                                        |                          |
|                    | Leaf litter moisture (%)             | 2%–5%, 5%–10%                  | 11.11                                                                                | 0.01                     |
|                    | Leaf litter depth (cm)               | 6–8 and >8 cm                  | 619.74                                                                               | 0.6                      |
|                    | Soil moisture (%)                    | 9%–15%, 15%–20%                | 11.11                                                                                | 0.01                     |
|                    | Soil texture                         | Sandy loam, sandy loam–loam    | 550.52                                                                               | 0.5                      |
| Climatic criterion| Annual temperature average (°C)      | 18–19 °C and >19 °C            | 644.80                                                                               | 0.6                      |
|                    | Annual relative humidity average (%) | 57%–60%, 60%–65%               | 936.76                                                                               | 0.9                      |
|                    | Annual precipitation average (mm)    | 602–605 and 605–609 mm         | 312.85                                                                               | 0.3                      |
|                    | Annual wind velocity average (m/s)   | 9.5–11, >11 m/s                | 313.79                                                                               | 0.3                      |
| Human criterion    | Distance from road (m)               | 0–200 and 200–400 m            | 711.16                                                                               | 0.7                      |
|                    | Distance from settlement (m)         | 0–1000 and 1000–2000 m         | 194.14                                                                               | 0.2                      |
|                    | Distance from farmland (m)           | 0–1000 and 1000–2000 m         | 642.25                                                                               | 0.6                      |
| Fire risk (total)  |                                      | Very high and high risk        | 956.81                                                                               | 0.92                     |

3.3. Fire risk potential maps obtained from three methods and validation

The composite fire risk potential maps derived from fuzzy AHP method, spatial correlation method and the Dong model have been shown in Figure 4. In each fire risk map, the individual cells have been ranked from very low to very high, based on their predicted fire risk.

Results of qualitative validation of fire risk potential maps derived from three methods have also been shown in Figure 4. The quantitative validation of fire risk potential maps using three methods has also been shown in Table 9.

![Figure 4](image-url). Fire risk potential maps based on the fuzzy AHP and its validation (left panel), the spatial correlation method and its validation (center panel), and the Dong model and its validation (right panel).
This study was done to evaluate the efficiency of the three methods, fuzzy AHP method, spatial correlation method and Dong model to predict the fire high-risk areas and to provide the fire risk potential map in a part of Hyrcanian forests of Iran.

Results of analysis of the fire risk potential map using fuzzy AHP showed that 14.45% of study area has very high potential and 24.29% of study area has high potential for forest fire. In addition, the medium, low and very low potential for forest fire in study area are 28.85%, 23.6% and 8.81% respectively. Therefore, based on the fuzzy AHP method, most of study area has high and very high potential for forest fire.

Results of overlaying of the map of actual fires on the forest fire risk potential map derived from fuzzy AHP method in DTNZ forests showed that the actual fires patterns largely followed the fire risk patterns. The burned regions in the study area have high correlation with the very high and high-risk regions in the forest fire risk map derived from fuzzy AHP method. A total of 80% of actual burned area was located in the very high and high-risk regions, whereas 17% of actual burned area was located in the medium risk regions, and only 3% of actual burned area was located in very low and low risk regions. These results demonstrate the acceptable accuracy of the fire risk model developed based on the fuzzy AHP method in this study.

Results of overlaying of the map of actual fires on the forest fire risk potential map derived from fuzzy AHP method in DTNZ forests showed that the actual fires patterns largely followed the fire risk patterns. The burned regions in the study area have high correlation with the very high and high-risk regions in the forest fire risk map derived from fuzzy AHP method. A total of 80% of actual burned area was located in the very high and high-risk regions, whereas 17% of actual burned area was located in the medium risk regions, and only 3% of actual burned area was located in very low and low risk regions. These results demonstrate the acceptable accuracy of the fire risk model developed based on the fuzzy AHP method in this study.

The results from the analysis of the fire risk map using the spatial correlation method showed that 20% of the study area had very high risk and 33% of the study area had high risk for forest fire. In addition, the percentage of medium, low and very low risk areas were 26%, 16% and 5%, respectively. Thus, the spatial correlation method showed that most of the study area had high and very high potential for forest fire.

Results of overlaying of the map of actual fires on the forest fire risk potential map derived from fuzzy AHP method in DTNZ forests showed that the pattern of actual fires largely followed the fire risk patterns, because the burned regions in the study area have high correlation with the very high and high-risk areas in the forest fire risk map derived from the spatial correlation method. Totally, 92% of actual burned regions were located in the very high and high-risk areas. In addition, 6% of burned areas were located in the medium risk regions. The area of the low and very low risk regions in the burned area was very limited (2%). These results demonstrate the acceptable accuracy of the fire risk model developed based on the spatial correlation method in this study.

The results from the fuzzy AHP and correlation approaches are similar to the results of other research showing that actual burned areas show strong agreement with high risk areas in forest fire risk maps (Chuvieco & Congalton 1989; Dong et al. 2005; Martinez et al. 2009; Vadrevu et al. 2009; Sowmya & Somashekar 2010; Mahdavi et al. 2012; Eskandari et al. 2013a; Eskandari & Chuvieco 2015). However, in this study, modelling of fire risk using fuzzy AHP in a MCDM framework or based on the novel approach of using spatial correlation of environmental and human factors with actual fires, both led to accurate fire risk potential maps.

Table 9. Quantitative validation of fire risk potential maps from the fuzzy AHP, spatial correlation, and Dong model approaches, using actual fires. This table shows the actual area burned (ha) for four fires in DTNZ forests, and the area of modelled very high and high risk classes in actual fires with correlation value between model predictions and actual maps, for the fuzzy AHP, correlation, and Dong model approaches.

| Actual fires | Actual burned area (ha) | Fuzzy AHP | | | Spatial correlation | | | Dong model | |
|---------------|------------------------|-----------| | | Very high and high-risk classes in actual fires (ha) | Correlation | | Very high and high-risk classes in actual fires (ha) | Correlation | | Very high and high-risk classes in actual fires (ha) | Correlation |
| 1             | 313.79                 | 254.46    | 0.81 | | 297.06 | 0.94 | | 96.44 | 0.31 |
| 2             | 443.69                 | 409.09    | 0.92 | | 426.24 | 0.96 | | 299.36 | 0.67 |
| 3             | 212.14                 | 170.28    | 0.80 | | 203.47 | 0.95 | | 121.17 | 0.57 |
| 4             | 69.87                  | 0.0084    | 0.0001 | | 30.03 | 0.42 | | 11.01 | 0.15 |
| Total         | 1039.50                | 833.85    | 0.80 | | 956.81 | 0.92 | | 528.0012 | 0.51 |
In contrast, results of analysis of the fire risk map using the Dong model showed that 15% of the study area had very high risk, and 23% of study area had high risk for fire occurrence. In addition, the medium, low and very low risks for forest fire occurrence in study area were 29%, 25% and 8% respectively. Thus, based on the Dong model, most of the study area had high and very high risk for fire occurrence.

Results of overlaying of the actual fires map on the fire risk potential map derived from the Dong model in DTNZ forests showed that the patterns of actual fires were relatively similar to the fire risk patterns. The burned regions in the study area had correlations of only moderate strength with the high and very high-risk areas in the fire risk map. A total of 51% of actual burned area was located in the high and very high-risk areas. In addition, 30% of actual burned areas were located in the medium risk regions, and 19% of actual burned area was located in very low and low risk regions. These results relatively are similar to the results of other researches that showed that the burned areas properly are according to the high-risk areas in the forest fire risk map (Chuvieco & Congalton 1989; Dong et al. 2005; Martinez et al. 2009; Vadrevu et al. 2009; Sowmya & Somashekar 2010; Mahdavi et al. 2012; Eskandari et al. 2013a; Eskandari & Chuvieco 2015). Although results of similar studies done in the Baihe forest region of China by the Dong model showed that 80% of high-risk areas were located in the burned area (Dong et al., 2005), our results show that the Dong model has more efficiency for evaluating fire risk potential in Chinese forests than in Iranian Northern forests. It is important to note that this model was developed for use in Chinese forests regarding to special conditions of these forests. Thus, the Dong model had only medium efficiency for detecting high-risk areas for fire in Hyrcanian forests of Northern Iran.

5. Conclusion

Based on the results of the fuzzy AHP and spatial correlation methods, most of the study area has very high and high risk for forest fire, meaning that, DTNZ forests will very likely be exposed to fires in the future. Therefore, taking preventive measures against future fires occurrence will be essential in the high-risk areas. Regarding the high accuracy of the fuzzy AHP and spatial correlation methods for fire risk modelling in this study, prediction of the future fires occurrence in DTNZ forests is possible using fire risk potential maps obtained from these methods. Because the actual fires have occurred in the high and very high-risk areas, it can be expected that future forest fires would also occur in the high and very high-risk areas of fire risk maps obtained from these methods. Therefore, the local fire management system should take actions to predict, prevent and control the future fires in the high and very high-risk areas.

It is suggested that land description should be made for very high and high-risk areas in fire risk maps, with special consideration for facilities for firefighting and accessibility to forest roads in the high and very high-risk areas. It is also suggested that other effective factors in forest fire occurrence with the proper weight can also be added to these forest fire risk models in the future studies. The models produced in this research can be modified regarding all effective factors in forest fire occurrence in each area, to continue to increase the agreement between fire risk prediction maps and locations of actual fires.

Acknowledgements

The authors would like to thank Kambiz Barari (in Mazandaran Natural Resources Administration-Iran) for providing some of the required data and maps.

Disclosure statement

No potential conflict of interest was reported by the authors.
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