Trees, Forests and People 17 (2024) 100614

Contents lists available at ScienceDirect

Trees, Forests and People

journal homepage: www.sciencedirect.com/journal/trees-forests-and-people

Hoping the best, expecting the worst: Forecasting forest fire risk in Algeria using fuzzy logic and GIS

Louiza Soualah [a,b], Abdelhafid Bouzekri [b], Haroun Chenchouni [b,c,*]

[a] *Institute of Urban Technology Management, University of Constantine 3, 25000 Constantine, Algeria*
[b] *Laboratory of Algerian Forests and Climate Change (LAFCC), Higher National School of Forests, 40000 Khenchela, Algeria*
[c] *Laboratory of Natural Resources and Management of Sensitive Environments (RNAMS), University of Oum El Bouaghi, 04000 Oum El Bouaghi, Algeria*

ARTICLE INFO

Keywords:
Forest fires
Algeria
Risk assessment
Fuzzy logic
Geographic information system (GIS)
Bioclimatic factors
Geomorphological factors
Human activities
Vulnerability mapping
Fire risk map
Mediterranean forests

ABSTRACT

Forest fires pose severe threats to ecosystems and communities globally, especially in vulnerable semi-arid regions like North Africa. Understanding the key factors influencing forest fire dynamics is essential for effective management and mitigation. This study aims to comprehensively analyze forest fire risk patterns in Djebel El Ouahch's massif (Algeria), focusing on integrating bioclimatic, fuel, geomorphological, and human factors through advanced fuzzy logic and geographic information system (GIS) techniques. Climatic station data, satellite imagery, and GIS were employed to map bioclimatic parameters, land cover, and geomorphological features. Fuzzy logic systems were applied to integrate these factors, assigning appropriate weights based on their significance. The resulting forest fire prediction model was defuzzified to generate predictive maps indicating varying vulnerability levels within the study area. Predictive maps delineated areas of low to high forest fire risk. Low-risk zones were characterized by sparse vegetation, while high-risk regions featured densely vegetated slopes near human settlements. The study identified critical factors influencing vulnerability, emphasizing the impact of climate, terrain, and human activities. Urgent attention was directed toward high-risk areas, necessitating tailored fire prevention measures and strategic urban planning to minimize human-induced risks. The results underscored the complex interaction of natural and anthropogenic factors in shaping forest fire susceptibility. Understanding these dynamics facilitates evidence-based policymaking, enhancing forest fire preparedness, biodiversity preservation, and community safety. Additionally, the study emphasized the need for continuous research incorporating real-time climate data and socio-economic factors to refine predictive models. This research provided valuable insights into forest fire risk patterns in Djebel El Ouahch, serving as a foundation for targeted fire management strategies. By bridging the gap between theoretical knowledge and practical application, this study contributes significantly to sustainable forest management and disaster mitigation efforts globally, emphasizing the importance of proactive measures in safeguarding vulnerable ecosystems and communities.

1. Introduction

Forests, the lifeblood of our planet, stand as vast, interconnected ecosystems that harbor an extraordinary diversity of flora and fauna, playing a pivotal role in maintaining ecological balance (Eldredge, 2000). These natural sanctuaries contribute significantly to the Earth's biodiversity, water cycles, and carbon sequestration, serving as crucial buffers against climate change (Bonan, 2008; Pan et al., 2011). However, these sanctuaries of biodiversity face a dire threat: forest fires, among the most devastating natural disasters globally (Meng et al., 2015). The impact of these fires reverberates across the globe, not only decimating acres of greenery but also disrupting climate patterns and posing significant threats to both ecosystems and human settlements. Nowhere is this menace more acute than in regions characterized by dense forests, especially under semi-arid climate conditions (Farfán et al., 2021), a description befitting the mountainous terrain of the Mediterranean region and North Africa (Chafai et al., 2023; Moreno-de-Las-Heras et al., 2023). In the northern regions of Algeria, the juxtaposition of high forest density and proximity to inhabited areas creates a precarious scenario, rendering these lands particularly vulnerable to recurrent outbreaks (Guettouche et al., 2011). The complex relationship between forests, climate, and fire underscores the

* Corresponding author.
E-mail address: chenchouni@gmail.com (H. Chenchouni).

https://doi.org/10.1016/j.tfp.2024.100614

Available online 23 June 2024

urgent need for a comprehensive understanding of the factors driving forest fires in this delicate ecosystem (Gupta et al., 2023; Gajendiran et al., 2024).

Understanding the complex nexus between climate change, severe drought, and forest fires in vulnerable regions like the Mediterranean region is not fully addressed, and still requires a multidisciplinary approach, integrating cutting-edge methodologies and empirical research findings (Bentchakal et al., 2021; Gallardo-Salazar et al., 2023). Climate change-induced shifts in temperature and precipitation patterns are well-documented in studies by IPCC (2021), significantly amplifying the risk of forest fires in these fragile habitats (Allen et al., 2010). Additionally, climate forcings from arid regions, such as the Sahara Desert, exacerbate the vulnerability of forests to ignition and/or die-off (Chenchouni, 2010; Allen et al., 2015; Hantson et al., 2017; Jones et al., 2022).

The ecological fragility of North African ecosystems further underscores the urgency of advanced research techniques. Variations in temperature and moisture disrupt delicate ecological balances, rendering forest vegetation more susceptible to diseases, pests, and ultimately, fires (van Lierop et al., 2015). Utilizing advanced modeling techniques enables a detailed understanding of these ecological dynamics, highlighting the complex relationships between changing climatic conditions and forest vulnerability (Thrippleton et al., 2020; Forzieri et al., 2021; Abdelhamid et al., 2023).

Human communities residing in close proximity to forested areas face heightened risks related to forest fires (Ganteaume et al., 2013). The integration of advanced methodologies like fuzzy logic, coupled with Geographic Information Systems (GIS), could held the key to deciphering the complex relationships of forest fire, climate change, and community vulnerability. By employing fuzzy logic systems, renowned for their adaptability in modeling complex environmental phenomena (Mohd Adnan et al., 2015), researchers can capture the uncertainty inherent in ecological systems. Coupled with GIS, which provides spatial context and allows for mapping of vulnerable zones (Abedi Gheshlaghi et al., 2020; Shatnawi, 2022), these advanced tools pave the way for a profound understanding of the forest fire phenomenon. Importantly, this understanding does not just stop at comprehension but extends to effective mitigation strategies. Informed decision-making, guided by advanced modeling techniques, is essential for policymakers. By meticulously analyzing data and employing predictive modeling using fuzzy logic, researchers can offer invaluable insights into the formulation of proactive mitigation policies (Devisscher et al., 2016). These policies, grounded in empirical evidence, can significantly reduce the vulnerability of these regions. Several studies have demonstrated the efficacy of such evidence-based strategies in mitigating economic losses and safeguarding communities (Aklah et al., 2023; Segura Dorado et al., 2023).

Various methodologies have been employed to predict forest fire risk, each with its strengths and limitations. Traditional methods often rely on historical fire data and basic statistical models (Chuvieco et al., 2010). More recent approaches incorporate remote sensing data and machine learning algorithms to enhance prediction accuracy (Jain et al., 2020). However, these methods can sometimes lack the flexibility and adaptability needed to account for the complex interactions of bioclimatic, geomorphological, and human factors. Fuzzy logic, known for its capability to handle uncertainty and model complex environmental phenomena, has been successfully applied in various environmental studies but less so in the specific context of forest fire prediction in Algeria (Iliadis et al., 2002; Mohd Adnan et al., 2015) especially in the forest-urban interface. When combined with GIS, which provides spatial analysis and mapping capabilities, fuzzy logic enables the creation of highly detailed and context-specific prediction models (Abedi Gheshlaghi et al., 2020). This study advances this field by integrating these methodologies to develop a predictive model that is specifically tailored to the unique bioclimatic and geomorphological conditions of North astern Algeria. This approach not only enhances prediction accuracy but also provides actionable insights for local forest management and policy-making.

This study delves into this pressing issue, seeking to unravel the complexities of forest fire risk patterns in northern Algeria, employing advanced methodologies like fuzzy logic and GIS to pave the way for informed and effective mitigation strategies. Algeria annually grapples with a staggering reality: over 300 square kilometers of precious forest land succumb to flames (Arfa et al., 2009). This susceptibility arises from a complex interaction of factors, encompassing the hot Mediterranean climate, geographical features, and the composition of the forests themselves (Trucchia et al., 2023). Understanding the dynamics of forest fires necessitates a holistic analysis of multiple contributing elements. For a fire to ignite and propagate, a confluence of factors—including the availability of combustible material, environmental morphology, climatic conditions, and human activities—must align synergistically (Abedi Gheshlaghi et al., 2020; Farfán et al., 2021; Gupta et al., 2023).

Addressing this critical issue demands meticulous scrutiny of every potential ignition source and exacerbating factor. Efforts to combat forest fires hinge on the development of accurate and comprehensive forest fire risk maps, which serve as linchpins in the strategic management and safeguarding of forested regions (Abedi Gheshlaghi, 2019). Remote sensing technology, a cornerstone of contemporary environmental monitoring, plays a pivotal role in gathering indispensable data for the creation of these crucial maps (Arar and Chenchouni, 2012; Shatnawi, 2022; Bouzekri et al., 2023).

Researchers have tirelessly pursued various approaches and algorithms to delineate fire hazard zones, integrating remote sensing data with GIS (Abedi Gheshlaghi, 2019). Notably, fuzzy logic, a versatile modeling tool, has gained traction among scholars for assessing forest fire risk (Abedi Gheshlaghi et al., 2020). Fuzzy logic systems, lauded for their adaptability, have found widespread applications in diverse fields such as modeling, forecasting, and classification (Iliadis et al., 2002, 2010).

This study is unique in its application of advanced fuzzy logic and GIS techniques to predict forest fire risk in an urban area located in Algeria. This integration of methods allows for a nuanced understanding of fire dynamics that is specific to this ecologically diverse and climatically unique area. Unlike previous studies in North Africa that have focused on natural habitats at different regions or used less sophisticated modeling techniques, the current approach provides a comprehensive and highly accurate prediction model tailored to the specific conditions of this vulnerable urban region.

In the context of Algeria's forested landscape, this study embarks on a comprehensive exploration, leveraging the synergistic potential of fuzzy logic and GIS for modeling and mapping forest fire-prone areas. By amalgamating these advanced methodologies, this research endeavors to enhance our understanding of forest fire risk patterns in the Constantine region. Through meticulous analysis and modeling, the aim was to contribute significantly to the development of proactive strategies, empowering local communities and authorities to mitigate the devastating impact of forest fires effectively. This interdisciplinary approach not only represents a scientific endeavor but also stands as a testament to our collective commitment to preserving our natural heritage and ensuring the safety and well-being of communities inhabiting these vulnerable zones. Accordingly, the primary objective of this research was to analyze the multifaceted elements contributing to forest fire risk in northeastern Algeria. The study also aimed: (i) to investigate the role of environmental factors, including vegetation density and topography, in fire propagation; (ii) to examine the impact of human activities, such as agricultural practices and urban encroachment, on forest fire initiation and spread; (iii) to develop a comprehensive risk prediction model utilizing fuzzy logic and GIS techniques; and (iv) to evaluate the effectiveness of existing mitigation strategies and propose evidence-based recommendations for enhancing forest fire preparedness and response in the Constantine region.

2. Materials and methods

2.1. Study area

The focal point of this research centers on the sprawling expanse of Djebel El Ouahch, located in the northeastern region of Constantine (Fig. 1) and encompassing an area of 577 km^2. This vast territory spans across seven municipalities, comprising two arboretums and six forests. Djebel El Ouahch experiences a typical Mediterranean climate, characterized by scorching, arid summers succeeded by mild humid winters. Notably, the predominant tree species in this forested region comprises blue gum (*Eucalyptus globulus* Labill.), cork oak (*Quercus suber* L.), Aleppo pine (*Pinus halepensis* M.), and Mediterranean cypress (*Cupressus sempervirens* L.)

The selection of Djebel El Ouahch as our study area was underpinned by its exceptional ecological diversity, harboring a plethora of rare species. However, the area's significance is further underscored by the alarming annual recurrence of forest fires. These devastating infernos relentlessly sweep through the landscape, leaving in their wake the obliteration of millions of hectares each year. This unfortunate reality amplifies the urgency of our research, compelling us to delve deep into understanding the complexities of this ecosystem and its vulnerabilities.

2.2. Data sources

The data utilized in this study was a compilation from various sources. Fig. 2 illustrates the source of data and its factor generated. To gather information on climatic variables like temperature, wind speed, and atmospheric humidity, a dataset spanning 31 years was acquired from National Hydraulic Resources Agency (ANRH), drawing data from weather stations distributed across the study area (36°17′N, 6°37′E, 694 m). Satellite images from the Sentinel-2 program, a satellite mission developed by the European Space Agency (ESA) under the Copernicus program (https://dataspace.copernicus.eu/),were employed. These images underwent processing through the SISPPEO platform (Satellite Imagery & Signal Processing Packages for Earth Observation), operated by French National Institute for Agriculture, Food and Environment INRAE (https://inrae.github.io/SISPPEO/), to derive the normalized vegetation index and normalized water index. Furthermore, land cover mapping and the spatial distribution of vegetation species were extracted directly from Sentinel-2 satellite imagery.

Incorporating geographical considerations, we incorporated factors such as slope degree, slope aspect, and altitude, all derived from a high-resolution digital elevation model with specific bands capable of providing images a 30-meter resolution (https://www.opendem.info/link_dem.html). Additionally, human-related factors, including proximity to roads and settlements, were obtained from OpenStreetMap "OSM" (https://www.openstreetmap.org/#map=5/28.413/1.653). This multifaceted data compilation underpinned research efforts of this study.

2.3. Bioclimatic factors

Climatic conditions and drought of summer season are the first determiner of sensitivity of a forest to fires; In Mediterranean area temperature, humidity and wind speed are the involved elements in the outbreak and spread of fires (Ganteaume et al., 2013). Djebel El Ouahch forest located in mountainous chain of Talien Atlas that characterizes by a divergence between the influences of Mediterranean climate of Tellian Atlas in the North and the Saharan influences by the Saharan Atlas in the South the bioclimatic floors varying from the type semi-arid in the South to sub-humid in the North (Mrad et al., 2018).

In summer period (July–August) temperature is usually very high varying from 25 °C to 30 °C; therefore, wildfire forest at this time of year has stimulated especially on the diurnal heat wave that activate the fire ignition occurrence. In this case, the peak values of temperature are the trigger of fire forest occurrence.

Air humidity considered as a meteorological predictor of fire occurrence and spread (Konca-Kędzierska and Pianko-Kluczyńska, 2018). In the Constantine region, during summer period, aridity has a negative effect on the water content of vegetation and its moisture especially the ground cover of forest floor which lead to the availability of combustible material, because the decreasing of forest floor moisture causes the augmentation of ignitions numbers and sensitivity of forest fires.

Wind speed considered as a main driving factor of fires spread and

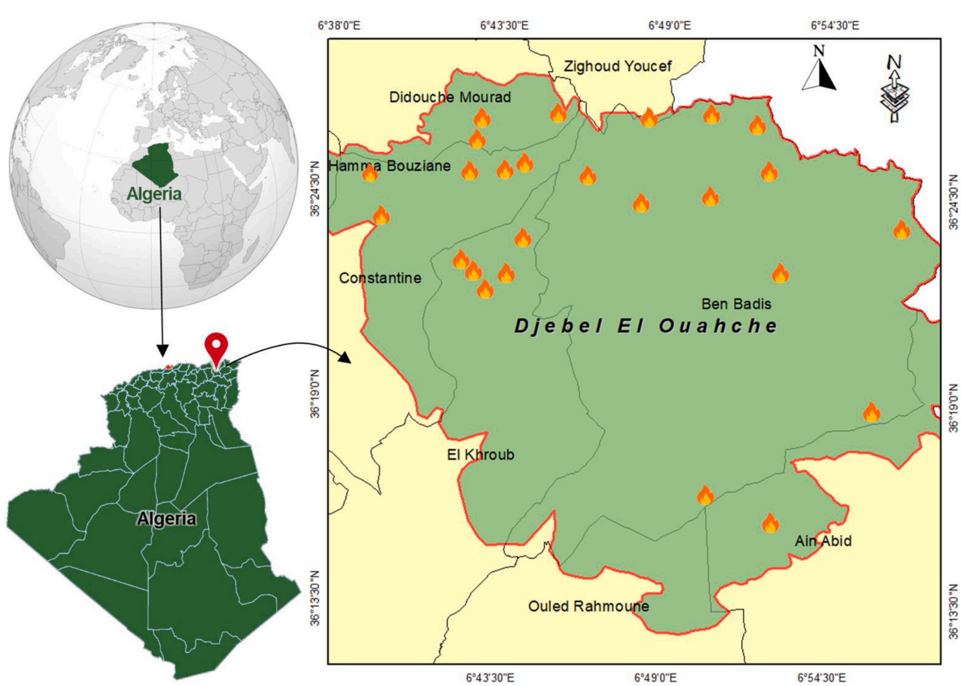

Fig. 1. Location of the study area 'Djebel El Ouahch' in the Constantine Province, northeastern Algeria. The orange icons of fire in the right map indicate the locations of previous forest fires.

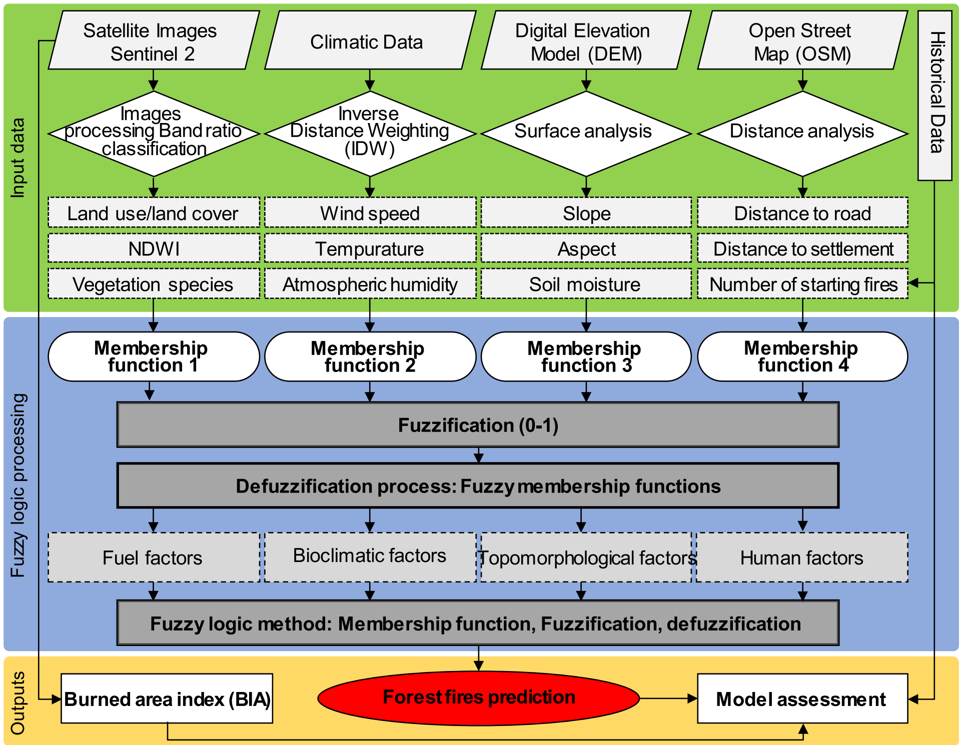

Fig. 2. Flowchart of general method used for mapping forest fire prediction mapping.

the first responsible for catastrophic fires (Koutsias et al., 2012). Algeria in summer suffers from a severe dry and hot wind blow from south to north of the country that coincides and meets up with high temperature of the mountain forests. The monthly wind speed map used in this study established by Renewable Energy Development Centre of Algeria.

2.4. Fuel factors

Fuel availability depends on the vegetation cover both its type and density that are responsible for spread and outbreak of fires according to combustible material, fire forest does not occur in bare land or water surfaces, only forests, bushes, tree layer and grass land that have susceptibility to fire. For this purpose, the land cover map is used to exclude the areas of non-vegetation, and to include all the vegetation classes.

The wood fuel load, tree size and phytomass along the study area was estimated on the basis of the three following analyzed parameters: water content on vegetation (NDWI), land cover and the spatial distribution of vegetation species.

Fuel material units were grouped into four types to define the vegetation combustibility available to burn according to land cover and forest classes. Table 1 illustrates land cover types.

Normalized difference water index NDWI was employed to limit the areas of active biomass and the dry vegetation substance on trees and grasses, where the NDWI is responsible for detecting the water content inside the leaves of vegetation (Gao, 1996). NDWI values are varying from -1 to 1, values close to 0 represent dry vegetation and little percentage of water content on leaves, whereas values close to 1 represent active biomass and dense water content on green leaves. The NDWI was calculated as follows:

$$NDWI = (Green - NIR)/(Green + NIR)$$

where: *Green* refers to the reflectance value in the green wavelength band, and *NIR* refers to the reflectance value in the near-infrared wavelength band..

The spread and outbreak of fire has a strong relationship with the physiological characteristics of phytomass. This characteristic varying according to plant species, where in the case of needle leaves and resinous pine trees, fire spreads rapidly and increased the flammability, whereas in the case of the cork oak that has a thick bark that protects it against fires and allows it to retain moisture and decreased the combustibility. Mariel (1995) developed a model to estimate the susceptibility of trees to combustibility according to vegetation species that illustrated on the Table 1.

2.5. Geomorphological factors

During the fire, geomorphology is associated with wind behavior on the spread and directions of fires in which the physiographic characteristics of forest play an important role to predict on real time the fires patterns (Erten et al., 2004).

Slope is one of the most important factors affecting the forest fire danger (Baltaci and Yildirim, 2020). Previous studies indicate that fires spread out fast on the up-slopes and move slowly on the down-slopes (Sivrikaya et al., 2011; Adab et al., 2013). Table 1 shows five classes according to its impact on fire spread. The slope map of the study area generated by digital elevation model (DEM) showed that the most distributed class is steep slope.

Aspect is an important geographical factor responsible for the outbreak and spread of forest fires according to its conditions of sunshine and humidity. However, understanding the distribution of the fire by aspect can help in developing strategies for controlling and mitigating the fire. Table 1 show the contribution of aspects on the fires spread that represented by weights.

2.6. Human factors

The statistical of previous forest fires (2010–2022) established by forest administration in Constantine province were located in areas near roadsides and population settlements. Therefore, in order to gather all types of human interventions that make forests prone to fires either way accidental or man-made, distance from roads and settlements were

Table 1
Classification of factors and weights of forest fire risk.

Factors	Classes	Risk	Weight
Land cover	Water bodies / urban	Low	1
	Agriculture and arboriculture	Moderate	2
	Shrubland and pastures	High	3
	Forest and maquis	Very high	4
Vegetation species	No vegetation	Very low	1
	Cork oak forest	Low	2
	Mediterranean cypress–grassland	Moderate	3
	Aleppo pine–Evergreen oak maquis	High	4
	Pure and mixed forests of eucalyptus, cypress, pine, and cedar	Very high	5
NDWI	−1.00–0.20	Very low	1
	0.20–0.33	Low	2
	0.33–0.46	Moderate	3
	0.46–0.60	High	4
	0.60–1.00	Very high	5
Temperature (°C)	15.00–15.25	Very low	1
	15.25–15.39	Low	2
	15.39–15.52	Moderate	3
	15.52–15.70	High	4
	15.70–16.00	Very high	5
Air humidity (%)	7.62–7.65	Very low	1
	7.65–7.68	Low	2
	7.68–7.71	Moderate	3
	7.71–7.75	High	4
	7.75–7.78	Very high	5
Wind speed (m/s)	2.65–3.70	Very low	1
	3.70–4.34	Low	2
	4.34–4.93	Moderate	3
	4.93–5.61	High	4
	5.61–7.45	Very high	5
Slope degree (%)	0–5	Low	1
	6–15	Moderate	2
	16–35	High	3
	<36	Very high	4
Aspect	North, North east	Low	1
	West, West south	Moderate	2
	East, East south, East north	High	3
	South east, South west	Very high	4
Soil moisture	−1.00 – −0.25	Very low	1
	−0.25 – −0.14	Low	2
	−0.14 – −0.04	Moderate	3
	−0.04 – 0.09	High	4
	0.09 – 1.00	Very high	5
Distance to roads (m)	0–305	Very low	1
	305–771	Low	2
	771–1430	Moderate	3
	1430–2363	High	4
	2363–4100	Very high	5
Distance to settlements (m)	0–1390	Very low	1
	1390–2853	Low	2
	2853–4390	Moderate	3
	4390–6036	High	4
	6036–9328	Very high	5
Number of forest fires	0–1	Low	1
	1–3	Moderate	2
	3–8	High	3

calculated by the GIS software QGIS version 3.28.3 (https://www.openstreetmap.org)

Forest covers near habitats or settlements are more susceptible to fire starts because the wrong habitation and cultural practices of the local populations those lead to accidental fires (Jaiswal et al., 2002). Roadsides considered as the area of starting ignitions either by accident, negligence or deliberate actions roads such as the jets of cigarettes, barbecues, tourist trips and picnic (Joaquim et al., 2007; Ganteaume et al., 2013; Eugenio et al., 2016). Maps of distances to road and settlements were used to evaluate the human factors that affect the forest fire proneness according to its proximity to human being. Table 1showsthe intervals of distance classes, generally forest fire risk increases with the increasing distance to road and settlement.

2.7. Fuzzy logic process

Fuzzy logic is a multi-criteria technique that engages a membership function in order to develop a fuzzy reference system (Iliadis et al., 2010). Membership functions are used to determine degree of membership of all pixels of thematic layers on the finale map of forest fire prediction, this membership value ranges between 0 (no membership) and 1 (full membership that indicate to which degree an element belongs to fuzzy set (Bellman and Zadeh, 1970). In this research linear membership function is used for the fuzzification and remapping of the 12 factors responsible for forest fires prediction that is computed as described in the following equation:

$$A = \{x_1 / \mu(x_1), x_2 / \mu(x_2), \ldots\ldots X_n / \mu(x_n)\}$$

where $\mu_A(x)$ is the association of x in A, and $\mu\ A\ (x){:}\ U \rightarrow [0, 1]$

The twelve causative factors, namely temperature (T), atmospheric humidity (AH), wind speed (WS), land cover (LC), water content on vegetation (WCV) represented by NDWI, vegetation species (VS), slope (S), aspect (AS), soil moisture (SM), distance to road (DR), distance settlement (DS), and number of starting fires (NSF); were combined to create forest fires prediction map using fuzzy logic model that based on the description of the influence of each factor on the global process of fires occurring and out-breaking. Table 2 describe the pair-wise comparison between factors.

The correlation among various factors was assessed before initiating the Fuzzy logic modeling process. To ensure the robustness of the analysis, Pearson correlation tests were employed to examine the relationships between the quantitative variables: NDMI, NDWI, air temperature, air humidity, wind speed, aspect, slope, distance to road, and distance to settlement. This step was crucial for identifying and eliminating variables with high correlation, thereby minimizing multicollinearity and enhancing the reliability of the Fuzzy logic model. In this study, variables had no multicollinearity as the absolute value of all the correlation coefficients was less than 0.7 (Fig. 3). The correlation tests revealed that the strongest positive correlation was observed between air temperatutre and air humidity ($r = 0.67$), whereas the stongest negative correlation was obtained between NDMI and NDWI ($r = -0.65$).

The fuzzy inference system used to give each factor its weight has constructed according to models and expertise related to forest fire prediction; where relationships among factors scaled according to importance of each factor for fires patterns as illustrated in table 3 and table 4 (Carrega, 1991; Alexandrian et al., 1999; Carrega, 2008; Adab et al., 2013; Arpaci et al., 2014; Argañaraz et al., 2015; Feizizadeh et al., 2015; Pourtaghi et al., 2015; Eugenio et al., 2016; Satir et al., 2016; Abedi Gheshlaghi et al., 2020).The operator using in the defuzzification process of the fuzzy set is algebraic sum and The weights were in the range (0.0, 1.0), and their sum was always equal to 1. They can be interpreted as percentages.

The obtained fuzzificated thematic layers were combined on GIS software according to its weights as the following equation:

Table 2
Fuzzy Scale of relative importance between factors.

Fuzzy number	Linguistic	Triangle scale of fuzzy number
9	Absolute importance	(8,9,10)
8	Middle value of 7 and 9	(7,8,9)
7	Very strong importance	(6,7,8)
6	Middle value between 5 and 7	(5,6,7)
5	Strong importance	(4,5,6)
4	Middle value between 3 and 5	(3,4,5)
3	Weak importance	(2,3,4)
2	Middle value between 1 and 3	(1,2,3)
1	Equal importance	(1,1,1)

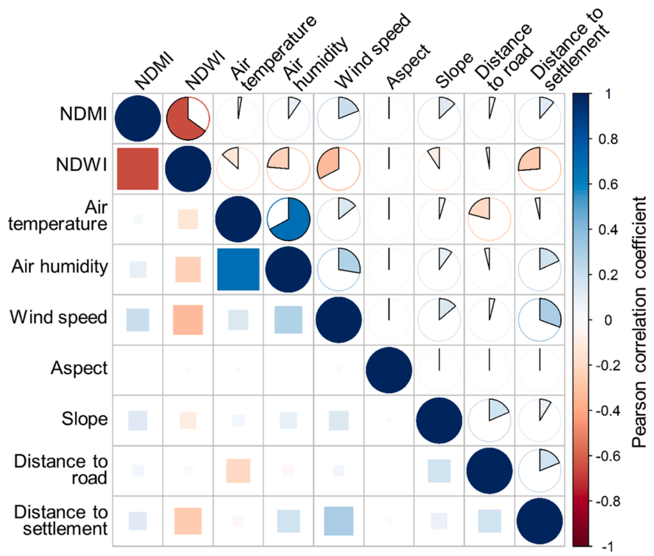

Fig. 3. Pearson correlation matrix of quantitative variables prior fuzzy logic model preprocessing.

$$FFRP = \sum_{i=1}^{10} \left(w_i \times A_i \right)$$

Where: *FFRP* is the average of the fuzzy membership functions; W_i is the weight value of the factor *i*; and A_i is the membership function of the factor *i*. Values of the final fuzzy process are varying from 0 to 1

2.8. Normalized burn ratio (NBR)

The burned area index (BAI) and Normalized burn ratio (NBR) are widely used to measure the state and severity of fires that is a band ratio between near infrared and short-wave infrared (Escuin et al., 2008). The NBR has a numerical range from −1 and 1, negative values refer to bare soil whereas positive values indicate areas with vegetation. It is calculated as follows:

$$NBR = (NIR - SWIR)/(NIR + SWIR)$$

Where *NBR* is normalized burned ratio, *NIR* is the near infrared band and *SWIR* is the short-wave infrared band (Escuin et al., 2008).

To assess the model's precision in detecting and quantifying forest fire risk probability, a Pearson correlation test was conducted. This statistical analysis involved comparing observed data of burned areas, represented by the NBR, with the predicted forest fire risk generated by the fuzzy logic model. The Pearson correlation test provided a quantitative measure of the relationship between the observed and predicted variables, contributing to the overall evaluation of the model's accuracy and predictive capability.

3. Results and discussion

3.1. Mapping factors involved in forest fire

Environmental station data and the techniques of the inverse distance weighting were used to map the spatial distribution of bioclimatic parameters responsible for the outbreak and the spread of fires. Fig. 4 illustrates the spatial distribution of the fuzzification of these parameters (Temperature, atmospheric humidity and wind speed). Where the results of temperature are varying from 15 to 16 °C and the higher values observed in the north of the study area. The slight difference in mean air humidity between 7.62 and 7.78 requires consideration of how these variations corresponds to forest fire behavior. The data of wind speed is comfort with the morphology that increased into 7 m/s in the mountainous areas on the north and decreased into 3 m/s on the south west part of the study area. In the semi-arid regions of North Africa, which experiences dual climatic conditions due to its transitional characteristics, temperature and atmospheric humidity exhibit various patterns influenced by wind behavior. The winds in this area blow from both the north and the south, with the Sirocco winds originating from the Sahara Desert and contributing to hot, dry conditions, while the northern winds bring humidity. Our methodology integrates all climatic parameters to derive a composite factor. This approach aims to mitigate temperature and humidity anomalies, thereby addressing the irregularities caused by variable wind patterns.

The processing of satellite images of Sentinel 2 allowed to classify the land cover classes and vegetation species and calculate the water content on vegetation; that displayed on the Fig. 5 and shows predominance of the agricultural lands and in the second place the pastoral lands followed by the forest and shrub-lands. The range of NDWI values, spanning from −0.86 to 0.71, reflects the variability in vegetation moisture content across the study area. Areas with high water content can be identified with higher positive NDWI values. Conversely, areas with low water content show lower or negative NDWI values. Vegetation species were grouped into the following classes: pure and mixed forests of eucalyptus and/or cypress with Aleppo pine, and Atlas cedar (*Cedrus atlantica*); cork oak forest and evergreen oak maquis (degraded oak forest); grassland planted with cypress; and barren lands (no vegetation). Fuel stock estimation using remote sensing technologies is critical for predicting fire behavior over large areas. In this study, fuel availability was employed as a key driver to model fire behavior, considering factors such as fuel moisture content, quantity, continuity, and distribution. The proposed vegetation measurement techniques enable precise estimation of various fuel attributes within forest and shrubland

Table 4
Weightage of factors used in modeling and predicting forest fire risk.

Factor categories	Bioclimatic factors	Fuel factors	Geomorphological factors	Human factors
Bioclimatic factors	1	7	3	7
Fuel factors		1	5	9
Geomorphological factors			1	3
Human factors				1

Table 3
Fuzzy Scale of relative between causative factors.

Bioclimatic factors				Fuel factors				Geomorphological factors				Human factors			
	T	AH	WS		LC	WCV	VS		S	AS	SM		DR	DS	NSF
T	1	7	9	LC	1	3	5	S	1	3	5	DR	1	5	7
AH		1	5	WCV		1	7	AS		1	9	DS		1	9
WS			1	VS			1	SM			1	NSF			1

(AH: atmospheric humidity, AS: aspect, DR: distance to road, DS: distance human settlement, LC: land cover, NSF: number of starting fires, S: slope, SM: soil moisture, T: temperature, VS: vegetation species, WCV: water content on vegetation, WS: wind speed).

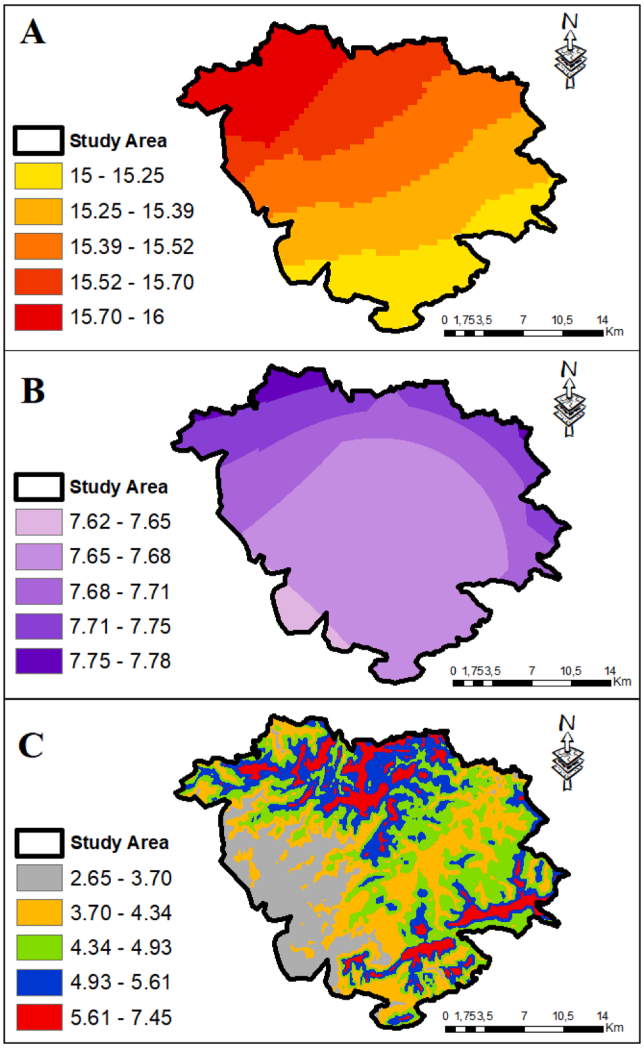

Fig. 4. Maps displaying the classification of climatic factors, A: temperature (in °C), B: atmospheric humidity (in %), and C: wind speed (in m/s).

communities. This method enhances the accuracy of fire prediction models, thereby improving our ability to manage and mitigate wildfire risks effectively. Numerous studies have demonstrated and evidenced the efficacy of remotely sensed data in computing fuel parameters (D'Este et al., 2021; Aragoneses et al., 2024; Collins et al., 2024).

The surface analysis of the study area's DEM generated the two layers of the geomorphological parameters slope and exposure that showed respectively on the Fig. 6A and 6B. These two factors are widely used to predict the movement and spreading of fires along the forests. The layer of slopes extending from 0 to 53.97°, shows the diversity of the terrain steepness, with higher values represent a steeper slope that are located in the south of the study area which can be related to the intensity of forest fires. Djebel El Ouahch massif is predominantly oriented towards the south-east and south directions, the two aspects together facing in these directions cover more than 31 % of the total area. This information is useful for understanding how the fire may spread based on wind direction. The area facing the North-East and North directions covers over 22 % of the total area; these aspects are likely to be cooler and wetter due to lower exposure to sunlight, which may impact the rate of fire spread. Eastern aspect covers about 8.58 % of the total area, and the Western aspect covers approximately 10.98 % of the total forest area, these two aspects combined cover just under 20 % of the forest area. The flat aspect covers more than 9 %. Flat areas typically have low slopes, which can result in slow propagation of fires. Geomorphological

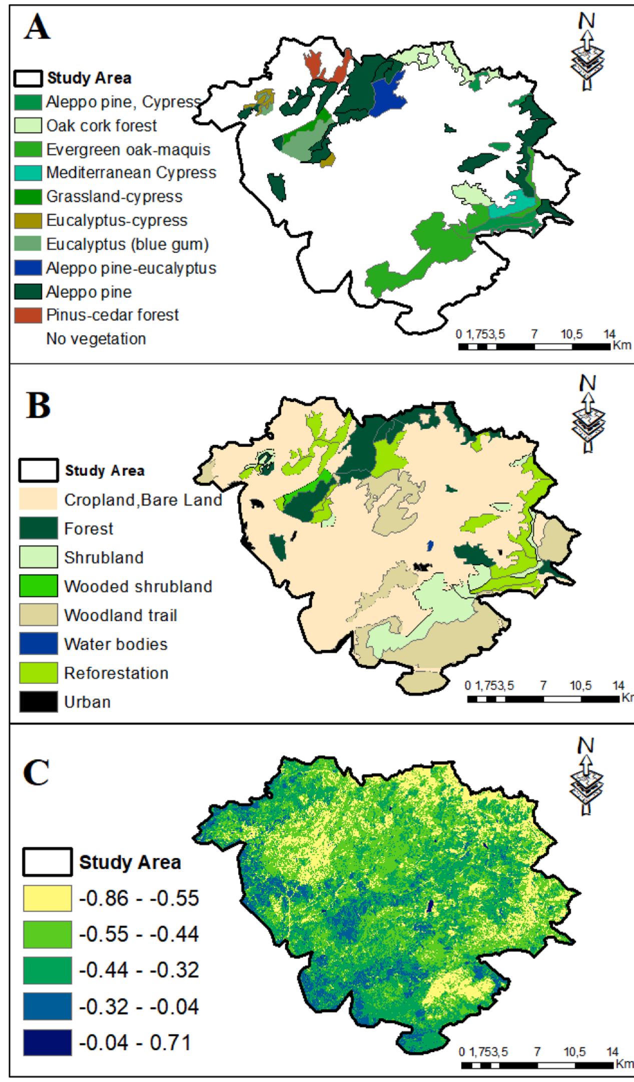

Fig. 5. Classification of fuel factors related to the vegetation, A: vegetation species, B: land cover, C: NDWI.

conditions remain constant and exhibit no anomalies that could influence fire behavior or spread. Therefore, these geomorphological parameters are considered foundational in this method of forest fire forecasting. All other factors are evaluated in relation to these stable topographic settings, making them the primary support predictors in the model. This approach ensures that the topographic context provides a consistent baseline around which other variables, such as vegetation, fuel load, and moisture content, are analyzed.

Human activities and the criminal acts of people in or beside the forests in Mediterranean region considered as the cause of starting fires and ignitions (Ganteaume et al., 2013; Koutsias et al., 2015). The open street map of Constantine province was used to create the maps of distance to roads and settlements (Fig. 7A and 7B). Historical and statistical data of fires of the study area during the last ten years were used to create a map of number of starting of fires by administrative units and showed that the region superposed with dense roads and agglomerations suffered from a high number of fires. The urban-forest interface is particularly susceptible to fires due to the high degree of interaction between human activity and vegetation. This increased contact has led to a notable rise in forest fires attributable to human activities, with anthropogenic factors responsible for up to 90 % of fires globally (Conedera and Tinner, 2000; Kolanek et al., 2021). Many of these anthropogenic factors are interconnected; for instance, the incidence of

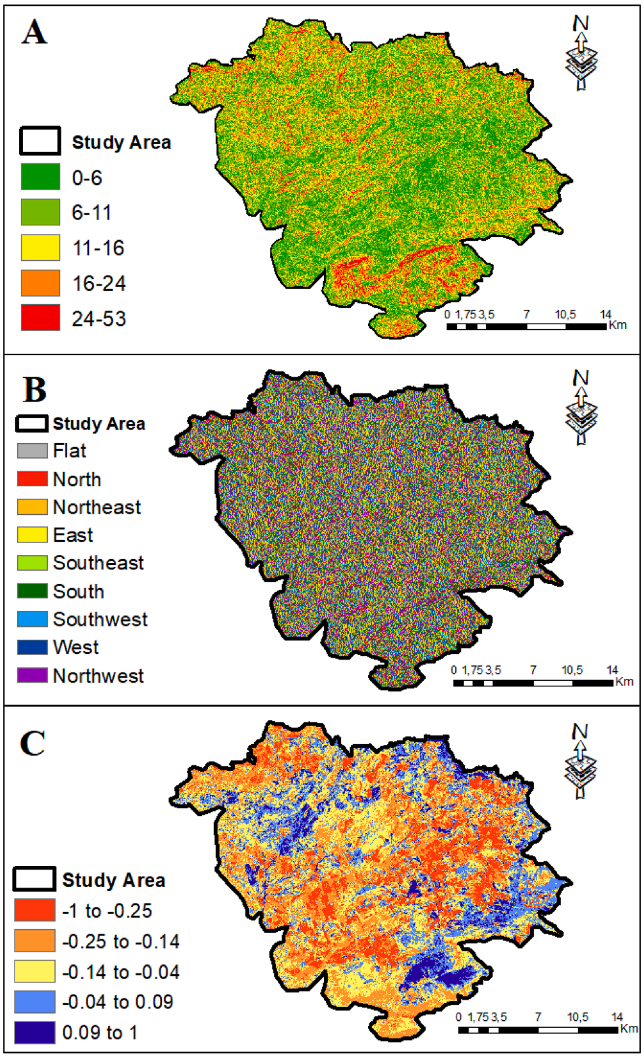

Fig. 6. Classification of geomorphological factors, including: slope in % (A), aspect (B), and NDMI (C).

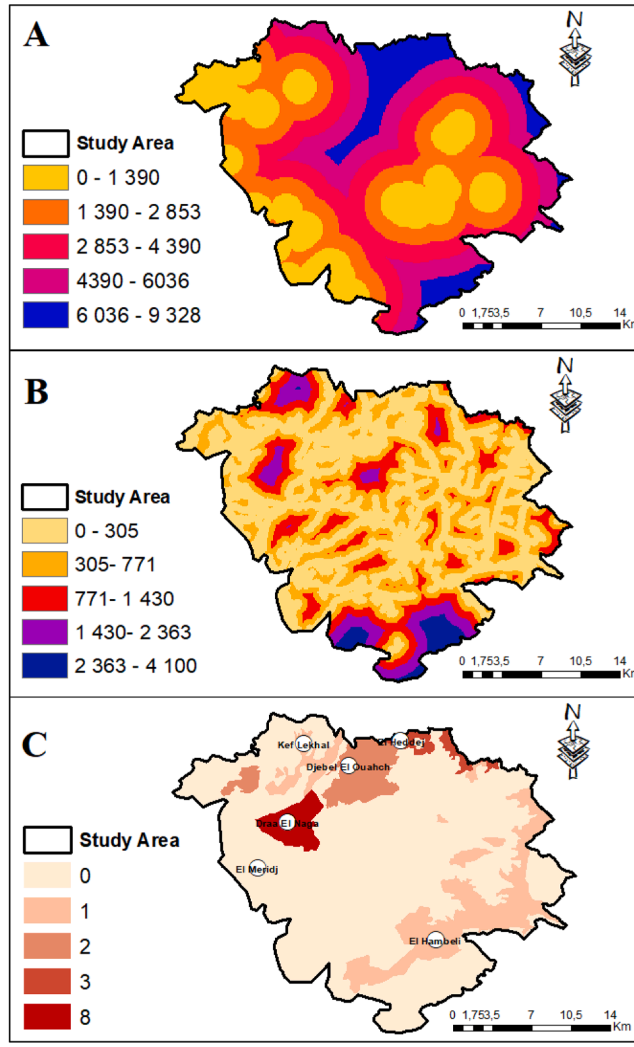

Fig. 7. Maps of human factor classifications. A: Distance to settlement (in m), B: distance to roads (in m), and C: number of starting forest fires.

fires is correlated with the proximity of roads and settlements. Additionally, the extended boundary length between forests and populated areas exacerbates fire risk, as it heightens the likelihood of human penetration into forested regions, thereby increasing the vulnerability to fire incidents.

3.2. Fuzzy logic method

The mapped layers obtained by digitalization, satellite images processing or interpolation have been used to fuzzified the descriptive or digital information and make it ranging from 0 to 1 where values near to 1 mean the strong membership with the fires occurring.

The process of fuzzy system based on the relationship among the factors and the indicators of fires prediction. The predicted maps of each factor were created by combining mathematically under criteria of fuzzy sets. Table 5 represents the weights of under criteria of each factor that used calculated to overlap the different layer used to predict and evaluate the fires risk.

The defuzzification process of the three bioclimatic factors by using the weights resulted from the membership function has given the final climatic map factor (Fig. 8):

Table 5
Fuzzy weights of the specific parameters used in modeling forest fire in NE Algeria.

Variable category	Parameters	Weights
Bioclimatic factors	Temperature	0.67
	Atmospheric humidity	0.23
	Wind speed	0.10
Fuel factors	Land cover	0.54
	Water content on vegetation	0.35
	Vegetation species	0.11
Geomorphological factors	Slope	0.54
	Aspect	0.35
	Soil moisture	0.11
Human factors	Distance to road	0.61
	Distance human settlement	0.29
	Number of starting fires	0.10

$$\begin{aligned} \textit{Bioclimatic factor} &= (0.67 \times \textit{Temperature}) \\ &+ (0.23 \times \textit{Atmospheric humidity}) \\ &+ (0.10 \times \textit{Wind speed}) \end{aligned}$$

The overlapping of land cover classes, the estimated of water content on vegetation and the distribution of vegetation species indicated the potential fuel available to be burned and the vegetation susceptibility to fires and ignitions:

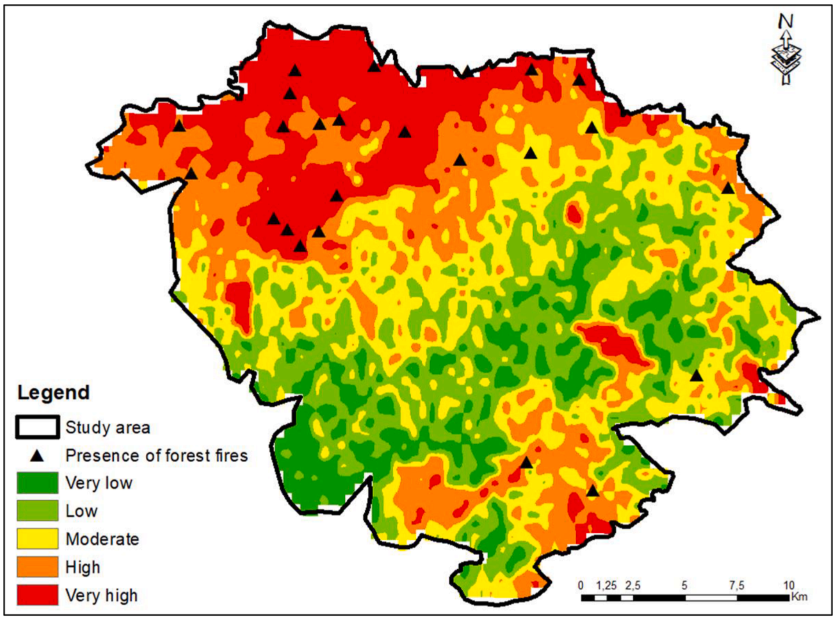

Fig. 8. The prediction map of Djebel El Ouahch region to forest fires.

$$Fuel\ factor = (0.54 \times Land\ cover) + (0.35 \times NDWI) + (0.11 \times Vegetation\ species)$$

The aggregation of the resulting layers of slope, aspect and soil moisture has been identified the geomorphological influence on the prediction of fire patterns, where:

$$Geomorphological\ factor = (0.54 \times Slope) + (0.35 \times Aspect) + (0.11 \times Soil\ moisture)$$

$$Forest\ fires\ prediction = (0.57 \times Bioclimatic\ factor) + (0.26 \times Fuel\ factor) + (0.11 \times Geomorphological\ factor) + (0.06 \times Human\ factor)$$

The combination of distance map to roads and settlements and the number of starting fires layer was used to generate the final human effect on the forest fire hazard:

$$Human\ factor = (0.61 \times Distance\ to\ road) + (0.29 \times Distance\ to\ settlement) + (0.10 \times Number\ of\ starting\ fires)$$

3.3. Forest fire prediction

The fire prediction map was generated by defuzzification according to the influence of bioclimatic factors, fuel factors, geomorphological factors and human factors. Values in Table 6 showed the final fuzzy weights w_i for factors that indicate the important impact of bioclimatic factor and in the second order the impact of fuel available to burn, followed by topomorphology and human effects.

The environmental and human factors were fuzzificated by the Guassian probability and GIS techniques for the prediction of the sensitivity of Djebel El Ouahch's massif to forest fires during the summer period. The obtained fuzzy weights (w_i) for bioclimatic, fuel, geomorphological, and human factors were 0.57, 0.26, 0.11, and 0.06, respectively. Accordingly, the obtained predicting model of forest fire was:

Table 6
Categorization of area and corresponding forest fire risk percentages.

Fuzzy Prediction	Risk class	Area (km^2)	Area(%)
0.35–0.58	Very low	61.74	10.96
0.58–0.67	Low	120.49	21.39
0.67–0.76	Moderate	142.38	25.27
0.76–0.86	High	133.17	23.64
0.86–0.97	Very high	105.52	18.73

Fig. 8 illustrates the different situation of forest fires sensitivity from non-potential risk to critical situation, which starts by areas with a very low risk, surrounded by areas with low risk, followed by areas moderately sensitive to forest fires and areas highly susceptible to fires, whilst the very high risk comes in the last class with the red color.

The forest fires prediction map is calculated by fuzzy logic model and classified according to the following fuzzy prediction values (0.35–0.58), (0.58–0.67), (0.67–0.76), (0.76–0.86) and (0.86–0.97) that classified into the following thematic classes, very low, low, moderate, high, and very high, forest fires sensitivity areas respectively. Areas with very low risk of forest fires are located in the middle of the study area and are corresponded to rocky land and bare land, whereas the areas that have recorded a low or slight sensitivity to fires are dominated by a sparse vegetation and summer wheat–fallow systems. The moderate vulnerability to risk of fires represents one quarter (25%) from the total of the study area, which is corresponding to areas of shrub-lands and eucalyptus plantations with a slight slope between 6% and 11% and its aspect is dominated by the northwest aspect that receive less quantity of sunshine. Twenty-four percent of the study area has high level of forest fires hazard, which presents an area of 13,317 ha, and is mainly located in foothill or piedmont of Djebel El Ouahch Mountain. This is due to the predominance of the wooded shrub-lands in the presences of the resinous trees of Aleppo Pine mixed with cypress. The critical situations of forest fires are in the up mountain region and record 19% of the study area of very high sensitivity to fires. This could be explained by rough and high steeply steeped area. That favoring the turbulence jumping of fires and the acceleration of the fire front especially with the dry climatic conditions of high temperature and the velocity of winds. In addition, the human effect by the high number of starting fires in the last ten years, in which create conflagration causing a severe damage in the loss of denser vegetation cover of oak and cedar. These degrees of vulnerability to fires are depending on the intensity of vegetation cover and its type where the humidity of vegetation and its quantity of water are susceptible to severe dry climatic conditions of summer period. The occurring of ignitions has a strong relationship with the human existence and the high negative influence of approximated population to roads and agglomerations.

The values of burned area index were transformed by QGIS software into thematic map and represented in the Fig. 9, that show the different level of fire severity from unburned area to severe fire, and the spatial distribution indicates that more than a half of the study area touched by a severe fire located in all cardinal directions of the study area that including Aleppo pine as an essential specie of vegetation and distinguished by its vulnerability to wildfires.

Based on the susceptibility of Djebel El Ouahch region to fires occurring assessed using fuzzy process of causative factors, the potential risk of fires in the forest-urban interface as illustrated in the Fig. 10 by overlapping the prediction map of fires and interface habitat is very considered in the northern part of the study area that coincide with the very high class of hazard vulnerability and the dense inhabitant area inside the forest massif, in which need to urgent intervention to mitigate the effect of this problem and reviving the forest management plans.

The results of assessing the fuzzy logic predicting accuracy revealed a positive and statistically significant relationship between the observed data (represented by NBR) and the predicted values (Fig. 11). The Pearson's correlation coefficient indicated a positive association, suggesting that as the predicted forest fire risk increased, there was a corresponding increase in the observed burned areas. The *p*-value being very low (< 0.0001) reinforced the statistical significance of this relationship. With a 95 % confidence interval of 0.137–0.222, the accuracy is substantiated, further supporting the reliability of the fuzzy logic model in predicting forest fire risk. In addition, the validation of the map obtained through Fuzzy logic modeling was conducted using fire incidence data. The validation matrix revealed an overall accuracy of 88.4 %, indicating a strong correlation between the predicted and actual fire occurrences. Specifically, the validation accuracy reached 92.4 % in areas predicted to have a very high forest fire risk, demonstrating the model's effectiveness in identifying regions with the greatest susceptibility. In areas classified as having high and moderate fire risk, the validation accuracy was 81.9 % and 72.0 %, respectively, reflecting the model's reasonable performance in these zones. This validation underscores the reliability of the Fuzzy logic model in predicting forest fire risks across different risk levels in the Djebel El Ouahch region.

The spatial distribution of bioclimatic parameters, including temperature, atmospheric humidity, and wind speed, elucidates the climatic conditions influencing forest fire outbreaks. Higher temperatures in the northern regions of the study area intensify the vulnerability to fires, especially when coupled with variations in humidity and wind speed. The diversity in slope steepness and aspects, especially the south-facing slopes, significantly impacts fire spread. Steeper slopes and drier conditions in these areas create ideal conditions for rapid fire propagation (Holsinger et al., 2016). Human factors, represented by proximity to roads and settlements, highlight the significant influence of human activities on fire occurrences (Ganteaume et al., 2013; Costafreda-Aumedes et al., 2017). These factors collectively emphasize the complex interactions between environmental and human elements in forest fire dynamics (Ghefar et al., 2024).

Utilizing fuzzy logic, the study integrated these diverse factors, assigning appropriate weights based on their significance in fire prediction (Jain et al., 2020). The final forest fire prediction map, derived from a combination of bioclimatic, fuel, geomorphological, and human factors, demonstrates the varying sensitivity of different regions within Djebel El Ouahch's massif. Areas characterized by sparse vegetation, rocky terrain, and lower human presence exhibit lower fire risk. In contrast, densely vegetated regions, especially those dominated by Aleppo Pine and cypress, coupled with steep slopes and proximity to human activities, pose a higher risk. The burned area map further validates these predictions, showcasing severe fires in areas with high vulnerability (Abedi Gheshlaghi et al., 2020).

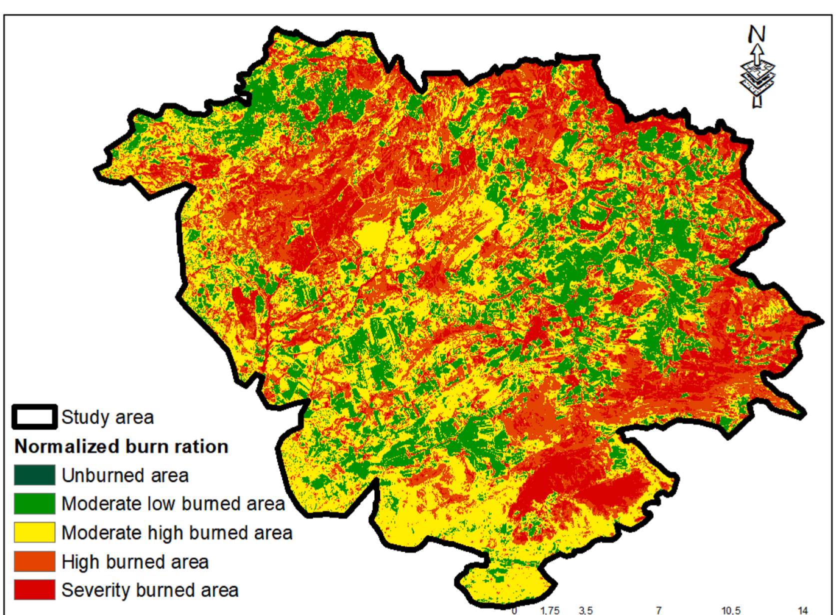

Fig. 9. Map of burned area (normalized burn ratio 'NBR') at Djebel El Ouahech.

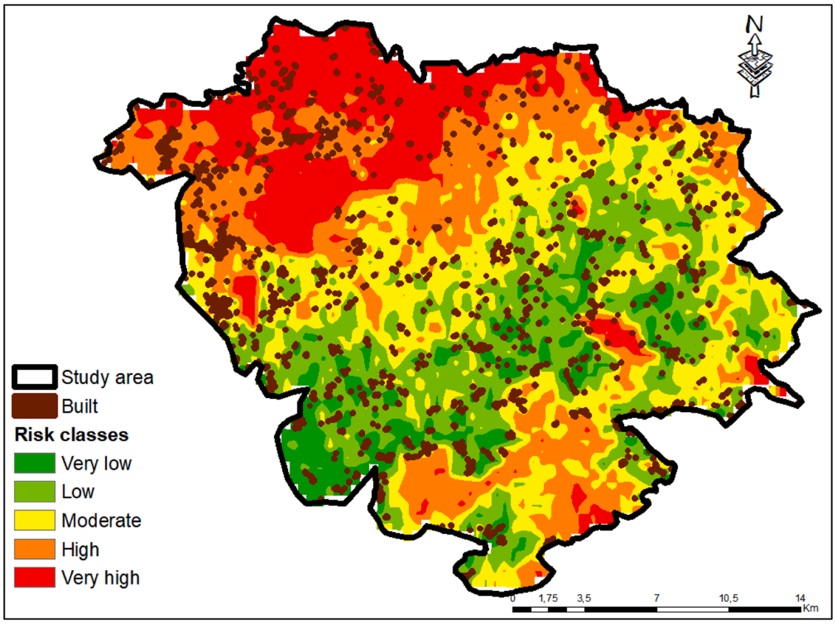

Fig. 10. The Vulnerability of Forest Interface Habitats map of Djebel El Ouahch.

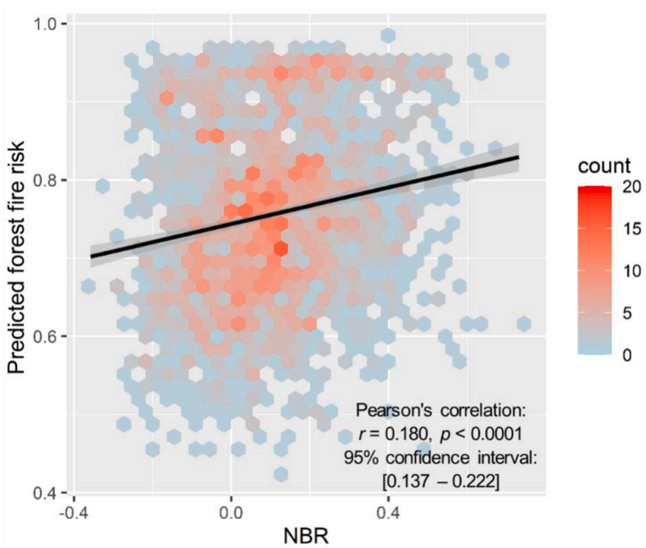

Fig. 11. Relationship between normalized burn ratio (NBR) and predicted values of forest fire risk. The solid line represents a linear regression with 95 % confidence regions in light grey.

4. Conclusion

This study conducted a detailed analysis of forest fire risk patterns in Djebel El Ouahch, integrating bioclimatic, fuel, geomorphological, and human factors using fuzzy logic and GIS techniques. The resulting predictive maps revealed a nuanced understanding of vulnerability levels, spanning from areas with sparse vegetation indicating low risk to densely vegetated slopes near human settlements signaling high risk. These findings emphasize the pivotal influence of climate, terrain, and human activities on forest fire susceptibility. The implications are profound: immediate attention is imperative for high-risk zones, necessitating tailored fire prevention measures, community engagement initiatives, and strategic urban planning to mitigate human-induced risks. Recognizing the detailed connections between natural and anthropogenic factors enables the formulation of evidence-based policies, enhancing forest fire preparedness, biodiversity preservation, and community safety. This research not only advances the scientific understanding of forest fire dynamics but also serves as a crucial tool for sustainable forest management and global disaster mitigation efforts. Moving forward, it is crucial to focus on dynamic modeling incorporating real-time climate data for enhanced prediction accuracy. Additionally, delving into socio-economic factors shaping human activities can provide invaluable insights, ensuring the conservation of North African ecosystems and the well-being of communities in vulnerable zones.

Funding

This study was not funded by any source.

CRediT authorship contribution statement

Louiza Soualah: Writing – original draft, Methodology, Investigation. **Abdelhafid Bouzekri:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Data curation, Conceptualization. **Haroun Chenchouni:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

References

Abdelhamid, D., Neffar, S., Chenchouni, H., 2023. Decoding the interplay between tree traits, seed production, and cone-boring insect damage using advanced modeling to unveil the intricacies of Atlas cedar (*Cedrus atlantica*) forests. EuroMediterr. J. Environ. Integr. 8 (4), 875–891. https://doi.org/10.1007/s41207-023-00419-6.

Abedi Gheshlaghi, H., 2019. Using GIS to develop a model for forest fire risk mapping. J. Indian Soc. Remote Sens. 47 (7), 1173–1185. https://doi.org/10.1007/s12524-019-00981-z.
Abedi Gheshlaghi, H., Feizizadeh, B., Blaschke, T., 2020. GIS-based forest fire risk mapping using the analytical network process and fuzzy logic. J. Environm. Plann. Manag. 63 (3), 481–499. https://doi.org/10.1080/09640568.2019.1594726.
Adab, H., Kanniah, K.D., Solaimani, K., 2013. Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques. Nat. Hazards 65, 1723–1743. https://doi.org/10.1007/s11069-012.
Aklah, Z.T., Al-Safi, A., Abdali, M.H., 2023. Predicting high-risk individuals in disease outbreaks using fuzzy logic-based contact tracing model. Nonlinear. Dyn. https://doi.org/10.21203/rs.3.rs-3249976/v1 under review.
Alexandrian, D., Esnault, F., Calabri, G., 1999. Forest fires in the mediterranean area. Unasylva 50 (2), 197. http://www.fao.org/3/x1880e/x1880e07.htm.
Allen, C.D., Breshears, D.D., McDowell, N.G., 2015. On underestimation of global vulnerability to tree mortality and forest die-off from hotter drought in the Anthropocene. Ecosphere 6 (8), 1–55. https://doi.org/10.1890/ES15-00203.1.
Allen, C.D., Macalady, A.K., Chenchouni, H., Bachelet, D., McDowell, N., Vennetier, M., et al., 2010. A global overview of drought and heat-induced tree mortality reveals emerging climate change risks for forests. For. Ecol. Manage. 259 (4), 660–684. https://doi.org/10.1016/j.foreco.2009.09.001.
Aragoneses, E., García, M., Ruiz-Benito, P., Chuvieco, E., 2024. Mapping forest canopy fuel parameters at European scale using spaceborne LiDAR and satellite data. Remote Sens. Environ. 303, 114005 https://doi.org/10.1016/j.rse.2024.114005.
Arar, A., Chenchouni, H., 2012. How could geomatics promote our knowledge for environmental management in Eastern Algeria? J. Environ. Sci. Technol. 5 (5), 291–305. https://doi.org/10.3923/jest.2012.291.305.
Arfa, A.M.T., Benderradji, M.E.H., Alatou, D., 2009. Analyse des bilans des incendies de forêt et leur impact économique en Algérie entre 1985-2006. New Medit 8 (1), 46–51. https://doi.org/10.4000/cybergeo.32304.
Argañaraz, J.P., Pizarro, G.G., Zak, M., Landi, M.A., Bellis, L.M., 2015. Human and biophysical drivers of fires in Semiarid Chaco mountains of Central Argentina. Sci. Total Environ. 520, 1–12. https://doi.org/10.1016/j.scitotenv.2015.02.081.
Arpaci, A., Malowerschnig, B., Sass, O., Vacik, H., 2014. Using multi variate data mining techniques for estimating fire susceptibility of Tyrolean forests. Applied Geography 53, 258–270. https://doi.org/10.1016/j.apgeog.2014.05.015.
Baltaci, U., Yildirim, F., 2020. Effect of slope on the analysis of forest fire risk. Hacettepe J. Biol. Chem. 48 (4), 373–379. https://doi.org/10.15671/hjbc.753080.
Bellman, R.E., Zadeh, L.A., 1970. Decision-making in a fuzzy environment. Manage Sci. 17 (4), 141–273. https://doi.org/10.1287/mnsc.17.4.B141.
Bentchakal, M., Medjerab, A., Chibane, B., Rahmani, S.E.A., 2021. Meteorological drought and remote sensing data: an approach to assess fire risks in the Algerian forest. Model. Earth. Syst. Environ. 8, 3847–3858. https://doi.org/10.1007/s40808-021-01323-0, 2022.
Bonan, G.B., 2008. Forests and climate change: Forcings, feedbacks, and the climate benefits of forests. Science 320 (5882), 1444–1449. https://doi.org/10.1126/science.1155121.
Bouzekri, A., Alexandridis, T.K., Toufik, A., et al., 2023. Assessment of the Spatial Dynamics of Sandy Desertification Using Remote Sensing in Nemamcha region (Algeria). Egypt. J. Remote Sens. Space Sci. 26 (3), 642–653. https://doi.org/10.1016/j.ejrs.2023.07.006.
Carrega, P., 1991. A meteorological index of forest fire hazard in Mediterranean France. Int. J. Wildland. Fire 1 (2), 79–86. https://doi.org/10.1071/WF9910079.
Carrega, P., 2008. Le risque d'incendies de forêt en région méditerranéenne: compréhension et évolution. In: Actes des colloques de l'AIC, Sep 2008. Montpellier, France, pp. 11–23. https://hal.archives-ouvertes.fr/hal-00470225.
Chafai, C., Bentouati, A., Rabhi, K., Sghaier, T., Arar, A., Bachir, A.S., 2023. Using GIS and AHP techniques to evaluate the forest site quality in the Ouled Yagoub National Forest (North-East, Algeria). Genetics Biodivers. J. 7 (2), 94–108.
Chenchouni, H., 2010. Drought-induced mass mortality of Atlas cedar forest (*Cedrus atlantica*) in Algeria. In: Parrota, J.A., Carr, M.A. (Eds.), Proc. 33th IUFRO World Congr., August 23–28, 2010. Seoul. The International Forestry Review.
Chuvieco, E., Giglio, L., Justice, C., 2010. Global characterization of fire activity: Toward defining fire regimes from Earth observation data. Glob. Change Biol. 14 (7), 1488–1502. https://doi.org/10.1111/j.1365-2486.2008.01585.x.
Collins, L., Guindon, L., Lloyd, C., Taylor, S.W., White, S., 2024. Fractional cover mapping of wildland-urban interface fuels using Landsat, Sentinel 1 and PALSAR imagery. Remote Sens. Environ. 308, 114189 https://doi.org/10.1016/j.rse.2024.114189.
Conedera, M., Tinner, W., 2000. The Interaction between forest fires and human activity in Southern Switzerland. In: Innes, J.L., Beniston, M., Verstraete, M.M. (Eds.), Biomass burning and its inter-relationships with the climate system. Advances in global change research, Vol 3. Springer, Dordrecht, pp. 247–261. https://doi.org/10.1007/0-306-47959-1_14.
Costafreda-Aumedes, S., Comas, C., Vega-Garcia, C., 2017. Human-caused fire occurrence modelling in perspective: a review. Int. J. Wildland. Fire 26 (12), 983–998. doi:10.1071/WF17026.
D'Este, M., Elia, M., Giannico, V., Spano, G., Lafortezza, R., Sanesi, G., 2021. Machine learning techniques for fine dead fuel load estimation using multi-source remote sensing data. Remote Sens. 13 (9), 1658. https://doi.org/10.3390/rs13091658.
Devisscher, T., Boyd, E., Malhi, Y., 2016. Anticipating future risk in social-ecological systems using fuzzy cognitive mapping: the case of wildfire in the Chiquitania, Bolivia. Ecol. Soc. 21 (4), 18. https://doi.org/10.5751/ES-08599-210418.
Eldredge, N., 2000. Life in the balance: humanity and the biodiversity crisis. Princeton University Press.
Erten, E., Kurgun, V., Musaoglu, N., 2004. Forest fire risk zone mapping from satellite imagery and GIS: a case study. In: 20th Congress of the international society for photogrammetry and remote sensing. Istanbul, Turkey, pp. 222–230.
Escuin, S., Navarro, R., Fernández, P., 2008. Fire severity assessment by using NBR (Normalized Burn Ratio) and NDVI (Normalized Difference Vegetation Index) derived from LANDSAT TM/ETM images. Int. J. Remote Sens. 29 (4), 1053–1073. https://doi.org/10.1080/01431160701281072.
Eugenio, F.C., dos Santos, A.R., Fiedler, N.C., Ribeiro, G.A., da Silva, A.G., dos Santos, Á. B., Paneto, G.G., Schettino, V.R., 2016. Applying GIS to develop a model for forest fire risk: a case study in Espírito Santo, Brazil. J. Environ. Manage. 173, 65–71. https://doi.org/10.1016/j.jenvman.2016.02.021.
Farfán, M., Dominguez, C., Espinoza, A., Jaramillo, A., Alcántara, C., Maldonado, V., et al., 2021. Forest fire probability under ENSO conditions in a semi-arid region: a case study in Guanajuato. Environ. Monit. Assess. 193 (10), 684. https://doi.org/10.1007/s10661-021-09494-0.
Feizizadeh, B., Omrani, K., Aghdam, F.B., 2015. Fuzzy analytical hierarchical process and spatially explicit uncertainty analysis approach for multiple forest fire risk mapping. GI_Forum 2015, 72–80. https://doi.org/10.1553/giscience2015s72.
Forzieri, G., Girardello, M., Ceccherini, G., Spinoni, J., Feyen, L., Hartmann, H., et al., 2021. Emergent vulnerability to climate-driven disturbances in European forests. Nat. Commun. 12, 1081. https://doi.org/10.1038/s41467-021-21399-7.
Gajendiran, K., Kandasamy, S., Narayanan, M., 2024. Influences of wildfire on the forest ecosystem and climate change: a comprehensive study. Environ. Res. 240 (2), 117537 https://doi.org/10.1016/j.envres.2023.117537.
Gallardo-Salazar, J.L., Sáenz-Romero, C., Lindig-Cisneros, R., López-Toledo, L., Blanco-García, J.A., Endara-Agramont, Á.R., 2023. Three decades of remote sensing analysis of forest decline related to climate change: a bibliometric study. Cuadernos de Investigación Geográfica 49 (1), 69–87. https://doi.org/10.18172/cig.5639.
Ganteaume, A., Camia, A., Jappiot, M., San-Miguel-Ayanz, J., Long-Fournel, M., Lampin, C., 2013. A review of the main driving factors of forest fire ignition over Europe. Environ. Manage 51, 651–662. https://doi.org/10.1007/s00267-012-9961-z.
Gao, B.C., 1996. NDWI—A normalized difference water index for remote sensing of vegetation liquid water from space. Remote Sens. Environ. 58 (3), 257–266. https://doi.org/10.1016/S0034-4257(96)00067-3.
Ghefar, M., Morsli, B., Bouazzaoui, A., 2024. Assessing the impact of anthropogenic activities on land use and land cover changes in the semi-arid and arid regions of Algeria. Environ. Monit. Assess. 196 (4), 383. https://doi.org/10.1007/s10661-024-12524-2.
Guettouche, M.S., Derias, A., Boutiba, M., Guendouz, M., Boudella, A., 2011. A fire risk modelling and spatialization by GIS. J. Geogr. Inf. Syst. 3 (3), 254. https://doi.org/10.4236/jgis.2011.33022.
Gupta, S.K., Kanga, S., Meraj, G., Kumar, P., Singh, S.K., 2023. Uncovering the hydro-meteorological drivers responsible for forest fires utilizing geospatial techniques. Theor. Appl. Climatol. 153, 675–695. https://doi.org/10.1007/s00704-023-04497-y.
Hantson, S., Scheffer, M., Pueyo, S., Xu, C., Lasslop, G., van Nes, E.H., et al., 2017. Rare, intense, big fires dominate the global tropics under drier conditions. Sci. Rep. 7 (1), 14374. https://doi.org/10.1038/s41598-017-14654-9.
Holsinger, L., Parks, S.A., Miller, C., 2016. Weather, fuels, and topography impede wildland fire spread in western US landscapes. For. Ecol. Manage. 380, 59–69. https://doi.org/10.1016/j.foreco.2016.08.035.
Iliadis, L.S., Papastavrou, A.K., Lefakis, P.D., 2002. A computer-system that classifies the prefectures of Greece in forest fire risk zones using fuzzy sets. Forest Policy Econ. 4 (1), 43–54. https://doi.org/10.1016/S1389-9341(01)00079-X.
Iliadis, L., Skopianos, S., Tachos, S., Spartalis, S., 2010. A fuzzy inference system using Gaussian distribution curves for forest fire risk estimation. In: Papadopoulos, H., Andreou, A.S., Bramer, M. (Eds.), Artificial intelligence applications and innovations. AIAI 2010. IFIP advances in information and communication technology. Berlin, Heidelberg,. Springer, pp. 376–386. https://doi.org/10.1007/978-3-642-16239-8_49.
IPCC, 2021. In: Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., et al. (Eds.), Climate change 2021: The physical science basis. Contribution of working group I to the sixth assessment report of the intergovernmental panel on climate change. Cambridge, United Kingdom and New York, NY, USA. Cambridge University Press. https://doi.org/10.1017/9781009157896.
Jain, P., Coogan, S.C., Subramanian, S.G., Crowley, M., Taylor, S., Flannigan, M.D., 2020. A review of machine learning applications in wildfire science and management. Environm. Rev. 28 (4), 478–505. https://doi.org/10.1139/er-2020-0019.
Jaiswal, R.K., Mukherjee, S., Raju, K.D., Saxena, R., 2002. Forest fire risk zone mapping from satellite imagery and GIS. Internat. J. Appl. Earth Observat. Geoinformat. 4 (1), 1–10. https://doi.org/10.1016/S0303-2434(02)00006-5.
Joaquim, G.S., Bahaaeddin, A.E., Josep, R.C., 2007. Remote sensing analysis to detect fire risk locations. In: GeoCongres-2007. Quebec, Canada.
Jones, M.W., Abatzoglou, J.T., Veraverbeke, S., Andela, N., Lasslop, G., Forkel, M., et al., 2022. Global and regional trends and drivers of fire under climate change. Rev. Geophys. 60 (3), e2020RG000726 https://doi.org/10.1029/2020RG000726.
Kolanek, A., Szymanowski, M., Raczyk, A., 2021. Human activity affects forest fires: the impact of anthropogenic factors on the density of forest fires in Poland. Forests 12 (6), 728. https://doi.org/10.3390/f12060728.
Konca-Kędzierska, K., Pianko-Kluczyńska, K., 2018. The influence of relative humidity on fires in forests of Central Poland. Forest Res. Papers 79 (3), 269–279.
Koutsias, N., Arianoutsou, M., Kallimanis, A.S., Mallinis, G., Halley, J.M., Dimopoulos, P., 2012. Where did the fires burn in Peloponnisos, Greece the summer

of 2007? Evidence for a synergy of fuel and weather. Agric. For. Meteorol. 156, 41–53. https://doi.org/10.1016/j.agrformet.2011.12.006.

Koutsias, N., Kalabokidis, K., Allgöwer, B., 2015. Fire occurrence patterns at landscape level: beyond positional accuracy of ignition points with kernel density estimation methods. Nat. Hazards 35, 555–574. https://doi.org/10.1007/s11069-004-1790-9.

Mariel, A., 1995. Cartographie du niveau de risque d'incendie: exemple du massif des Maures. Cemagref report.

Meng, Y., Deng, Y., Shi, P., 2015. Mapping forest wildfire risk of the world. In: Shi, P., Kasperson, R. (Eds.), World Atlas of natural disaster risk. IHDP/future earth-integrated risk governance project series. Springer, Berlin, Heidelberg, pp. 261–275. https://doi.org/10.1007/978-3-662-45430-5_14.

Mohd Adnan, M.R.H., Sarkheyli, A., Mohd Zain, A., Haron, H., 2015. Fuzzy logic for modeling machining process: a review. Artif. Intell. Rev. 43, 345–379. https://doi.org/10.1007/s10462-012-9381-8.

Moreno-de-Las-Heras, M., Bochet, E., Vicente-Serrano, S.M., Espigares, T., Molina, M.J., Monleón, V., et al., 2023. Drought conditions, aridity and forest structure control the responses of Iberian holm oak woodlands to extreme droughts: a large-scale remote-sensing exploration in eastern Spain. Sci. Total Environ. 901, 165887 https://doi.org/10.1016/j.scitotenv.2023.165887.

Mrad, D., Djebbar, Y., Hammar, Y., 2018. Analysis of trend rainfall: case of north-eastern Algeria. J. Water Land Develop. (36), 105–115. https://doi.org/10.2478/jwld-2018-0011.

Pan, Y., Birdsey, R.A., Fang, J., Houghton, R., Kauppi, P.E., Kurz, W.A., et al., 2011. A large and persistent carbon sink in the world's forests. Science 333 (6045), 988–993. https://doi.org/10.1126/science.1201609.

Pourtaghi, Z.S., Pourghasemi, H.R., Rossi, M., 2015. Forest fire susceptibility mapping in the Minudasht forests, Golestan Province. Iran. Environ. Earth. Sci. 73, 1515–1533. https://doi.org/10.1007/s12665-014-3502-4.

Satir, O., Berberoglu, S., Donmez, C., 2016. Mapping regional forest fire probability using artificial neural network model in a Mediterranean forest ecosystem. Geomat. Nat. Hazards Risk 7, 1645–1658. https://doi.org/10.1080/19475705.2015.1084541.

Segura Dorado, J., Anacona Mopan, Y.E., Solis Pino, A.F., Paz Orozco, H., 2023. Fuzzy analytical network techniques for selecting suitable temporary refuge sites in Paez, Colombia. J. Intellig. Fuzzy Syst. 45 (3), 5107–5121. https://doi.org/10.3233/JIFS-231453.

Shatnawi, N., 2022. AHP and fuzzy logic geospatial approach for forest fire vulnerable zones. Decis. Sci. Lett. 11 (4), 399–406. https://doi.org/10.5267/j.dsl.2022.8.001.

Sivrikaya, F., Akay, A.E., Oğuz, H., Yenilmez, N., 2011. Mapping forest fire danger zones using GIS: a case study from Kahramanmaraş. In: 6th International symposium on ecology and environmental problems, 17, p. 20.

Thrippleton, T., Lüscher, F., Bugmann, H., 2020. Climate change impacts across a large forest enterprise in the Northern Pre-Alps: dynamic forest modelling as a tool for decision support. Eur. J. For. Res. 139 (3), 483–498. https://doi.org/10.1007/s10342-020-01263-x.

Trucchia, A., Meschi, G., Fiorucci, P., Provenzale, A., Tonini, M., Pernice, U., 2023. Wildfire hazard mapping in the eastern Mediterranean landscape. Int. J. Wildland Fire 32 (3), 417–434. https://doi.org/10.1071/WF22138.

van Lierop, P., Lindquist, E., Sathyapala, S., Franceschini, G., 2015. Global forest area disturbance from fire, insect pests, diseases and severe weather events. For. Ecol. Manage. 352, 78–88. https://doi.org/10.1016/j.foreco.2015.06.010.