

Article

Comparison between Post-Fire Analysis and Pre-Fire Risk Assessment According to Various Geospatial Data

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Abstract: Wildfires in forest ecosystems exert substantial ecological, economic, and social impacts. The effectiveness of fire management hinges on precise pre-fire risk assessments to inform mitigation efforts. This study aimed to investigate the relationship between predictions from pre-fire risk assessments and outcomes observed through post-fire burn severity analyses. In this study, forest fire risk was assessed through the Fuzzy Analytical Hierarchy Process (FAHP), in which fire-oriented factors were used as input. The degree of burn was determined by the Random Forest method using 11,519 training points and 400 test points on Sentinel-2 satellite images under three different classes. According to the results obtained from 266 selected test points located within the forest, all primary factors put forth increased high burn severity. Climate, in particular, emerged as the most significant factor, accounting for 52% of the overall impact. However, in cases of high fire severity, climate proved to be the most effective risk factor, accounting for 67%. This was followed by topography with 50% accuracy at a high fire intensity. In the risk assessment based on the FAHP method, climate was assigned the highest weight value among the other factors (32.2%), followed by topography (27%). To evaluate the results more comprehensively, both visually and statistically, two regions with different stand canopy characteristics were selected within the study area. While high burn severity had the highest accuracy in the Case 1 area, moderate burn severity had the highest in the Case 2 area. During the days of the fire, the direction of spreading was obtained from the MODIS images. In this way, the fire severity was also interpreted depending on the direction of fire progression. Through an analysis of various case studies and literature, this research underlines both the inherent strengths and limitations of predicting forest fire behavior-based pre-fire risk assessments. Furthermore, it emphasizes the necessity of continuous improvement to increase the success of forest fire management.

Keywords: forest fire; remote sensing; risk assessment; Manavgat; fuzzy analytic hierarchy process (FAHP)



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1. Introduction

Forest fires, which are prevalent in various biomes globally, alter the scope and structural characteristics of forested areas. Consequently, these changes disrupt the provision of ecosystem services and products, introducing uncertainties into the trajectory of these alterations [1]. Within the context of global climate change, the frequency of severe forest fires tends to rise, necessitating an accelerated adjustment of forest fire regimes [2]. Forest fires are complex natural disturbances that significantly influence ecosystem dynamics [3] and have profound impacts on human societies [4,5]. A continuous increase in fire danger and the extent of burned areas in Mediterranean ecosystems across diverse global regions

is expected due to factors such as global warming, population growth, and irregular land use [6,7]. This increase underscores the growing significance assigned to forest fire risk and susceptibility [8], as well as to post-fire studies [9,10]. To enhance firefighting success, risk-based possibilities, and their management information should be integrated into decision-support systems through strategic and operational synthesis [11,12]. Achieving effective fire decision support necessitates a precise clarification of uncertainties associated with risk. Therefore, it is crucial to explain the uncertainties arising from spatial patterns, understand their origins, and make up-to-date decisions regarding fire prevention and explosion probability [13,14].

With the increasing frequency of severe wildfires, comprehension and prediction of fire behavior have become essential for effective forest management. Pre-fire risk assessments play a crucial role in anticipating fire behavior, directing resource allocation, and stimulating preparedness [15,16]. Pre-fire risk assessments encompass numerous factors contributing to fire behavior in forested areas, including forest type, fuel load, moisture content, weather patterns, and topography. Models such as the Fire Spread Probability Model and the Fire Potential Index influence these inputs to estimate fire behavior and potential spreading, leading to the formation of proactive fire management strategies.

In forest fire risk mapping, diverse methods are employed, including logistic regression [13], GIS-based decision support systems [17], maximum entropy [18], machine learning [19,20], artificial neural network analytics [21], analytical hierarchy processes [22], and fuzzy analytic hierarchy processes [23,24]. GIS-based Multi-Criteria Decision Analysis (MCDA) is an intelligent approach that transforms spatial and non-spatial data into usable information alongside the decision maker's judgment to facilitate critical decisions [25]. Analytical Hierarchy Process (AHP) and Fuzzy Analytical Hierarchy Process (FAHP) are commonly presented in the literature as GIS-based MCDA methods preferred for risk analysis in various sectors [26,27]. However, AHP's susceptibility to subjectivity in determining criteria roles within a pairwise comparison matrix is acknowledged. To mitigate this issue, methods for improving AHP have been developed [28,29]. Fuzzy logic methods can be integrated into the post-AHP decision-making process to evaluate criteria and utilize fuzzy membership functions, enhancing the accuracy of results [25,27]. Despite the numerous criteria constituting fire risk in FAHP fire risk analysis, it facilitates the hierarchical weighting of criteria and their sub-criteria importance levels. This proves to be critical in risk management by enabling the storage of a quantitative database essential for deciding on measures to minimize the impact of variables related to risk factors [23].

The mortality rate of vegetation is directly influenced by fire characteristics, which in turn are determined by the spatial distribution of varying weights assigned to forest fire risks. Determining tree mortality in various forested areas with different burn indices [10] is crucial for establishing a sustainable basis in forestry to support post-fire recovery [2]. The extent of mortality depends on several factors, including the physiological parts of the tree that have been damaged [9,30], burn ratio [2], burn severity [31], fire behavior factors, and specific tree characteristics [10,32]. Identifying distinct burning intensities across the burned area yields crucial data for strategically planning post-fire spatial treatment within the framework of sustainable forest management.

Post-fire analysis involves evaluating fire severity, burn patterns, and the effectiveness of suppression efforts. By comparing these outcomes with predictions made during pre-fire assessments, we can identify discrepancies and assess the accuracy of the assessment models. Numerous case studies have demonstrated situations in which pre-fire risk assessments failed to accurately predict fire behavior due to unexpected changes in weather, ignition points, or fire behavior feedback [33,34]. Several factors contribute to the differences between pre-fire predictions and post-fire outcomes in forest ecosystems. Rapid shifts in weather conditions, anomalies in ignition sources, and changes in fuel availability can substantially change fire behavior [2,35].

A fire event is the realization of the predicted risk distribution at a single level in space (pixel or raster scale). This is a complicated phenomenon necessitating a complex structure

that considers many factors influencing fire ignition and spreading [36]. Fire behavior probabilities differ from fire occurrence statistics, as they are based on spatial and temporal factors that control the growth of fire. The probability of burning a specific area depends on the fuel characteristics, topography, current weather conditions, and direction of fire spread, which enables each fire to reach that location [15]. Although it is known that topography, weather, and fuels are factors directing fire behavior, there is still a lack of understanding of the contribution level of each condition to the spatial arrangement of fire severity [37].

Additionally, uncertainties regarding the input data quality, model assumptions, and calibration procedures can introduce errors in pre-fire risk assessments. Improving the accuracy of pre-fire risk assessments in forested areas requires addressing the unique challenges of these ecosystems. Incorporating real-time weather data, high-resolution fuel maps, and advanced fire behavior models tailored to forests can enhance prediction reliability. Regular validation and updating of assessment models using post-fire data are crucial for filtering predictions. The occurrence of fires in the investigated area was primarily attributed to climate anomalies characterized by extremely high air temperatures and drought. It is vital to consider these factors in the context of sustainable development goals related to land use and cover [38], as well as the quality and quantity of ecosystem services [1].

According to the EFFIS 2021 database [39], Türkiye recorded the highest total area burned, specifically for the Manavgat Fire. It stands out with the largest burned area among the recorded incidents in Turkey, the European Mediterranean, North Africa, and the Middle East. This study aims to assess the risk of fire spread based on pre-fire behavior during the Manavgat Fire in 2021 and to examine the post-fire situation by detecting burn severity using satellite images. In addition, this study explored the accuracy of pre-fire risk assessments in predicting post-fire outcomes in forest ecosystems. This study contributes to the limited research on the spread of forest fires.

The structure of this article is as follows: Section 1 introduces and briefly discusses the challenges and methodologies within the field of fire risk assessment. In the second section, the study provides initial information about the study area and data, followed by an explanation of the employed methods. The third section elucidates the study's outcomes, presenting detailed assessments for the two designated test regions. Discussions are presented in Section 4, and Section 5 provides a summary of the conclusions.

2. Materials and Methods

2.1. Study Area

This study focused on the Manavgat Region in Antalya, which is characterized by a typical Mediterranean climate. The area has hot and dry summers along with mild and rainy winters. Utilizing digital elevation model data provided by the Ministry of National Defense- General Directorate of Mapping of the Republic of Türkiye, the average elevation and slope within the study area were 489 m and 21.71 degrees, respectively. The predominant forest type in the region is Turkish red pine (*Pinus brutia* Ten.) and evergreen Mediterranean shrubs. Agricultural activities are concentrated in areas with lower slopes [40]. This research encompasses the fire zone that has been burned occurred 28 July 2021–6 August 2021. The fire persisted for approximately 10 days. The affected zone includes various land use and land cover (LULC) classes, such as settlements, industrial and agricultural areas, rocky terrains, and wetland areas (Figure 1).

The expectation of potential wildfires in forested areas and the subsequent analysis of their impacts constitute significant aspects. While interventions during a fire event may influence the extent of its spread, prior knowledge of the degree to which forested areas are affected by the fire provides a significant input for risk analyses. The utilization of land cover information appears as a critical parameter in the estimation and evaluation of these predictions. In extensive forested areas affected by wildfires, remote sensing data stands out as a critical source for the rapid generation and updating of such information.

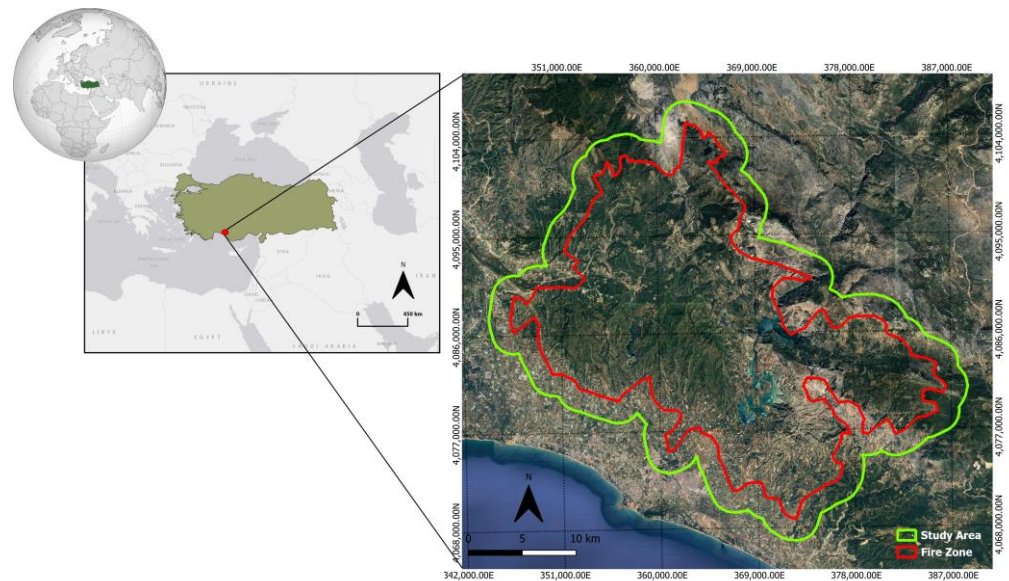


Figure 1. Study area.

2.2. Data

In this study, data obtained from various sources were incorporated. Due to the extensive geographical coverage of the study area, satellite images with varying resolutions were employed to extract information from the field. Furthermore, satellite imagery is commonly employed in the assessment of outcomes following fire incidents. MODIS satellite images were utilized to assess the spreading of the forest fire that occurred in the region. A Landsat satellite image was employed to determine surface temperatures, while a Sentinel-2 image was used to determine burn severity. To verify the accuracy of the results, high-resolution SPOT 7 and Pleiades satellite patterns, along with aerial photographs specific to the region, were utilized. Codes from the CORINE classification were used in the analysis of LULC. Additionally, ground surveys were conducted to validate the results, involving an examination of land cover/use conditions and the implementation of spectral measurements (Figure 2). The general characteristics of the data utilized in the study are presented in Table 1.

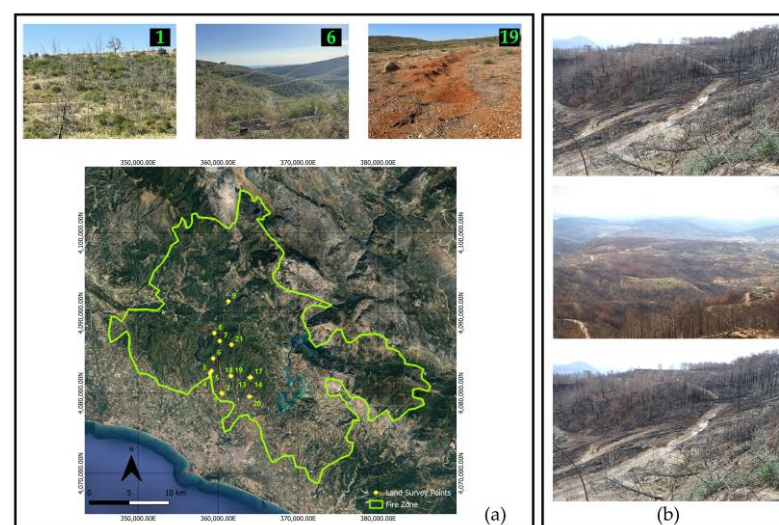


Figure 2. (a) Samples from field measurements (b) Examples of trees affected to varying degrees by the fire and a sample of a completely burned forest area.

Table 1. General characteristics of the data used.

Data	Operator	Global/Local	Extracted Information	Spatial Resolution (m)	Source
Landsat	NASA and the U.S. Geological Survey (USGS)	Global	Land Surface Temperature	30	https://landsat.gsfc.nasa.gov/data/ (accessed on 20 December 2023)
Sentinel-2	European Space Agency (ESA)	Global	Normalized Difference Vegetation Index, Burn Severity Classes (by Classification)	10, 20, 60	https://www.esa.int/Applications/Observing_the_Earth/Copernicus/Sentinel-2 (accessed on 20 December 2023)
Digital Elevation Model	Republic of Türkiye General Directorate of Mapping	Local	Slope, Elevation, Terrain Aspect	2, 50	https://www.harita.gov.tr/ (accessed on 22 December 2023)
Aerial Photos SPOT—Pleiades	AIRBUS	Global	Visual Interpretation Visual Interpretation	0, 25 1.5–0.5	
Open Street Map	Open Street Map	Global	Land Use/Land Cover Classes		https://www.openstreetmap.org/ (accessed on 20 December 2023)
European Forest Fire Information System (EFFIS)	European Commission, EU Copernicus Program	European, Middle East, and North African countries (A total of 43 countries)	Active Fire Points	-	https://effis.jrc.ec.europa.eu/about-effis (accessed on 20 December 2023)
Fire Information for Resource Management System (FIRMS)	NASA LANCE	Global	Active Fire Points	-	https://firms.modaps.eosdis.nasa.gov/ (accessed on 20 December 2023)
Copernicus Land Monitoring Service	European Environment Agency's Copernicus Land Monitoring Service	Global, European continent	Soil Water Index (SWI) LULC Classes	1000 (SWI) Minimum Mapping Unit (MMU) of 25 hectares (ha) (LULC)	https://land.copernicus.eu/en (accessed on 20 December 2023)
ESA World Cover	European Space Agency (ESA)	Global	LULC Classes	10	https://esa-worldcover.org/en (accessed on 20 December 2023)
Stand Structure Map	Republic of Türkiye General Directorate of Forestry	Local	Development Stage, Closure Rate, Fuel Content	-	https://www.ogm.gov.tr/en/organization/general-information (accessed on 20 December 2023)
Meteorological Measurements	Turkish State Meteorological Service	Local	Relative Humidity, Air Temperature, Precipitation	-	https://www.mgm.gov.tr/eng/forecast-cities.aspx (accessed on 20 December 2023)

2.3. Methodology

In this study, the outcomes of the risk analysis conducted prior to the 2021 Manavgat wildfire were compared with the results of burn severity derived from satellite imagery. Figure 3 represents the general flow diagram of the methodology used in the study.

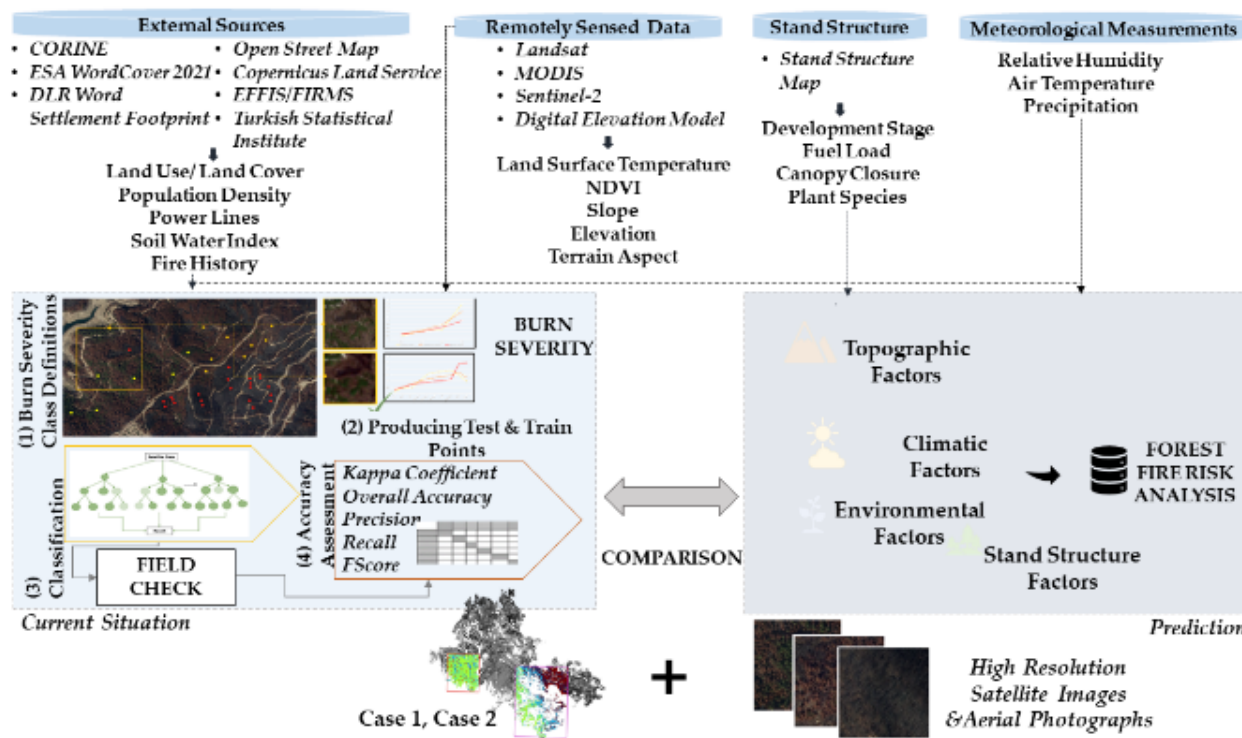


Figure 3. General flow diagram of the methodology used.

2.3.1. Burn Severity

The degree of burn in the Sentinel-2 satellite image was determined through classification using the Random Forest method [41]. A total of 11,519 training points representing different LULC classes and 400 test points belonging to areas affected by fire in three different classes, named “Low Burn Severity”, “Moderate Burn Severity”, and “High Burn Severity”, were produced from the fire zone. SPOT, Pleiades, and Aerial Photos were used for the visual interpretation and production of spectral signatures. This approach enabled the creation of reliable and accurate training and test points as well as an understanding of the spectral differences between the classes. Spectral signatures and statistical parameters were also considered to determine burn severity class definitions and thresholds between classes [42].

The burn severity classification has reached an overall accuracy of 0.81, and the obtained results have been utilized as input data for risk assessment.

2.3.2. Risk Assessment

Weather conditions, especially daily and seasonal drying and cooling cycles based on surface fuel moisture, have short-term and long-term effects [43]. Daily fire danger rating systems based on meteorological variables have also been developed [44]. Increasing high temperatures enhance transpiration, rapidly reducing the moisture content of fuel types and creating suitable conditions for ignition temperature [45].

The fuel moisture content (FMC), defined as the ratio between the ten-hour-time-lag fine-fuel moisture and extinction moisture, plays a crucial role in forest fires [46]. The flammability of vegetation cover is largely dependent on the moisture content of fine dead fuels. Moisture changes occur most rapidly in this fuel type. Therefore, the accuracy of the moisture content in such fuels is a vital component of fire management and the fire

danger rating system, contributing to the shortening of ignition time [47] and controlling fire behavior, forming the key factors [48,49].

Topography interacts with climate in terms of fire behavior characteristics. In dry weather conditions, topography has less of an effect than in wet weather conditions. Regional or temporal climate variations that reduce fuel moisture make much of the land susceptible to fire spread at various topographic positions [50].

The distribution of fuel material characteristics in the field varies significantly, directly impacting fire risk and behavior in different spatial areas [51]. A crucial precondition for successful fire management, including risk assessment studies, is the accurate determination of the fuel load and associated fuel characteristics [52]. In the risk assessment part of this study, forest structural characteristics and fuel load data were used to incorporate fuel material characteristics by developing indices for surface and crown fuels using dead surface and crown fuel material amounts. Data from fuel studies conducted in pine and hardwood forests throughout Antalya were used to determine fuel indices [23,53]. The fuel loads in the study area were estimated by taking the average loads of the same stands in a study conducted for Antalya [54–57]. They were derived by interpolation from similar distinctive features, such as leaf biomass, stand density, developmental stage, rocky growing environment, pine stands, and maquis vegetation types. Coefficients ranging from 0.7 to 1.4 were used in the interpolation of fuel quantities for mixed forest structures of needle-leaved and broad-leaved tree species in comparison to pine forests. It is assumed that broad-leaved forests have a higher fuel load than needle-leaved forests.

The Fuzzy AHP Model (FAHP)

In this study, the FAHP was used to determine the importance levels of the criteria that constitute fire risks and their sub-criteria weighted according to relevant factors. The 4 main criteria of fire risk and their respective intervals of sub-criteria were established in a hierarchical manner for the FAHP risk assessment (Figure 4). By applying the pairwise comparison matrices of the Chang extent analysis method step-by-step [23,58], the weights of the criteria and sub-criteria were determined in accordance with a valid consistency index. The consistency ratio (CR) and consistency indices were used to analyze the consistency of the pairwise comparison matrices. Particular attention was paid to a consistency index of <0.1 . The fuzzy scale of relative importance developed by [59] was employed to quantify the relative weights (Table 2).

Table 2. Used fuzzy scale of relative importance.

Qualitative Scale of Importance	Triangular Fuzzy Scale	Triangular Fuzzy Reciprocal Scale
Almost equal	(1, 1, 1)	(1, 1, 1)
Equally important	(1/2, 1, 3/2)	(2/3, 1, 2)
Strongly more important	(1, 3/2, 2)	(1/2, 2/3, 1)
Very strongly more important	(3/2, 2, 5/2)	(2/5, 1/2, 2/3)
Absolutely more important	(2, 5/2, 3)	(1/3, 2/5, 1/2)

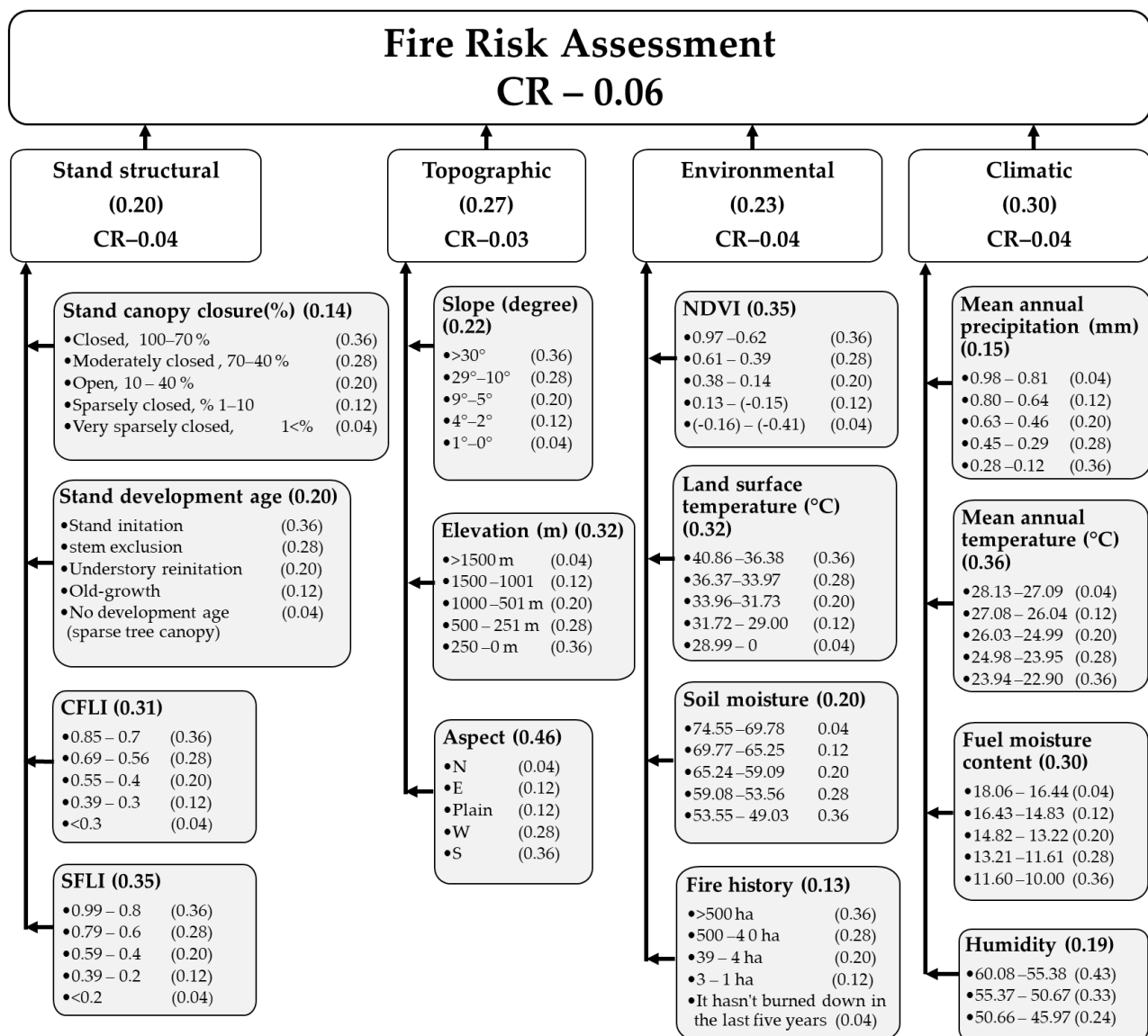


Figure 4. The weights of the criteria, sub-criteria and factors used in FAHP.

3. Results

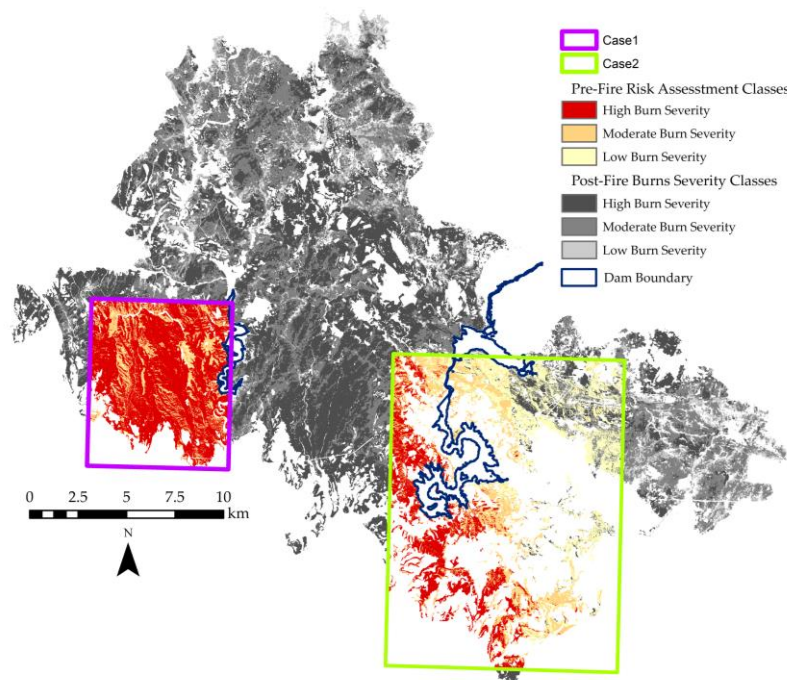
In this study, a comparison was conducted between the risk assessment based on the pre-fire data and the post-fire situation, specifically examining the outcomes from 266 selected test points located within the forest in the study area (Table 3). All primary factors demonstrated a sensitive impact in areas with elevated burn severity. Notably, climate emerged as the most important factor, constituting 67% of the overall effect. In prior risk determination using the FAHP method, the climate had already been assigned as the highest weight value, accounting for 32.2%, among other factors. Topography emerged as the second-most significant risk factor for burn severity, with 27% among other factors in the assessment. The risk weights of the additional environmental and stand structure factors contributing to burn severity followed a similar ranking pattern in the FAHP risk assessment.

Table 3. Main factors: SFLI, CFLI, and complete pre-fire risk analysis accuracy analysis scores.

Factors	F-Score			Overall Accuracy
	Low Burn Severity	Moderate Burn Severity	High Burn Severity	
Topographic Factors	0.2581	0.4110	0.5089	0.4167
Climatic Factors	0.4634	0.3710	0.6705	0.5288
Environmental Factors	0.0779	0.4184	0.4800	0.3936
Stand Structure Factors	0.3648	0.2074	0.4660	0.3640
SFLI	0.4953	0.3846	0.2439	0.4131
CFLI	0.4129	0.4533	0.2105	0.3846
Pre-Fire Risk Analysis	0.4959	0.2920	0.5432	0.4476

Given that the 2021 fire was the largest in both the country and the European Mediterranean region, it is evident that climatic factors played a significant role in its expansion. Among the climatic risk factors, the cumulative effect of annual average temperature and flammable substance content contributed to 66% of the total weight, highly influencing fire expansion. In terms of topography, the terrain aspect had the highest weight at approximately 46%, whereas elevation had the highest weight at approximately 32%. In the FAHP risk assessment, the Stand Fuel Loading Index (SFLI) and Canopy Fuel Loading Index (CFLI) were subsumed under the stand structure, collectively representing 66% of the weight within this primary factor. When compared to burn severity levels, these indices exhibited higher accuracy in areas characterized by low and moderate burn severity.

To perform a more comprehensive evaluation of the results both visually and statistically, two regions with distinct canopy characteristics were chosen within the study area (Figure 5).

**Figure 5.** Pre-fire risk assessment results within Case1 and 2 boundaries and post-fire burn severity.

In Case 1, the F-score, particularly for severe and moderate fire severity levels, demonstrated greater accuracy compared to low severity (Table 4). Case 1 encompassed the

initial outbreak point of the fire (or the closest distance). This implies that the fire started significantly from the ignition point. In Case 2, a reduction in high fire severity was noted, with a prevalence of more moderate-severity fires. Case 2 included the dam area and larger agricultural fields, which appeared to function as barriers to mitigating high fire severity.

Table 4. Accuracy metrics for the case areas.

		Case 1	Case 2
F-score	Overall Accuracy	0.4490	0.3429
	Low BurnSeverity	0	0.0909
	Moderate Burn Severity	0.4	0.5185
	High Burn Severity	0.5882	0.3810

One of the essential factors influencing the expansion of fire in forested areas is the external intervention made to control the fire. The direction of spread during the days when the fire continued was evaluated in conjunction with the results obtained from the MODIS images, as depicted in Figure 6. This figure illustrates the development and severity of the fire from its initial outbreak, which was controlled. The fire commenced on 28 July 2021, advancing with high intensity towards the south in the mountainous area within the first 24 h. On the 3rd day, as the fire predominantly moved towards the north in sporadic locations, it also moved towards the east. By the 4th day, the fire reached the Case 2 area, located further east. In this section, although the intensity decreased due to LULC and the dam, it remained active over the forest areas, progressing over the northeastern mountainous region of this section for an additional 3–4 days. During the same period, the fire moved north. In this region, there are deep valleys and long mountain slopes. Generally, the fire remained active in the mountainous region during the last 3–4 days of the fire. It is understood that during these final 3–4 days, the fire was also effective in the region between Case 1 and Case 2. Overall, the variable topography in the northern regions facilitated local winds during the fire, and it was observed that the progression of the fire frequently changed according to wind direction. The higher elevation in the northern regions, prevalence of low-vegetation rocky areas, and absence of Scots pine and hard-soiled vegetation cover contributed to easier control of the fire. The fire initially progressed towards the south in the mountainous area with strong northerly winds. The higher density of settlements and agricultural areas further south can be explained by the lower fuel materials. On the 3rd day, when the fire turned towards the north and then to the east, it could be attributed to finding new fuel material sources and a more effective topography. The threat posed by the fire to settlements reaching the south in the first two days shifted the firefighting organization to this region. The reason for fire weakening and moving towards the north and then to the east on the 3rd day was due to the presence of a weaker firefighting organization in this region.

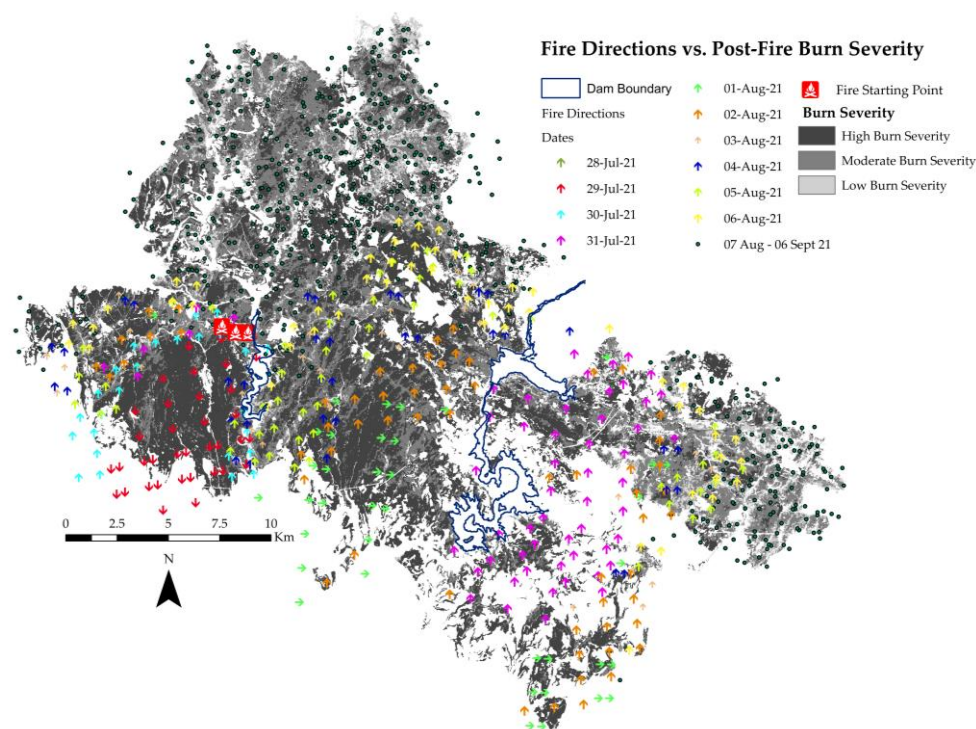


Figure 6. Fire expansion directions based on MODIS Data.

4. Discussion

The fire behavior risk model in the study demonstrated higher accuracy in areas with both high and low fire severity, explaining the expected relationship with burn intensity. However, the overall accuracy was lower for areas burning at moderate severity. Fire behavior risk was assessed in five classes, while burn severity was evaluated in three classes. It is particularly evident that the intermediate classes of both models affect each other's accuracy over the entire area. Areas with high fire severity included regions categorized as very high-risk and those characterized as high-risk areas. A similar situation is expected in areas with very low-risk and low-risk classes and low fire severity. Overall, a high level of accuracy was not observed in the comparison of the fire behavior risk model results with burn severity. Various factors, including differences in the data types and weighting schemes for both models, can explain this situation [60]. In similar studies, areas with high fire severity showed higher accuracy with high-risk classes than with other severity and risk classes. However, in our study and others, the accuracy never exceeded 60% [16,36,61]. It is crucial to further investigate whether changes in the weights of the inputs influencing the fire severity occur in each spatial area. In this regard, the relationship between fire risk's main inputs and burn severity was also examined separately. The values considered in risk analysis are generally sensitive to possible fire behaviors by providing different responses. In particular, large fires, where predicting fire progression becomes challenging due to difficulties in estimating emerging fire characteristics, are defined as uncharacteristic [15]. Quantitative fire risk analysis and models conducted aim to describe the distribution of risk and to predict its occurrence degree.

Numerical and computational models used to understand and predict nonlinear environmental events like fire are often complex, and currently, there is no other tool than modeling them separately for each space (pixel or raster scale) [15]. To move to the next stage, it is crucial to use more local data and include neighborhood relationships between different fuel types affecting fire severity in the analysis [61]. In this study, surface and crown fuel index values obtained from previous fuel load studies conducted in the region were used for pre-fire risk assessment according to fire risk levels. In these indices, distinctions between needle and broad-leaved tree species and sclerophyll vegetation were

included in the index calculations. Indices based on fuel loads show that the canopy and surface fuel indices of pine and deciduous forest stand types are higher compared to other tree species. This observation is attributed to the flammability of these pine and deciduous species linked to post-fire regeneration based on their fire regime characteristics [62]. The significant difference between the surface flammable index and crown fuel index values in older stands is explained by the decrease in the crown fuel load as trees age, starting the aging process [57] and leading to a decrease in the probability of crown fire initiation [63].

In addition to the fuel properties, stand canopy closure and development age were added. It was observed that in areas where the sub-criteria features of topography change rapidly over short distances, fire severity also exhibits parallel variability. To accurately describe the potential fire severity in fire risk maps, attention should be paid to region-growing techniques based on the neighborhood relationships of fuel or vegetation that prioritize similar structures. As such, areas with similar vegetation structures will be combined to prioritize the fuel properties that increase fire severity. The grouped areas with enlarged vegetation or fuel characteristics can be expected to be converted into average values by combining climate and topography characteristics. It is evident that climate data will affect broader areas. Achieving accuracy in the actual degree of fire severity with fire hazard risk mapping that includes such approaches will be possible. Models and all data required for determining fire risk and severity should be easily accessible, and relevant institutions and authorities should be able to integrate them into their systems. All data necessary for implementing the models should be integrated into national and international spatial data infrastructure [16]. Only in this way it can be understood that extremely large fires can be achieved, or prevented measures for their non-occurrence should be known in advance.

The comparison of post-fire analyses in forests with pre-fire risk assessments highlights the need to enhance prediction methodologies. Although pre-fire assessments are valuable tools, their accuracy depends on the integration of real-world data and continuous model refinement. The dynamic nature of forest ecosystems necessitates adaptable and robust assessment approaches. The fuel properties of forest ecosystems constantly change under the influence of natural forces, depending on time and space. When indirect and direct interventions due to human influences are added to this process, it is clear that they do not show uniform development. Fire risk is also directly affected by spatial and temporal process changes. Effective forest fire management requires precise pre-fire predictions to mitigate adverse effects on ecosystems and human communities. Although pre-fire risk assessments provide valuable insights, the disparities between predicted and actual fire behavior emphasize the need for continuous refinement. By integrating real-time data, advanced modeling techniques, and learning from post-fire analyses, pre-fire risk assessments can evolve into more reliable tools for proactive forest fire management.

5. Conclusions

Research revealing both fire risk and burn severity in the same fire is crucial for improving the accuracy of models when studying these aspects separately. Additionally, it will provide essential tools for spatially planning fire management measures, such as prescribed fires, thinning for fire mitigation, establishing fire break zones, developing a network of fire roads, determining locations for fire pools, and deploying fire monitoring tools. Furthermore, it can facilitate the development of high-accuracy burn severity mapping. These mappings can establish valid criteria that affect the success of post-fire adaptation and restoration activities. Sharing studies based on comparing the effects of fires that occur in areas where national or international fire risks are identified will strengthen decision-making frameworks for coping with the challenges encountered in fire management efforts. Such a network will significantly contribute to reducing global environmental issues like sustainable forest management, carbon management, and climate change.

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Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

AHP	Analytical Hierarchy Process
FAHP	Fuzzy Analytical Hierarchy Process
GIS	Geographic Information System
MCDA	Multi-Criteria Decision Analysis
CORINE	Coordination of Information on the Environment
LULC	Land Use Land Cover
NDVI	Normalized Vegetation Index
FMC	Fuel-Moisture Content
CR	Consistency Ratio
CFLI	Canopy Fuel Loading Index

References

1. Roces-Díaz, J.V.; Santin, C.; Martínez-Vilalta, J.; Doerr, S.H. A Global Synthesis of Fire Effects on Ecosystem Services of Forests and Woodlands. *Front. Ecol. Environ.* **2022**, *20*, 170–178. [\[CrossRef\]](#)
2. Tepley, A.J.; Thomann, E.; Veblen, T.T.; Perry, G.L.W.; Holz, A.; Paritsis, J.; Kitzberger, T.; Anderson-Teixweria, K.J. Influences of Fire–Vegetation Feedbacks and Post-Fire Recovery Rates on Forest Landscape Vulnerability to Altered Fire Regimes. *J. Ecol.* **2018**, *106*, 1925–1940. [\[CrossRef\]](#)
3. McLauchlan, K.K.; Higuera, P.E.; Miesel, J.; Rogers, B.M.; Schweitzer, J.; Shuman, J.K.; Tepley, A.J.; Varner, J.M.; Veblen, T.T.; Adalsteinsson, S.A.; et al. Fire as a Fundamental Ecological Process: Research Advances and Frontiers. *J. Ecol.* **2020**, *108*, 2047–2069. [\[CrossRef\]](#)
4. Xu, R.; Yu, P.; Abramson, M.J.; Johnston, F.H.; Samet, J.M.; Bell, M.L.; Haines, A.; Ebi, K.L.; Li, S.; Guo, Y. Wildfires, Global Climate Change, and Human Health. *New Engl. J. Med.* **2022**, *383*, 2173–2181. [\[CrossRef\]](#) [\[PubMed\]](#)
5. Kalogiannidis, S.; Chatzitheodoridis, F.; Kalfas, D.; Patitsa, C.; Papagrigoriou, A. Socio-Psychological, Economic and Environmental Effects of Forest Fires. *Fire* **2023**, *6*, 280. [\[CrossRef\]](#)
6. Brotons, L.; Aquilué, N.; De Cáceres, M.; Fortin, M.J.; Fall, A. How Fire History, Fire Suppression Practices and Climate Change Affect Wildfire Regimes in Mediterranean Landscapes. *PLoS ONE* **2013**, *8*, e62392. [\[CrossRef\]](#) [\[PubMed\]](#)
7. Moreira, F.; Ascoli, D.; Safford, H.; Adams, M.A.; Moreno, J.M.; Pereira, J.M.; Catry, F.X.; Armesto, J.; Bond, W.; González, M.E.; et al. Wildfire Management in Mediterranean-type Regions: Paradigm Change Needed. *Environ. Res. Lett.* **2020**, *15*, 011001. [\[CrossRef\]](#)
8. Chicas, S.D.; Nielsen, Ø.J. Who Are the Actors and What Are the Factors That Are Used in Models to Map Forest Fire Susceptibility? A Systematic Review. *Nat. Hazards* **2022**, *114*, 2417–2434. [\[CrossRef\]](#)
9. Kavanagh, K.L.; Dickinson, M.B.; Bova, A.S. A Way Forward for Fire-Caused Tree Mortality Prediction: Modeling A Physiological Consequence of Fire. *Fire Ecol.* **2010**, *6*, 80–94. [\[CrossRef\]](#)
10. Kwon, S.; Kim, S.; Kim, J.; Kang, W.; Park, K.H.; Kim, C.B.; Girona, M.M. Predicting Post-Fire Tree Mortality in A Temperate Pine Forest, Korea. *Sustainability* **2021**, *13*, 569. [\[CrossRef\]](#)
11. Thompson, M.P.; Calkin, D.E. Uncertainty and Risk in Wildland Fire Management: A Review. *J. Environ. Manag.* **2011**, *92*, 1895–1909. [\[CrossRef\]](#)
12. Miller, C.; Ager, A.A. A Review of Recent Advances in Risk Analysis for Wildfire Management. *Int. J. Wildland Fire* **2013**, *22*, 1–14. [\[CrossRef\]](#)
13. Martinez, J.; Vega-Garcia, C.; Chuvieco, E. Human-caused Wildfire Risk Rating for Prevention Planning in Spain. *J. Environ. Manag.* **2009**, *90*, 1241–1252. [\[CrossRef\]](#)
14. Rodrigues, M.; Riva, J. Assessing the Effect on Fire Risk Modeling of the Uncertainty in the Location and Cause of Forest Fires. In *Advances in Forest Fire Research*; Viegas, D.X., Ed.; Universidade de Coimbra: Coimbra, Portugal, 2014; pp. 1061–1072. [\[CrossRef\]](#)
15. Finney, M.A. The Challenge of Quantitative Risk Analysis for Wildland Fire. *For. Ecol. Manag.* **2005**, *211*, 97–108. [\[CrossRef\]](#)

16. Maniatis, Y.; Doganis, A.; Chatzigeorgiadis, M. Fire Risk Probability Mapping Using Machine Learning Tools and Multi-Criteria Decision Analysis in the GIS Environment: A Case Study in the National Park Forest Dadia-Lefkimi-Soufli, Greece. *Appl. Sci.* **2022**, *12*, 2938. [\[CrossRef\]](#)
17. Saglam, B.; Boyatan, M.; Sivrikaya, F. An Innovative Tool for Mapping Forest Fire Risk and Danger: Case Studies from Eastern Mediterranean. *Scott. Geogr. J.* **2023**, *139*, 160–180. [\[CrossRef\]](#)
18. Sari, F. Identifying Anthropogenic and Natural Causes of Wildfires by Maximum Entropy Method-Based Ignition Susceptibility Distribution Models. *J. For. Res.* **2023**, *34*, 355–371. [\[CrossRef\]](#)
19. Bot, K.; Borges, J.G. A Systematic Review of Applications of Machine Learning Techniques for Wildfire Management Decision Support. *Inventions* **2022**, *7*, 15. [\[CrossRef\]](#)
20. Akıncı, H.A.; Akıncı, H. Machine Learning Based Forest Fire Susceptibility Assessment of Manavgat District (Antalya), Turkey. *Earth Sci. Inform.* **2023**, *16*, 397–414. [\[CrossRef\]](#)
21. Satir, O.; Berberoglu, S.; Donmez, C. Mapping Regional Forest Fire Probability Using Artificial Neural Network Model in A Mediterranean Forest Ecosystem. *Geomat. Nat. Hazards Risk* **2016**, *7*, 1645–1658. [\[CrossRef\]](#)
22. Nuthammachoti, N.; Stratoulis, D. A GIS- and AHP-Based Approach to Map Fire Risk: A Case Study of Kuan Kreng Peat Swamp Forest, Thailand. *Geocarto Int.* **2021**, *36*, 212–225. [\[CrossRef\]](#)
23. Güngöroğlu, C. Determination of Forest Fire Risk with Fuzzy Analytic Hierarchy Process and its Mapping with the Application of GIS: The Case of Turkey/Çakırlar. *Hum. Ecol. Risk Assess. Int. J.* **2017**, *23*, 388–406. [\[CrossRef\]](#)
24. Parajuli, A.; Manzoor, S.A.; Lukac, M. Areas of the Terai Arc landscape in Nepal at Risk of Forest Fire Identified by Fuzzy Analytic Hierarchy Process. *Environ. Dev.* **2023**, *45*, 100810. [\[CrossRef\]](#)
25. Feizizadeh, B.; Roodposhti, M.S.; Jankowski, P.; Blaschke, T. A GIS-based Extended Fuzzy Multi-Criteria Evaluation for Landslide Susceptibility Mapping. *Comput. Geosci.* **2014**, *73*, 208–221. [\[CrossRef\]](#) [\[PubMed\]](#)
26. Bakırman, T.; Gümüşay, M.U.; Musaoğlu, N.; Tanık, A.G. Development of Sustainable Wetland Management Strategies by using Analytical Hierarchy Process (AHP) and Web-Based GIS: A Case Study from Turkey. *Trans. GIS* **2021**, *26*, 1589–1608. [\[CrossRef\]](#)
27. Sinha, A.; Nikhil, S.; Ajin, R.S.; Danumah, J.H.; Saha, S.; Costache, R.; Rajaneesh, A.; Sajinkumar, K.S.; Amrutha, K.; Johny, A.; et al. Wildfire Risk Zone Mapping in Contrasting Climatic Conditions: An Approach Employing AHP and F-AHP Models. *Fire* **2023**, *6*, 44. [\[CrossRef\]](#)
28. Sari, F. Forest Fire Susceptibility Mapping via Multi-Criteria Decision Analysis Techniques for Mugla, Turkey: A Comparative Analysis of VIKOR and TOPSIS. *For. Ecol. Manag.* **2021**, *480*, 118644. [\[CrossRef\]](#)
29. Sivrikaya, F.; Küçük, Ö. Modeling Forest Fire Risk Based on GIS-Based Analytical Hierarchy Process and Statistical Analysis in Mediterranean Region. *Ecol. Inform.* **2022**, *68*, 101537. [\[CrossRef\]](#)
30. Hood, S.M. Physiological Responses to Fire That Drive Tree Mortality. *Plant Cell Environ.* **2021**, *44*, 692–695. [\[CrossRef\]](#)
31. Etchell, H.; O'Donnell, A.J.; McCaw, M.L.; Grierson, P. Fire Severity Impacts on Tree Mortality and Post-Fire Recruitment in Tall Eucalypt Forests of Southwest Australia. *For. Ecol. Manag.* **2020**, *459*, 117850. [\[CrossRef\]](#)
32. Peterson, D.L.; Ryan, K.C. Modeling Postfire Planning Conifer Mortality for Long-Range Planning. *Environ. Manag.* **2012**, *10*, 797–808. [\[CrossRef\]](#)
33. Ager, A.; Vaillant, N.M.; Finney, M.A. Integrating Fire Behavior Models and Geospatial Analysis for Wildland Fire Risk Assessment and Fuel Management Planning. *J. Combust.* **2011**, *2011*, 572452. [\[CrossRef\]](#)
34. Calkin, D.E.; Thompson, M.P.; Finney, M.A.; Hyde, K.D. A Real-Time Risk Assessment Tool Supporting Wildland Fire Decision Making. *J. For.* **2011**, *109*, 274–280. [\[CrossRef\]](#)
35. Pausas, J.G.; Keeley, J.E. Wildfires and Global Change. *Front. Ecol. Environ.* **2021**, *19*, 387–395. [\[CrossRef\]](#)
36. Paz, S.; Carmel, Y.; Jahshan, F.; Shoshany, M. Post-fire Analysis of Pre-fire Mapping of Fire-Risk: A Recent Case Study from Mt. Carmel (Israel). *For. Ecol. Manag.* **2010**, *262*, 1184–1188. [\[CrossRef\]](#)
37. Estes, B.L.; Knapp, E.E.; Skinner, C.N.; Miller, J.D.; Preisler, H.K. Factors Influencing Fire Severity Under Moderate Burning Conditions in The Klamath Mountains, Northern California, USA. *Ecosphere* **2017**, *8*, e01794. [\[CrossRef\]](#)
38. Wei, M.; Zhang, Z.; Long, T.; He, G.; Wang, G. Monitoring Landsat Based Burned Area as an Indicator of Sustainable Development Goals. *Earth's Future* **2021**, *9*, e2020EF001960. [\[CrossRef\]](#)
39. San-Miguel-Ayán, J.; Durrant, T.; Boca, R.; Maiani, P.; Libertá, G.; Artés-Vivancos, T.; Oom, D.; Branco, A.; de Rigo, D.; Ferrari, D.; et al. *Forest Fires in Europe, Middle East and North Africa 2021*; JRC130846; Publications Office of the European Union: Luxembourg, 2022. [\[CrossRef\]](#)
40. *Forest Management Plan, Stand Structure Map*; Republic of Türkiye General Directorate of Forestry: Ankara, Türkiye, 2021. (In Turkish)
41. Roy, D.P.; Huang, H.; Boschetti, L.; Giglio, L.; Yan, L.; Zhang, H.H.; Li, Z. Landsat-8 and Sentinel-2 Burned Area Mapping-A Combined Sensor Multi-Temporal Change Detection Approach. *Remote Sens. Environ.* **2019**, *231*, 111254. [\[CrossRef\]](#)
42. İsmailoğlu, İ.; Musaoğlu, N. Burn Severity Assessment with Different Remote Sensing Products for Wildfire Damage Analysis. In Proceedings of the SPIE, San Diego, CA, USA, 4 October 2023; Volume 12685, p. 126850U. [\[CrossRef\]](#)
43. Bennett, M.; Fitzgerald, S.; Parker, B.; Main, M.; Perleberg, A.; Schnepf, C.; Mahoney, R. Reducing Fire Risk on Your Forest Property. A Pacific Northwest Extension Publication. 2010, 618. Available online: <https://catalog.extension.oregonstate.edu/sites/catalog/files/project/pdf/pnw618.pdf> (accessed on 20 December 2023).

44. Pereira, M.G.; Trigo, R.M.; da Camara, C.C.; Pereira, J.M.; Leite, S.M. Synoptic Patterns Associated with Large Summer Forest Fires in Portugal. *Agric. For. Meteorol.* **2005**, *129*, 11–25. [\[CrossRef\]](#)
45. Bonora, L.; Conese, C.; Marchi, E.; Tesi, E.; Montorselli, N.B. Wildfire Occurrence: Integrated Model for Risk Analysis and Operative Suppression Aspects Management. *Am. J. Plant Sci.* **2013**, *4*, 705–710. [\[CrossRef\]](#)
46. Bradshaw, L.; Deeming, J.E.; Burgan, R.E.; Cohen, J.D. *The 1978 National Fire-Danger Rating System: Technical Documentation*; General Technical Report INT-169; USDA Forest Service, Intermountain Forest and Range Experiment Station: Ogden, UT, USA, 1984.
47. Possell, M.; Bell, T.L. The Influence of Fuel Moisture Content on The Combustion of Eucalyptus Foliage. *Int. J. Wildland Fire* **2013**, *22*, 343–352. [\[CrossRef\]](#)
48. Syphard, A.D.; Rustigian-Romsos, H.; Mann, M.; Conlisk, E.; Moritz, M.A.; Ackerly, D. The Relative Influence of Climate and Housing Development on Current and Projected Future Fire Patterns and Structure Loss across Three California Landscapes. *Glob. Environ. Change* **2019**, *56*, 41–55. [\[CrossRef\]](#)
49. Sharples, J.J.; McRae, R.H.D.; Weber, R.O.; Gill, A.M. Simple Indices for Assessing Fuel Moisture Content and Fire Danger Rating. *Fire Note* **2010**, *65*, 637–646. [\[CrossRef\]](#)
50. Flatley, W.T.; Lafon, C.W.; Grissino-Mayer, H.D. Climatic and Topographic Controls on Patterns of Fire in the Southern and Central Appalachian Mountains, USA. *Landsc. Ecol.* **2011**, *26*, 195–209. [\[CrossRef\]](#)
51. Fernandes, P.M. Combining Forest Structure Data and Fuel Modelling to Classify Fire Hazard in Portugal. *Ann. For. Sci.* **2009**, *66*, 415. [\[CrossRef\]](#)
52. Bond-Lamberty, B.; Wang, C.; Gower, S. Aboveground and Belowground Biomass and Sapwood Area Allometric Equations for Six Boreal Tree Species of Northern Manitoba. *Can. J. For. Res.* **2002**, *32*, 1441–1450. [\[CrossRef\]](#)
53. Güngöroğlu, C.; Güney, Ç.O.; Sarı, A.; Serttaş, A. In Proceedings of the Estimation of Fuel Load in Maquis Type Vegetation of Antalya. International Symposium on New Horizons in Forestry, Isparta, Turkey, 18–20 October 2017.
54. Küçük, Ö.; Bilgili, E.; Sağlam, B. Estimating Crown Fuel Loading for Calabrian Pine and Anatolian Black Pine. *Int. J. Wildland Fire* **2008**, *17*, 147–154. [\[CrossRef\]](#)
55. Küçük, Ö.; Sağlam, B.; Bilgili, E. Canopy Fuel Characteristics and Fuel Load in Young Black Pine Trees. *Biotechnol. Biotechnol. Equipment* **2007**, *21*, 235–240. [\[CrossRef\]](#)
56. Sağlam, B.; Küçük, Ö.; Bilgili, E.; Dinç Durmaz, B.; Baysal, İ. Estimating Fuel Biomass of Some Shrub Species (Maquis) in Turkey. *Turk. J. Agric. For.* **2008**, *32*, 349–356.
57. Yurtgan, M.; Baysal, İ.; Küçük, Ö. Fuel Characterization and Crown Fuel Load Prediction in Non-Treated Calabrian Pine (*Pinus Brutia* Ten.) Plantation Areas. *iForest-Biogeosci. For.* **2022**, *15*, 458–464. [\[CrossRef\]](#)
58. Chang, D.Y. Applications of the Extent Analysis Method on Fuzzy AHP. *Eur. J. Oper. Res.* **1996**, *95*, 649–655. [\[CrossRef\]](#)
59. Kahraman, C.; Ertay, T.; Büyüközkan, G. A Fuzzy Optimization Model for QFD Planning Process Using Analytic Network Approach. *Eur. J. Oper. Res.* **2006**, *171*, 390–411. [\[CrossRef\]](#)
60. Szpakowski, D.M.; Jensen, J.L.R.; Butler, D.R.; Chow, T.E. A Study of The Relationship Between Fire Hazard and Burn Severity in Grand Teton National Park, USA. *Int. J. Appl. Earth Obs. Geoinf.* **2021**, *98*, 102305. [\[CrossRef\]](#)
61. Trucchia, A.; Meschi, G.; Fiorucci, P.; Provenzale, A.; Tonini, M.; Pernice, U. Wildfire Hazard Mapping in The Eastern Mediterranean Landscape. *Int. J. Wildland Fire* **2023**, *32*, 417–434. [\[CrossRef\]](#)
62. Saura-Mas, S.; Paula, S.; Pausas, J.G.; Lloret, F. Fuel Loading and Flammability in the Mediterranean Basin Woody Species with Different Post-Fire Regenerative Strategies. *Int. J. Wildland Fire* **2010**, *19*, 783–794. [\[CrossRef\]](#)
63. Mitsopoulos, I.D.; Dimitrakopoulos, A.P. Canopy Fuel Characteristics and Potential Crown Fire Behavior in Aleppo pine (*Pinus halepensis* Mill.) Forests. *Ann. For. Sci.* **2007**, *64*, 287–299. [\[CrossRef\]](#)

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