International Journal of Geoheritage and Parks 10 (2022) 84–96

Contents lists available at ScienceDirect

International Journal of Geoheritage and Parks

journal homepage: http://www.keaipublishing.com/en/journals/international-journal-of-geoheritage-and-parks/

Research Paper

Application of multi-criteria decision making models to forest fire management

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ARTICLE INFO

Article history:
Received 27 September 2021
Received in revised form 22 February 2022
Accepted 24 February 2022
Available online 4 March 2022

Keywords:
Arasbaran forest
Forest firefighting
TOPSIS
SAW

ABSTRACT

The study of the effective factors for forest fire prevention policy can help to reduce long term extensive environmental fire damage. In other words, forest fire management is the result of a complex interaction of many criteria. The present study aims to analyze the most effective criteria for the Arasbaran forest, Iran, based on the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) and the Simple Additive Weighting (SAW) methods. The five top optimal criteria selection by the TOPSIS method identified that, "association and cooperation between the executive and responsible institutions" is ranked highest ($CCi+=0.85$). "Lack of deterrence law in dealing with forest fire offenders in human-caused forest fires" has the second rank ($CCi+=0.84$), followed by "Lack of up-to-date scientific information on susceptible areas in the region", "Increasing the cooperation of NGOs and increase public trust", and "Lack of forest road network access to ignite regions" ($CCi+=$ 0.789, 0.787, and 0.77, respectively). The five top optimal criteria resulting from the SAW method showed that "Local people participations" provided the highest score ($FS = 0.39$), followed by "association and cooperation between the executive and responsible institutions ($FS = 0.39$), "Increasing the cooperation of non-governmental organizations (NGOs), "increasing public trust" ($FS = 0.36$), "Raising awareness of the position of natural resources among local peoples and attracting their cooperation" ($FS = 0.35$), and "Optimal use past experiences" ($FS = 0.34$). From these results, we find that collaboration between institutions is a major requisite for successful fire management, and should be done in parallel with involvement of local actors in a combined synergistic bottom-up top-down approach. We suggest that the impact of ecological and environmental factors on the occurrence and spread of forest fires (as complementary factors) should be investigated to demonstrate the best criteria for comprehensive management strategies in future studies.

1. Introduction

Forests cover about one-third of the Earth's surface and are essential elements of many, if not most protected areas. Forests are fundamental natural resources that play essential roles in 1) purifying the air by reducing the effects of greenhouse gases and 2) carbon sequestration, 3) aiding flood prevention, soil protection, and preventing erosion. These to help move towards forest sustainable development (Zandebasiri and Pourhashemi, 2016). On the flip side, forests are prone to fire and forest fires can

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https://doi.org/10.1016/j.ijgeop.2022.02.005
2577-4441/

become a threat to the ecological and economic services of the forest ecosystem and have some potentially negative impacts on ecosystems, and above mentioned positive roles. A forest fire can cause serious destructing in forest composition, biodiversity, and structure (Carvalho et al., 2019; Sharma, Kanga, Nathawat, Sinha, & Pandey, 2012). In addition, forest fires are known as one of the major causes of ecological disturbance and environmental concerns, especially in mountainous deciduous forests (Vadrevu, Eaturu, & Badarinath, 2010).

Iran has witnessed many forest fires and it seems that the region is a susceptible to this type of disaster. Forest fires have become a significant problem in Iran. Annual fires destroy more than 6000 ha of Iran's forest lands and cause also economic damages (Eskandari and Eskandari, 2021). According to the FAO (Food and Agriculture of the United Nations), Iran annually loses 0.06% of its forest due to fire and ranks the fourth in terms of forest destruction due to forest fire among the Middle East and North African countries (Ghazanfar Pour et al., 2017).

Proper conservation strategies for preventing forest fires could be an effective way to reduce the damages of this natural hazard (Moayedi, Mehrabi, Bui, Pradhan, & Foong, 2020). This is important as forest fires play an influential role in forest ecosystem services. Therefore, it is essential to predict forest fire detrimental effects on natural resources and ecosystem services (Vila-Vilardella et al., 2020). Research has shown that forest fires are enhanced by change in climate such as longer dry seasons, rainfall reduction, and frequent extreme temperatures (Pourghasemi, Gayen, Lasaponara, & Tiefenbacher, 2020).

The increasing frequency and severity of wildfires has become a major problem in certain regions of Iran. Forest fires have become an important issue in recent years, and many studies have been conducted on forest fire susceptibility analysis using various kinds of statistical models and various work is being done in different parts of the world on different aspects of this issue, for example:

1. For Iran, Pourghasemi, Gayen, Lasaponara, & Tiefenbacher, 2020 assessed the forest fire susceptibility in Fars province in Iran and produced the forest fire inventory map by using machine learning techniques and spatial modeling.

2. For China, Yang et al. (2019) proposed a demand forecasting model based on Index Fuzzy Segmentation (IFS) and Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) to effectively predict the number of firefighting helicopters needed in forest fires. Results demonstrated that the demand forecasting model based on these two methods (IFS and TOPSIS) has strong feasibility and rationality, which provides a robust method for predicting the number of forest firefighting helicopter demand resources.

3. In Iran, Ghazanfar Pour et al. (2017) identified the most influential factors of the forest fire control at Golestan Forest in the north of Iran by Strength, Weakness, Opportunity, and Threat (SWOT) and Analytic Hierarchy Process (AHP) models. The results showed that the measure of solidarity between organizations, the accessibility of the different parts of the forest, and the forest road network structure were the most vital factors in forest fire management.

4. In Torkey, Gungoroglu (2017) determined Turkish forest fire risk criteria consisting of socio-economic, topographic, climatic, and stand structure using the Fuzzy Analytic Hierarchy Process (FAHP) method and produced a risk map with low to high risks levels.

5. In general, Zandebasiri and Pourhashemi (2016) examined the strengths and weaknesses of some of the Multiple Criteria Decision Making (MCDM) methods consisting of AHP, Fuzzy Analytic Hierarchy Process (FAHP), Analytic Network Process (ANP), TOPSIS, VlseKriterijuska Optimizacija I Komoromisno Resenje (VIKOR), Weighted Sum Method (WSM), Data Envelopment Analysis (DEA), Strength, Weakness, Opportunity, and Threat (SWOT) Voting methods, Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE), and Elimination and Choice Translating Reality (ELECTRE) to choose an optimal way for decision making in forest management. AHP and SWOT methods were preferred in forest management among all multiple criteria decision-making methods.

For India, Sharma, Kanga, Nathawat, Sinha, & Pandey, 2012 analyzed the knowledge-based information to make strategies for forest fire management by using a Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) approach. Findings included the ranges of low to high forest fire risk zones according to environmental features such as topography, climate conditions, slope, and aspect.

Due to the diverse plant composition and mountainous conditions of Arasbaran forests, and due to the threat of forest fires on the native people livelihood in this region, investigation of the various aspects of forest fire seems to be essential for strategic planning and improving the efficiency of forest fire suppression efforts in the area.

This work aims to analyze the comparison of two the most frequently used multi-criteria decision-making methods (Simple Additive Weighting (SAW) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS)) for determining the most important forest fire prevention factors and management strategies in the Arasbaran Forest region. This study type of work has not been done in this region before.

2. Methods and materials

2.1. Description of the study area

Arasbaran forest (160,000 ha) is situated between longitude 46° 39′ 50″ and 47° 1′ 48″ E and latitude 38° 43′ 41″ to 39° 8′ 11″ N in the East Azarbayjan province, Northwest of Iran. The location of the mountainous study area is shown in Fig. 1. The main tree species are broad-leaved consisting of *Quercus macranthera*, *Quercus petraea*, *Carpinus betulus*, *Acer campestre*, *Acer monspessulanum,* and many shrubs species. *Taxus baccata* and *Juniperus foetidissima* are the main conifers of this region. The average annual temperature range is 2–17°C and the average total annual precipitation is 300–600 mm. This area is characterized by special climatic features, high biodiversity, and the presence of rare fauna and flora species. Arasbaran has been placed

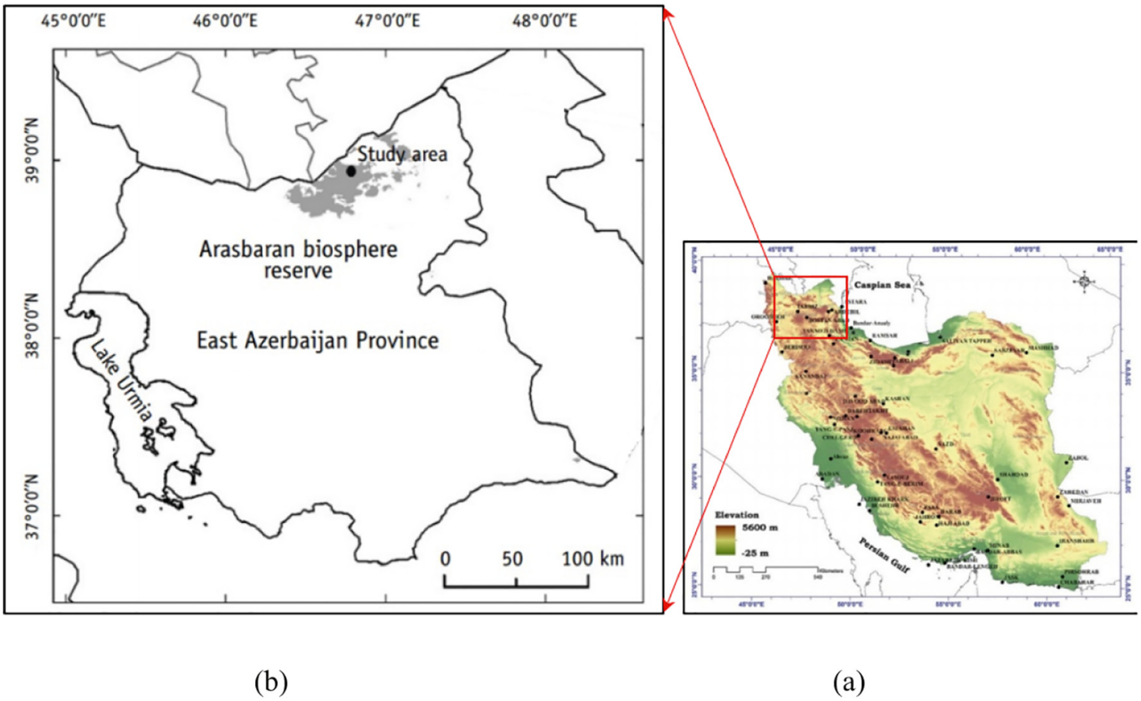

Fig. 1. The geographic location of the study area (Arasbaran Biosphere Reserve) in Iran (a) and East Azarbayjan Province in the northwest of Iran (b)

among the nine Iranian biosphere reserves under the UNESCO's Man and Biosphere program (Abedi and Abedi, 2020; Sagheb Talebi et al., 2014).

2.2. Determination models

According to the objectives of this study, 29 criteria were designed (Table 1). Criteria were selected to determine the most important causes of fires and the related firefighting management by a specialist team and by literature review (Amiri et al., 2017; Collins, Price, & Penman, 2018; Etongo, Kanninen, Epule, & Fobissie, 2018; Ghazanfar Pour et al., 2017). Afterward, questionnaires were designed as given in Table 2 (In Annex) for evaluating the importance of each criterion. 15 experts who had an average of 10 years of work experience in the forestry department and more than half of the members had a master of science (MSc) degree in the field of Natural Resource Management and were specialists in Forestry and Rangeland and Watershed Management (Table 3 in Annex) filled out the questionnaires, while present, according to their expert opinion. The criteria value for prioritizing the scoring of the initial matrix was from 1 to 9. The experts' team was asked to determine the value of each criterion based on a scale ranging from 1 to 9 for selecting the most effective criteria. Experts assigned the higher numerical value to the more important criteria, and conversely, lower numbers were assigned to less important criteria (Table 4 in Annex). Based on the criteria listed in Table 1, survey questionnaires (Table 2 in Annex) included a rating scale from 1 to 9 to weigh each factor relative to the other (Etongo, Kanninen, Epule, & Fobissie, 2018). The survey questionnaires were set up during the forest fire season in 2020.

Multi-criteria decision-making (MCDM) techniques are helpful tools that aid decision-makers to select options in the case of discrete problems. These refer to choosing the best alternative among a limited set of decision alternatives in terms of multiple, usually conflicting criteria. In other words, the MCDM technique is based on obtaining the alternative that approaches the most ideal alternative (Roszkowska, 2011).

Among many multi-criteria techniques, TOPSIS and SAW were selected in this study, as they are the most frequently used methods.

2.3. Technique for order performance by similarity to ideal solution (TOPSIS)

TOPSIS is one of the most widely-used classical multi-criteria decision-making methods that was first developed in 1981 by Hwang and Yoon (Hwang & Yoon, 1981). According to the concept of this method, the alternatives are sorted according to their distance from ideal (positive) and inappropriate (negative) solutions at the beginning. Then, the best alternative should have the shortest distance from the positive ideal solution and the farthest from the negative ideal solution (Balioti et al., 2018; Suder and Kahraman, 2018).

Table 1
The list of descriptions, positive and negative impacts of all criteria.

Criteria	Descriptions	Positive/Negative impact
C1	Association and cooperation between the executive and responsible institutions	Positive
C2	Cooperation and communication of neighboring provinces	Positive
C3	Local people participations	Positive
C4	Optimal use of past experiences	Positive
C5	Allocating additional funding as appropriate	Positive
C6	Providing detailed management plans	Positive
C7	Lack of firefighters and inadequate implementation of prevention and fire extinguishing operations.	Negative
C8	Poor forest monitoring, especially during peak fire times	Negative
C9	Lack of up-to-date scientific information on susceptible areas in the region such as forecasting maps, determining the amount of damage to the forest, etc.	Negative
C10	Lack of dedicated firefighting equipment (such as clothing and portable tools) and high costs of providing other advanced equipment for the organization (such as helicopters)	Negative
C11	Lack of natural or man-made ponds for water storage	Negative
C12	Lack of equipped search and rescue (SAR) bases inside the forest	Negative
C13	Lack of deterrence law in dealing with forest fire offenders in human-caused forest fires	Negative
C14	Lack of forest road network to access the ignited regions	Negative
C15	Lack of infrastructure for special equipment such as identifying suitable locations for helicopter landing, placing water tanks in the forest, etc.	Negative
C16	Lack of adequate guards, especially in susceptible areas and important areas in terms of endangered plant species	Negative
C17	Construction of stations for measuring effective environmental factors such as anemometer station, temperature recording, etc. in fire susceptible areas inside the forest	Positive
C18	Preparation of identification maps of susceptible areas and their updating.	Positive
C19	Upgrading the wireless and fire alarm networks	Positive
C20	Identifying the susceptible area for firefighting such as natural water reservoirs, rivers, and firelines	Positive
C21	Raising awareness of the natural resources position among local people and attracting their cooperation	Positive
C22	Promoting the position of responsible organizations and cooperation between organizations in charge of crisis management	Positive
C23	Increasing the cooperation of non-governmental organizations (NGOs) and increasing public trust	Positive
C24	Reducing the motivation of local youth to help	Negative
C25	Lack of financial credit	Negative
C26	Lack of equipment	Negative
C27	Lack of strategic view of forests and natural resources	Negative
C28	Lack of attention to the degraded areas after the fire and consequently increasing the land-use change	Negative
C29	Lack of empowerment of executive administrations.	Negative

The TOPSIS method compares the complex of alternatives by identification of weights for each criterion, uses a standardized weight score for each criterion, and calculates geometric distances between each alternative and the ideal variant according to the best score for each criterion (Holota et al., 2017).

The computational steps of the TOPSIS method are the following (Caliskan, 2017; Ghasemian, Yavari, Majed, Mohmoodi, & Javadian, 2018; Holota et al., 2017; Seyedmohammadi, Sarmadian, Jafarzadeh, Ghorbani, & Shahbazi, 2018; Zandebasiri and Pourhashemi, 2016):

1- Establishing a decision matrix (A_{ij}): This matrix consists of 15 rows and 29 columns. It was formed based on the given weight (from 1 to 9) to each criterion by each expert. Number 1 was assigned to the least important criteria and number 9 was assigned to the extremely important criteria. Numbers 2 to 8 were the intermediate importance that had varying degrees of importance from very low to very high (Table 4 in Annex).

$$A_{ij} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ a_{m1} & a_{m2} & \dots & a_{mn} \end{bmatrix} \rightarrow \begin{bmatrix} 9 & 8 & \dots & 6 \\ 8 & 1 & \dots & 8 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ 9 & 1 & \dots & 1 \end{bmatrix}$$

2- Calculating the normalized decision matrix (R_{ij}) based on the normalized value (r_{ij}): This matrix was calculated by dividing the numerical value of each criterion (1 to 9) by the sum of the total values of that criterion, according to the following formula:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad i = 1, 2, \dots, m \; j = 1, 2, \dots, n$$

$$R_{ij} = \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1n} \\ r_{21} & r_{22} & \dots & r_{2n} \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ r_{m1} & r_{m2} & \dots & r_{mn} \end{bmatrix} \rightarrow \begin{bmatrix} 0.09 & 0.08 & \dots & 0.08 \\ 0.08 & 0.039 & \dots & 0.10 \\ . & . & . & . \\ . & . & . & . \\ . & . & . & . \\ 0.09 & 0.04 & \dots & 0.01 \end{bmatrix}$$

3- Calculating the weighted normalized decision matrix (V_{ij}) by Matric Multiplication function and multiplying the normalized decision matrix (R_{ij}) by its associated weights matrix ($W_{n\times n}$):

$$V_{ij} = R_{ij} \times W_{n\times n} = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix}$$

4- Determining the positive ideal ($A+$) and negative ideal ($A-$) solution: The largest number obtained by multiplying the matrices in the previous step was selected as the positive ideal solution ($A+$) and the smallest number as the negative ideal solution ($A-$) for each criterion.

$$A^{+} = \left\{ \left(\max v_{ij} | \, j \in J \right), \left(\min v_{ij} | \, j \in J' \right), (i = 1, 2, \dots, m) \right\} = \left(v_1^{+}, v_2^{+}, \dots, v_n^{+} \right) or \, \{v_j^{+}$$

$$A^{-} = \left\{ \left(\min \; v_{ij} | \, j \in J \right), \left(\max \; v_{ij} | \, j \in J' \right), (j = 1, 2, \dots, n) \right\} = (v_1^{-}, v_2^{-}, \dots, v_n^{-}) or \, \{v_j^{-}\}$$

5- Calculating separation measures of m-dimensional Euclidean distance from each alternative to the positive ideal solutions (A^{+}) as D^{+} and m-dimensional Euclidean distance from each alternative to the negative ideal (A^{-}) solutions as D^{-}.

$$D_i^{+} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{+} \right)^2} \quad i = 1, 2, \dots, m$$

$$D_i^{-} = \sqrt{\sum_{j=1}^{n} \left(v_{ij} - v_j^{-} \right)^2} \quad j = 1, 2, \dots, n$$

6- Calculating the relative closeness to the ideal solution ($CCi+$) by using the following formula, ranking the preference orders of calculated values from the highest to the lowest value, choosing criteria with the maximum $CCi+$ value as the top rank, and then arranging the other ranks.

$$CC_i^{+} = \left[\frac{D_i^{-}}{D_i^{+} + D_i^{-}} \right]; 0 \le CC_i^{+} \le 1; \quad i = 1, 2, \dots, m$$

Where:
A_{ij}: Decision matrix
$a_{11} \dots a_{mn}$: value corresponding to ith criteria
r_{ij}: Normalized value
R_{ij}: Normalized decision matrix
V_{ij}: Weighted normalized matrix
W_i: Weight of the ith criterion
$A+$: Positive ideal solution
$A-$: Negative ideal solution
D_j+: Separation measures (distance) to positive-ideal solution
D_j-: Separation measures (distance) to negative-ideal solution
CC_j+: Relative closeness to the ideal solution
j: the weight of the jth criterion or attribute

2.4. Simple additive weighting (SAW)

SAW is a simple and commonly used scoring technique. The SAW method multiplies the normalized value of the criteria (n_{ij}) by the importance of the criteria (w_{gij}) and the criterion with the highest score is selected as the preferred one. In other words, an evaluation score is calculated for each criterion by multiplying the scale value of the criterion by the weight of relative importance and then summing all criteria. The ASW process, calculating the normalized values for positive and negative criteria, is as follows (Afshari, Mojahed, & Yusuff, 2010; Roszkowska, 2011; Seyedmohammadi, Sarmadian, Jafarzadeh, Ghorbani, & Shahbazi, 2018):

1- Constructing a pairwise comparison matrix for criteria (n × n, e.g. in here 29 (Vila-Vilardella et al., 2020). The weights of criteria have been computed by using the comparison matrix (A matrix containing information of questionnaire with a value of 1 to 9 for each criterion).
2- Constructing a decision matrix (m × n, e.g. in here 29 (Gungoroglu, 2017). Indicating the relative importance of the criterion in the columns compared to the criterion in the rows.
3- Calculating the normalized decision matrix for positive and negative criteria as follows:

- The normalized value for positive criteria by dividing the criterion value of the comparison matrix by the maximum value for each positive criterion:

$$n_{ij} = \frac{g_{ij}}{g_{max}}$$

- The normalized value for negative criteria by dividing the minimum value for each negative criterion in comparison matrix by the criterion value of comparison matrix:

$$n_{ij} = \frac{g_{min}}{g_{ij}}$$

4- Evaluation of the final score of each criterion by multiplying the normalized value of the criterion by its importance as follow:

$$FS = \sum \left(w_{gij} \times n_{ij} \right) \sum w_{gij} = 1$$

Where:
g_{ij}: Criterion value
g_{max}: Maximum value for each positive criterion
g_{min}: Minimum value for each negative criterion
n_{ij}: Normalized value
FS: Final Score

3. Results

The results of optimal criteria selected by the TOPSIS method showed that C1 which was "association and cooperation between the executive and responsible institutions" has the first rank ($CC_i^+ = 0.85$). C13 which was "Lack of deterrence law in dealing with forest fire offenders in human-caused forest fires" has the second rank ($CC_i^+ = 0.84$) and followed by C9 ('Lack of up-to-date scientific information on susceptible areas in the region such as forecasting maps, determining the amount of damage to the forest, etc.' $CC_i^+ = 0.789$), C23 (Increasing the cooperation of non-governmental organizations (NGOs) and increase public trust; $CC_i^+ = 0.787$) and C14 (Lack of forest road network to access the ignite regions; $CC_i^+ = 0.77$). Therefore, there were recognized as the first top-five criteria. In addition, C17 (Construction of stations for measuring effective environmental factors such as anemometer station, temperature recording, etc. in susceptible areas inside the forest; $CC_i^+ = 0.17$), C19 (Upgrading the wireless and fire alarm networks; $CC_i^+ = 0.12$) and C2 (Cooperation and communication of neighboring provinces; $CC_i^+ = 0.10$) were introduced as the least effective criteria in forest fire prevention strategies by the TOPSIS method, respectively (Figs. 2–4).

According to the results of the SAW method, 'Local people participation' ranked first (FS = 0.39). 'Association and cooperation between the executive and responsible institutions' was in second place (FS = 0.39). 'Increasing the cooperation of non-governmental organizations (NGOs) and increasing public trust' (FS = 0.36), 'Raising awareness of the natural resources position among local people and attracting their cooperation' (FS = 0.35), and 'optimal use of past experiences' (FS = 0.34) were among the criteria with the highest ranking, respectively (Fig. 5).

4. Discussion

According to the results of this study, we determined the top main forest fire management strategies based on MCDM methods. The association and cooperation between the executive and responsible institutions, Local people participation, Lack

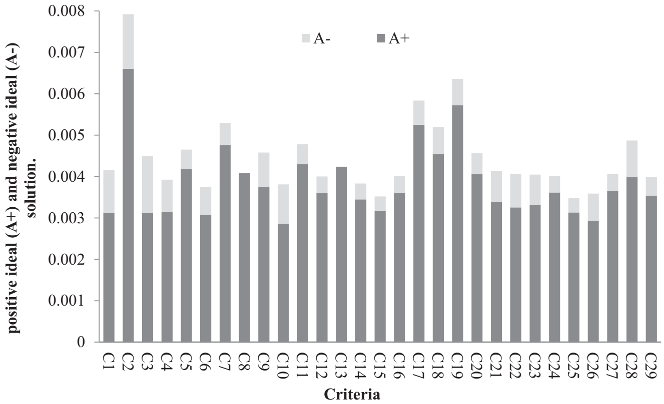

Fig. 2. Separation measures of positive ideal solution (A+) and negative ideal solution (A−) for TOPSIS model.

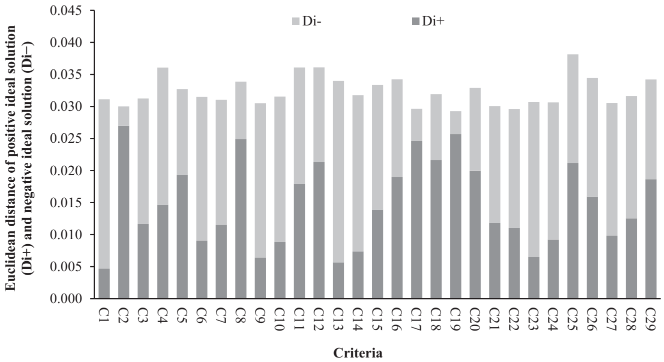

Fig. 3. Separation measures of m-dimensional Euclidean distance of positive ideal solution (Di+) andnegative ideal separation solution (Di−) for TOPSIS model.

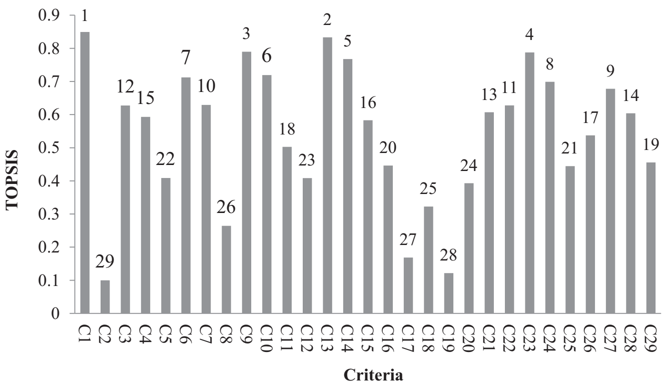

Fig. 4. Importance of each criterion after TOPSIS model implementation.

of up-to-date scientific information on susceptible areas in the region such as forecasting maps, determining the amount of damage to the forest, etc., Lack of deterrence law in dealing with forest fire offenders in human-caused forest fires, Increasing the co-operation of non-governmental organizations (NGOs), and increasing public trust were the highest priority criteria by using TOPSIS and SAW models.

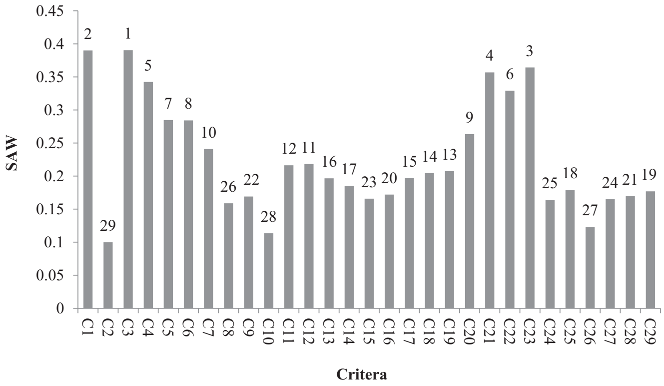

Fig. 5. Importance of each criterion after the SAW model implementation.

Association and cooperation between the executive and responsible institutions (C1) were ranked first because many other factors are a subset of that, such as the purchase of suitable equipment for firefighting and sending auxiliary forces requires coordination between organizations. Thus, proper management coordination is considered to be essential to all other activities.

Local people participation (C3) was recognized in the second rank. Their most effective help includes knowing the forest shortcut routes and helping to the finding fire area quickly and not to waste time, as well as assisting firefighting operations. Unfamiliarity with the routes to reach the fire points and loss of time to find them was identified problems in the Arasbaran forest fire. Thus, as well as proper top down management, proper bottom-up coordination is considered essential. In essence, the best option if a fully coordinated system of local actors and institutional bodies.

Contrary to expectations, the procurement of equipment (C7) was not among the top rankings according to experts' opinions, because sometimes devices are provided but do not have proper efficiency in different types of fires in the region. In addition, as mentioned, this process requires coordination between organizations, which was introduced as the top rank.

Our results are compared to those obtained in other regions of the world. Comparing these results with other studies showed that study on the main factors to manage the fires in exotic species plantations of Zimbabwe by Jimu and Nyakudya (2018) agreed with our results. They also displayed the need for cooperation among government and timber estate owners and community leaders. In addition, enacting forest fire policies, raising education and fire awareness campaigns, strengthening the linkage between indigenous communities and government, managing the maintain fire prevention were introduced as the additional main strategies.

Meteorological variables are directly and indirectly correlated with the occurrence, propagation, and distribution of wildfires such as precipitation and air temperature. According to this, fire hazard zonation is a significant factor for the management the beginning, the duration, and the end of fire hazard according to the reports of Eugenio et al. (2019). These factors can be are close to the criteria C8 and C9 in our study that were ranked a moderately important.

Providing a high-quality forest fire susceptibility map was proposed as an important element for fire risk management by Moayedi, Mehrabi, Bui, Pradhan, & Foong, 2020 in the Golestan Province, northern Iran. Moreover, obtaining susceptibility analysis of natural hazards, preparing maps as a guide in the risk management and prevention of the fire, as a fundamental prerequisites for future planning and risk management in any region were emphasized in the same study (by Moayedi, Mehrabi, Bui, Pradhan, & Foong, 2020). In our study, this criterion i.e. Lack of up-to-date scientific information on susceptible areas in the region such as forecasting maps, determining the amount of damage to the forest, etc. (C9), was ranked third as the most influential criterion.

Investigation on the sixty published studies covering 20 years (1997–2017) on forest fire management in Portugal showed that the legal criterion and fire legislation were the crucial aspects of fire management strategies (Mourao & Martinho, 2019). In addition, the related studies argued that good knowledge of causes, the relative motivations, and spatial and temporal distribution of forest fires is crucial for the design of prevention policies based on the literature review (Ganteaume et al., 2013).

Different MCDM techniques suit the different kinds of decision situations (Eldrandaly et al., 2009). Therefore, different kinds of MCDM approaches have been suggested in the decision analysis literature. The identification of the risk zones of forest fire according to past occurrence and preparation of a risk map with low to high risk levels in the Taradevi forest range of Shimla Forest Division (Himachal Pradesh) in India indicated this strategy could play an important role in fire prevention, control, and management of disasters within a quick response times. In other words, determining the regions with a high, moderate, and low susceptibility to fire with knowledge-based factors is be a practical strategy for anticipating fire risk. We used such criterion as C9 in our study and it was ranked third in the TOPSIS method.

The combination of MCDM methods has shown that this combination was easy to implement in participatory forest planning to suggest a wide array of management plans. Therefore, the combined MCDM approach can be used for ranking a set of long-term management plans with consideration to multiple objectives (Nilsson, Nordstrom, & Ohman, 2016). A comparison of the results of ranking in our study revealed that the two MCDM methods had similar results: Criterion 1 and 23 were identified as the best and Criterion 2 as the weakest effective criteria in fire management in both methods. Therefore, we demonstrated that to select and rank the most effective forest fire management strategies, the combination of TOPSIS and SAW methods can be effective. Also, participatory forest planning using AHP and TOPSIS concluded that this combination would increase the identification accuracy of the most suitable planning criteria for all stakeholders in Vilhelmina municipality, northern Sweden (Nilsson, Nordstrom, & Ohman, 2016).

The analysis of the most important MCDM method strengths and weaknesses in forest management plans in Iran concluded that the TOPSIS method was the optimal method based on its highest score in evaluation "accuracy of results" (Zandebasiri and Pourhashemi, 2016). It seems the method has the highest score among others methods due to defining positive and negative ideal options that cause the high accuracy. The TOPSIS method evaluates a large number of alternatives. This method has a relatively simple implementation but, the low sensitivity of analysis and team decision-making are the disadvantages of this method (Nilsson, Nordstrom, & Ohman, 2016; Zandebasiri and Pourhashemi, 2016). In addition, The TOPSIS method has been used to predict the demand for the required number of forest firefighting helicopters in the event of forest fires in Chinese forests (Yang et al., 2019).

Experts' knowledge is a basic source of information for making effective management decisions. Many MCDM methods determine the reasonable factors for management in different forests (Sharma, Kanga, Nathawat, Sinha, & Pandey, 2012). Also, a great range of techniques have been used to introduce effective factors and implemented widely in different regions. But, the best or the most suitable method is not clearly defined, so several MCDM methods are used to ensure the correct decision (Vinogradova, 2016). Their results, include the top ranking of each criterion are combined and presented as the top rankings of each method. Therefore, the simultaneous use of methods and the presentation of their most important criteria is the only solution to identify the best criteria (Eldrandaly et al., 2009).

5. Conclusion

The present study has revealed that efficient forest fire management and firefighting are influenced by various criteria. The results of this study, based on the expert knowledge of forest firefighting integrated into the two MCDM methods (TOPSIS and SAW) showed that "the association and cooperation between the executive and responsible institutions", "increasing the cooperation of non-governmental organizations (NGOs)", and "increasing the public trust" were the most effective factors criterion in fire management in the Arasbaran forest region.

In contrast, "the communication of neighboring provinces" was the least effective criterion in fire management in the Arasbaran forest region.

The main result is that if local, bottom up actions, and well coordinated management are combined, an optimal situation is created to support other factors, such as good risk maps, or suitable equipment. Without this across the board coordination and synergy, successful forest fire prevention and mitigation is unlikely to be achieved.

The results also showed that a combination of MCDM methods such as TOPSIS and SAW can help to prioritize criteria of varying degrees of importance and provide a clear idea, in this case, of the important factors in forest fire management.

Appendix A. Annex tables

Table 2
Questionnaire.

The importance and impact of the following criteria on fire crisis management in Arasbaran forests

Please enter the numbers 1 (least important) to 9 (most important) in front of each factor according to your expert opinion:

Profile of respondents: Years of work experience: Education: Specialization:

Impacts	Criteria		Increasing importance → 1	2	3	4	5	6	7	8	9
Positive	C1	Association and cooperation between the executive and responsible institutions									
	C2	Cooperation and communication of neighboring provinces									
	C3	Local people participations									
	C4	Optimal Use of past experiences									
	C5	Allocating additional funding as appropriate									
	C6	Providing detailed management plans									
Negative	C7	Lack of firefighters and inadequate implementation of prevention and fire extinguishing operations.									
	C8	Poor forest monitoring, especially during peak fire times									
	C9	Lack of up-to-date scientific information on susceptible areas in the region such as forecasting maps, determining the amount of damage to the forest, etc.									
	C10	Lack of dedicated firefighting equipment (such as clothing and portable tools) and high costs of providing other advanced equipment for the organization (such as helicopters)									
	C11	Lack of natural or man-made ponds for water storage									
	C12	Lack of equipped search and rescue (SAR) bases inside the forest									

	C13	Lack of deterrence law in dealing with forest fire offenders in human–caused forest fires									
	C14	Lack of forest road network to access the ignited regions									
	C15	Lack of infrastructure for special equipment such as identifying suitable locations for helicopter landing, placing water tanks in the forest, etc.									
	C16	Lack of adequate guards, especially in susceptible areas and important areas in terms of endangered plant species									
Positive	C17	Construction of stations for measuring effective environmental factors such as anemometer station, temperature recording, etc. in fire susceptible areas inside the forest									
	C18	Preparation of identification maps of susceptible areas and their updating.									
	C19	Upgrading the wireless and fire alarm networks									
	C20	Identifying the susceptible area for firefighting such as natural water reservoirs, rivers, and firelines									
	C21	Raising awareness of the natural resources position among local people and attracting their cooperation									
	C22	Promoting the position of responsible organizations and cooperation between organizations in charge of crisis management									
	C23	Increasing the cooperation of non-governmental organizations (NGOs) and increasing public trust									
Negative	C24	Reducing the motivation of local youth to help									
	C25	Lack of financial credit									
	C26	Lack of equipment									
	C27	Lack of strategic view of forests and natural resources									
	C28	Lack of attention to the degraded areas after the fire and consequently increasing the land-use change									
	C29	Lack of empowerment of executive administrations.									
Other cases:											

Table 3
Profile of respondents.

Years of work experience	Abundance (%)
<5	13.3
5–10	60
>10	26.67
Level of education survey	**Abundance (%)**
A.D	6.67
Diploma	6.67
BSc.	20
MSc.	60
Ph.D.	6.67
Specialization	**Abundance (%)**
Range management	20
Forest conservation unit	20
Watershed management	13.3
Land audit	6.67
Geomatics engineering	6.67
Soil science	6.67
Forestry	26.67

Note: A.D: Associate Degree, BSc: Bachelor of Science, MSc: Master of Science, Ph.D.: Doctor of Philosophy.

Table 4
Initial decision matrix.

	Respondents														
Criterion	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**	**14**	**15**
1	**9**	**8**	**8**	**9**	**7**	4	6	4	3	4	**7**	**9**	5	**8**	**9**
2	*2*	*1*	*1*	*1*	*1*	*1*	4	5	*2*	*1*	3	*1*	*1*	*1*	*1*
3	**7**	**8**	5	4	**7**	6	**9**	5	5	**7**	**8**	**9**	**9**	**7**	4
4	**7**	5	*2*	3	**8**	**8**	**7**	4	**7**	**8**	**8**	3	**8**	**8**	*2*
5	**7**	4	*2*	**7**	3	*1*	**8**	3	3	*2*	**8**	**9**	**8**	*2*	**7**
6	5	*2*	4	5	5	4	6	3	6	3	5	4	**8**	6	**9**
7	**9**	6	**8**	**8**	4	5	6	**7**	6	*1*	**9**	**9**	**8**	5	**8**
8	**8**	3	**8**	*1*	*2*	5	5	**8**	**7**	*2*		5	**8**		5
9	**9**	**7**	3	4	*2*	6	5	**7**	*2*	3	**7**	6	**7**	**8**	**7**
10	**9**	**9**	**8**	**9**	**7**	3	**7**	6	**9**	3	**7**	**9**	**8**	6	**9**
11	5	3	*2*	**7**	3	*1*	6	6	**9**	*2*	5	**9**	6	**7**	*1*
12	**9**	**8**	**8**	**8**	6	*1*	4	*1*	**7**	3	5	**9**	**8**	*1*	**8**
13	4	3	**8**	5	3	6	5		*2*	*1*	4	6	**8**	**9**	**9**
14	**9**	**9**	**8**	*1*	**7**	*1*	6	4	3	5	**7**	5	**9**	**7**	**9**
15	**8**	**9**	**8**	**9**	**7**	3	4	*1*	**9**	*2*	**7**	**9**	**9**	4	**9**
16	**9**	**8**	**7**	4	**8**	3	**7**	*2*	**7**	*1*	6	**9**	5	*2*	**8**
17	6	5	*2*	*2*	5	*1*	4	3	5	*2*	5	**9**	6	*1*	3
18	**7**	6	*2*	*2*	*2*	*1*	5	*2*	6	*2*	4	5	4	4	*1*
19	*2*	4	*2*	*1*	4	3	5	*2*	5	*1*	6	**7**	**9**	*1*	*2*
20	6	**8**	4	3	3	3	4	*2*	5	*2*	**7**	**7**	**8**	5	*1*
21	5	5	5	5	**8**	**9**	**8**	4	5	*2*	**7**	**8**	**9**	5	**7**
22	**8**	**7**	3	3	**8**	5	6	4	6	*2*	5	**8**	**8**	6	6
23	6	**7**	3	*2*	**9**	4	**8**	6	5	4	**7**	**9**	**9**	**8**	**7**
24	4	3	4	**9**	**8**	**8**	**8**	5	**9**	*1*	5	4	4	6	**8**
25	**9**	**9**	**8**	**9**	6	*1*	6	**9**	**9**	*2*	5	**9**	**7**	*1*	**9**
26	**8**	**9**	**8**	**9**	5	*2*	**7**	**9**	**9**	4	**7**	**9**	**8**	3	**9**
27	4	5	3	**7**	6	3	**7**	3	6	*1*	**9**	**9**	**9**	**7**	6
28	3	**9**	*2*	5	6	3	5	6	5	*2*	**9**	5	**7**	**7**	4
29	6	**8**	*2*	4	5	4	6	5	**8**	*2*	**8**	**7**	6	6	*1*

Note: More important criteria are bold and red. Less important criteria are italic and blue.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ijgeop.2022.02.005.

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