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Modeling Wildfire Risk Using GIS-Integrated Analytical Hierarchy Process Method: A Case Study of Zouagha Forest (Northeastern Algeria)

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Abstract

The growing demand for land increases the risk of forest fire, threatening ecosystems and human health. This study integrates Geographic Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA) to assess natural phenomena through fire susceptibility mapping in the Zouagha Forest, northeastern Algeria. This forest area, vital both environmentally and economically, frequently faced fires. In this study, factors that affect fire risk and spread included slope, aspect, Topographic Wetness Index (TWI), altitude, distance from roads, urban areas, and water resources, Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and flammability of species. The analytical Hierarchy Process (AHP) was used to determine the significance of these various factors, and it was found that anthropogenic factors (proximity to roads and urban areas) were the most important. Fire map results indicated that 61.71% of the forest area was at high and very high risk, with 9.18% specifically at very high risk of fire. The accuracy of the map was validated using the Receiver Operating Characteristic (ROC) curve method, achieving an 81% accuracy rate. Historical wildfire ignition points confirmed the model's reliability, with over 83% located in high- or very high-risk areas. This model will undoubtedly assist local decision-makers and firefighters in implementing preventive measures and taking necessary precautions to reduce the damage caused by fires in this region.

Keywords: Wildfire, AHP, GIS, ROC, fire susceptibility, Zouagha Forest.

1. Introduction

Forests play a pivotal role as a critical natural asset in sustaining ecological systems. They serve as carbon sinks, safeguard the variety of soil and biological species, cleanse the atmosphere while generating oxygen, and are instrumental in managing and enhancing the quality of water resources (Baskent and Keles, 2009; Demeke and Afework, 2014; Pourtaghi et al., 2015; Sivrikaya and Küçük, 2022). In recent years, severe and record-setting wildfires have occurred around the world due to rising global temperatures and advancing climate change. This critical disaster is particularly widespread in numerous Mediterranean nations (Seidl et al., 2014; Kouachi et al., 2024). With Algeria being no exception, this country has historically experienced an unparalleled succession of vast, extreme wildfires (Madoui, 2002; Kouachi et al., 2024). In the summer of 2023, a record-breaking heatwave affected ecological and socio-economic assets globally (Sahar et al., 2018; World Bank, 2023; Kouachi et al., 2024). These fires have resulted in human casualties and may lead to severe degradation of forest habitats in this country, with significant portions potentially beyond restoration (Meddour-Sahar, 2015; Kouachi et al., 2024). According to Laala et al. (2020), approximately1,700 forest fires occur each year, resulting in devastation of 36,000 hectares, which represents 0.9% of the nation's forest assets. In 2017, the impact was particularly severe, with many firefighters injured, numerous homes destroyed, and over 53,984 hectares burned, including 28,841 hectares of forest, 10,398 hectares of maquis, and 14,745 hectares of scrubland across 36 provinces in Algeria. This area is almost three times larger than the 18,370 hectares affected by fires in 2016, a significant increase linked to unfavorable weather conditions.

Anticipatory models indicated that climate change will likely prolong the fire season and intensify droughts in the coming years (Krawchuk et al., 2009; Kloster and Lasslop, 2017; Wu et al., 2021). This scenario could potentially result in fires of a more devastating nature (Yavuz et al., 2018; Sakellariou et al., 2020; Sivrikaya and Küçük, 2022). In this critical situation, prevention emerges as the paramount strategy, standing as the sole efficacious measure to counteract this calamity (Xofis et

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al., 2020). Traditional methods for evaluating forest fire risk play a crucial for their role in on-site validation and verification. Despite their utility, these methods are often associated with high costs, significant time investment, and a lack of precision (Colak and Sunar, 2020). In the past few years, Geographic Information Systems (GIS) and remote sensing technologies have become potent instruments for understanding, evaluating, and reducing the threat of forest wildfires by analyzing various factors influencing fire risk and the speed of its propagation, including topography, vegetation types, and human activities such as proximity to roads and settlements. Given the variability in the relevance of factors across various research areas, it is imperative to calculate the significance of each individual factor (Zhao et al., 2021). Decision-makers have employed GIS-based Multiple Criteria Decision Analysis (MCDA) methods to model parameters of forest utilization and assess fire hazards. The Analytical Hierarchy Process (AHP) is frequently used as one of the predominant MCDA techniques to address intricate spatial challenges in forestry (Gülci, 2014; Akay and Sahin, 2019). In the Mediterranean region, a study conducted by Demir and Akay (2024) in Turkey employed the AHP in conjunction with GIS to create a map indicating fire risk for the Mersin Forest. In the Parambikulam Tiger Reserve located in Kerala (India), research was carried out to identify potential fire risk areas using GIS methods. The study also assessed the impact of various factors on the start of a fire. These factors encompassed land cover types, slope angle, aspect, Topographic Wetness Index (TWI), and distance from settlements, roads, tourist spots, and anti-poaching camp sheds. The AHP was employed to assign weights to these factors (Nikhil et al., 2021). Gianluigi Busico (2019) implemented an integrated method using GIS and AHP for forecasting forest fire hazards in the Campania region, southern Italy. The methodology took into account 12 different factors, utilizing the AHP technique to assign weights to these factors. The study area was categorized into five different risk levels, ranging from very low to very high. The model predictions were validated using fire alerts, which showed a strong correlation between the predicted and actual fires. These studies demonstrate the effectiveness of combining GIS and AHP in predicting forest fires. It is important to note that the specific factors and weights used in the AHP method may vary depending on the specific characteristics of the area being studied.

The primary objective of this study is to evaluate the effectiveness of combining these methods in creating a fire risk map for the Zouagha forest, located in the Mila province of northeastern Algeria, an ecosystem under significant ecological stress due to recurrent wildfires. Between 2011 and 2023, 172 fire incidents were recorded, resulting in a total of 2,099.72 hectares burned. The year 2019 was especially devastating, with 564 hectares burned forests (GDF, 2024). In line with Laala et al. (2020), the wildfire risk is further exacerbated by the rapid expansion of Wildland-Urban Interface (WUI) areas, which grew by 51% between 2009 and 2019, increasing community exposure to wildfire threats. This study aimed to leverage a novel integration of GIS and AHP to model wildfire risk specifically for this forest, incorporating unique factors such as vegetation flammability and human-induced influences. The decision to study this area was primarily driven by its rich biodiversity, highlighting the forest's ecological importance and role in maintaining regional balance, while also serving as a valuable economic asset due to its cork production, which supports various local economic activities. The findings would provide invaluable assistance to ecosystem custodians and firefighting personnel in their efforts to combat forest conflagrations. Furthermore, it would equip administrators with the necessary knowledge to implement preventive measures against such fires, thereby enhancing the resilience of the forests.

2. Materials and Methods

2.1. Study Area

The study area, Zouagha forest, is situated in the northeastern part of Algeria, specifically within the province of Mila. Geographically, it is positioned between latitudes 36°'3130''N and 36°'3530''N, and longitudes 5°59'30''E and 6°10'30''E. The Zouagha forest, with its diverse fauna, holds significant ecological value. It is home to a variety of mammals, including the weasel, genet, striped hyena, porcupine, mongoose, red fox, common jackal, European rabbit, and hare. The forest also provides habitat for a diverse range of bird species, including both terrestrial and aquatic birds. Most of these include the great cormorant, white headed, and duck. The Flora of the forest is equally remarkable, with superior plants such as Cork oak, with an annual production cycle estimated at 3,000 quintals per rotation, Algerian oak, medicinal plants like the common caper, rosemary, carob, bay laurel, and strawberry tree further enhance biodiversity (GDF, 2024).

The Zouagha forest is characterized by a Mediterranean subhumid climate, with prolonged dry periods (May to August) and irregular precipitation (600-800 mm annually), creating ideal conditions for fire ignition and spread. July and August are the peak fire months, accounting for 29 and 23 incidents, with August alone responsible for 54.61% of the total burned area (GDF, 2024). Despite these challenges, the causes of most fires remain unknown, underscoring the urgent need for targeted research and risk mitigation strategies.

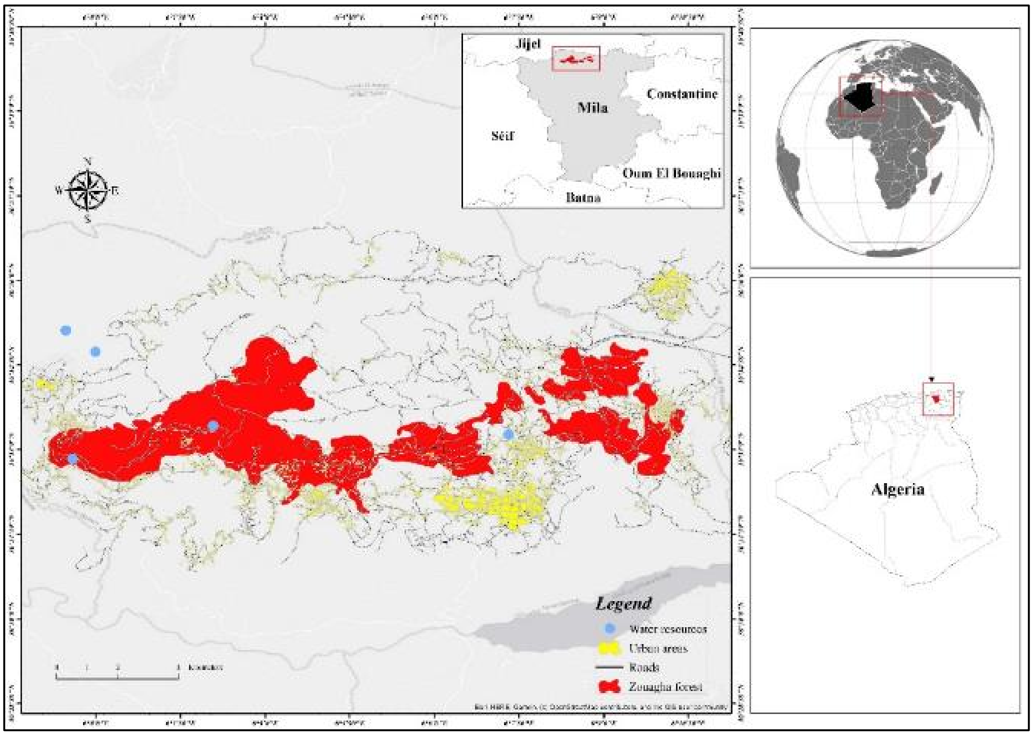

Figure 1. Study Area showing major roads, urban areas, and water resources

2.2. Data Characterization Criteria Selection

As part of the study, previous scientific literature (Bentekhici et al., 2020; Sivrikaya and Küçük, 2022; Demir and Akay, 2023) were referenced and conducted a national questionnaire targeting forestry experts and fire specialists to identify key factors influencing the likelihood and spread rate of fire. According to Al-Qassab (2021), the geographical factors, whether natural or human-induced, do not influence any phenomenon in the same way. Instead, a geographical phenomenon is the outcome of the interplay among a set of factors, rather than the mere accumulation of these factors. Each factor holds its relative significance, serving as an indicator of the extent to which it is impact on the issue at hand. This information is crucial in understanding the dynamics at play and can significantly contribute to the formulation of effective strategies and interventions. Three categories of factors have been discerned, topographic, environmental, and forestry and ten sub-factors (slope, aspect, TWI, altitude, distance from roads, urban areas, and water resources, Normalized Difference Vegetation Index-NDVI, Normalized Difference Water Index-NDWI, and flammability of species), that significantly contribute to the probability of a fire occurrence and amplify its rate of propagation. The data undergo a reclassification process to create a new benchmark, divided into five levels, extremely high, high, moderate, low, and extremely low, with each category assigned a corresponding weight (Ribeiro et al., 2008).

2.2.1. Topographic Factors

Understanding the attributes of the terrain, including the form of the land, slope, orientation and altitude, offers insights into the initiation, propagation speed and direction of the fire. (Şakar, 2010; Demir and Akay, 2024). As a topographic factor, slope (SLP), aspect (ASP), TWI and altitude (ALT) were considered. The gradient of the terrain is a pivotal factor in forest fires, impacting the initiation, characteristics, velocity, and intensity of these conflagrations (Maktite and Faleh, 2017; Bentekhici et al., 2020; Sari, 2021; Sivrikaya and Küçük, 2022). As the fire ascends a slope, its spread rate accelerates. Additionally, when the slope becomes steeper, the fire spreads even faster, leading to ignition of canopy fuels and an increased fire risk. (Butler et al., 2007; Bonora et al., 2013; Antoniya and Gerdzheva, 2014; Güngoroglu, 2017; Sivrikaya and Küçük, 2022). In the context of the northern hemisphere, it is generally observed that slopes facing the south and southwest are more susceptible to fires. This is primarily due to their increased exposure to sunlight, resulting in lower humidity levels and elevated fuel temperatures. These conditions collectively contribute to a heightened risk of fire incidents (Van Hoang et al., 2020). The topographic wetness index significantly impacts fire occurrence and spread. Dry areas are susceptible to rapid fire propagation, whereas wet areas are less likely to ignite (Dieu et al., 2016; Çolak and Sunar, 2020; Zhao et al., 2021). Altitude also influences fire behavior and response. According to Bentekhici et al. (2020), high-altitude regions, due to their influence on humidity, wind patterns, and human presence, exhibit specific characteristics. These areas are associated with dense vegetation and contain wetlands that serve as fuel and air sources. The combination of low temperatures and substantial annual precipitation results in reduced flammability, leading to a low risk of fire.

The topography of the study area was characterized using the Aster Global Digital Elevation Model (DEM) with a spatial resolution of 30 m, which was obtained from the USGS website (https://earthexplorer.usgs.gov/). This step was typically performed using ArcGIS Spatial Analyst tools. Slope and aspect were calculated based on the gradient and direction of the terrain. At the same time TWI was derived by combining slope data with flow accumulation, which reflects the potential for water accumulation in the landscape.

2.2.2. Environmental Factors

Environmental factors are directly related to the risk of ignition associated with both manmade and natural features, such as buildings, roads, and settlements. In most cases, the likelihood of ignition increases near these features, mainly due to human activities, whereas rivers generally act as natural firebreaks and therefore reduce ignition risk (Mitchell, 2013; Sari, 2021). These activities include leaving campfires unattended, discarding lit cigarettes on the ground, burning crop residues on agricultural land to prepare fields for new crops, burning grassland for livestock management, and utilizing smoke for honey harvesting (Vilar et al., 2010; Sivrikaya, 2022). For environmental factors, distance from roads (DSR) and urban areas (DSA) and distance from water resources (DSW) were utilized in this study. The potential for a fire outbreak is closely tied to the presence of roads and urban areas (Talbi, 2019; Anteur, 2021). Fire outbreaks occur more frequently in proximity to forest roads and urban areas. As one approaches roads, dwellings including isolated houses, farms, villages, and towns, the risk of fire increases significantly. According to Ju et al. (2023), distance from water resources is crucial for fire safety and firefighting efforts, significantly impacting the control and suppression of fires. In other words, as the distance from these resources decreases, the rate of fire spread also decreases.

Data related to the distance from roads and urban areas was obtained from (https://extract.bbbike.org/), and proximity to water resources data was acquired from the General Directorate of Forestry; to derive maps showing these factors, the Multiple Ring Buffer analysis tool in ArcGIS was utilizes. This tool generated concentric buffer zones around the provided points of water resources, roads and urban area data, allowing to visualize and analyze proximity.

2.2.3. Forest Factors

NDVI is employed to track photosynthetic activity and offers insights into vegetation biomass (Jiang et al., 2006; Mohajane et al., 2021; Pham, 2021). The following expression was used to calculate NDVI (Freden et al., 1973):

$$\mathrm{NDVI} = (\mathrm{NIR} - \mathrm{RED}) / (\mathrm{NIR} + \mathrm{RED}) \qquad (1)$$

NIR: Reflectance in the near infrared spectrum (Band 5)
RED: Reflectance of light in the red portion of the visible spectrum (Band 4)

The NDVI ranges from -1 to +1, with higher values corresponding to dense vegetation and increased vulnerability to fire (Gouveia et al., 2012; Truong et al., 2023). Conversely, lower values indicate non-vegetation cover (Pham, 2021). NDWI is another useful tool for measuring the presence and extent of water in a given area. In forested regions, high NDWI values can also indicate areas with elevated soil moisture content. This information can be valuable for understanding and predicting fire behavior and spread, as soil moisture levels can significantly influence the flammability and propagation of wildfires (Teng et al., 2021; Truong et al., 2023). The NDWI is calculated as follows (McFeeters, 1996):

$$NDWI = (GREEN - NIR)/(GREEN + NIR) \qquad (2)$$

GREEN: Reflectance in the green portion of the spectrum (Band 3)
NIR: Reflectance in the near infrared spectrum (Band 5)

Flammability of species (FMS) is another important factor as all vegetation, wet or dry, is flammable to varying degrees (Çolak and Sunar, 2020). Belkaid (2016) asserts that fire diffusion varies with vegetation structure and composition, notably influenced by consistency and stratification of woody volume. Fewer strata slow fire spread, whereas multiple strata (herbaceous, shrubby, arboreal) enhance it due to increased biomass. For example, Algerian oak forests, with only herbaceous and arboreal layers, limit the impact of fires on tree crowns. Boudy (1955) highlights the vulnerability ofcork oak forests, where herbaceous and shrubby strata, like Erica arborea and Arbutus unedo, facilitate fire reaching the trees. A Landsate 8 satellite image, procured from the U.S. Geological Survey, dated June, 26, 2023, was chosen for the analysis.

Supervised classification was conducted for classifying the satellite image. To facilitate this classification, a field survey was carried out on June 25, 2023. The aim of the survey was to identify and geolocate test areas corresponding to various land cover types. This study employed a series of image processing techniques, integrated with GIS data and the Analytic Hierarchy Process (AHP), to assess wildfire risks in the Zouagha region, as illustrated in the methodological flowchart (Figure 2).

2.3. Background of the Model

Multicriteria decision analysis (MCDA) is an approach for making decisions based on multiple evaluation criteria. This method utilizes mathematical and information tools to evaluate the scores and weights assigned to different evaluation criteria (Ju et al., 2023). One of the most commonly used techniques of MCDA is the Analytic Hierarchy Process (AHP). It was introduced by Thomas Saaty in the 1970s.

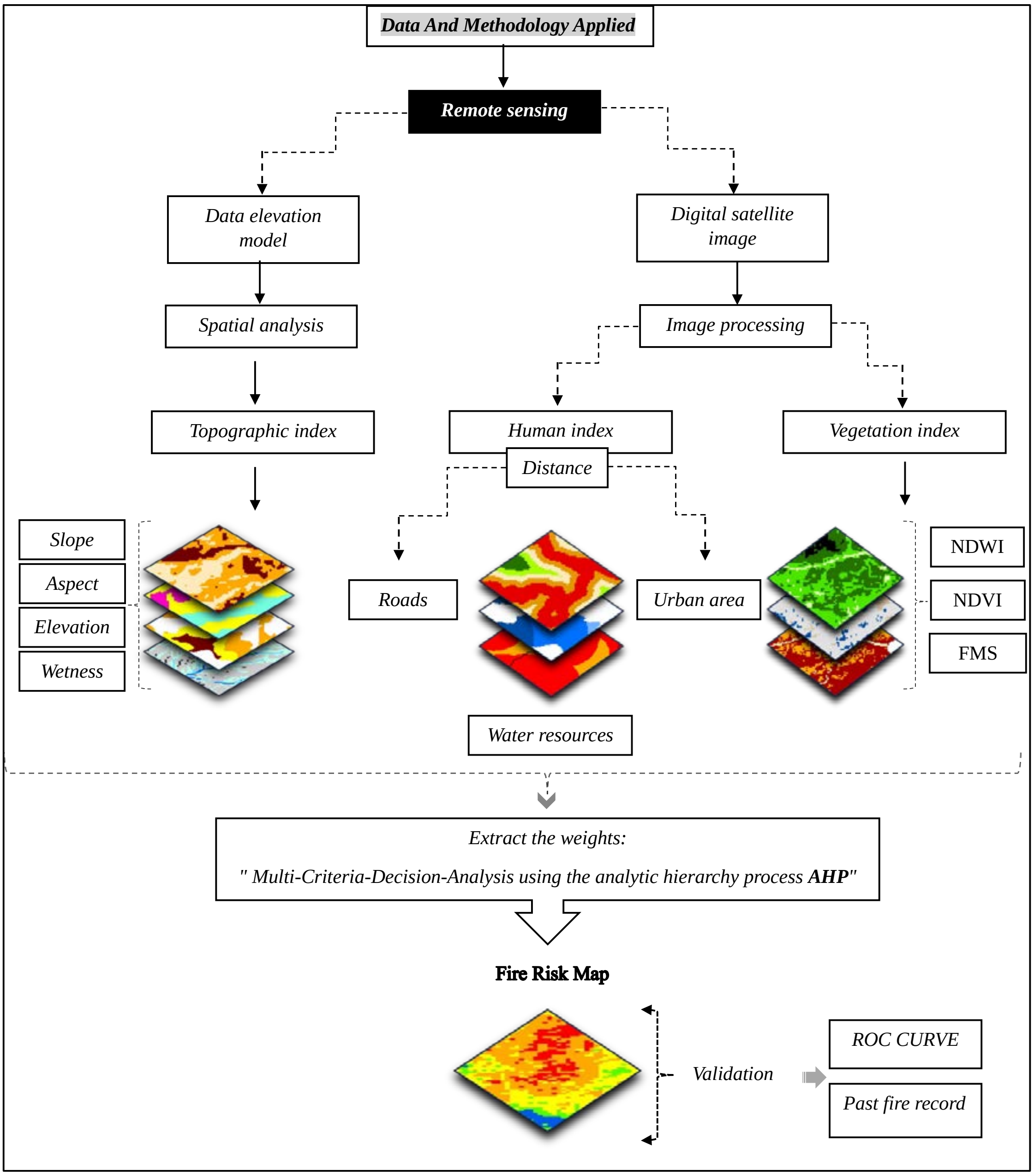

Figure 2. Fire risk model development

AHP was utilized to assess the weight allocation for each factor, topographic (altitude, slope, aspect, and wetness index), anthropogenic factor (proximity to roads, urban areas, and water resources), and vegetation (including NDVI, NDWI and Flammability of species). This method simplifies complex problems by breaking them down into a hierarchical structure. It establishes a scale of importance ranging from 1 to 9 (Table 1).

Table 1. Scale of relative importance (Saaty, 2008)

Scales	Relative Importance
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2, 4, 6, 8	Intermediate

In order to weight the criteria in the multi-criteria decision support process, a questionnaire must be prepared and distributed to decision makers for the purpose of determining the relative importance of each criterion (Al-Qassab, 2021). In this study, a questionnaire was prepared to specifically target foresters and experts in this study to determine the degree of influence of each factor (Table 2). The weighted average of the sample responses to all alternatives for each criterion was calculated using the Equation 3. AHP pairwise comparison matrix for each criterion is indicated in Table 3.

$$\bar{x} = \frac{\sum \mathrm{XiWi}}{\sum \mathrm{Wi}} \quad (3)$$

$\bar{x}$: The weighted average of the sample responses on all alternatives for each criterion

Xi: Number of answers for the alternative

Wi: The Numeric value of the same alternative

$\sum Wi$: Sample volume

Table 2. Survey results on the relative importance of each criterion

Scale	AHP Values	SLP	ASP	TWI	NDVI	FMS	DSR	DSA	DSW	NDWI	ALT
Equal	1	30	30	0	28	0	0	0	0	3	13
Moderate	3	37	10	36	5	7	3	0	0	40	60
Strong	5	25	49	26	25	79	2	0	20	31	25
Very Strong	7	8	30	30	42	12	7	20	49	26	2
Extreme	9	0	2	8	0	2	88	80	31	0	0
TOTAL		100	100	100	100	100	100	100	100	100	100
Weighted Average		3.22	5.33	3.2	6.86	5.18	8.6	8.6	7.22	4.6	3.32

Table 3. AHP pairwise comparison matrix

	SLP	ASP	TWI	NDVI	FMS	DSR	DSA	DSW	NDWI	ALT
SLP	1	0.5	0.5	1	0.5	0.16	0.16	0.25	0.5	1
ASP	2	1	1	2	1	0.25	0.25	0.5	1	2
TWI	2	1	1	2	1	0.25	0.25	0.5	1	2
NDVI	1	0.5	0.5	1	0.5	0.16	0.16	0.25	0.5	1
FMS	2	1	1	2	1	0.25	0.25	0.5	1	2
DSR	6	4	4	6	4	1	1	2	4	6
DSA	6	4	4	6	4	1	1	2	4	6
DSW	4	2	2	4	2	0.5	0.5	1	2	4
NDWI	2	1	1	2	1	0.25	0.25	0.5	1	2
ALT	1	0.5	0.5	1	0.5	0.16	0.16	0.25	0.5	1
Sum	27	15.5	15.5	27	15.5	4	4	7.75	15.5	27

Within the AHP, the pairwise comparisons within a judgment matrix are deemed sufficiently consistent if the resulting Consistency Ratio (CR) is below 10% (Saaty, 1980). The CR is determined through a series of calculations. Initially, the Consistency Index (CI) was estimated by summing the columns of the judgment matrix and then multiplying the resultant vector by previously obtained the vector of priorities to approximate the maximum eigenvalue, denoted as λmax. Subsequently, the CI was computed using the formula:

$$CI = \frac{\lambda\, max\text{-n}}{\text{n-1}} \tag{4}$$

The CR was then derived by dividing the CI by the Random Consistency Index (Table 4). If the CR exceeds 0.1, it is advisable to conduct further analysis and reassess the pairwise comparisons (Saaty and Vargas, 2012). The formula used to calculate CR is:

$$CR = \frac{CI}{RI} \tag{5}$$

Lastly, using the weights of factors, having CR of 0.001% (Table 5), the fire risk index (FRI) was calculated using Equation 6. The classes, rank, and weight of the fire risk factors used in this study are shown in Table 6.

$$\begin{aligned} FRI = {} & (SLP \times 0.03) + (ASP \times 0.07) + \\ & (\mathrm{TWI} \times 0.07) + (\mathrm{NDVI} \times 0.03) + \\ & (\mathrm{FMS} \times 0.07) + (\mathrm{DSR} \times 0.25) + \\ & (\mathrm{DSA} \times 0.25) + (\mathrm{DSW} \times 0.13) + \\ & (\mathrm{NDWI} \times 0.07) + (\mathrm{ALT} \times 0.03) \end{aligned} \tag{6}$$

2.4. Validation

The prediction accuracy and validation of the fire risk map, created using the AHP method, were assessed using the Receiver Operating Characteristic (ROC) curve method, which has proven effective across various disciplines (Satir et al., 2016; Silva et al., 2020; Sivrikaya and Küçük, 2022; Demir and Akay, 2023). The ROC curve is a graphical approach used to interpret the relationship between specificity and sensitivity. In this method, the x-axis represents the false positive rate (specificity), while the y-axis represents the true positive rate (sensitivity). The Area Under Curve (AUC) in the ROC curve indicates the statistical success of the prediction ability. They are typically divided into five categories, Unsatisfactory (0.5-0.6), Satisfactory (0.6-0.7), Good (0.7 -0.8), Very good (0.8-0.9) and Excellent (0.9-1.0) (Yeşilnacar, 2005; Gheshlaghi et al., 2019; Demir and Akay, 2023).

Table 4. Random consistency index (RI) (Saaty, 1990)

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.89	1.12	1.24	1.32	1.41	1.45	1.49

Table 5. Calculation of factors weights and CR value

Factors	SLP	ASP	TWI	NDVI	FMS	DSR	DSA	DSW	NDWI	ALT	Sum	Weight	Sum/Weight
SLP	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.35	0.03	10.00
ASP	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.67	0.07	10.02
TWI	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.67	0.07	10.02
NDVI	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.35	0.03	10.00
FMS	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.67	0.07	10.02
DSR	0.21	0.26	0.26	0.21	0.26	0.24	0.24	0.26	0.26	0.21	2.47	0.25	10.05
DSA	0.21	0.26	0.26	0.21	0.26	0.24	0.24	0.26	0.26	0.21	2.47	0.25	10.05
DSW	0.14	0.13	0.13	0.14	0.13	0.12	0.12	0.13	0.13	0.14	1.34	0.13	10.02
NDWI	0.07	0.06	0.06	0.07	0.06	0.06	0.06	0.06	0.06	0.07	0.67	0.07	10.02
ALT	0.03	0.03	0.03	0.03	0.03	0.04	0.04	0.03	0.03	0.03	0.35	0.03	10.00

Table 6. The classes, rank, and weight of the fire risk factors

Factor	Class	Rank	Weight	Fire Risk Classes
Slope (%)	0–5 5–10 10–20 20–25 > 25	1 2 3 4 5	0.03	Very low Low Moderate High Very high
Aspect (degrees)	North East West South	2 3 4 5	0.07	Low Moderate High Very high
TWI	< (-1) (-3) – (-1) (-5) – (-3) (-7) – (-5) > -7	1 2 3 4 5	0.07	Very low Low Moderate High Very high
NDVI	0.06–0.2 0.2–0.3 0.3–0.4 0.4–0.5 > 0.5	1 2 3 4 5	0.03	Very low Low Moderate High Very high
Flammability of species	Bare ground Zeen oak Oak cork	2 4 5	0.07	Low High Very high
Distance from roads (m)	>400 300–400 200–300 100–200 <100	1 2 3 4 5	0.25	Very low Low Moderate High Very high
Distance from urban areas (m)	> 3,000 2,000–3,000 1,000–2,000 < 1,000	2 3 4 5	0.25	Low Moderate High Very high
Distance from water resources (m)	< 1,000 1,000 –2,000 2,000 –3,000 3,000–4,000 > 4,000	1 2 3 4 5	0.13	Very low Low Moderate High Very high
NDWI	> (-0.2) (-0.3) – (-0.2) (-0.4) – (-0.3) (-0.5) – (-0.4) < (-0.5)	1 2 3 4 5	0.07	Very low Low Moderate High Very high
Altitude (m)	>1,000 850–1,000 700–850 600–700 <600	1 2 3 4 5	0.03	Very low Low Moderate High Very high

This study employed the "ROC-ArcSDM" extension servers as an effective tool for analyzing categorical maps (George et al., 2022; Parajuli et al., 2023), within the ArcGIS 10.8 environment to test the validity of fire risk map. The historical data on previous fires that occurred in the Zouagha forest, which was obtained from the General Directorate of Forestry, were used for validation. Then, it was superimposed with the fire risk map of the study area to assess the correlation between locations and the likelihood of occurrence indicated in the generated map.

3. Results

3.1. Fire Risk Factors

3.1.1. Topographic Factors

The maps of influencing factors according to their fire risk classes are indicated in Figure 3. The slope data was reclassified to establish a new classification benchmark divided into five levels corresponding to risk levels, very high, high, moderate, low, and very low. The majority of the Zouagha forest area was at low (52.12%) and moderate (31.71%) risk levels. Only a few steep areas (0.31 %) were classified as high risk; the majority of these are located in the northeastern part of the region.

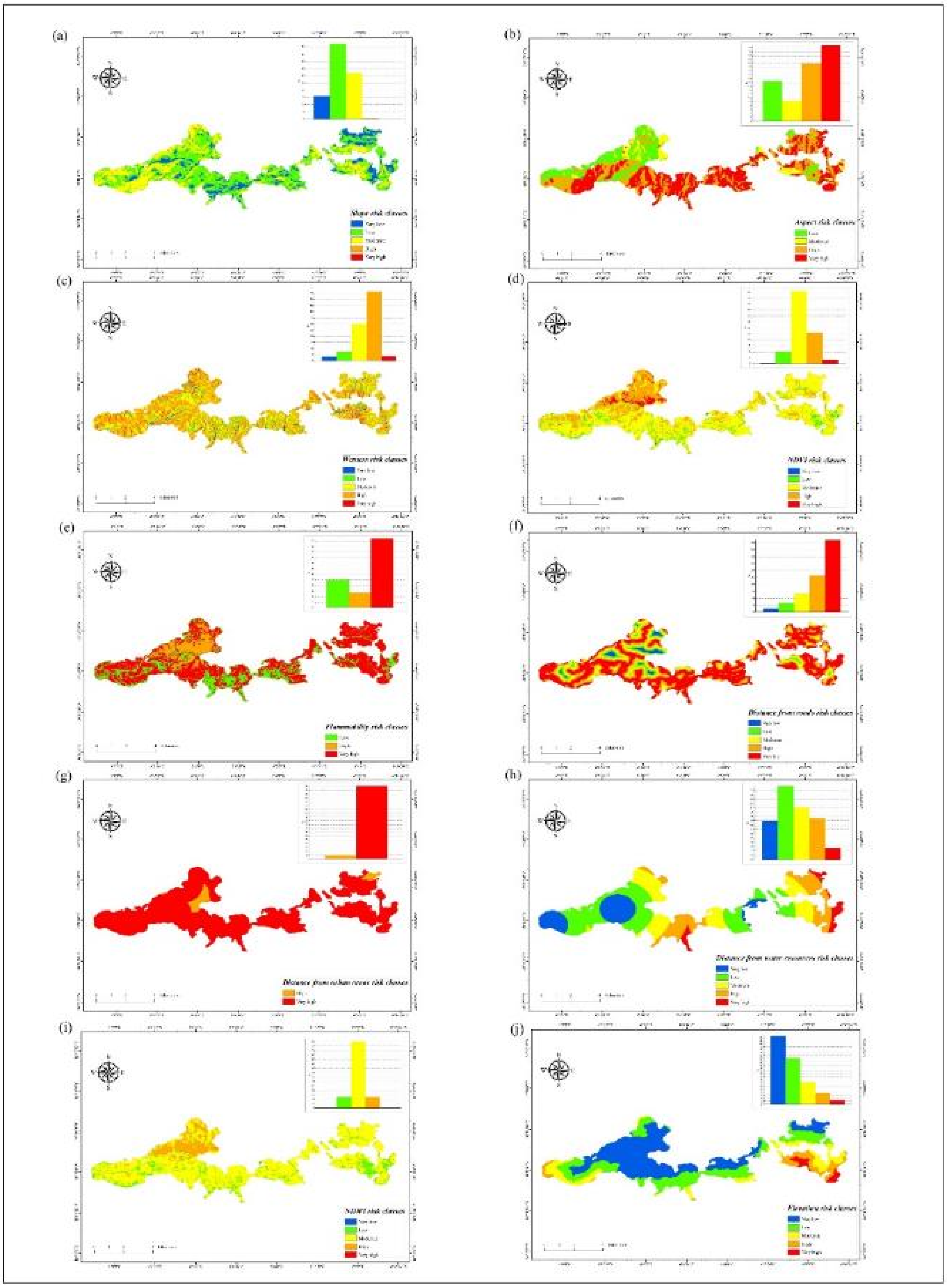

Figure 3. The maps of influencing factors according to their fire risk classes: (a) slope, (b) aspect, (c) TWI, (d) NDVI, (e) flammability, (f) distance from roads, (g) distance from urban areas, (h) distance from water resources, (i) NDWI, and (j) altitude

An analysis of the study area revealed that 39.09% of area was characterized by southern exposure, placing it at high risk of fire. The majority of these high-risk zones are concentrated in the southeastern and eastern parts of the region. Additionally, 20.64% of the area exhibits northern exposure, while western and eastern exposures account for 29.82% and 10.44%, respectively. For TWI factor, the high-risk area comprised the largest percentage at approximately 56.38%, encompassing the entire forest, particularly in the far eastern and northwestern regions. This was followed by the moderate risk category, which accounts for 29.93%. The lower risk categories had much smaller proportions, with low risk at 7.32%, very low risk at 3.09%, and very high risk at 3.27% of the total forest area. As depicted in Figure 3, the most significant proportion of the area corresponded to altitudes higher than 1000 m, representing a very low risk and accounting for 44.94% of the surface area. This was followed by the 850-1000 meters range, classified as low risk at 30.3%, and the 750-850 meters range, which falls into the moderate risk category at 14.48%. In contrast, the very high and high risk constituted a significantly smaller proportion of the area, with 2.63% and 7.63%, respectively; most of them are concentrated in the extreme southeastern part of the forest.

3.1.2. Environmental Factors

In this study, a distribution limit of 100 meters was established from roads, as proximity to these roads is linked to an increased fire risk. According to the findings (Figure 3), the fire risk was categorized as high to very high risk classes in the central region when roads are located less than 200 meters from the forest, which affects approximately 77.83% of the total forest area. The risk was moderate when the distance from roads ranges between 200 and 300 meters, representing 13.5% of the forest area. In contrast, areas where roads were situated more than 400 meters away from the forest had very low fire risk, accounting for only 2.36% of the total forest area. In terms of population distribution, the areas with a very high risk, where the dwellings were located within 1000 meters, account for 95.45% of the area. As for the areas with high risk, where dwellings were located at a distance ranging from 1,000 to 2,000 meters, they represent a small proportion, constituting only 4.54%. Therefore, the Zouagha forest contains areas that are highly susceptible to fire outbreaks (Figure 3). Buffer zones were created around water resources to allocate forest fire levels to the region, considering their proximity to these points. The greater the distance from the water sources, the higher the risk of fire spreading. The distances were divided into five categories "<1000, 1000-2000, 2000-3000, 3000-4000, >4000 meters". These categories were also labeled with qualitative descriptors, and it was found that the risk was very low for 17.95%, low for 33.87%, moderate for 24.11%, high for 18.94%, and very high for 5.1% in the eastern sections of the forest (Figure 3).

3.1.3. Forest Factors

Regarding NDWI index, the moderate risk comprised the largest proportion at 75.09% while the other categories had much smaller percentages, with low risk representing 12.41% and high-risk accounting for 12.38%, covering the northeastern part of the area (Figure 3). Areas with a high risk of fire were associated with regions of high vegetation density, where NDVI values were elevated. The class of very high risk related to vegetation density constituted 2.9% of the total surface area, concentrated in the northeastern of the forest. High-density areas accounted for 26.01%, while medium-density areas, which carry a moderate risk, were 60.86% of the surface area. Lastly, areas of low and very low density, which presented the least risk, comprised 10.2% of the total area (Figure 3). Four land cover classes were identified through the supervised classification of the satellite imagery. The Cork oak constituted more than half of the forest area, covering 1,907 hectares, which accounted for 61.99% of the total area and was dispersed throughout the zone. The Algerian oak spanned 384 hectares, making up 12.48% of the total area, and was primarily found in the northeastern part of the forest (Figure 3). The Afares oak occupied just 1% of the total surface area. The fourth class represents bare ground covered 755.43 hectares, which was approximately 24.55% of the forest area.

3.2. Forest Fire Risk Map

The forest fire risk map was a central and critical outcome of this study, providing valuable insights into the spatial distribution of fire risk across the study area. The fire risk map in Figure 4 revealed that 9.18% of the Zouagha forest area (282.58 hectares) was classified as very high risk, predominantly located in the central and eastern sections of the forest. These zones require immediate attention and targeted mitigation strategies due to their heightened vulnerability. Additionally, 52.53% of the area (1615.94 hectares) fallen under the high-risk category, underscoring the widespread susceptibility of the forest to fire incidents. Areas with a moderate risk accounted for 29.66% (912.62 hectares), while low-risk and very low-risk zones constituted 7.35% and 1.26%, respectively. The detailed result of the spatial analysis not only highlights fire-prone areas but also serves as a foundational tool for policymakers, forest managers, and local authorities to prioritize resource allocation and implement preventive measures to safeguard ecological and socio-economic assets in the region.

The ROC curve for the forest fire risk map is depicted in Figure 5. The AUC value for the fire risk map was 0.818, signifying a very good level of accuracy. The results demonstrated that 83.72% of wildfire ignition points occurred in areas designated as high or very high risk for wildfires, underscoring the model's effectiveness in identifying vulnerable regions.

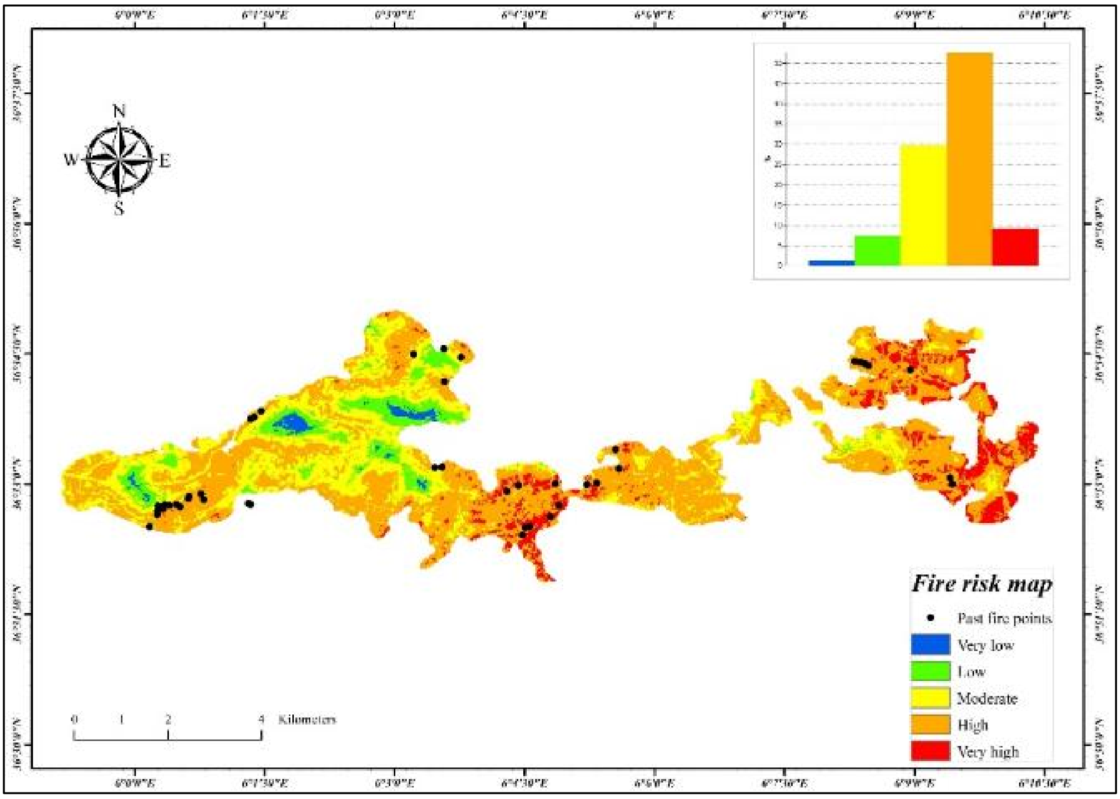

Figure 4. Zouagha forest fire risk map using AHP method

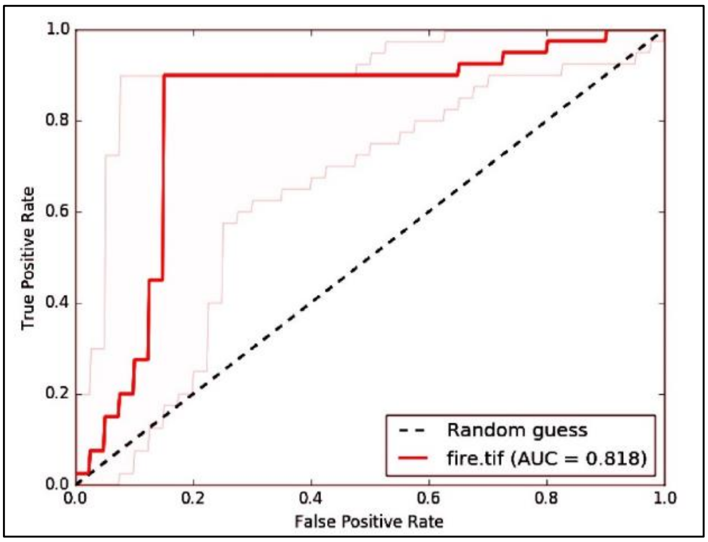

Figure 5. The ROC curve of the forest fire risk map

3. Discussion

In this study, a fire risk model was developed for the Zouagha forest, highlighting the most fire-prone zone and the contributing factors. The model was constructed based on topographical, environmental, and forestry criteria, which had significant and varying impacts on the likelihood of fire occurrence in this region. The weight of each factor was determined using the AHP method. This model facilitates protection efforts and speeds up firefighting interventions, while also allowing for the proposal of plans to establish monitoring towers to report fires as swiftly as possible. The AHP results, based on expert opinions, indicated that human-related factors (distance from roads and urban areas) are the most significant, accounting for 50% of the total influence. This suggested that areas with higher population densities are more susceptible to fires. These findings are consistent with previous studies conducted by Laala et al. (2020), which showed that areas with very high fire risk were those with many human-made spaces next to natural vegetation, these areas can easily catch fire due to human carelessness. Matin et al. (2017) and Parajuli et al. (2020) also determined that the rise in forest fire occurrences was attributed to human activities, with discarded cigarette butts often serving as a catalyst.

The distance from water resources was identified as the second most influential factor, with a 13% impact. This factor was significantly mirroring the findings of Akay and Şahin (2019), who noted that while tree species and stages are crucial factors in forest fires, the distance to water resources also plays a significant role in determining the occurrence of forest fires.

The third most significant weighted factors, which accounts for 28% of the total impact, included aspect, wetness, NDWI and species flammability, each contributing 0.07. This area comprised 61.99% Cork oak trees, a species highly susceptible to fire due to the presence of grassy, shrub and tree fuel layers that facilitates the rapid fire spread of flames (Belkaid, 2016; Boudy, 1955). The factors wetness, NDWI, and aspect indicated that the region was more vulnerable to fires due to lower humidity levels, with 39.09% of the area having a southern exposure, in agreement with previous studies (Ndalila, 2018; Ju et al., 2023), which showed that fire risk changes based on direction. Typically, the south facing direction receive more sunlight, resulting in warmer temperatures and lower humidity levels. Consequently, the soil and vegetation in this area are drier and more susceptible to fires, which can spread more rapidly.

Concerning the slope, NDVI, and altitude, the results diverged from those of Zhao et al., (2021) indicating that altitude significantly affects the likelihood of forest fires in Laoshan (China). Areas at lower altitudes are more accessible to people, which increases the chance of accidental fires, such as those caused by discarded cigarette butts (Rasooli and Bonyad, 2019). The study indicated that altitude played a significant role in determining the probability of forest fires in this region. However, in the Zouagha forest, altitude has a minimal impact, weighing in at just 0.03. This is primarily because the majority of the Zouagha forest area, 44.94%, is situated at an altitude above 1,000 meters. At the same time, this factor is crucial for forest fire risk in Laoshan, its influence is considerably less in the region due to the varied terrain, particularly in terms of slope. In a similar study conducted by Fekir et al. (2022) in western Algeria also found this to be the case. It was observed that the majority of the Louza forest area is characterized by flat terrain, with low and moderate slopes accounting for 42.17% and 54.52% of the area, respectively. This distribution suggests that the slope has a minimal influence on the likelihood of forest fires. Similarly, in the Zouagha forest, the terrain analysis indicated that steep areas were scarce, with the majority of the land classified as low risk (52.12%). This low-risk classification was attributed to the low slopes, which had a minimal impact on fire probability, reflected in the low weight of 0.03 assigned to the slope factor.

Researchers have different opinions on the impact of the NDVI on fire risk. Some use it extensively to indicate vegetation cover and its influence on forest fire likelihood. They argue that as vegetation cover increases, the NDVI value becomes higher, leading to a higher probability of fire, as indicated in his study. Conversely, others believe that low NDVI values represent inhabited areas with less vegetation cover, thus increasing fire risk, which was supported by previous studies (Pengcheng Zhao., 2021). This discrepancy creates ambiguity regarding the NDVI's impact, justifying the varied expert opinions on its importance. This study assigned it a weight of 0.03. The ROC curve demonstrated that the map achieved an accuracy of 81%, which is considered high for wildfire risk mapping. The findings revealed that 83.72% of wildfire ignition points were located in regions identified as having high or very high wildfire risk. This outcome supports the conclusions of prior investigations, which demonstrated the effectiveness of the ROC curve in ensuring the prediction accuracy, as it achieved an AUC of 81.75% (Tiwari et al., 2020) and 77.15% (Özcan et al., 2024).

The results of this research are consistent with recent research conducted in Mediterranean region that utilize GIS and AHP for wildfire risk assessment. For instance, Pallikarakis and Konstantopoulou (2024) used a similar approach in Greece, identifying vegetation type and human activities as key risk factors. However, present study provided a tailored assessment that reflects the unique ecological and socioeconomic conditions of the study area by incorporating distinctive local factors, such as Cork oak flammability, a characteristic species in certain Mediterranean regions, which has flammability properties that can significantly influence the fire risk. Rivière et al. (2023) conducted a participative GIS-AHP approach to identify vulnerability hotspots in southeastern France. However, their study prioritized socioeconomic and environmental factors without delving into species-specific flammability. The regional specificity of the present study not only enhanced the precision of the assessment for the Zouagha forest but also offered a scalable framework for other Mediterranean regions with similar Cork oak-dominated ecosystems, such as parts of Morocco, Tunisia, and southern Spain.

This study provided a significant step forward in understanding and managing wildfire risk in the Zouagha forest by combining GIS and AHP with local data and expert input. The use of 30 m resolution data provided a solid foundation for regional-scale analysis, enabling actionable insights for local authorities and forest managers to implement targeted fire prevention strategies and allocate resources effectively in high-risk areas. While the model incorporated key factors such as Cork oak flammability, it acknowledged limitations, including the exclusion of critical variables like wind speed and temperature, as well as the reliance on expert judgment, which can introduce bias. Future improvements could integrate higher-resolution datasets to capture finer-scale variations, include additional factors, and employ a larger and more diverse panel of experts, as well as alternative methods like entropy-based weighting, to enhance accuracy and objectivity. Despite these limitations, the study established a robust foundation for both practical applications and future research, contributing to the preservation of this ecologically and economically important region.

Finally, the findings of this study must be also considered in the broader context of climate change, which is expected to exacerbate wildfire risk in Mediterranean region. Climate change is projected to increase the frequency, intensity, and duration of heatwaves and droughts, thereby creating more favorable conditions for wildfires. As temperatures rise and precipitation patterns become more erratic, the moisture content of vegetation, including cork oak, will likely decrease, making these forests more susceptible to ignition and spread of fires.

4. Conclusion

The fire map generated in this study revealed a significant threat, with 61.71% of the Zouagha forest classified as high to very high risk. Human-related factors were the most significant, accounting for half of the total influence. The ROC curve validation demonstrated an 81% accuracy rate for the map, with historical wildfire ignition points confirming the model's reliability, as over 83% of these points were situated in high or very high-risk areas. This underscores the urgent need for proactive fire management strategies and preventive measures. Overall, this study highlights the importance of combining GIS techniques with the AHP method in fire susceptibility mapping, as AHP facilitates a systematic determination of risk factors by weighting their relative importance. This approach enhances the precision of identifying high-risk areas, thereby supporting more informed and effective fire prevention and management decisions. Ongoing research is essential to address evolving challenges, and the research offers valuable insights into exploring the implications of climate change on wildfire risk. Integrating climate scenarios into the analysis can provide a more comprehensive understanding of future fire risks. Future research could benefit from applying machine learning techniques to refine flammability and risk assessments. Additionally, incorporating high-resolution spatial data and regularly updating models with new data will ensure more precise and dynamic assessments.

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