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Spherical Fuzzy AHP and Spherical Fuzzy TOPSIS-Based Goal Programming for Forest Fire Resource Allocation of Kastamonu Province

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Abstract

Aim of study: The study aims to assess the risk of wildfires in Kastamonu to develop a resource allocation plan through an optimization approach for strategic resource allocation in firefighting.

Area of study: The total forest area in Kastamonu was 876314 hectares. The region around the Ilgaz Mountains, which are in the inland areas away from the coastline, was found to be vulnerable to fire risk.

Material and method: Four major criteria and twelve sub-criteria that affect fire occurrence were assessed using SF-AHP. The weights were shortlisted using SF-TOPSIS. After determining the fire-vulnerable regions, resource allocation was done using goal programming.

Main results: Proximity to power lines was found to be the most important factor affecting the forest fire risk, with a weight of 13.5%, followed by humidity levels with a weight of 12.6%. Human factors and meteorological factors played a crucial role in determining the fire risk. The results revealed that the highest fire risk occurred in the Taşköprü district.

Research highlights: This study contributed to the literature with a new approach in which fuzzy-based risk analysis and goal programming models were used for the first time.

Keywords: Forest Fires, SF-AHP, SF-TOPSIS, Goal Programming

Kastamonu İlinin Orman Yangını Kaynak Tahsisi için Spherical Bulanık AHP ve Spherical Bulanık TOPSIS Tabanlı Hedef Programlama

Öz

Çalışmanın amacı: Bu çalışma Kastamonu'nun orman yangını riski yüksek olan ilçesini belirleyerek kaynak tahsis planlaması yapılması amaçlanmıştır. Model orman yangınlarına en uygun ekipmanların atanmasını hedeflemektedir.

Çalışma alanı: Kastamonu 876314 hektar orman alanına sahiptir. Kıyıdan uzak iç kesimlerde bulunan Ilgaz Dağları'nın çevresi yangın riski açısından hassastır.

Materyal ve yöntem: 4 ana kriter ve alt kriterlerin belirlenmesi için SF-AHP yöntemi uygulanmış, ağırlıkların hesaplanması için ise SF-TOPSIS yöntemi tercih edilmiştir. Yangın riskine etki eden bölgelerin belirlenmesinden sonra, hedef programlama yöntemi ile kaynak tahsisi planlaması gerçekleştirilmiştir.

Temel sonuçlar: Orman yangını riski açısından en kritik % 13.5 ağırlıkla elektrik hatlarına yakınlık olup bu kriteri % 12.6 oranında nem seviyesi takip etmektedir. İnsan kaynaklı etkenlerin ve meteorolojik koşulların yangın riskini belirlemede önemlidir. Yapılan analizler sonucunda Taşköprü ilçesi en risklidir.

Araştırma vurguları: Literatürde ilk kez bulanık tabanlı risk analizi ve hedef programlama modeli birleştirilerek yeni bir yaklaşım sunulmuştur.

Anahtar Kelimeler: Orman Yangınları, SF-AHP, SF-TOPSIS, Hedef Programlama

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Introduction

Approximately 12 million hectares of land worldwide were destroyed due to forest fires in 2019 (Tezcan & Eren, 2022). Forests are considered one of the most crucial natural resources that provide many services in terms of ecological, economic, and social services. Forests play an important role in climate change regulation, conservation of biodiversity, carbon sequestration, conservation of water and soil resources, and many more. The loss of these crucial services happens when there is damage to the forest due to forest fires. The risk of forest fires in forests worldwide has increased in recent years due to many reasons like climate change, drought, human negligence, etc. The loss due to forest fires is not only limited to the loss of vegetation but also includes human lives, properties, and regional economies in forest fire-prone regions worldwide. Türkiye is one of the regions that are highly prone to forest fires due to the presence of 12 million hectares of forest lands. In the summer season, forest lands in Türkiye are often damaged due to the dry climate and the chances of forest fires in the region (Alkayış et al., 2020).

In Türkiye, for example, 2021 has been recorded as a catastrophic year in terms of forest fires. In this year alone, 11 of the 20 largest forest fires recorded in the past 50 years occurred, including many mega-fires. As a result, 139503 hectares of forest ecosystems were destroyed in 2.793 incidents of forest fires (Kavzoğlu, 2016).

The area destroyed covers 1395 km², which is roughly twice the area of Singapore, which covers 710 km². Between 2012 and 2021, 750 forest fires were recorded in Kastamonu. The major solution that has been used to manage forest fires has been the extinguishing of forest fires as soon as they are identified. However, it has not been emphasized how to manage and mitigate forest fire risks. The forestry authorities need to use all their capacity to effectively manage forest fires through land, air, and sea operations (Kavzoğlu, 2016).

In this regard, this study examined Kastamonu Province in terms of forest fire risk assessment. The relevant criteria were identified in the literature, and the weight values were determined using Spherical Fuzzy Analytical Hierarchy Process (SF-AHP). The districts were also ranked using Spherical Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (SF-TOPSIS). Following the determination of the risk zones using historical forest fire data from the most vulnerable district, a goal programming model was formulated for the allocation of resources. The optimal allocation of firefighting tools to the regions was achieved. The regional data was collected from the General Directorate of Forestry, while the settlement and road data were collected from open sources.

The second part of the study dealt with the relevant literature review, whereas the third part of the study presented an in-depth analysis of the methodological framework of the study, including SF-AHP, SF-TOPSIS, and goal programming methods. The fourth part of the study presented an in-depth analysis of the fire-inducing criteria, the importance of the study area in terms of fire risk, the most vulnerable district in the study area, and the resource allocation strategy based on past fire incidents. The fifth part of the study presented the results obtained in the study, whereas the final part presented the general conclusions and recommendations for further study.

Literature Research

An assessment of 21 recent studies was carried out, with particular emphasis on the application of Multi-Criteria Decision Making (MCDM) methods. A consolidated overview of the studies focusing on wildfire issues is shown in Table 1. The literature was classified based on the research objectives, geographic areas, methodological frameworks, and evaluation criteria, as shown in Table 1. Among various techniques, the AHP-GIS hybrid approach emerged as the most frequent tool for wildfire risk mapping due to its capacity for multi-layered data integration. A high concentration of the studies implementing this specific methodology was focused on the Turkish region (Coban & Erdin, 2020; Sari, 2021; Sivrikaya & Küçük, 2022). Iran, characterized by an arid and semi-arid climate, exhibited high forest fire susceptibility due to dense vegetation and human activities (Abedi Gheshlaghi et al., 2020; Ghanbari Motlagh et al., 2022). Although India experiences fluctuating humidity levels due to the monsoon climate, its high temperatures increase the risk of forest fires, making it a suitable case study (Lamat et al., 2021; Nikhil et al., 2021). Similarly, Bosnia and Herzegovina, which has extensive forested regions, faces significant fire hazards in areas with Mediterranean climatic influences, particularly during the summer months (Gigović et al., 2018). Recent studies have also incorporated machine learning (ML) techniques in forest fire risk assessment. Fire hazards have been analyzed using ML methods alongside AHP-GIS techniques (Ersoy et al., 2025). Additionally, ecological variables such as soil moisture have been considered in fire risk analyses (Nuthammachot & Stratoulias, 2021). (Tezcan & Eren, 2023) examined fire risk factors such as proximity to power lines, agricultural areas, and dry vegetation. (Sari, 2021) conducted a comprehensive analysis by integrating AHP-VIKOR-TOPSIS-GIS techniques, further enhancing the decision-making process in forest fire risk assessment.

Table 1. Consolidated overview of research regarding forest fire risk evaluation and resource management scheduling

Author	Purpose of the study	Field of application	Method	Criteria
(Gigović et al., 2018)	Wildfire threats were delineated and spatially visualized.	Bosnia and Herzegovina	AHP-GIS	1*, 3*, 5*, 6*, 7*, 8*, 11*, 12*
(Nami et al., 2018)	A predictive cartography for forest fire likelihood was established.	Iran	GIS	3*, 5*, 6*, 7*, 11*, 12*, 13*
(Abedi Gheshlaghi et al., 2020)	Comprehensive models for forest fire susceptibility mapping were constructed.	Iran	FANP-GIS	1*, 3*, 4*, 5*, 6*, 7*, 11*, 12*
(Asori et al., 2020)	Fire risk maps were generated.	Ghana	AHP-GIS	1*, 3*, 4*, 5*, 6*, 7*, 11*
(Coban & Erdin, 2020)	Forest fire risk was assessed.	Türkiye	AHP-GIS	1*, 3*, 4*, 5*, 6*, 7*, 9*, 11*, 12*, 14*, 17*, 23*, 24*
(Novo et al., 2020)	Forest fire risk maps were produced.	Spain	AHP	5*, 6*, 7*, 11*, 12*, 25*
(Van Hoang et al., 2020)	Forest fire hazard maps were established.	Vietnam	AHP-GIS	1*, 2*, 3*, 4*, 5*, 6*, 11*, 12*, 13*
(Lamat et al., 2021)	Forest fire hazard maps were created.	India	AHP-GIS	3*, 4*, 5*, 6*, 7*, 15*, 25*
(Nikhil et al., 2021)	Fire risk zones were mapped.	India	AHP-GIS	6*, 7*, 11*, 12*
(Nuthammachot & Stratoulias, 2021)	A forest fire risk assessment was conducted.	Thailand	AHP-GIS	3*, 5*, 6*, 7*, 12*, 13*, 16*
(Sari, 2021)	Fire-susceptible areas were identified.	Türkiye	AHP-VIKOR-TOPSIS-GIS	1*, 3*, 4*, 5*, 6*, 7*, 9*, 10*, 11*, 12*, 13*, 14*, 15*, 16*
(Abdo et al., 2022)	Forest fire susceptibility maps were generated.	Syria	AHP-GIS	1*, 2*, 3*, 4*, 5*, 6*, 7*, 11*, 12*
(Ghanbari Motlagh et al., 2022)	Fire risks in forested regions were identified.	Iran	ANP-GIS	1*, 3*, 5*, 6*, 7*, 8*, 11*, 12*, 13*, 16*, 17*
(Sivrikaya & Küçük, 2022)	Wildfire susceptibility across the Mediterranean territory was systematically modeled.	Türkiye	AHP-GIS- İstatistiksel endeks	1*, 3*, 4*, 5*, 6*, 7*, 11*, 12*, 13*, 15*, 17*, 24*
(Sinha et al., 2023)	Fire risk maps were developed.	India	AHP-FAHP	6*, 11*, 12*, 16*, 25*
(Tezcan & Eren, 2023)	Criteria affecting forest fires were evaluated.	Türkiye	PFAHP-ANP-AHP	1*, 2*, 4*, 5*, 6*, 7*, 9*, 10*, 12*, 14*, 15*, 16*
(Ersoy et al., 2025)	A fire hazard assessment was conducted.	Türkiye	AHP, GIS, ML	1*, 2*, 3*, 4*, 11*, 12*, 17*, 16*, 25*
(Malik et al., 2025)	Forest fire sensitivity was analyzed.	Jammu	FAHP-GIS	4*, 6*, 7*, 9*, 11*, 12*
(Tezcan & Eren, 2025b)	Districts at risk of forest fires have been evaluated.	Türkiye	PFAHP, PFTOPSIS, Sensitivity analysis	1*, 2*, 4*, 5*, 6*, 7*, 9*, 12*,
(Riga, 2025)	Fire hazard maps were produced.	Greece	AHP-GIS	1*, 2*, 3*, 4*, 5*, 6*, 7*, 9*, 11*, 13*, 15*
(Uçar et al., 2025)	A forest fire risk assessment was carried out.	Türkiye	FAHP-GIS	1*, 2*, 3*, 4*, 6*, 7*, 11*, 17*
(Tezcan & Eren, 2025)	A literature review on forest fire resource planning was conducted.		Literature review	
In this study	After identifying forest fire risk zones, resource allocation planning was performed.	Kastamonu	SF-AHP, SF-TOPSIS, Goal programming	1*, 2*, 4*, 5*, 6*, 7*, 10*, 12*, 14*, 16*, 27*, 28*

*1: Temperature, 2: Humidity, 3: Precipitation, 4: Wind, 5: Elevation, 6: Slope, 7: Aspect, 8: Vegetation density, 9: Vegetation type, 10: Biomass density, 11: Distance to roads, 12: Distance to settlemets, 13: Distance to rivers, 14: Distance to power lines, 15: Population density, 16: Land use, 17: Distance to farmland, 18: Leaf litter depth, 19: Leaf litter moisture, 20: Soil texture, 21: Soil moisture, 22: Distance to water sources, 23: Age of stand development, 24: Crown slosure, 25: Forest fire dataset, 26: Facing direction, 27: Dry vegetation 28: Altitude.

There have been various studies on the wildfire resource allocation problem. These studies have addressed vehicle routing problems (Matos et al., 2023; Van der Merwe, 2015; Wu et al., 2019; Tezcan et al., 2021), decision support systems (Brown et al., 2021; Granda et al., 2023; Suarez et al., 2024), stochastic programming (Bashiri et al., 2021; Forootani et al., 2021; Zhang et al., 2023), integer programming (Tezcan & Eren, 2025c, 2025a) and simulation (Li et al., 2019; Palacios-Meneses et al., 2023; Tapia et al., 2021).

The contributions of this study to the literature are outlined below:

Application area: In recent years, the frequency of forest fires in Türkiye has increased (Kavzoğlu, 2016). Kastamonu province has been considered one of the critical regions in terms of fire risk due to its extensive forest cover and topographic characteristics. The climatic conditions of the region, particularly low humidity levels and high temperatures during summer, have exacerbated fire hazards. Additionally, intensive agricultural activities, the close proximity of residential areas to forests, and various anthropogenic activities have significantly increased the likelihood of fire outbreaks. Although the risk of forest fires in Kastamonu has been identified in previous studies, no comprehensive research has been conducted on the effective planning and allocation of firefighting equipment.

Methodology: Forest fire occurrences have been influenced by multiple factors, and their interactions often involve uncertainties and contradictions. Addressing these uncertainties has been essential in prioritizing fire risks in Kastamonu province. Accordingly, this study has incorporated both quantitative and qualitative data. First, the high fire-risk districts of Kastamonu were identified using the SF-AHP and SF-TOPSIS techniques. Subsequently, a goal programming model was developed to optimize the allocation of firefighting equipment for the most high-risk district. The model has included parameters that account for the existing firefighting equipment capacity. To optimize this process, IBM ILOG CPLEX Optimization software was utilized, ensuring an efficient approach for solving large-scale problems.

Evaluation: Forest fires have been among the most severe natural disasters, causing devastating effects on ecosystems and human settlements. Therefore, identifying fire risk zones and strategically allocating firefighting equipment has been crucial for decision-makers. In this study, spherical fuzzy sets and goal programming were applied for the first time in forest fire management. By integrating the operational constraints of firefighting equipment into the model, an effective fire management strategy was formulated for Kastamonu province. The findings of this study have provided valuable insights for decision-makers in firefighting operations and contributed to the development of more effective intervention strategies.

Material and Methods

The methodological framework and operational phases of the SF-AHP, SF-TOPSIS, and Goal Programming approaches are detailed within this section.

Spherical Fuzzy AHP and Spherical Fuzzy TOPSIS

Spherical Fuzzy Sets (SFS) were established in 2019 by Kutlu and Karaman as a three-dimensional extension of fuzzy logic (Gündoğdu, 2019). Figure 1 provides a comparative geometric visualization of NS, PFS, IFS, and SFS. Furthermore, the analysis delineates the specific differences between Neutrosophic Fuzzy Sets (NFS) and Secondary Type Intuitionistic Fuzzy Sets (IFS2).

In this method, the sum of the membership (μ), non-membership (v), and hesitancy (π) values was required to be less than 1. This limitation was redefined in the NFS approach. Additionally, an independent instability membership degree formula was introduced.

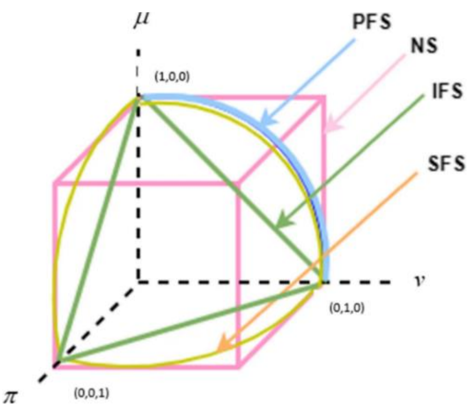

Figure 1. Geometric representations of NS, PFS, IFS and SFS

In a Multi-Criteria Decision-Making (MCDM) problem, the global fuzzy environment involved the identification of decision-makers, and the alternatives were evaluated based on predefined criteria. Let $X = \{x_1, x_2, \dots, x_m\}$ $(m \geq 2)$ be a disjoint set of m feasible alternatives, and let $C = \{C_1, C_2, \dots, C_n\}$ represent a finite set of criteria. Additionally, let $w = \{w_1, w_2, \dots, w_n\}$ denote the weight vector that satisfies all criteria, where $0 \leq w_j \leq 1$ and $\sum_{j=1}^{n} w_j = 1$. The SF-AHP method was illustrated in Figure 2, while the SF-TOPSIS method was explained in detail in Figure 3. The linguistic scale used in these methods was presented in Table 2.

Table 2. Spherical Fuzzy linguistic scale

Linguistic term	(μ, v, π)	Score index (SI)
Absolutely more importance (AMI)	(0.9, 0.1, 0.0)	9
Very high importance (VHI)	(0.8, 0.2, 0.1)	7
High importance (HI)	(0.7, 0.3, 0.2)	5
Slightly more importance (SMI)	(0.6, 0.4, 0.3)	3
Equally importance (EI)	(0.5, 0.4, 0.4)	1
Slightly low importance (SLI)	(0.4, 0.6, 0.3)	1/3
Low Importance (LI)	(0.3, 0.7, 0.2)	1/5
Very low importance (VLI)	(0.2, 0.8, 0.1)	1/7
Absolutely low importance (ALI)	(0.1, 0.9, 0.0)	1/9

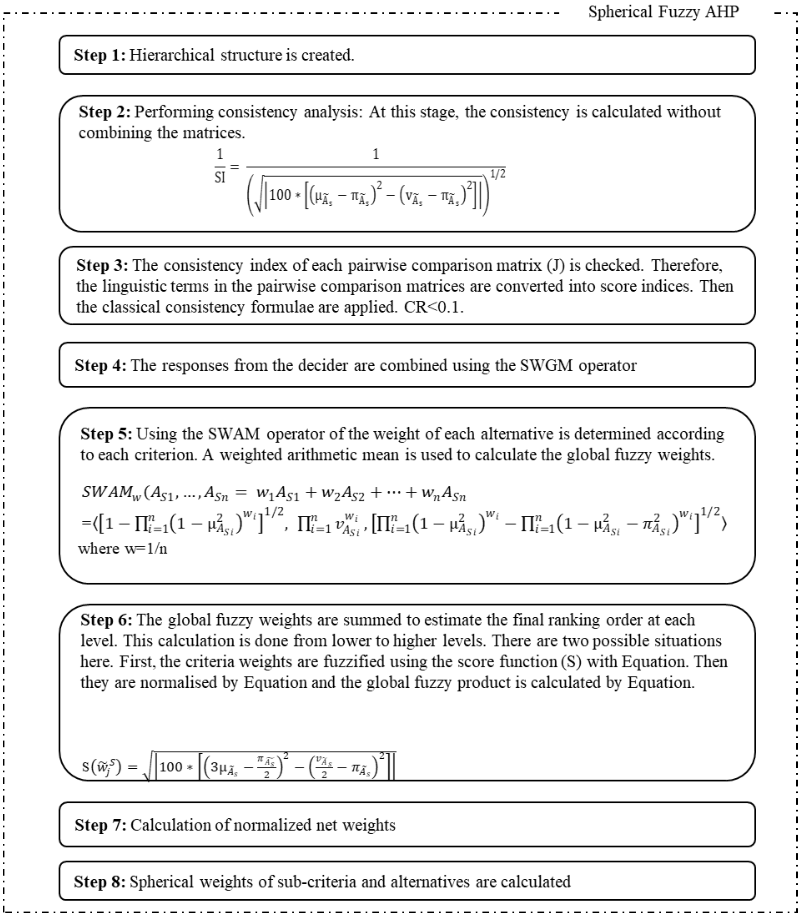

Figure 2. Procedural framework and operational phases of the Spherical Fuzzy AHP approach

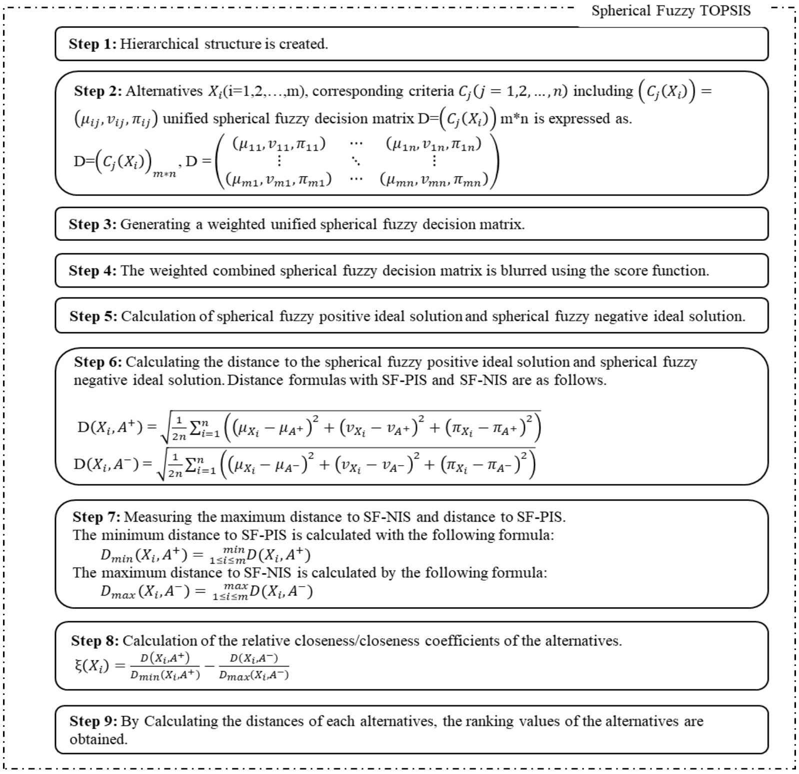

Figure 3. Operational sequence and algorithmic stages of the Spherical Fuzzy TOPSIS methodology

Goal Programming

Individuals constantly face decision-making situations and must solve various real-life problems. In such cases, multiple criteria need to be considered to reach an optimal solution. Therefore, multi-criteria decision-making techniques should be employed. Goal programming is a widely used method with numerous applications. In formulating the goal programming method, the first step is to identify the decision variables, which should be determined based on the specific application area (Ergün, 2006). When constructing the goal programming model, the formulation process involves defining the objective function, constraints, and decision variables (Gür et al., 2017).

Goal programming primarily aims to minimize the variance between target levels and achieved outcomes. In linear programming, such deviations are referred to as slack variables in the simplex algorithm, whereas in goal programming, they are reinterpreted as deviation variables. These deviations are categorized into two types: positive and negative deviations from each goal. The objective function is formulated using these deviation variables (Dağdeviren & Eren, 2001). The general formulation is presented below.

$$MinZ = [P_1 w_1 (d_1^+, d_1^- + \cdots + P_k w_k (d_k^+ d_k^-))] \quad (1)$$

subject to

$$\sum_{j=1}^{n} a_{ij} x_j - d_i^+ + d_i^- = b_i \qquad (\forall_i) \quad (2)$$

$$d_i^+, d_i^-, x_j \geq 0 \quad (3)$$
$$i = 1, \dots, m \quad , \quad j = 1, \dots, n$$

Where x_j represents the decision variables, b_i denotes the desired value for objective i, n is the total number of decision variables, and m is the total number of constraints. P_k represents the priority level, w_k denotes the weight, and a_{ij} are the parameters. Since the objective is to minimize deviations from the target values, deviation variables are considered in two dimensions: positive and negative. However, positive and negative deviations cannot occur simultaneously; thus, one of the deviation variables must always be equal to zero. Once the undesired deviation variables are identified, the formulation can be established.

d_i^+: positive deviation variable $\quad i = 1, \dots, m$
d_i^-: negative deviation variable $\quad i = 1, \dots, m$

The goal is to minimize both positive and negative deviations across all variables (Özder, 2015). Consequently, this approach provides a model capable of achieving multiple objectives simultaneously.

In this study, the basic goal programming method was preferred. Because the problem structure requires multiple goals to be considered simultaneously, this classical approach is also suitable, as the parameters do not contain uncertainty, and the solution is interpretable. More advanced goal programming types (e.g., weighted or priority) can be evaluated in future studies on this basic model.

Application

Kastamonu Province, located in Türkiye, is at risk of forest fires. Although the geographical location in the Black Sea region generally maintains high humidity levels, thermal increases and humidity deficits in the summer months serve as the primary factors for increased susceptibility to wildfires. The systematic implementation of this research in the Kastamonu province is depicted in Figure 4. The main focus of this research is the comparative ranking of 16 districts with respect to fire hazards in order to develop a special resource management framework. The methodological phases are comprehensively articulated, relying on decision matrices formulated by ten subject-matter experts profiled in Table 3. Every expert generated a discrete matrix, yielding a comprehensive set of 10 matrices to support the SF-AHP and SF-TOPSIS computational procedures.

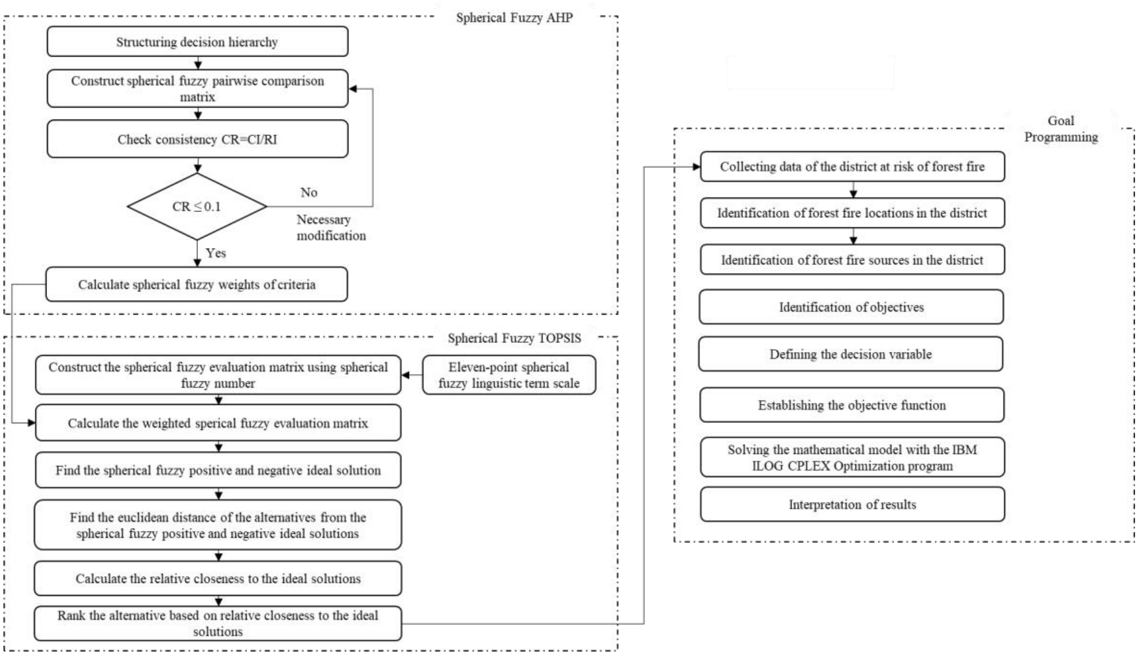

Figure 4. Application flow

Table 3. Expert team knowledge

Expert number	Stakeholder	Directorates	Duration of experience
E1	Afforestation department	Silvicultural surveying and project administration	19
E2		Regional department of afforestation and reforestation	10
E3		Strategic planning and performance assessment directorate	15
E4		Administrative unit for private silvicultural initiatives	6
E5	Department of ecosystem services	Division of non-timber and herbal forest products	21
E6		Management branch for forest ecosystem services	14
E7		Directorate for biological diversity and forest conservation	9
E8		Office for forest-based recreation and site management	10
E9	Forest administration and planning department	Forest governance and administrative operations directorate	13
E10		Monitoring, follow-up, and regulatory compliance branch	18

Explanation of Criteria

Four main criteria and twelve sub-criteria contributing to forest fire risk were identified from the literature. Table 4 presents these criteria. Analyzing the table reveals that the identified criteria influence not only the occurrence of forest fires but also their spread.

Table 4. Explanation of criteria

Criteria	Sub-Criteria	Definition
Climate (C1) (Rothermel, 1983; Van Hoang et al., 2020)	Wind (C11)	The speed and direction of the wind contribute to the spread of forest fires. Winds ranging from 3.0 m/s to 8.8 m/s typically lead to large-scale forest fires.
	Humidity (C12)	Humidity in combustible materials can contribute to fire ignition. By reducing heat during ignition, flammable materials require more energy to ignite. The humidity content of combustible materials in the top layer decreases convective heat transfer and flame development. Therefore, studies on coniferous tree needles have shown that variations in humidity content necessitate different amounts of energy or heat for combustion. The humidity content of leaves has a lesser effect on the initiation of a crown fire compared to the height below the crown. However, theoretically, leaf humidity content has a significant impact on the rate of crown fire spread.
	Temperature (C13)	Weather conditions with temperatures exceeding 40 °C and relative humidity below 20% present a high risk of forest fires. Under such conditions, fires can spread rapidly due to wind effects, making them difficult to control. In light of these factors, air temperature is a critical parameter to consider.
Vegetation (C2) (Ghanbari Motlagh et al., 2022)	Biomass density (C21)	On the other hand, biomass is the total weight in a forest stand, which includes the roots, trunks, leaves, barks, and branches. Standing volume is the total volume of the stems above a certain diameter that are alive and productive. From the two terms, it is evident that an increased biomass density in the study area increases the chances of a fire.
	Dry vegetation (C22)	Vegetation plays a significant role in forest fires. Factors such as density, type, coverage, composition, and developmental stages of vegetation influence fire risk. Tree species are particularly important in determining the ignition and behavior of forest fires. Coniferous and dry species, such as red pine, create especially favorable conditions for fire.
	Altitude (C23)	Although humans have settled at various altitudes, ranging from sea level to extreme elevations, the 0–1.500 m range is generally more suitable for habitation. As a result, vegetation density and diversity vary with altitude.
Topography (C3) (Sari, 2021)	Aspect (C31)	The east-facing slopes receive more sunlight than the west-facing slopes, and the north-facing slopes receive more sunlight than the south-facing ones. Consequently, the east and south slopes are exposed to direct heating. Sun exposure dries vegetation and soil, increasing the likelihood of fire.
	Slope (C32)	Fires spread faster from higher to lower elevations. Therefore, slope has a linear relationship with forest fire risk. As the slope increases, the risk of forest fire also increases. Thus, the hill is effective in two aspects of fires: the direction of the fire and the rate of spread.
	Elevation (C33)	The distance between surface fuels and aerial fuels is a critical physiological factor in the initiation of crown fires. Under-canopy height refers to the distance from the lowest live branch of a tree to the canopy surface. Along with dead branches, lichen, and suspended fuels are also considered. Given these factors, fires often start on upward slopes and rapidly spread downhill.
Socioeconomic (C4) (Tezcan et al., 2022; Tezcan & Eren, 2023)	Land use (C41)	Forest fires are caused by accidents and carelessness in agricultural areas. Every year, there are farming fires that can be extinguished without crossing into forest areas. Situations such as garden clearing and stubble burning are agriculturally caused forest fires.
	Distance to settlemets (C42)	Human activity in settlements increases the risk of forest fires. The 0-50 m range is the most risky, and between 50-200 m is determined as the second-degree risky area.
	Distance to power lines (C43)	Most of Türkiye's villages are located in forests. In addition, due to ownership problems in Türkiye, power lines between provinces and districts are routed through forested areas. Energy distribution companies are responsible for maintaining these power lines. However, forest fires occur due to the lack of maintenance of the routes through which the lines pass.

Explanation of Alternatives

The forested territory of Kastamonu encompasses an extensive 876.314 hectares. This total comprises 695.763 hectares of dense, high-density forest and 180.551 hectares categorized as gapped canopy structures (URL-1, 2025). Such statistics underscore the province's significant ecological wealth and robust biodiversity. The spatial distribution of wildfire susceptibility for the region is illustrated in Figure 1. Upon analyzing the figure, it is observed that Kastamonu ranks second in terms of fire risk, highlighting a significantly high fire hazard. Therefore, the selected study area is Kastamonu.

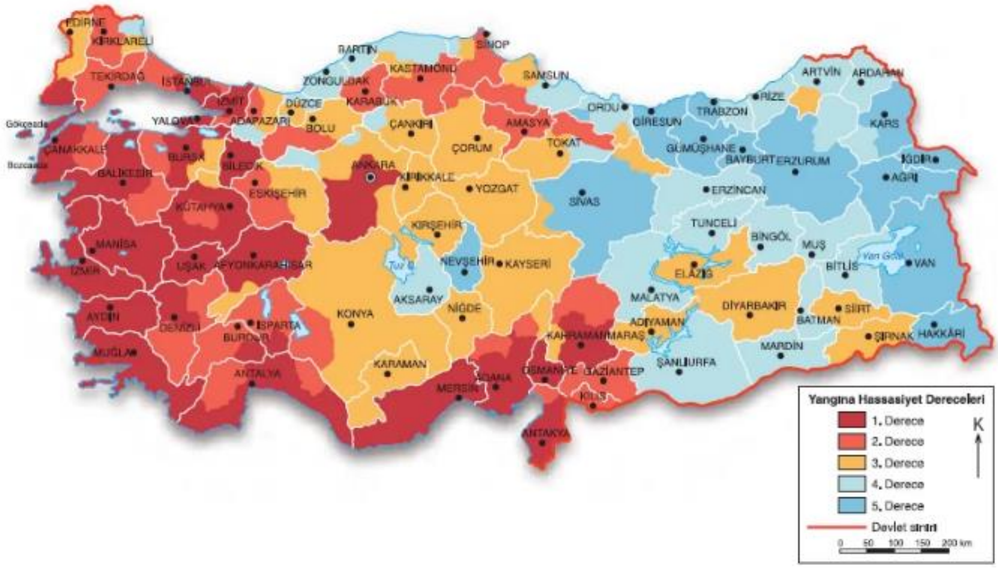

Figure 5. Forest fire risk map

The primary causes of fires in the Kastamonu region include both human-induced and natural factors. Human causes include inadequately put out picnic and camping fires, burning stubble, discarded cigarette butts, and power transmission line sparks. Natural causes are mainly lightning and drought. Moreover, topography and wind factors are very important in determining the speed and direction of fire movement. The forested regions in the inland areas of Kastamonu are especially at risk of fires, particularly those that are remote from the coast and the Ilgaz Mountains. In this respect, it is very important to correctly determine the risk of forest fires and take preventive measures to maintain ecological balance. Table 5 shows the districts of Kastamonu Province, and Figure 6 shows the hierarchical structure. From the analysis of the figure, it is clear that several criteria and sub-criteria affect forest fires.

Table 5. Alternative districts

Alternatives no	Alternatives
A1	Araç
A2	Azdavay
A3	Bozkurt
A4	Cide
A5	Çatalzeytin
A6	Datay
A7	Hanönü
A8	İhsangazi
A9	İnebolu
A10	Karadere
A11	Merkez
A12	Küre
A13	Pınarbaşı
A14	Samatlar
A15	Taşköprü
A16	Tosya

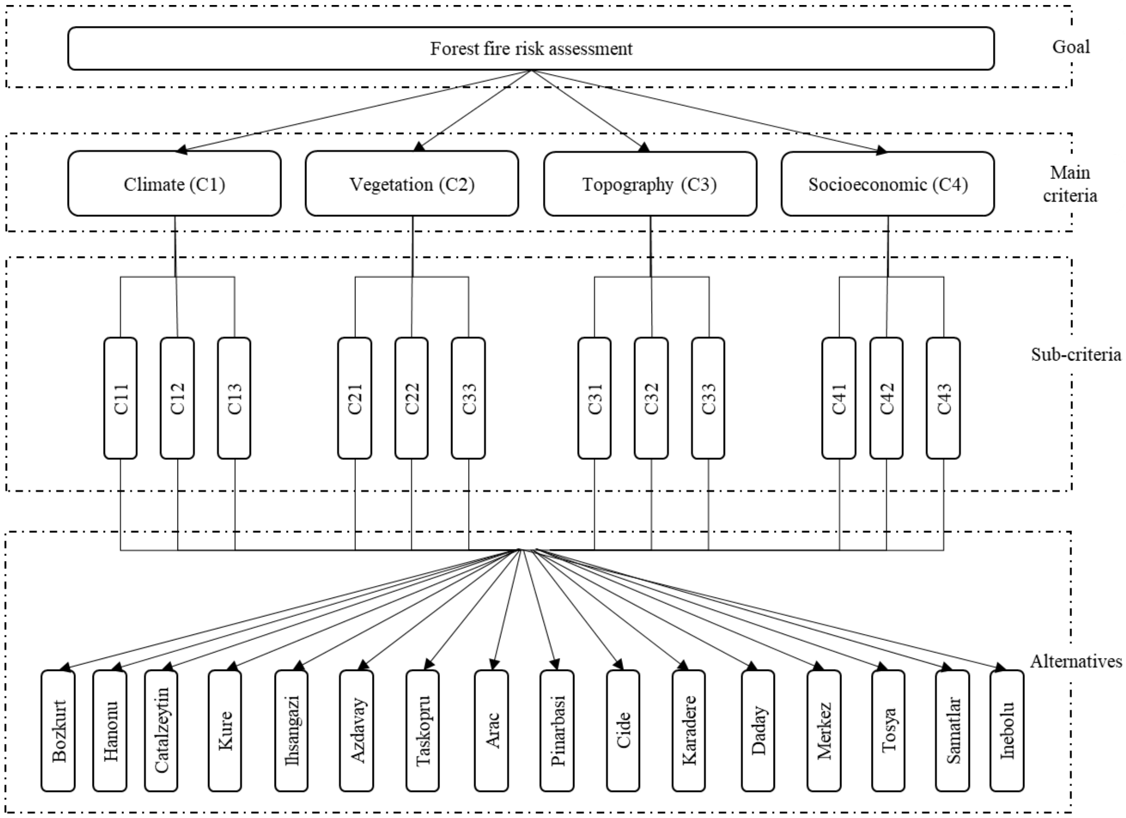

Figure 6. Hierarchical structure

The Weighting of Criteria with The SF-AHP Method

The evaluation of the determined criteria was carried out through the professional judgment of a panel of 10 subject matter experts. The experts evaluated the primary and secondary criteria independently by using the universal fuzzy linguistic metrics as presented in Table 2 to form the initial decision matrices. In order to quantify the relative weights of the main criteria, a pairwise comparison matrix was formulated as presented in Table 6.

For each of the subordinate factors, a pairwise comparison matrix was developed using the universal fuzzy linguistic terms identified in Table 2. The criteria matrices for the sub-criteria including climate (C1), vegetation (C2), topography (C3), and socioeconomic factors (C4) are presented in Table 7. The spherical fuzzy significance levels for the criteria were then determined. The results, including spherical fuzzy, defuzzified, normalized local, and global weights, are systematically presented in Table 8.

Table 6. Pairwise comparison matrix of the main criteria obtained with SWGM

Criteria	C1	C2	C3	C4
C1	(0.50,0.40,0.40)	(0.67,0.33,0.23)	(0.64,0.34,0.24)	(0.78,0.21,0.11)
C2	(0.33,0.67,0.23)	(0.50,0.40,0.40)	(0.47,0.51,0.30)	(0.64,0.36,0.26)
C3	(0.35,0.62,0.24)	(0.51,0.47,0.30)	(0.50,0.40,0.40)	(0.66,0.34,0.24)
C4	(0.21,0.78,0.11)	(0.36,0.64,0.26)	(0.34,0.66,0.24)	(0.50,0.40,0.40)

Table 7. Pairwise comparison matrix of sub-criteria obtained with SWGM

Criteria	C11	C12	C13
C11	(0.50,0.40,0.40)	(0.32,0.68,0.22)	(0.38,0.62,0.28)
C12	(0.68,0.32,0.23)	(0.50,0.40,0.40)	(0.58,0.40,0.32)
C13	(0.62,0.38,0.28)	(0.42,0.57,0.32)	(0.50,0.40,0.40)
	C21	C22	C23
C21	(0.50,0.40,0.40)	(0.44,0.55,0.31)	(0.58,0.41,0.30)
C22	(0.54,0.45,0.32)	(0.50,0.40,0.40)	(0.67,0.33,0.24)
C23	(0.40,0.60,0.29)	(0.46,0.56,0.24)	(0.50,0.40,0.40)
	C31	C32	C33
C31	(0.50,0.40,0.40)	(0.53,0.45,0.32)	(0.68,0.32,0.23)
C32	(0.45,0.55,0.32)	(0.50,0.40,0.40)	(0.61,0.38,0.30)
C33	(0.32,0.68,0.22)	(0.39,0.61,0.29)	(0.50,0.40,0.40)
	C41	C42	C43
C41	(0.50,0.40,0.40)	(0.36,0.64,0.25)	(0.34,0.66,0.25)
C42	(0.62,0.39,0.26)	(0.50,0.40,0.40)	(0.49,0.51,0.30)
C43	(0.65,0.36,0.26)	(0.49,0.51,0.31)	(0.50,0.40,0.40)

Table 8. Criteria weights

No.	Spherical fuzzy weights	Clarified weights	Normalized local weights	Global weights
C11	(0.490,0.413,0.368)	12.746	0.264	0.085
C12	(0.694,0.227,0.342)	18.966	0.393	0.126
C13	(0.618,0.295,0.374)	16.520	0.343	0.110
C21	(0.607,0.301,0.378)	16.167	0.330	0.081
C22	(0.677,0.244,0.346)	18.448	0.377	0.092
C23	(0.544,0.365,0.366)	14.361	0.293	0.072
C31	(0.680,0.242,0.344)	18.539	0.386	0.099
C32	(0.622,0.290,0.378)	16.612	0.346	0.088
C33	(0.492,0.408,0.370)	12.816	0.267	0.068
C41	(0.129,0.412,0.366)	1.256	0.053	0.010
C42	(0.230,0.282,0.357)	4.655	0.198	0.036
C43	(0.651,0.270,0.356)	17.607	0.749	0.135
C1	(0.829,0.098,0.257)	23.487	0.320	
C2	(0.666,0.221,0.362)	18.004	0.245	
C3	(0.689,0198,0.353)	18.730	0.255	
C4	(0.506,0.361,0.365)	13.219	0.180	

From an examination of the results in Table 8, the weight of the main criteria of climate (C1), vegetation (C2), topography (C3), and socioeconomic factors (C4) is found to be 0.320, 0.245, 0.255, and 0.180, respectively. The weight of climate (C1) is found to be the highest at 32% in assessing forest fire risk because this criterion is considered to be crucial in determining the occurrence of forest fires. Topography (C3) follows this criterion at 25.5%, while vegetation (C2) follows at 24.5%. The socioeconomic criterion (C4) has the lowest weight at 18%. Figure 7 visually represents the criteria weights.

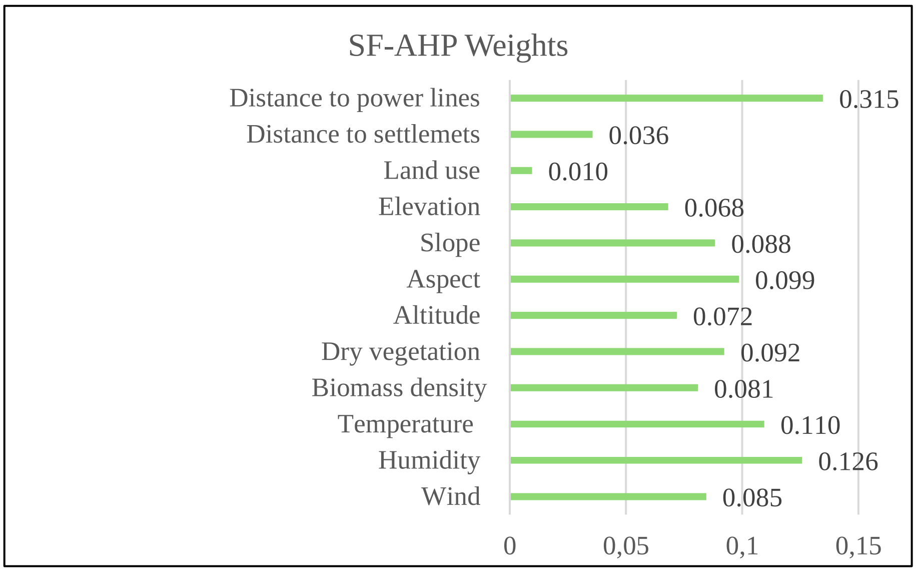

Figure 7. Spherical fuzzy weights

Ranking of Alternatives with The SF-TOPSIS Method

The alternative districts were evaluated and ranked using the SF-TOPSIS technique. In the Methods section, the stages of the SF-TOPSIS technique were applied. The decision matrices, created by 10 experts using the fuzzy linguistic scale provided in Table 2, are presented in Table 9 and Table 10. The stages were implemented using the calculated criteria weights. In addition to identifying the district with the highest forest fire risk, proximity indices were also determined.

Table 9. SWAM based collective decision matrix

	C11	C12	C13	C21	C22	C23	C31	C32	C33	C41	C42	C43
A1	0.11, 0.51, 0.41	0.14, 0.43, 0.42	0.11, 0.50, 0.41	0.10, 0.50, 0.45	0.12, 0.47, 0.41	0.11, 0.48, 0.44	0.13, 0.47, 0.39	0.14, 0.43, 0.44	0.08, 0.56, 0.43	0.02, 0.54, 0.44	0.05, 0.45, 0.42	0.33, 0.50, 0.45
A2	0.11, 0.51, 0.40	0.12, 0.48, 0.42	0.10, 0.51, 0.41	0.11, 0.49, 0.43	0.14, 0.42, 0.41	0.09, 0.53, 0.44	0.11, 0.49, 0.40	0.10, 0.50, 0.45	0.09, 0.55, 0.42	0.03, 0.52, 0.42	0.03, 0.55, 0.42	0.33, 0.49, 0.43
A3	0.09, 0.55, 0.42	0.11, 0.48, 0.42	0.13, 0.45, 0.44	0.11, 0.49, 0.43	0.15, 0.40, 0.43	0.11, 0.50, 0.39	0.15, 0.40, 0.41	0.11, 0.48, 0.43	0.09, 0.55, 0.43	0.02, 0.55, 0.42	0.04, 0.48, 0.43	0.33, 0.48, 0.43
A4	0.07, 0.58, 0.42	0.12, 0.46, 0.43	0.12, 0.46, 0.43	0.12, 0.47, 0.40	0.15, 0.42, 0.40	0.06, 0.64, 0.35	0.10, 0.52, 0.40	0.09, 0.55, 0.40	0.10, 0.53, 0.42	0.02, 0.56, 0.41	0.04, 0.49, 0.40	0.33, 0.54, 0.36
A5	0.10, 0.52, 0.43	0.11, 0.48, 0.42	0.12, 0.47, 0.43	0.11, 0.49, 0.41	0.15, 0.41, 0.41	0.11, 0.52, 0.37	0.15, 0.40, 0.40	0.12, 0.47, 0.42	0.09, 0.56, 0.43	0.02, 0.57, 0.41	0.03, 0.53, 0.42	0.33, 0.53, 0.43
A6	0.10, 0.52, 0.43	0.12, 0.46, 0.43	0.09, 0.52, 0.45	0.07, 0.57, 0.41	0.11, 0.48, 0.41	0.10, 0.54, 0.39	0.12, 0.46, 0.41	0.11, 0.49, 0.43	0.07, 0.57, 0.44	0.02, 0.57, 0.42	0.03, 0.58, 0.41	0.33, 0.63, 0.38
A7	0.06, 0.63, 0.39	0.10, 0.52, 0.42	0.09, 0.54, 0.41	0.08, 0.59, 0.39	0.10, 0.51, 0.40	0.06, 0.64, 0.39	0.07, 0.60, 0.38	0.07, 0.61, 0.41	0.06, 0.62, 0.40	0.02, 0.58, 0.40	0.02, 0.60, 0.42	0.33, 0.61, 0.36
A8	0.08, 0.58, 0.41	0.09, 0.52, 0.45	0.09, 0.54, 0.39	0.11, 0.49, 0.43	0.11, 0.49, 0.42	0.11, 0.49, 0.41	0.13, 0.45, 0.41	0.09, 0.53, 0.43	0.06, 0.65, 0.38	0.02, 0.58, 0.42	0.04, 0.48, 0.44	0.33, 0.54, 0.43
A9	0.09, 0.56, 0.42	0.12, 0.47, 0.40	0.12, 0.47, 0.42	0.09, 0.53, 0.44	0.09, 0.54, 0.39	0.08, 0.55, 0.43	0.09, 0.54, 0.42	0.10, 0.52, 0.41	0.07, 0.60, 0.40	0.02, 0.61, 0.41	0.04, 0.49, 0.41	0.33, 0.57, 0.42
A10	0.07, 0.57, 0.43	0.08, 0.57, 0.37	0.10, 0.51, 0.42	0.09, 0.52, 0.44	0.09, 0.55, 0.43	0.06, 0.60, 0.46	0.07, 0.56, 0.44	0.06, 0.61, 0.41	0.07, 0.59, 0.43	0.01, 0.65, 0.41	0.02, 0.66, 0.38	0.33, 0.51, 0.42
A11	0.08, 0.57, 0.42	0.09, 0.51, 0.43	0.08, 0.56, 0.44	0.09, 0.52, 0.44	0.09, 0.52, 0.44	0.07, 0.59, 0.43	0.10, 0.49, 0.43	0.11, 0.48, 0.44	0.06, 0.62, 0.44	0.02, 0.60, 0.44	0.03, 0.53, 0.38	0.33, 0.54, 0.41
A12	0.08, 0.57, 0.40	0.09, 0.54, 0.42	0.09, 0.52, 0.44	0.08, 0.55, 0.44	0.09, 0.53, 0.43	0.07, 0.57, 0.44	0.08, 0.53, 0.45	0.07, 0.59, 0.43	0.06, 0.62, 0.39	0.02, 0.62, 0.42	0.02, 0.60, 0.41	0.33, 0.61, 0.40
A13	0.09, 0.55, 0.41	0.13, 0.46, 0.41	0.10, 0.50, 0.44	0.09, 0.53, 0.42	0.08, 0.57, 0.39	0.07, 0.60, 0.42	0.10, 0.51, 0.41	0.08, 0.56, 0.44	0.07, 0.61, 0.40	0.02, 0.61, 0.40	0.02, 0.64, 0.39	0.33, 0.58, 0.42
A14	0.08, 0.55, 0.42	0.09, 0.53, 0.40	0.09, 0.54, 0.42	0.09, 0.54, 0.42	0.08, 0.58, 0.38	0.05, 0.63, 0.43	0.06, 0.58, 0.44	0.09, 0.51, 0.46	0.06, 0.63, 0.41	0.01, 0.64, 0.42	0.02, 0.63, 0.39	0.33, 0.61, 0.43
A15	0.09, 0.55, 0.42	0.11, 0.48, 0.42	0.09, 0.56, 0.41	0.09, 0.52, 0.45	0.09, 0.53, 0.44	0.06, 0.60, 0.44	0.06, 0.58, 0.42	0.10, 0.50, 0.45	0.07, 0.60, 0.41	0.02, 0.63, 0.42	0.03, 0.56, 0.43	0.33, 0.56, 0.44
A16	0.09, 0.55, 0.41	0.11, 0.49, 0.41	0.09, 0.51, 0.45	0.10, 0.51, 0.44	0.10, 0.50, 0.43	0.07, 0.60, 0.43	0.08, 0.55, 0.43	0.11, 0.48, 0.45	0.07, 0.59, 0.42	0.02, 0.60, 0.42	0.03, 0.54, 0.44	0.33, 0.57, 0.43

Table 10. SWGM based collective decision matrix

	C11	C12	C13	C21	C22	C23	C31	C32	C33	C41	C42	C43
A1	0.30, 0.55, 0.40	0.38, 0.50, 0.38	0.32, 0.57, 0.39	0.32, 0.54, 0.42	0.36, 0.53, 0.38	0.32, 0.51, 0.43	0.33, 0.57, 0.36	0.32, 0.48, 0.42	0.26, 0.60, 0.40	0.07, 0.57, 0.41	0.13, 0.50, 0.41	0.34, 0.53, 0.42
A2	0.28, 0.58, 0.38	0.33, 0.57, 0.37	0.30, 0.60, 0.38	0.33, 0.54, 0.41	0.41, 0.47, 0.40	0.30, 0.56, 0.41	0.34, 0.55, 0.38	0.31, 0.55, 0.41	0.25, 0.61, 0.39	0.08, 0.55, 0.40	0.11, 0.60, 0.38	0.35, 0.53, 0.40
A3	0.26, 0.60, 0.40	0.35, 0.53, 0.40	0.37, 0.49, 0.42	0.32, 0.55, 0.41	0.42, 0.42, 0.42	0.27, 0.62, 0.35	0.41, 0.46, 0.40	0.32, 0.55, 0.41	0.27, 0.58, 0.40	0.06, 0.63, 0.37	0.11, 0.57, 0.39	0.31, 0.58, 0.38
A4	0.21, 0.67, 0.36	0.36, 0.52, 0.40	0.34, 0.53, 0.40	0.30, 0.60, 0.37	0.39, 0.51, 0.37	0.17, 0.74, 0.30	0.30, 0.60, 0.36	0.25, 0.66, 0.35	0.29, 0.56, 0.40	0.06, 0.64, 0.37	0.10, 0.63, 0.34	0.25, 0.67, 0.32
A5	0.28, 0.58, 0.40	0.33, 0.57, 0.37	0.34, 0.54, 0.40	0.31, 0.57, 0.39	0.42, 0.45, 0.41	0.25, 0.65, 0.34	0.42, 0.46, 0.40	0.33, 0.55, 0.39	0.24, 0.63, 0.38	0.07, 0.62, 0.38	0.10, 0.62, 0.36	0.28, 0.62, 0.37
A6	0.29, 0.55, 0.41	0.37, 0.51, 0.40	0.29, 0.58, 0.41	0.24, 0.66, 0.36	0.33, 0.56, 0.38	0.25, 0.64, 0.35	0.34, 0.54, 0.39	0.31, 0.56, 0.40	0.25, 0.59, 0.43	0.06, 0.61, 0.40	0.09, 0.66, 0.35	0.24, 0.68, 0.34
A7	0.19, 0.71, 0.33	0.32, 0.59, 0.36	0.28, 0.62, 0.37	0.23, 0.68, 0.34	0.30, 0.60, 0.36	0.20, 0.70, 0.34	0.25, 0.67, 0.34	0.24, 0.67, 0.36	0.22, 0.66, 0.37	0.06, 0.66, 0.37	0.09, 0.66, 0.36	0.23, 0.69, 0.33
A8	0.22, 0.65, 0.37	0.31, 0.58, 0.39	0.25, 0.65, 0.35	0.28, 0.60, 0.38	0.32, 0.58, 0.36	0.29, 0.57, 0.39	0.33, 0.57, 0.36	0.27, 0.62, 0.39	0.19, 0.71, 0.34	0.06, 0.64, 0.38	0.12, 0.53, 0.42	0.26, 0.63, 0.36
A9	0.25, 0.61, 0.40	0.36, 0.54, 0.38	0.34, 0.53, 0.41	0.30, 0.58, 0.41	0.30, 0.60, 0.37	0.27, 0.58, 0.41	0.29, 0.62, 0.36	0.29, 0.60, 0.39	0.22, 0.66, 0.37	0.06, 0.65, 0.38	0.11, 0.57, 0.38	0.28, 0.61, 0.38
A10	0.23, 0.63, 0.39	0.28, 0.64, 0.34	0.32, 0.56, 0.41	0.30, 0.56, 0.42	0.29, 0.62, 0.37	0.24, 0.62, 0.42	0.29, 0.59, 0.41	0.23, 0.68, 0.36	0.23, 0.64, 0.39	0.05, 0.70, 0.36	0.08, 0.68, 0.36	0.31, 0.57, 0.40
A11	0.22, 0.65, 0.38	0.28, 0.62, 0.37	0.26, 0.63, 0.38	0.30, 0.56, 0.41	0.32, 0.57, 0.40	0.25, 0.62, 0.39	0.33, 0.54, 0.40	0.30, 0.57, 0.41	0.20, 0.67, 0.38	0.05, 0.66, 0.39	0.09, 0.65, 0.34	0.29, 0.60, 0.38
A12	0.23, 0.65, 0.36	0.28, 0.63, 0.35	0.28, 0.60, 0.39	0.28, 0.60, 0.41	0.30, 0.59, 0.39	0.27, 0.60, 0.41	0.31, 0.57, 0.41	0.26, 0.64, 0.39	0.20, 0.69, 0.35	0.06, 0.67, 0.37	0.09, 0.64, 0.38	0.25, 0.65, 0.37
A13	0.26, 0.61, 0.39	0.37, 0.52, 0.38	0.32, 0.55, 0.42	0.28, 0.61, 0.38	0.28, 0.63, 0.36	0.24, 0.64, 0.38	0.30, 0.60, 0.37	0.28, 0.61, 0.39	0.21, 0.67, 0.36	0.06, 0.67, 0.35	0.09, 0.67, 0.36	0.28, 0.62, 0.38
A14	0.24, 0.62, 0.40	0.27, 0.64, 0.34	0.27, 0.62, 0.38	0.28, 0.60, 0.39	0.26, 0.66, 0.34	0.22, 0.66, 0.39	0.27, 0.62, 0.38	0.31, 0.55, 0.43	0.19, 0.70, 0.36	0.05, 0.70, 0.36	0.08, 0.68, 0.35	0.25, 0.64, 0.38
A15	0.27, 0.58, 0.41	0.36, 0.53, 0.39	0.27, 0.63, 0.37	0.32, 0.54, 0.43	0.32, 0.57, 0.40	0.24, 0.63, 0.41	0.28, 0.61, 0.39	0.33, 0.53, 0.43	0.23, 0.64, 0.39	0.06, 0.66, 0.38	0.10, 0.60, 0.39	0.28, 0.60, 0.39
A16	0.28, 0.58, 0.39	0.33, 0.58, 0.36	0.31, 0.56, 0.41	0.32, 0.55, 0.42	0.33, 0.54, 0.40	0.24, 0.64, 0.39	0.28, 0.62, 0.37	0.35, 0.51, 0.42	0.23, 0.64, 0.39	0.06, 0.67 ,0.37	0.11, 0.59, 0.40	0.28, 0.62, 0.38

Figure 8 illustrates the ranking of alternative districts based on the SWAM operator, while Figure 9 shows the ranking according to the SWGM operator. The SWGM operator, SWAM operator, and proximity coefficients are used to evaluate the criteria weights. According to both the SWAM and SWGM operators, Taşköprü is identified as the district with the highest fire risk. The district with the lowest risk, however, differs between the two methods: according to the SWAM operator, it is

İnebolu, while according to the SWGM operator, it is Çatalzeytin.

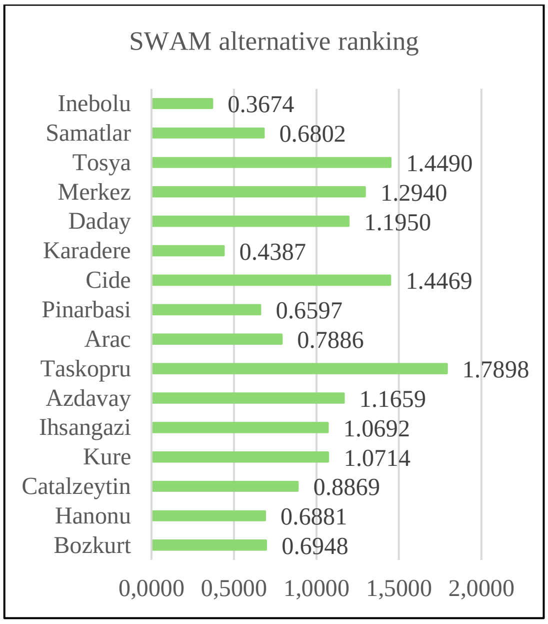

Figure 8. Ranking of alternatives according to SWAM with SF-TOPSIS method

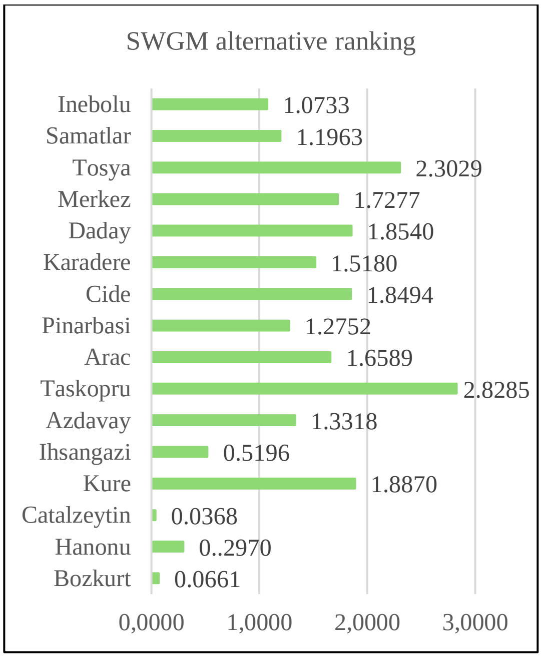

Figure 9. Ranking of alternatives according to SWGM with SF-TOPSIS method

Forest Fire Resource Allocation

The Taşköprü district of Kastamonu Province is at risk of forest fires. Based on past forest fire data for Taşköprü (URL-1, 2025), equipment planning will be conducted for four regions where fires are likely to occur. A mathematical model was developed to allocate equipment to these fire zones accordingly. Figure 10 illustrates four forest fire incidents in the Taşköprü district.

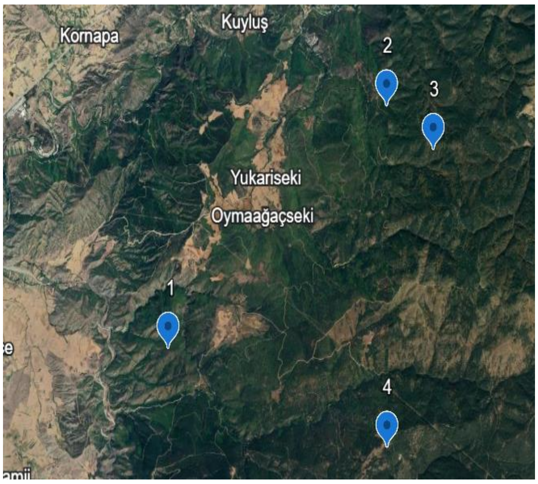

Figure 10. 4 forest fires in Taşköprü district

Parameters:
n = number of equipment
m = number of forest fires
i = equipment index i = 1,2,…,n
j = forest fire index j = 1,2,…,m

Decision variables:

$$x_{ij} = \begin{cases} 1, \text{If i. equipment is assigned to j. wildfire}, \\ 0, \quad \text{otherwise} \end{cases} \quad \forall_{i,j}$$

$d_{ik}^{+} = \text{i. positive deviation value k. target}$
$d_{ik}^{-} = \text{i. negative deviation value k. target}$

Objective function:

$$MinZ = \sum_{i=1}^{n}(d_{ik}^{+} + d_{ik}^{-}) \quad \forall_k \tag{4}$$

Subject to:

$$\sum_{i=1}^{n} x_{ij} \geq 1 \quad \forall_j \tag{5}$$
$$\sum_{j=1}^{m} x_{ij} \leq 1 \quad \forall_i \tag{6}$$
$$\sum_{i=1}^{n} x_{ij} - d_{i1}^{+} + d_{i1}^{-} = 34 \quad j = 1 \tag{7}$$
$$\sum_{i=1}^{n} x_{ij} - d_{i2}^{+} + d_{i2}^{-} = 24 \quad j = 2 \tag{8}$$
$$\sum_{i=1}^{n} x_{ij} - d_{i3}^{+} + d_{i3}^{-} = 17 \quad j = 3 \tag{9}$$
$$\sum_{i=1}^{n} x_{ij} - d_{i4}^{+} + d_{i4}^{-} = 49 \quad j = 4 \tag{10}$$
$$x_{ij} = 0 \ or \ 1 \quad \forall_{i,j} \tag{11}$$
$$d_{ik}^{+} + d_{ik}^{-} \geq 0 \ \forall_{i,k} \tag{12}$$

Equation (4) represents the objective function. Equation (5) ensures that one piece of equipment is assigned to each wildfire. Equation (6) guarantees that each piece of equipment is assigned to at most one wildfire. Equations (7)–(10) define the objective constraints of the problem, while Equations (11) and (12) establish the sign constraints.

Results and Discussion

Türkiye's Mediterranean and Aegean coastlines are among the regions with the highest risk of forest fires. Approximately 10.000 hectares of forested land are damaged by fires annually, negatively impacting not only ecosystems but also human settlements and biodiversity. A study conducted in Muğla Province aimed to create forest fire susceptibility maps, considering meteorological, topographic, environmental, economic, and forestry factors. Parameter weights were determined using the Analytical Hierarchy Process (AHP) method, and sensitivity analysis was performed using Geographic Information Systems (GIS) (Sari, 2021). In emergency planning, priority disaster areas were evaluated to enhance the effectiveness of response processes against forest fires. The goal was to minimize response times for rescue teams and determine the optimal firefighting routes for critical points. In this context, solution proposals were developed using the IBM ILOG CPLEX Optimization program as part of the decision-support process (Wu et al., 2019).

First, criteria identified in the literature were analyzed to determine factors influencing forest fire risks. Four main criteria climate (C1), vegetation (C2), topography (C3), and socioeconomic factors (C4) along with 12 sub-criteria, were selected. The Spherical Fuzzy Analytic Hierarchy Process (SF-AHP) technique was applied using a decision matrix developed by experts. The results indicate that climate (C1) poses the highest risk, with a weight of 0.320 (32%), making it the most significant factor in forest fire risk assessment. It is followed by topography (C3) at 25.5%, vegetation (C2) at 24.5%, and socioeconomic factors (C4) at 18%. These findings align with expectations, as climate conditions play a fundamental role in both the occurrence and spread of forest fires. The fact that the weights of vegetation (C2) and terrain (C3) are relatively close indicates that fire risk is affected equally by the natural environment and the physical properties of the terrain. This indicates that the fire spread dynamics, the flammability of vegetation, and the terrain properties of elevation and slope are directly related. The fact that socioeconomic factors (C4) are ranked last does not mean that they are unimportant; instead, they are extremely important in post-fire response activities and the social effects of fire disasters. Public awareness is extremely important in fire risk management, particularly in areas close to human settlements.

During the next phase of the research, the SF-TOPSIS approach was applied to rank the twelve districts of Kastamonu using the significance weights calculated in the SF-AHP analysis. Based on the fuzzy linguistic scale, the group of experts constructed the decision matrices required for the SF-TOPSIS$ computational process. For purposes of robustness comparison, the data aggregation process was carried out using both the SWAM and SWGM operators. Despite the presence of minor numerical oscillations, both operators correctly identified Taşköprü as the district most vulnerable to forest fire risks. The validity of this result is reinforced by the agreement achieved in the ten independent expert assessments. Moreover, the high ranking of Taşköprü is particularly important, since its enormous forest resources are absolutely vital for maintaining the region's ecological balance. Nevertheless, due to its climatic conditions and human factors, this region is extremely vulnerable to forest fires, requiring proactive fire prevention and protection policies.

The concluding part of the study entailed developing a Goal Programming (GP) model that was geared towards optimizing the strategic deployment of fire suppression resources within Taşköprü. This mathematical model was geared towards ensuring maximum efficiency in the distribution of firefighting equipment. To validate the robustness of this model, a scenario was set where four different areas within the region experienced simultaneous wildfires, and resources were allocated equally to each area. The regional resources deployed within this framework included 151 initial response resources, 36 reconnaissance resources, 10 water tankers, and a helicopter from the Kastamonu administration (URL-1, 2025). These resources were assigned based on necessity. Figure 11 shows the distribution of firefighting equipment in fire zones. First fire zone: In this zone, a total of 34 firefighting equipment were allocated, with 20 firefighting vehicles for the first response, 9 search vehicles, and 3 water supply vehicles. Second fire zone: In this zone, a total of 24 firefighting equipment were allocated, with 15 firefighting vehicles for the first response, 7 search vehicles, and 2 water supply vehicles. Third fire zone: In this zone, a total of 17 firefighting equipment were allocated, with 10 firefighting vehicles for the first response, 5 search vehicles, and 2 water supply vehicles. Fourth fire zone: This zone received the highest priority, with a total of 49 firefighting equipment allocated, including 30 firefighting vehicles for the first response, 15 search vehicles, 3 water supply vehicles, and 1 helicopter. This allocation strategy for firefighting equipment in fire zones was developed based on various factors, including the rate of fire spread, time for the firefighting equipment to respond, and capacity of the equipment.

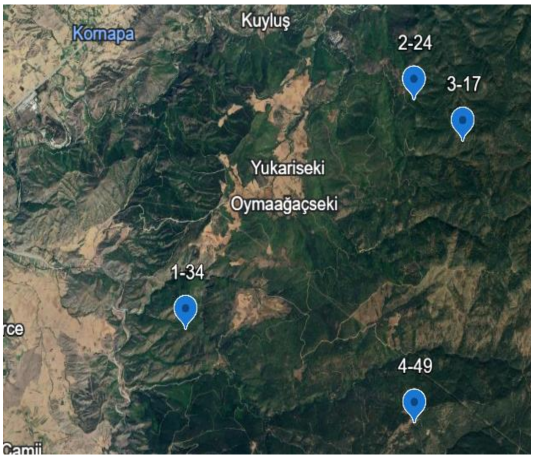

Figure 11. Distribution of equipment in the Taşköprü district

Conclusions

Forest fires are natural calamities that cause destruction to the environment. They have a wide range of impacts at the global level. The occurrence of forest fires is influenced by a number of factors. In this study, the risk factors associated with forest fires have been identified based on expert opinions. The regions have been ranked based on the risk levels. A strategic model has been developed through the integration of SF-AHP and SF-TOPSIS.

The most important factor in the risk of forest fires relates to the proximity to the power lines. This demonstrates the potential of sparks and short circuits from the power transmission lines to cause fires. It should be noted that the risk of fire is particularly high when the power lines are old and not well maintained. The second important factor in the risk of forest fires relates to the level of humidity. It should be noted that the level of humidity has a crucial role in the containment of forest fires. Low levels of humidity make the vegetation highly flammable.

The limitation of the study shows that the research on forest fire risk assessment using fuzzy multi-criteria decision-making methods is still limited. This study aims to contribute to filling the gap in the literature on the subject. However, it should be noted that forest fires are dynamic phenomena, and the criteria for the assessment might change in the future. Specifically, the long-term impacts of climate change are not entirely predictable. Moreover, the consideration of the operational variables in the fire response process was based on specific assumptions, and the real-world situation might differ from the simulation scenarios.

From the findings, it is clear that a policy can be formulated to help curb forest fire risks by focusing on maintaining and modernizing power lines, especially in areas considered to be at a greater risk. This can be achieved through the installation of microclimate monitoring systems, which can help track fluctuations in humidity levels. This, in turn, can be a significant step towards developing a strategy to help curb forest fire risks. Land use planning can also be considered, focusing on how to restrict activities in areas considered to be at a greater risk, and developing strategies to help curb vegetation.

Future studies could develop advanced mathematical models that account for changing climate conditions and rising temperatures. Further enhancements, such as integrating aerial firefighting vehicles, incorporating real-time meteorological data, and developing real-time fire monitoring systems, are expected to improve the accuracy and efficiency of the proposed model.

Ethics Committee Approval

N/A

Peer-review

Externally peer-reviewed.

Author Contributions

Conceptualization: B.T. and T.E.; Investigation: B.T.; Material and Methodology: B.T. and T.E.; Visualization: B.T. and T.E.; Writing-Original Draft: B.T.; Writing-review & Editing: B.T. and T.E. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare that they have no conflict of interest.

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