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Wildfire Vulnerability Assessment and Mapping Using Remote Sensing, GIS and Weighted Overlay Method in the Eastern Aures in Khenchela, Algeria

Procjena ranjivosti od šumskih požara i kartiranje pomoću daljinskih istraživanja, GIS-a i metode ponderiranog preklapanja u istočnom Auresu u Khencheli, Alžir

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Abstract

Wildfires are one of the natural disasters that cause harmful environmental and economic losses and pose a threat to ecosystems around the world. Consequently, measures must be carefully developed to predict their occurrence and mitigate their damage. This study aims to map the vulnerability to forest fires in the eastern Aures region of Algeria, which is exposed to frequent fires, by using Geographic Information Systems (GIS) and Remote Sensing (RS). In this respect, a geodatabase has been created, with 12 criteria influencing identifying areas of vulnerability to forest fires and grouping them into four main categories (forest characteristics, human factors, relief, and climate). In this context, the Weighted Overlay (WOA) technique was used, as this technique relies on calculating the numerical weights for each factor through the Analytical Hierarchy Process (AHP), and then the Forest Fire Vulnerability Index (FFVI) was derived. Through overlaying criterion, raster layers for each criterion and the results are represented in a vulnerability map. The vulnerability map shows very high, high, medium, low, and very low classes. High and very high vulnerabilities occupy 31.54% of the total studied surface. Moreover, the burned areas in the study area for 2021 were determined using Senti-nel-2 satellite images and calculating the Natural Burning Ratio (NBR) to assess the FFVI. We performed a spatial overlay between the NBR and the FFVI to validate the results. This overlay was translated into the ROC curve (receiver operating characteristic curve) using GIS software. The precision coefficient (AUC) was determined to be 0.778, indicating that the weighted overlay technique is effective. Therefore, it indicates that the WOA technique is effective and will help decision-makers improve emergency management and forest protection to minimize damage.

Keywords: weighted overlay method, eastern Aures, forest fire, Khenchela, vulnerability

Sažetak

Šumski požari jedna su od prirodnih katastrofa koje uzrokuju štetne ekološke i ekonomske gubitke te predstavljaju prijetnju ekosustavima diljem svijeta. Kao posljedica toga, moraju se pažljivo razviti mjere za predviđanje njihove pojave i ublažavanje njihove štete. Cilj ovoga istraživanja je kartirati ranjivost na šumske požare u istočnoj regiji Aures u Alžiru, koja je izložena čestim požarima, primjenom geografskoga informacijskog sustava (GIS) i metoda daljinskih istraživanja (RS). Izrađena je baza podataka s 12 kriterija koji utječu na identifikaciju područja ranjivosti na šumske požare i razvrstanim u četiri glavne kategorije (karakteristike šuma, ljudski čimbenici, reljef i klima). Primijenjena je tehnika ponderiranog preklapanja

(WOA), s obzirom na to da se ova tehnika oslanja na izračun numeričkih težina za svaki faktor kroz proces analitičke hijerarhije (AHP), a zatim je izveden indeks ranjivosti od šumskih požara (FFVI). Preklapanjem kriterija, rasterski slojevi za svaki kriterij i rezultat prikazani su na karti ranjivosti. Karta ranjivosti prikazuje vrlo visoke, visoke, srednje, niske i vrlo niske klase. Visoke i vrlo visoke ranjivosti zauzimaju 31,54 % ukupne istraživane površine. Opožarene površine za 2021. godinu na području istraživanja određene su korištenjem satelitskih snimaka Sentinel-2 i izračunavanjem omjera prirodnog izgaranja (NBR) kako bi se koristio u procjeni FFVI. Kako bismo potvrdili rezultate, proveli smo prostorno preklapanje između NBR-a i FFVI-a. Preklapanje je prevedeno u ROC krivulji (krivulja radne karakteristike prijamnika) pomoću GIS softvera. Koeficijent preciznosti (AUC) utvrđen je na 0,778, što upućuju na to da je tehnika ponderiranog preklapanja učinkovita i da će pomoći donositeljima odluka da poboljšaju upravljanje u hitnim slučajevima i zaštitu šuma kako bi se šteta svela na minimum.

Ključne riječi: metoda ponderiranog prekrivanja, istočni Aures, šumski požar, Khenchela, ranjivost

1. INTRODUCTION

Forest fires are one of the most common natural hazards that occur in many forest systems around the world and pose a major threat to ecologically fragile areas (Chaudhary et al. 2022; Payra et al. 2023). It is an unstoppable natural phenomenon that cannot be disregarded as forest fires are known as one of the most destructive disturbances within the forest ecosystem (Bhadoria et al. 2021; Enoh et al. 2021). However, there are some advantages to forest fires, for instance, the elimination of harmful microorganisms, fungi, insects and plant diseases. Likewise, the enrichment of the soil with nutrients and minerals emitted by residual ash (Ghorbanzadeh et al. 2019) has positive effects on biodiversity and succession of plants (Aragoneses & Chuvieco, 2021).

In the countries of the Mediterranean basin, fire has shown to be the main cause of the destruction of forests, as about 50,000 fires ravage 700,000 to 1 million hectares of Mediterranean forests (Meddour-Sahar et al. 2013). Seeing that Algeria is the main fire hotspot on the southern edge of the Mediterranean basin (Curt et al. 2020) where on average 40,000 hectares were annually burned between 1853 and 1945, with an average of 38,749 hectares per year between 1979 and 2009, and an average of 31,300 hectares between 2008 and 2017, according to the Conservation of Forests of the Province of Khenchela (CFPK) in 2018.

In the eastern Aures, forest fires cause enormous damage with thousands of hectares of vegetation being destroyed every year, which negatively affects the environment, since forests play an important role in the carbon cycle and the reduction of the effects of climate change, including high average temperatures, increased precipitation in winter and drier summers (Fekete & Nehren, 2023; Rahmani & Benmassoud, 2019; Satir et al. 2016)

In addition, the eastern part of the Aures, mainly the Province of Khenchela, was chosen as the study area due to the high number of forest fires in this region. In 2021 in particular, according to the CFPK there were more than 45 fires thus destroying around 9837.28 hectares. The eastern Aures Forest ecosystem also contains many protected plants, such as Atlantic cedars and Aleppo pines. Subsequently, these forests must be protected as they are considered a natural barrier to the risk of desertification in the region. However, in order to improve sustainable management and fire prevention of forests, a fire forecasting system should necessarily be developed, through the creation of maps of fire risk exposure using geospatial technologies. In this regard, many researchers conducted studies for the purpose of creating models for assessing the vulnerability of forests to fire using digital information systems (Albini, 1976; Brown & Smith, 2000; Chandler et al. 1983; Díaz-Delgado et al. 2004; Flannigan & Haar, 1986; Jones, 1966; Morandini et al. 1970; Payra et al. 2023; Rashid, 1987; Savage et al. 1972; Williams et al., 1985). In recent years, with the development of GIS and RS, many studies have been conducted on their use to study and manage the risk of forest fires (Ajin et al. 2016a; Ajin et al. 2016b; Alexandrian & Rigolot, 1992; Dong et al. 2005; Trabaud, 1970; Veena et al. 2017; Yin et al. 2004).

In the Mediterranean basin, (Arfa et al. 2019; Chuvieco & Congalton, 1989; Dagorne & Duche, 1990; Erten et al. 2004; Sakellariou et al. 2019) proposed models based on the calculation of geo-statistical indicators to assess the Forest Fire Risk Vulnerability using the techniques of GIS and RS, which have been tested on many forests around the world, such as China, India, Portugal, Iran, Tunisia and Algeria.

As a multi-criteria approach, the Analytical Hierarchy Process (AHP) (Saaty, 1980) represents one of the best methods for studying and analysing natural hazards, and stands for a commonly used analysis technique to solve complex decision-making processes involving multiple criteria, scenarios and factors (Bozdağ et al. 2016; Tomar et al. 2021). It was used by researchers to study and identify areas vulnerable to forest fires in several studies (Akay & Şahin, 2019; Atesoglu et al. 2014; Bentekhici et al. 2020; Coban & Erdin, 2020; Fekir et al. 2022; Lamat et al. 2021; Rahmani & Benmassoud, 2019). Nonetheless, the WOA method was chosen in this study, which was adopted by (Cetin et al. 2022; Sivrikaya & Küçük, 2022; Yathish et al. 2019) likewise, it represents a technique based on the integration of the AHP with the overlay process within the GIS environment.

Most importantly, vegetation cover is the main fuel for the outbreak and spread of fire in forests, meaning that the higher the density of vegetation, the faster and more intense the fires in the forest. Human activities are responsible for most of the ignition of forest fires around the world (FAO, 2007), through various activities closer to the forest. According to (Novo et al. 2020), 70% of forest fires occur near major roads, and the vulnerability of exposure to forest fires depends on infrastructure and social factors, as this latter determines where and to which extent forests are affected (Ghorbanzadeh et al. 2019). Furthermore, most fires start in agricultural environments, where they are set with the intention of controlling pests, cleaning up residues, renewing pastures and opening new agricultural boundaries (Guedes et al. 2020), while other variables are responsible for the outbreak and spread of fires, such as climatic variables (precipitation, temperature and wind speed) together with topographic variables (slope, aspect and elevation) (Martínez et al. 2009). Moreover, climate-driven factors are among the reasons that provide the favourable environment for the spread of fire in fuel, as paleo-climatic studies have indicated a greater accumulation of fires during a prolonged dry period combined with extreme weather conditions (Ngoc Thach et al. 2018; Rahaman et al. 2022). As for topographical factors, they are the precipitating factors responsible for the spread and expansion of the fire (Novo et al. 2020).

The objectives of this study are to localize and determine the spatial distribution of the Forest Fire Risk Vulnerability using GIS and RS technologies, understand the dynamics of fire, and identify the vulnerability areas which are very important for fire risk management. Moreover, this study was conducted in the eastern Aures region in the Province of Khenchela -Algeria, which is one of the most vulnerable to forest fire in Algeria according to CFPK .For this purpose, GIS-weighted overlay techniques were used to weight between 12 factors influencing the determination of forest fire vulnerability and calculate the Forest Fire Vulnerability Index (FFVI). The fire vulnerability map was tested using forest fire data from the year 2021, extracted from Sentinel-2 satellite imagery. The results will assist ecosystem and forest managers, as well as firefighters in combating wildfires.

1.1 Study area

The study area is located in the eastern part of Algeria, in the Aures Mountains, purposely in the eastern part of the desert Atlas separating the northern and desert regions of Algeria (Zeraib et al. 2022), in the geographical area between 06° 31’ and 07° 14’ East longitude and between 35° 00’ and 35° 30’ North longitude. Further, it is limited as follows: from the North by the Province of Oum El Bouaghi, from the west by the Province of Biskra, from the South by the steppes of the Province of Khenchela, and from the East by the Province of Tebessa (Figure 1). The global surface of the region is 5522.618 km^2, within the semi-arid Mediterranean climate zone, whereat it is characterized by hot and dry summer and cool and humid winter

(Kherchouche et al. 2019), the average temperature ranges between 30° and 38°, which sometimes exceeds 40°.

The study area comprises pure and mixed conifer forests. These forests are known to be dense and sensitive to very frequent fires in the summer. The dominant tree species are Aleppo pine (*Pinus halepensis*), Atlantic cedar (*Cedrus atlantica*), holm oak (*Quercus ilex*), Oxycedar juniper (*Juniperus oxycedrus*), and Phoenician juniper (*Juniperus phoenicea*). The study region is made up of a series of mountainous reliefs with an average slope of 30% that stretch from 662 to 2300 metres in south to north direction (Kherchouche et al. 2019; Rahmani & Benmassoud, 2019).

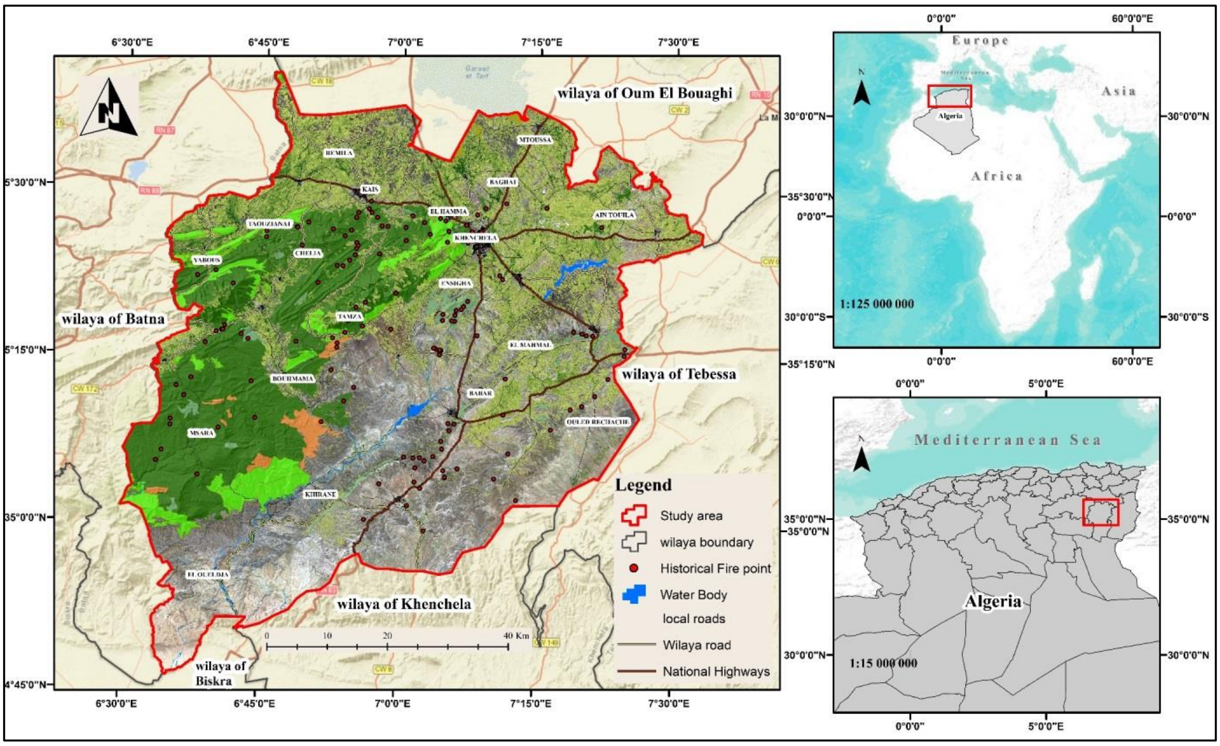


Figure 1 The location of the study area with historical fire point.

2. MATERIALS AND METHODS

2.1 Data collection

For the purpose of creating a geographical database for the study area, a map of plant diversity in the eastern Aures was obtained with a scale of 1:25000, which covers the period of 2008. It was created by the NBRD (National Bureau of Rural Development) and we used it to determine and reclassify the types of fuels and the forest stand once updated using GIS software. A Sentinel-2 satellite image was downloaded on 6 May 2020, and the normalized difference moisture index (NDMI) was calculated by use of the SNAP software.

Furthermore, settlement areas and vegetation moisture were obtained through Sentinel-2 satellite images after processing the same with the SNAP software. As for the road network, it was extracted from the road map created by the Directorate of Civil Protection of the Province of Khenchela (DCP). Likewise, we obtained a set of spatial point layers for agricultural investments which were created by the DGF. In addition, the distance to settlements, the distance to agricultural lands and the distance to roads was formed by the use of the GIS rapprochement tool. The shuttle radar topography mission (SRTM) was downloaded from the U.S. Geological Survey's Earth Explorer website (URL 1), through which the slope, aspect and elevation maps were created using topographic analysis tools in the GIS. Similarity, the climate data (annual temperature, average annual rainfall and wind speed) were obtained from the (WorldClim) website in a similar way, being downloaded as raster files, and then reclassified to conform to the model used to extract areas of vulnerability to forest fires. In the same context, two images of the Sentinel-2 satellite were downloaded on 14 August 2020 and 14 August 2021 from the European Space Agency Open Access Hub website (URL 2), and they were used to calculate the NBR for extraction purpose of the intensity and fire areas that affected the study area in the summer of 2021, which is considered one of the most severe fires in the region over the past 20 years, according to the DGF.

2.2 Selected variables

For the purpose of creating a vulnerability map for forest fires using weighted overlay analysis, four main criteria (forest structure, human factors, relief and climate) and twelve sub-criteria (combustibility index, forest stand, vegetation moisture, slope, aspect, elevation, distance from settlement, distance from agricultural area, distance from road, temperature, rainfall and wind speed) were determined. Upon viewing on various sources indicated in Table 1, the criteria were given a score from 1 to 7, where 1 indicates a weak vulnerability to fire and 7 indicates high vulnerability in Table 2.

Table 1 Parameters involved as criteria in forest fire vulnerability map generation

Criteria	Sub-criteria	Data sources	Type of data	Spatial resolution	Studies
Forest structure	**(IC)**	BNEDER, 2008	raster	-	(Alexandre et al. 2016; Guettouche et al. 2011; Rahmani & Benmassoud, 2019; Suryabhagavan et al. 2016; You et al. 2017)
	(SF)	BNEDER, 2008	vector	-	(Arca et al. 2020; Cetin et al. 2022; Türkeş & Altan, 2012)
	(NDMI)	Open Access Hub (copernicus.eu)	raster	10 m	(Abdo et al. 2022; Fornacca et al. 2018; Sari, 2021)
Human activity	**(DFS)**	Open Access Hub (copernicus.eu)	vector	30 m	(Adab et al. 2013; Al-Fugara et al. 2021; Jafarzadeh et al. 2017; Martínez et al. 2009)
	(DFR)	DCP**,** 2016	vector	-	(FAO, 2007; Gigović et al. 2018; Güngöroğlu, 2017; Jafarzadeh et al. 2017)
	(DFA)	DGF, 2020	vector	-	(Adab et al. 2013; Al-Fugara et al. 2021; Jafarzadeh et al. 2017; Martínez et al. 2009)
Topography	**(SL)**	EarthExplorer (usgs.gov)	raster	30 m	(Dupuy, 1995; Erten et al. 2004.; Jaiswal et al. 2002; Pourghasemi, 2016; Viegas, 2004)
	(AS)	EarthExplorer (usgs.gov)	raster	30 m	(Dong et al. 2005; Pourghasemi, 2016; Prasad et al. 2008; Sahana & Ganaie, 2017)
	(EL)	EarthExplorer (usgs.gov)	raster	30 m	(Ajin et al. 2016a; Rothermel, 1983; Vadrevu et al. 2010)
Climate	**(RA)**	WorldClim	raster	30 m	(Abdi et al. 2018; Güngöroğlu, 2017; Lamat et al. 2021)
	(WS)	WorldClim	raster	30 m	(Lamat et al. 2021; Pourghasemi, 2016)
	(TM)	WorldClim	raster	30 m	(Lamat et al. 2021; Pourghasemi, 2016)

IC - combustibility index, SF - forest stand, NDMI - normalized difference moisture index; DFS - distance from settlement, DFR - distance from road, DFA - distance from agriculture areas; SL - slope, AS -aspect, EL - elevation; RA - rainfall, WS - wind speed, TE - temperature.

Table 2 Classification criteria with 1-7 scale

Criteria	Sub-criteria	Unit	Very low (1)	Low (2)	Moderate (3)	High (4)	Very high (5)	Extreme (6)	Very extreme (7)
Forest structure	(IC)	Value	< 18	18-23	23-26	26 – 29	29 - 38	38 – 68	> 68
	(SF)	Class	Unclassi-fied	Cut	Old forest	Middle age	Irregular	Young forests	-
	(NDMI)	Value	> 0.25	0.25 – 0.06	0.06 - -0.04	-0.04 - -0.12	< -0.12	-	-
Human activity	(DFR)	m	< 200	200 - 400	400 - 600	600 - 800	> 800	-	-
	(DFS)	m	< 1000	1000 - 2000	2000 - 3000	3000 - 4000	> 4000	-	-
	(DFA)	m	< 500	500 - 1000	1000 - 1500	1500 - 2000	>2000	-	-
Topogra-phy	(SL)	%	< 2.5	2.5-7.5	7.5-12.5	12.5-20	>20	-	-
	(AS)	Class	Flat	North / Northeast	East / Northwest	Southeast/ west	Southwest	South	-
	(EL)	M	>1800	1400 - 1800	1000 - 1400	600 - 1000	< 600	-	-
Climate	(RA)	mm	>500	400 - 500	300 - 400	200 - 300	< 200	-	-
	(WS)	m/s	< 3.25	3.25 – 3.5	3.5 – 3.75	3.75 - 4	>4	-	-
	TM	°C	< 12	12 - 14	14 - 16	16 - 18	>18	-	-

2.2.1 Forest structure

Vegetation cover significantly affects the behaviour of forest fires because it is considered the primary fuel for the spread of fire. Therefore, it is the main focus of forest fire prevention efforts (Alexandre et al. 2016), as fires spread more in areas with dry and thick vegetation (Nikhil et al. 2021). As consequence, tree and plant species play an important role in assessing areas at risk of fire (Güngöroğlu, 2017). On the other hand, in this study we adopted the combustibility index (IC) as shown in equation (1) proposed by CEMAGREF (public research institute specialised in agricultural and environmental engineering research), which is an indicator that considers the biomass of fuel, the density of vegetation and the type of fuel:

$$IC = 39 + 0.23BV\ (E1 + E2 - 7.18) \qquad (1)$$

where:

BV is vital volume of plant composition; E1 is combustion rate of the tops of dominant trees and E2 is combustion rate of dominant woody or herbaceous plants.

According to the literature, young stand regions are most vulnerable to forest fires, while large areas are considered less vulnerable because large trees retain a greater amount of moisture (Türkeş & Altan, 2012). We obtained stand forest data from the DGF of the Province of Khenchela. We reclassified and converted those data into a raster layer using GIS software.

As for vegetation moisture, it plays an important role in the vulnerability of fuel to fire; thus, the higher the moisture of the fuel, the less likely it is to be exposed to fire. Figure 2 shows maps and standards forest structure. Therefore, bands 8 and 11 from the Sentinel-2 sensor were utilized to calculate normalized difference moisture index (2):

$$NDMI = \frac{B8\text{-}B11}{B8+B11} \tag{2}$$

where:

B8 is near infrared and B11 is short-wave infrared (SWIR1).

2.2.2. Human factor

In reality, the majority of forest fires is caused by human actions, including agricultural endeavours, hunting or campfires, together with all activities that depend on fire. Consequently, human presence near forests has a significant impact on the likelihood of fire outbreak (Al-Fugara et al. 2021; Martínez et al. 2009). According to the DGF, 97% of fires in the region are caused by humans.

The study area is known for many agricultural activities, such as fruit tree cultivation, livestock breeding and beekeeping, in particular on the western slopes near the area of Bouhmama and Chelia, with thousands of hectares of agricultural investments amid forests. Moreover, the area is known for the influx of tourists and visitors, mainly in spring and summer (Zeraib et al. 2022). As a consequence, the increase of human activity and movements near forests is followed by the increase in the fire vulnerability in those areas (Adab et al. 2013) and the maps of human factors are shown in Figure 2.

2.2.3 Relief

There is a consensus in the literature that the steeper the terrain, the higher the rate of spread of the fire and, accordingly, the greater the vulnerability to the forest fires risk (Cetin et al. 2022; Dupuy, 1995; Viegas, 2004). Besides, steep slopes do not only drain surface runoff in prompt manner, but dry out the inflamed material easily, and also increase the rate of fire spread (Huang et al. 2000). Likewise, fire travels more quickly to the top of the slopes by heating and drying and increases the combustion of available fuel (Güngöroğlu, 2017; Jaiswal et al. 2002).

The aspect indicates the compass orientation of the slope, and it is measured in degrees from the north clockwise. Its values range from 0 degrees to 360 degrees (Sahana & Ganaie, 2017). Moreover, it is also considered an important factor affecting the behaviour of the outbreak and spread of fire through the difference in solar radiation and the movement and type of winds (Enoh et al. 2021) in the eastern part of Aures. The southern parts in the summer are exposed to hot southern winds (Sirocco), and the northern parts are exposed to the north winds and are less hot, while the southern and south-western parts receive more sunlight, which leads to drying of the soil and vegetable fuel. Moreover, in contrast, fuel is usually drier and less dense on the southern slopes than fuel on the northern slopes (Prasad et al. 2008). Consequently, the southern and south-western parts are more sensitive to fires (Bentekhici et al. 2020; Sivri-kaya & Küçük, 2022).

Altitude is an important physiological factor pertaining to wind behaviour and fuel quality and as a result affects the vulnerability to fire hazard (Rothermel, 1983; Vadrevu et al. 2010). Moreover, the altitude of the region affects the climate as well, and in particular the average rainfall, the soil and air moisture (Ajin et al. 2016b; Mohajane et al. 2021) and low altitudes are, therefore, the most sensitive to fires due to high temperatures and low amounts of moisture; while high altitudes have a low vulnerability to fires (Bentekhici et al. 2020). Given the above-mentioned, maps of topographic parameters are illustrated in Figure 2.

2.2.4 Climate

The risks of forest fires and their behaviour are associated with meteorological variables, and in particular precipitation, temperature, wind speed and concentration of sunlight (Sivri-kaya & Küçük, 2022), as a high temperature in summer leads to increased evaporation and transition and contributes to rapid drying of fuels. As a result, favourable conditions for ignition temperature appear (Güngöroğlu, 2017).

Precipitation is without doubt important for regulating the water balance of fuel-rich forest and agricultural ecosystems and is also related to soil moisture. According to (Pellizzaro et al. 2007), soil moisture is closely linked to forest fires.

In addition, wind speed is necessary to determine the rate of fuel moisture loss, along with the rate and extent of fire spread, since it forms the main oxidizing – oxygen agent, the main component in the fire triangle (Asori, 2020). Maps of climatic parameters are illustrated accordingly in Figure 2.

After obtaining climate data from the world-climate website, which varied in spatial resolution, we converted it from raster grid format to point layers. Subsequently, we performed spatial interpolation using the IDW (*Inverse Distance Weighting*) method on these layers, and the results are shown in Figure 2.

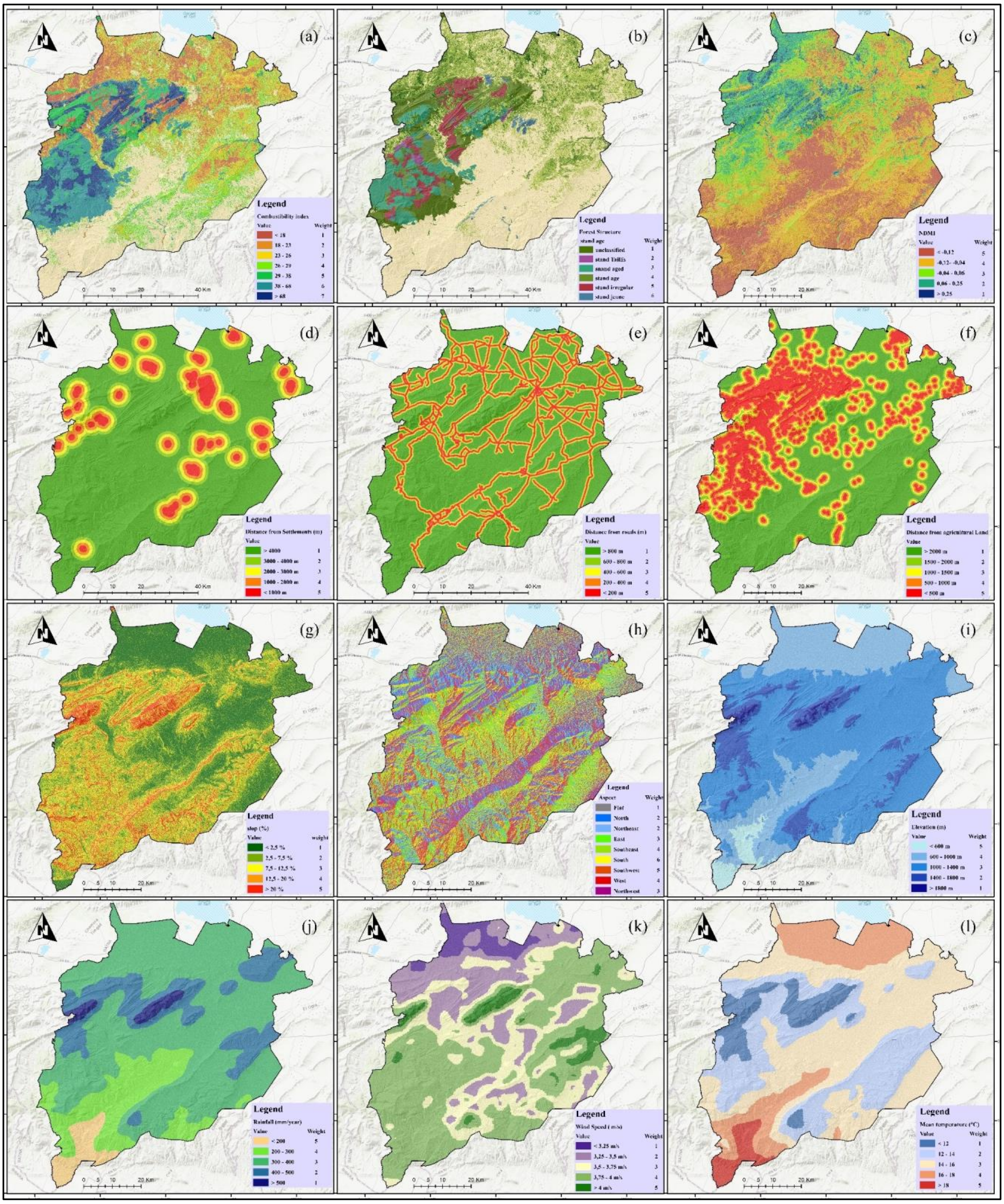


Figure 2 Criteria used in vulnerability analysis (a) combustion index; (b) stand forest; (c) NDMI; (d) distance from settlements; (e) distance from road; (f) distance from agricultural land; (g) slope; (h) aspect; (i) elevation; (j) rainfall; (k) wind speed and (l) mean temperature.

2.3 Weighted Overlay Technique (WOA)

Due to the complexity of the forest ecosystem events, in particular fire hazard, the WOA can generate solutions with user-defined approaches and requirements for the development of a forest fire exposure map in the eastern Aures (Sivrikaya & Küçük, 2022). Besides, the WOA is considered a AHP (Kumar et al. 2019) and is one of modern techniques in GIS, based mainly on giving weight to each of the factors affecting the vulnerability of forest fires and weighting between them. Figure 3 illustrates the methodology for mapping vulnerability to forest fires using the WOA:

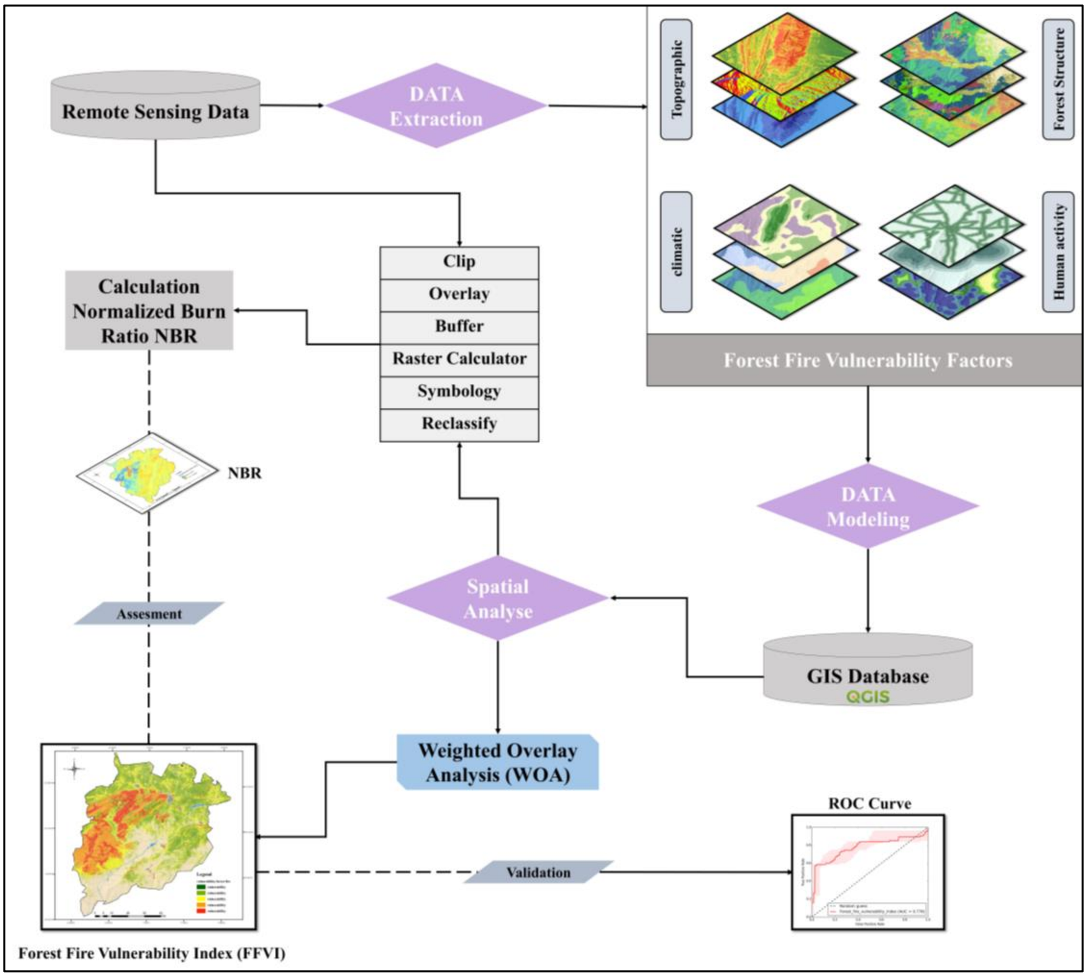


Figure 3 Flowchart for vulnerability mapping of forest fires using (WOA)

As illustrated in the figure above, and upon preparing all the layers for various influencing factors and creating a database, these models were reclassified after reviewing various literature sources, as shown in Table 1. As consequence, the relative weight of each factor was estimated, as this was performed by the AHP. The AHP is a commonly used multi-criteria analysis technique that is usually performed to analyse the comparison of various factors (Bozdağ et al.

2016; Jabbar et al. 2019), which was firstly introduced by (Saaty, 1990). Moreover, this technique is based on relative comparisons between various overlapping factors in a matrix that allows independent assessments to be made between each two factors separately using a numerical scale developed by (Saaty, 2012) and ranging from 1 to 9 in Table 3:

Table 3 Saaty rating scale

Intensity of Importance	Definition	Explanation
1	Equal importance	Two factors of equal impact
3	Moderate importance	More influential factor than the second
5	Strong importance	A factor that has a strong effect on the second factor
7	Very Strong or demonstrated	A factor strongly influencing the second factor
9	Extreme importance	A factor of paramount importance to the other factor
2, 4, 6, 8	For compromise between the above values	When importance is intermediate

In this study, various factors affecting fire vulnerability were compared in the pairwise comparison matrix and the weights for each of the factors were calculated. Besides, for more accurate results, the Consistency Ratio (CR) was calculated (Saaty, 1980):

$$CR = \frac{CI}{RI} \tag{3}$$

where:

CI is the consistency index that can be calculated following the equation:

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

where:

λ_{max} is the maximum eigenvalues, *n* is the size of the Matrix, and *RI* is the random inconsistency index.

If CR is $\leqslant 0.10$, it means that the pairwise comparison matrix has acceptable consistency, but if CR is $\geqslant 0.10$, it means that the pairwise comparison matrix has unacceptable consistency and pairwise comparisons must be repeated to attain more accurate results.

2.4 Validation of the forest vulnerability risk map

2.4.1 Calculation of the normalized burn ratio (NBR)

In addition to extracting the map of FFVI in the eastern Aures region, we calculated the burning ratio for the period of 2021, considering that the fires were of high intensity and the most significant in this year for the areas over the past 20 years, according to the DGF. According to (Escuin et al. 2008), the NBR is the most sensitive indicator of changes caused by fire in the pixels of the satellite image before and after the fire outbreak, and the NBR is based on the peak reflection of both vegetation and mineral soil to provide an indicator of the amount of vegetation present on the landscape before and after the fire event (Boulghobra, 2021). However, this indicator is based on the calculation of the natural difference between the infrared range and the short-wave infrared range whereat a high NBR value indicates healthy vegetation, a low value indicates bare ground and recently burned areas (Alcaras et al. 2022). In addition, we used the Sentinel-2 to calculate this indicator:

$$\mathrm{NBR} = \frac{\mathrm{NIR\text{-}SWIR2}}{\mathrm{NIR{+}SWIR2}} \tag{5}$$

where:

NIR is near infrared band and SWIR 2 is shortwave infrared 2 band

The main purpose of calculating the NBR indicator for the 2021 is to use the same in assessing the map of the FFVI in the eastern Aures, the fact of which is performed by matching the categories of burnt areas for the year 2021 with the categories of forest fire vulnerability areas.

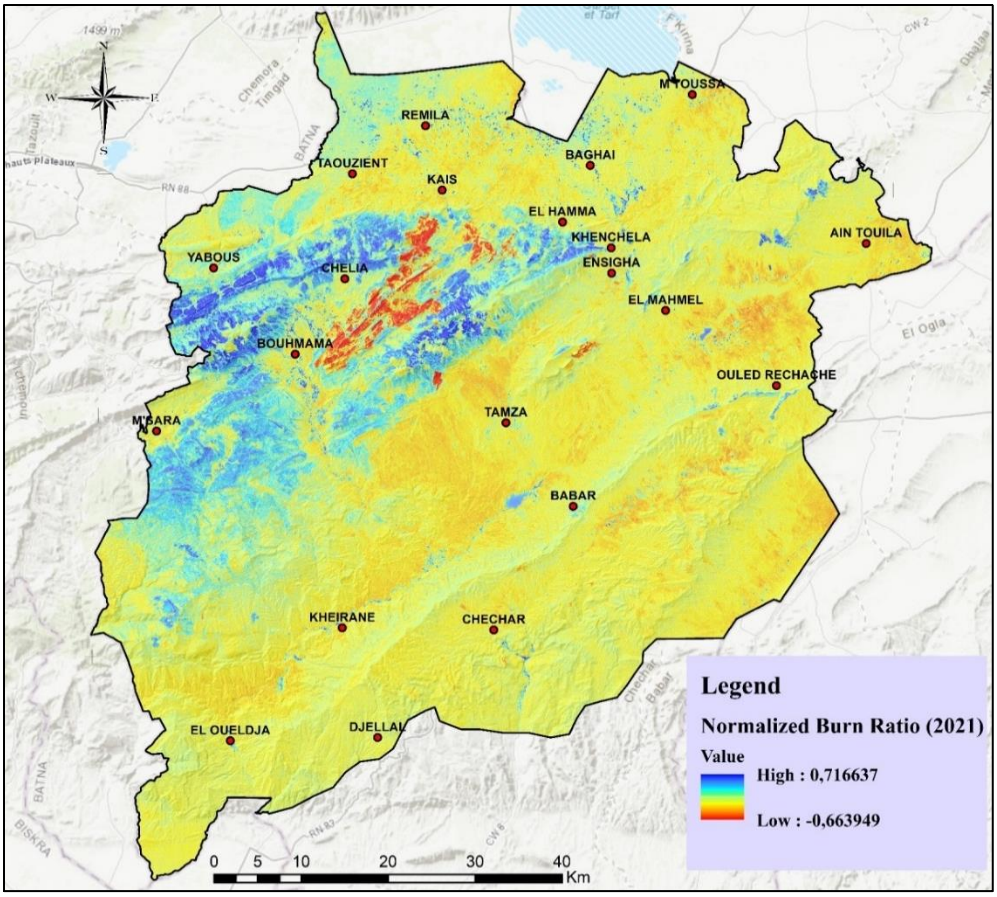


Figure 4 Burned area detection using normalized burn ratio (NBR) model

The accuracy of the FFVI map was verified by calculating the receiver operating characteristic (ROC) curve. This was achieved by overlaying the results with the burned areas extracted from the NBR index, using the Arc SDM plugin within the GIS software. The overlaying was translated into a statistical curve for the ROC curve. However, the ROC curve is a useful way to represent the quality of deterministic and probabilistic detection and prediction systems, a useful graph for examining the degree of trade-off between vulnerability and specificity. In addition, the ROC technique provides a powerful and fast verification method when compared with cross validation (Althouse, 2016; Jaafari et al. 2014; Nykänen et al. 2015), as the ROC curve plots the true positive rate on the Y-axis and the false positive rate on the X-axis whereat the values of the Area Under the Curve (AUC) range from 0.5 to 1.0, and have shown to be used to evaluate the accuracy of the model (Pourghasemi et al. 2016). In addition, the vulnerability of the model (by calculating the percentage of unstable pixels correctly predicted by the model) is plotted against the specificity of 1 (the percentage of unstable pixels predicted on the total) (Mohammady et al. 2012).

3. RESULTS

3.1 Mapping the vulnerability of forest fires in the eastern Aures

Creating a FFVI requires determining the importance of each criterion in order to calculate the weights via the AHP method. A paired comparison matrix was used to determine the weights for each factor in Table 3. A pairwise comparison was made between every two factors out of a total of 12 factors. In these matrimonial comparisons, we relied on the opinions of experts and engineers in the Forest Fire Department of the DGF. The reference values and weights are shown in Table 4, after which the CR value was calculated as 0.022, which means that the preference values for each criterion are consistent and acceptable. The double comparison matrix is shown below in Table 4.

Table 4 AHP pairwise comparison matrix and set weights

	IC	SF	NDMI	DFR	DFA	DFS	SL	AS	EL	WS	TM	RA	Weights
IC	1	2	3	4	5	6	7	8	9	9	9	9	**26.7%**
SF	1/2	1	3	3	4	5	6	7	8	8	8	8	**21.1%**
NDMI	1/3	1/3	1	2	3	4	5	6	7	7	7	7	**14.5%**
DFR	1/4	1/3	1/2	1	2	2	2	3	6	6	6	6	**9.1%**
DFA	1/5	1/4	1/3	1/2	1	1/3	2	3	5	5	5	5	**6.3%**
DFS	1/6	1/5	1/4	1/2	3	1	2	3	5	5	5	5	**7.5%**
SL	1/7	1/6	1/5	1/2	1/2	1/2	1	2	4	4	4	4	**4.6%**
AS	1/8	1/7	1/6	1/3	1/3	1/3	1/2	1	3	3	3	3	**3.3%**
EL	1/9	1/8	1/7	1/6	1/5	1/5	1/4	1/3	1	2	2	2	**2,.0%**
WS	1/9	1/8	1/7	1/6	1/5	1/5	1/4	1/3	1/2	1	2	2	**1.8%**
TM	1/9	1/8	1/7	1/6	1/5	1/5	1/4	1/3	1/2	1/2	1	2	**1.6%**
RA	1/9	1/8	1/7	1/6	1/5	1/5	1/4	1/3	1/2	1/2	1/2	1	**1.4%**

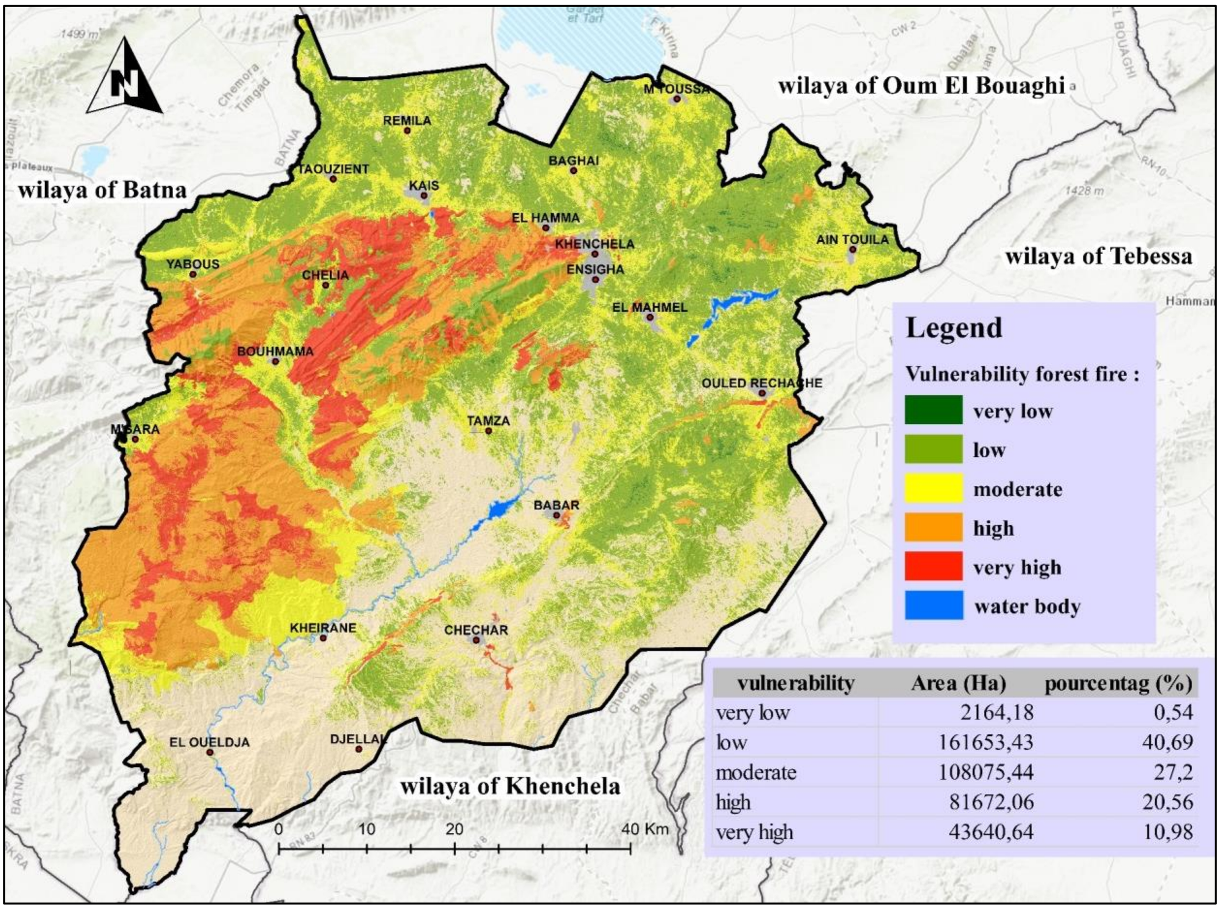
CR= 5.5 %

Afterwards, the weighted overlay method was used to calculate the FFVI by collecting the maps of the criteria and multiplying each criterion by its previously calculated weight:

$$FFVI = (IC\times0.267) + (SF\times0.211^{*}) + (NDMI\times0.145) + (DFR\times0.091) + (DFA\times0.063) + (DFS\times0.075) + (SL\times0.046) + (AS\times0.033) + (EL\times0.02) + (WS\times0.018) + (TM\times0.016) + (RA\times0.014) \quad (6)$$

where: FFVI is forest fires vulnerability index; IC is combustion index; SF is forest stand; NDMI is normalized difference moisture index; DFR is distance from road; DFA is distance from agricultural land; DFS is distance from settlements; Sl is slope; AS is aspect; EL is elevations; WS is wind speed; TM is temperature and RA is rainfall.

The criteria of forest structure are the most important criteria because they significantly affect the vulnerability of forest fires and their total percentage reaches 62.3%, followed by the criteria of human activity with 22.9%, where human activities are among the main causes of fire outbreak and thus increase the vulnerability to fire; topographic criteria, with 9.9%, which is considered one of the factors accelerating the spread of fire; and climate criteria with 4.8%, where climate plays the role of a natural link between fuel and fire. However, based on the expected forest fire exposure index, the fire exposure map is classified into five categories: very low, low, medium, high and extreme, as illustrated in Figure 5 below.



vulnerability	Area (Ha)	pourcentag (%)
very low	2164,18	0,54
low	161653,43	40,69
moderate	108075,44	27,2
high	81672,06	20,56
very high	43640,64	10,98

Figure 5 Vulnerability map of forest fires in eastern Aures

3.2 Validated forest fire vulnerability model

The final step in the research was to evaluate the vulnerability map for productive wildfires. The ROC curve is used to determine the accuracy of a fire risk map (Abdo et al. 2022; Adab, 2017; Pourghasemi et al. 2016; Satir et al. 2016; Silva et al. 2020; Sivrikaya & Küçük, 2022). The ROC curve was used to test the accuracy of the produced forest fire vulnerability maps (Fig. 6). It is a graphical method that allows us to compare the vulnerability index of wildfires and burned areas extracted from the NBR index. The suitability of the FFRI can be assessed from the area under a relative operating characteristic curve (AUC area under the curve) procedure (Pourghasemi, 2016; Swets, 1988), the AUC value ranges between 0.5 and 1, where 1 indicates a perfect fit and 0.5 indicates a random fit (Pourghasemi, 2016; Yesilnacar, 2005). The results showed that the weighted overlay method is an effective method for mapping vulnerability in the study area. It resulted in a good rating accuracy of AUC = 0.778 (Fig. 6).

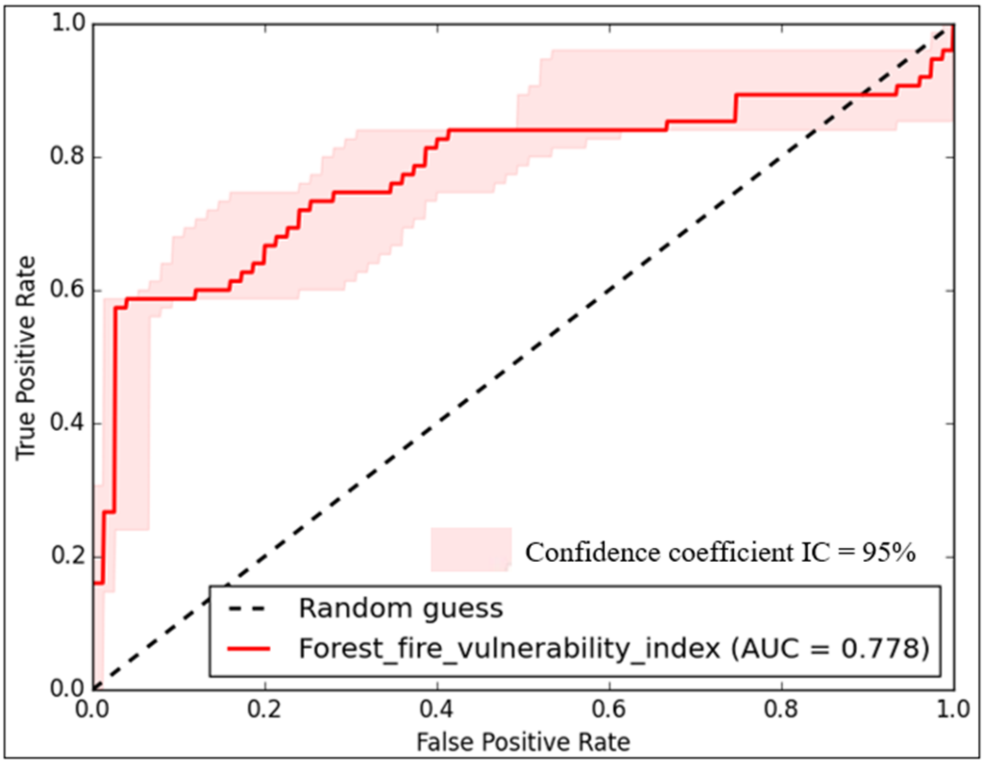


Figure 6 ROC curve for forest fire vulnerability map

4. DISCUSSION AND CONCLUSION

This study is an attempt to integrate RS data and the concept of GIS to locate the most vulnerable areas to forest fires in the eastern Aures. The weighted overlay technique was used to produce a vulnerability map for forest fires using a package of vector and raster data, together with a set of satellite images; we used the insights of specialists and engineers from the Forest Fire Department for the pairwise comparisons. According to the synthesized map (Fig. 5) and calculating the areas of each vulnerability level in the FFVI index, the identified vulnerability levels are as follows: (1) very low vulnerability of 0.54% of the total area of the forest massif is mainly covered by bare lands; (2) low vulnerability of 40.69% is covered by agricultural land; (3) medium vulnerability is 27.2%, and it is covered with Alfa and herbaceous plants; (4) high vulnerability class is 20.56%, and comprises dense forests covered with a mixture of juniper and Aleppo pine trees. The last class is (5) very high vulnerability that covers 3.65%, it is dense forest with a mixture of aleppo pine, cedar, and oak trees.

The main advantage of this study is the use of the NBR index when evaluating the results and accuracy of the vulnerability map, which reflects the reliability of the FFVI index, as we found more than 4000 hectares located in high and very high vulnerability areas (Fig. 4). The results show that these areas were characterized by a combination of different factors that can promote forest fires, especially dense forest cover, low humidity, high altitude, proximity to settlements, road networks, and areas of agricultural activities (Fig. 5). Furthermore, it was observed that most of the fires that occurred in 2021 were distributed in areas with steep slopes and on the slopes facing south (Fig. 4). This confirms that the factors of forest structure, relief, human activity, and climate are those that stimulate vulnerability to forest fires in the study area.

To assess the accuracy of the vulnerability map for forest fires, a ROC curve was created based on overlaying the FFVI index map with the NBR index map of the study area. Accuracy verification results indicated that the area under the curve for the FFVI index is 0.778. This implies that the model used in this study provided reliable results. Therefore, the findings of this study can help forest managers identify areas of vulnerability and their distribution in the field, take preventive measures, protect natural resources, endeavour to reduce human and material losses, and maintain ecological balance. In addition, this map will also help in determining the areas of installation of watchtowers, constructing water tanks, and organizing priorities in intervention when a danger occurs.

We believe that these techniques will be very helpful in the future for all of Algeria's forest areas, and that the government should create a national programme to forecast the likelihood of forest fires, identify areas of vulnerability, post the findings on a geospatial platform, and involve the public, professionals, and scientific community in the process.

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Data availability statement: Data are available upon request to the authors

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