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FOREST FIRE DETECTION BASED ON EARLIER PRE-FIRE CONDITIONS USING ANALYSIS HIERARCHIC PROCESS (AHP) IN A SEMI-ARID CLIMATE. A CASE STUDY: BELEZMA NATIONAL PARK, ALGERIA

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Abstract. GIS and remote sensing are the main techniques for spatial phenomena analysis, especially phenomena triggered by different factors such as fire hazards, climate change, transportation and land use. This study intends to measure forest fire vulnerability in Belezma National Park, one of Algeria's most important national parks and of high environmental value.

The NDVI, NDWI and LST indices are used to evaluate the vulnerability, using satellite data obtained in the same year between May and August. The AHP is then used to integrate the suggested fire model and validated using dendrochronology and Moran's methods.

The results demonstrated that vulnerability decreases relative to altitude; furthermore, the dry season is the period when most fires are triggered (timeline vulnerability factor), which was confirmed by finding out of 150–300-year-old non-burned trees in the low vulnerability area using dendrochronology method. In addition, a significant spatial correlation between elevation and vulnerability maps was found, with Moran's I score of 0.28.

Key words: forest fires, prediction, Belezma National Park, vulnerability, dendrochronology, AHP, semi-arid climates, Algeria

Introduction

One of the main factors causing deforestation and animal extinction worldwide is fire. Particularly in Batna province's semi-arid environment, fires have ravaged large areas of forest and countryside (rural area) in the Belezma National Park, and these are difficult to control and can spread fast depending on vegetation, weather, physical characteristics, human activity and the circumstances of the dry season, which lasts from July to August and is marked by high temperatures and dry winds.

This study aims to estimate the flammability (combustibility) of the semi-arid environment to forecast probable fire spots in the Belezma National Park by adopting the geographic information system (GIS) to investigate many spatial indices during the dry season. The used factors are the Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Land Surface Temperature (LST), the Normalized Difference Built-up Index (NDBI), timeline and elevation (See methodological section). The results of the suggested model are validated using two distinct techniques: first, a statistical method that measures the spatial correlation be-

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tween the vulnerability map and the fires that were recorded between 2018 and 2020, and second, a dendrochronology operation that looks for old, non-burned trees in the low vulnerability area to see if a fire occurred earlier.

Literature review

Large-scale forest fires are among the government's concerns and the policy of managing significant natural risks due to environmental and economic destruction and damages. For this reason, risk mitigation is a fundamental concept that consists of four parts: prevention or mitigation, preparedness, response and recovery (PPRR). The PPRR model relies on two main justifications: first, it depicts the stages or sequences of risk incidents, therefore providing information on the activities that take place before, during or following an incident. Secondly, the model classifies the agenda of available risk management strategies (Rogers *et al.* 2011).

A wildfire, wildland fire or rural fire is an unplanned, uncontrolled fire in an area of combustible vegetation starting in rural and urban areas. Depending on the type of vegetation that exists, a wildfire can be classified more particularly as a forest fire, desert fire, grass fire, hill fire, peat fire, prairie fire, vegetation fire or wildfire (Wehner *et al.* 2017; Pausas, Keeley 2021; Santos *et al.* 2021). These fires significantly negatively impact the climate, human health, society, and economy (Thomas *et al.* 2017). Numerous factors, including geographical, human activity, climatic patterns, and the number and structure of forest plants, influence how a fire spreads (Rasooli *et al.* 2018; Ghorbanzadeh *et al.* 2019; Santos *et al.* 2021; Yang *et al.* 2021). However, these factors do not change daily and do not alter in time, at least during the fire season; hence, a forest fire may be identified using different methods (Akbulak *et al.* 2018; Rasooli *et al.* 2018; Abedi Gheshlaghi 2019).

The Analysis Hierarchic Process (AHP) technique is the most used approach in environment and forest fires (Eskandari 2017; Nikhil *et al.* 2021; Nuthammachot, Stratoulias 2021). AHP is a multi-objective decision analysis that combines qualitative and quantitative analysis to address complex decisions with parameter ranking and ordering logically using the consistency ratio CI. In addition, the parameters are compared to each other using numerical values that represent the priorities of some parameters above others, which results in an accurate decision about the final goals (Pourghasemi *et al.* 2016; Sivrikaya, Küçük 2022).

Remotely sensed data is one of the proper techniques in forest fire research because the burned area (charcoal) residue and the vegetation scar produce longer-lasting spectral signals (spectral reflection) that enable the assessment of the fire's impacted area; according to Rasooli *et al.* (2018), the signal from burned areas is “therefore, more adequate to assess ecological and economic damages (compared with non-fire zones) and estimate atmospheric emissions”.

Machine learning and remote-sensing data based on neural network architecture and fire information for resource management system (FIRMS) hotspot data comprise another development in this research field (Yang *et al.* 2021). Also, Artificial Intelligence (AI) is a recent approach to forest fire prediction (Sakr *et al.* 2010; Yang *et al.* 2021; Iban, Sekertekin 2022).

There are several more forest fire prediction systems, such as the Canadian Forest Fire Danger Rating System (CFFDRS), which depends on manually created characteristics and necessitates the installation and upkeep of pricey ground-based devices (CFFDRS 2023).

In this paper, we focus on fighting forest fires within the prevention phase, since field experience has proven that most large-scale forest fires are exceptionally troublesome and arduous to extinguish, particularly when available resources are limited. As a result, it is necessary to develop a low-cost and effective prediction model using GIS and remote sensing to predict fires using earlier fire conditions in semi-dry climates.

Study area

The national park of Belezma is one of Algeria's most important national parks; it was established on November 3, 1984, by decree no. 84–326. It is located on the forested slopes of the Belezma mountain range, a subrange of the Aures Mountains, in the eastern portion of northern Algeria. It stretches over an area of 262.5 km^2 and is included between the following geographical coordinates: 35°25'N and 35°45'N; 5°50'E and 6°19'E, near the fifth largest city in the country, Batna.

The Belezma Park ecosystem consists of rich mosaic species such as pastures, forests, grasslands, thickets, mountain feet, rivers and mines. Numerous historical sites, caves, and tombs repre-

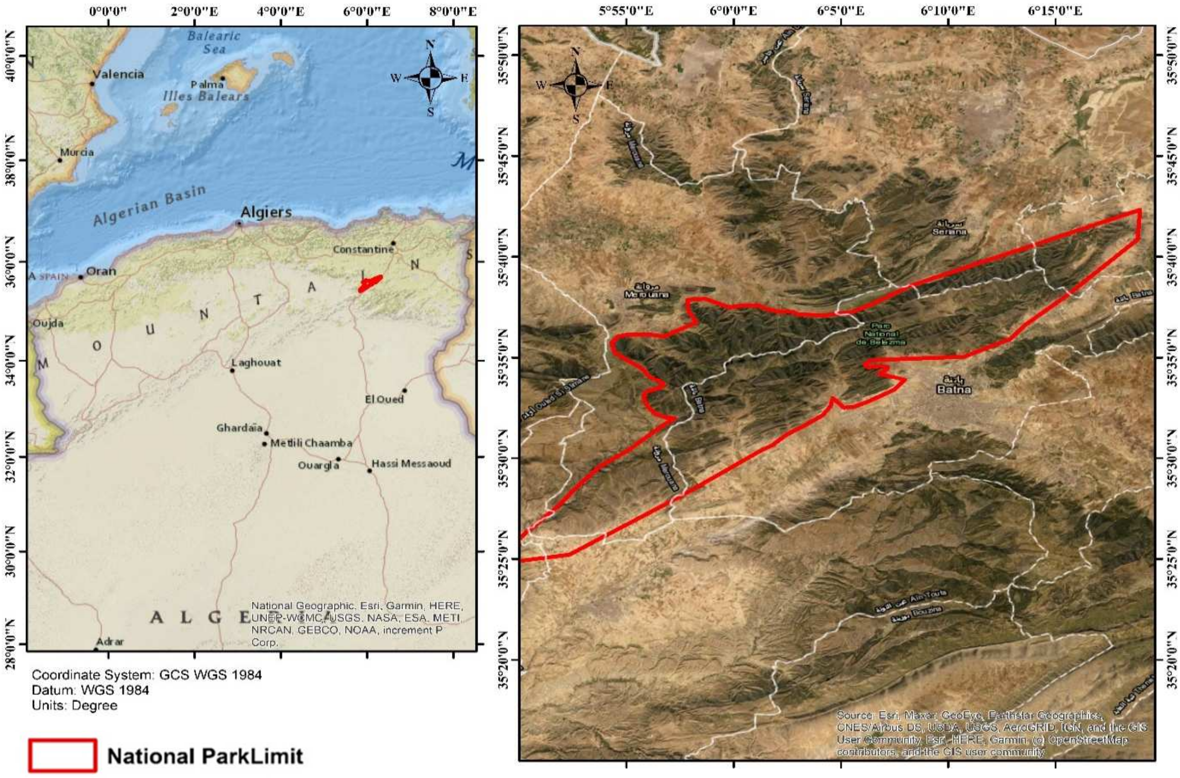

Fig 1. Geographic location of the Belezma National Park

sent traces of ancient civilisations. It is the largest forest of the Atlas cedar (*Cedrus Atlantica*) in Algeria and the Mediterranean, the main supply for handicrafts. Belezma contains 447 species of flora, including *Aleppo pine*, Holm oak, Common holly (*Ilex aquifolium*), *Juniperus Oxycedrus* and *Chrysanthemum*. In addition, the wildlife also includes 309 species, of which 59 are protected, such as the Bonelli's eagle (*Aquila Fasciata*) and the Barbary partridge (*Alectoris Barbara*).

An Atlas cedar (*Cedrus Atlantica*) forest occurs on a distinct slab, either in its primal form from 1800 m a.s.l. or in conjunction with holm oak (*Quercus ilex*) or juniper from 1200 m a.s.l. The south-eastern slope and its north and north-west exposures are home to the most picturesque cedar forests; in contrast, the cedar trees on the southern slopes have suffered from Saharan influences and are now in a deteriorated state.

The red juniper (*Juniperus Phoenicia*) or the prickly ash (*Fraxinus Dimorpha*) may coexist with the atlas cedar.

Methodological approach and data

To ascertain the vulnerability of Belezma Park to wildfire, we opted for a spatial model based on the following approaches:

1. define the criteria of vulnerability and compute the NDVI, NDBI, NDWI and LST indices; additionally, map the seasonal plants that may be highly combustible;
2. execute the spatial model using the GIS environment and map the spatial vulnerability using the equation provided by the Analysis Hierarchic Process (AHP) tool;
3. test and validate the AHP outputs based on two approaches – the first time, we verify the outputs on the ground using the dendrochronology method to locate 150–300-year-old non-burned trees in the low vulnerability area; moreover, calculate the spatial correlation between the vulnerability map and the local wildfire records.

Fire risk parameters

The fire parameters are divided into primary and secondary components (Fig. 2): timeline, human, topography, climate and vegetation.

1. Normalized Difference Vegetation Index (NDVI): the NDVI index is common and broadly used in remote sensing; it calculates the proportion between the top of atmosphere (TOA) reflectance of the red band (RED) and the near-infrared (NIR) band as follows (Pettorelli 2013; Huang *et al.* 2021):

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

The NDVI is a measure of surface reflectance and gives a quantitative estimation of vegetation growth and biomass (Vicente-Serrano *et al.* 2016; Wu *et al.* 2016) it is used widely in agriculture and forest studies. The ratio yields a measure of photosynthetic activity within values between -1 and 1. Low NDVI values indicate moisture--stressed vegetation, and higher values indicate a better density of green vegetation.

2. Normalize Difference Water Index (NDWI) is used for the water body examination; it uses green and near-infrared imagery to delineate open-water features and enhance their presence in remotely sensed digital imagery (Han-Qiu 2005; Serrano *et al.* 2019; Guha, Govil 2021). The NDWI reflects near-infrared radiation and visible green light to enhance such features while eliminating the presence of soil and terrestrial vegetation features. NDWI may also provide researchers and analysts with turbidity estimations of water bodies using remotely sensed digital data. The formula is:

$$\mathrm{NDWI} = \frac{(\mathrm{NIR-SWIR})}{(\mathrm{NIR+SWIR})} \qquad (2)$$

where: SWIR – short-wave infrared band.

3. The Normalized Difference Built-up Index (NDBI) uses the NIR and SWIR bands to emphasise manufactured and urban built-up areas. Prasomsup *et al.* (2020), Vorovencii (2020) and Zheng *et al.* (2021) propose to mitigate the effects of terrain illumination differences and atmospheric effects. The formula is as follows:

$$\mathrm{NDBI} = \frac{(\mathrm{SWIR-NIR})}{(\mathrm{SWIR+NIR})} \qquad (3)$$

The Normalize Difference Build-up Index value lies between -1 and +1; a negative value of NDBI represents water bodies, whereas the higher value represents built-up areas.

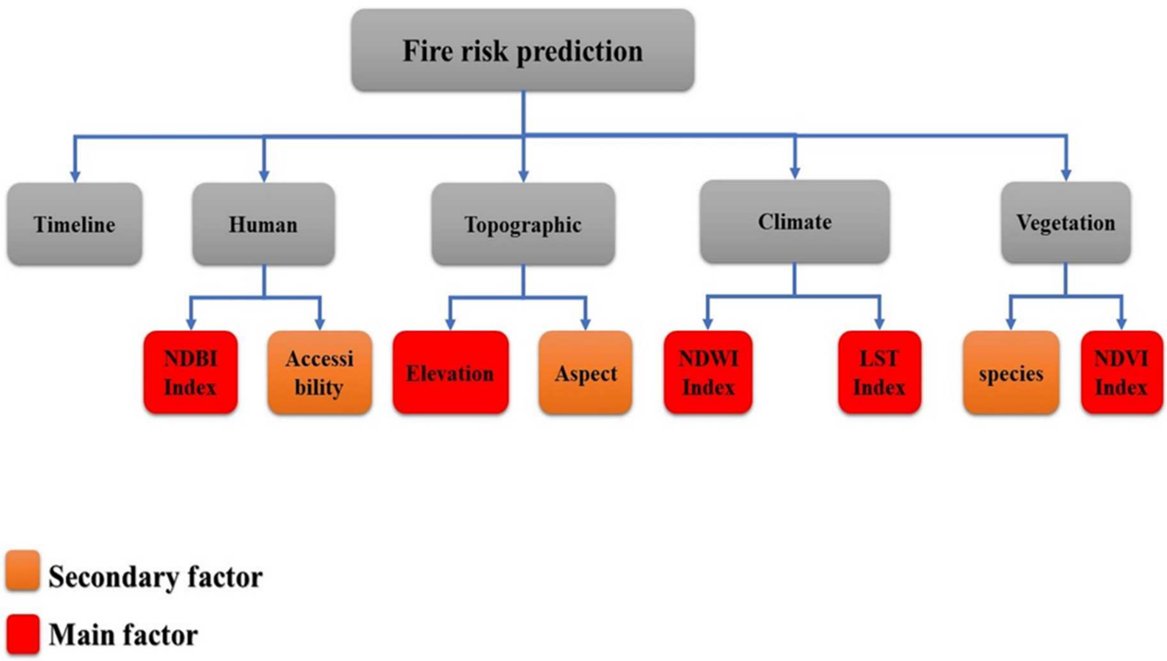

Fig. 2. Hierarchical forest fire parameters

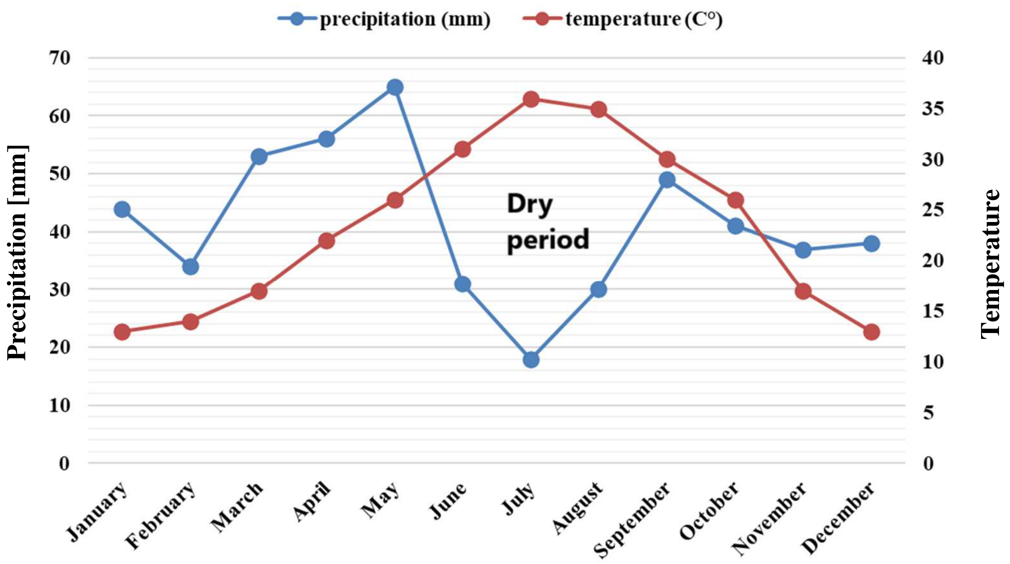

Fig. 3. Bannouls and Gaussen diagram represents dry season in Belezma Park
(data obtained from Hamla station – 2018)

4. The Land Surface Temperature (LST) is the radiative skin temperature of the land surface, as measured in the direction of the remote sensor. The simplified definition would be how hot the "surface" of the Earth would feel to the touch in a particular location; several factors can fundamentally influence the derivation of LST, including (Mumtaz *et al.* 2020; LST 2021). Temperature variations with viewing angles, sub-pixel inhomogeneities in temperature and cover, surface spectral emissivity at the channel wavelengths, atmospheric temperature and humidity variations, clouds and large aerosol particles such as dust.

Land surface temperature is applied in many environmental studies, particularly the applications related to water resources management and agriculture (Becker, Choudhury 1988; Karnieli *et al.* 2010; Chen *et al.* 2011; Sun *et al.* 2012; Rajeshwari, Mani 2014; Yang *et al.* 2015; Merchant *et al.* 2019). Because the imagery data used in this paper is Landsat 8 imagery, we calculated the LST based on the equations and the algorithms explained in the following papers (Avdan, Jovanovska 2016; Gao *et al.* 2020; Mumtaz *et al.* 2020; Li *et al.* 2023).

5. Timeline: according to the Bannouls and Gaussen diagram (Fig. 3), the dry season will have the highest annual temperature readings, with the exception of the July–August period, which will also have the highest number of recorded fires. The method used to identify the dry phase is based on the (Bagnouls, Gaussen 1957) paper. The result is confirmed by Lebiar (2023), which confirms that 58.90% of fires occurred between July and August.

The analytic hierarchy process (AHP)

Three factors (heat, fuel and oxygen) must exist for a fire to start; in this example, the fuel is grassland, the combustion fuse's temperature is the recorded LST, and the oxygen is present naturally. The NDWI, NDBI, aspect and elevation are additional factors that affect how quickly the fire spreads. Table 1 uses the fire triangle rule to rank the pre-fire variables.

The Analysis Hierarchic Process (AHP) of Saaty is a multi-criterion analysis method with logical consistency, hierarchical structuring, and the classification order of parameters according to priorities and importance through binary comparison; it was developed in the 1970s by Thomas L. Saaty, who partnered with Ernest Forman to develop expert choices in 1983. It is used for organising and analysing complex decisions for input parameters or phenomena according to their weight. The factors are weighted based on the influence and significance of each parameter.

The AHP approach uses binary comparison to classify parameters based on relevance and priority, logical coherence and hierarchical organisation. The following papers clarify the intensity

Table 1

Classification of factors according to their weight

Factors	Weight
NDVI (grassland species)	C1
LST	C2
NDWI	C3
NDBI	C3

Table 2

Forest fire vulnerability factors' order and weights

Weight (%)	Order	Factor
45.11	7	NDVI
40.55	5	LST
9.39	3	NDWI
4.92	3	NDBI

of the importance and classification of the parameters in an AHP analysis (Saaty 2008; Fenniche 2018; Piton *et al.* 2018; Rasooli *et al.* 2018; Sivrikaya, Küçük 2022).

To verify the degree of coherence among the decisions and the coherence of the data relationships, Saaty (1987) suggests the following equation:

$$CI = \frac{\lambda max - 1}{n - 1} \quad (4)$$

where: n – the number of criteria.

Table 2 represents the factors' orders and weights calculated using the AHP tool. The CI calculated previously is CI = 0.0449; this makes the chosen factors with the assigned weights have a logical relationship and be coherent with each other.

Test and validate the vulnerability map

Spatial distribution of recorded fire

Moran's I method (Spatial Autocorrelation 2021; ArcGis 2023; Chen 2023) is widely utilised in spatial analysis. Its main objective is to measure spatial autocorrelation, so a phenomena propriety at proximal locations can appear to be correlated, either positively or negatively, within a geographic space. The formula of Moran's I method is based on cross-products of the deviations from the mean and is calculated for n observations on a variable x at locations ij:

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \quad (5)$$

where: $\bar{x}$ – the mean of the x variable,
w_{ij} – the elements of the weight matrix,
S_0 is the sum of the elements of the weight matrix S_0.

Dendrochronology of existing trees

The second validation method is dendrochronology; according to Guibal, Guiot (2021): "Dendrochronology (or tree-ring dating) is the scientific method of dating tree rings (also called growth rings) to the exact year they were formed. As well as dating them, this can give data for dendroclimatology, the study of climate and atmospheric conditions during different periods in history from wood". Dendrochronology is a method of gathering data in the field in addition to laboratory analysis, which requires government authority to be carried out in a protected region (a lengthy process). Therefore, in order to maintain the credibility of our present study and the credibility of other researchers' works, we prefer to use the most recent data available from other researchers and institutions.

Data and tools

The data and tools used in this paper are collected from different sources and formats (raster, vector, table etc.). Table 1 summarises the data and sources.

Table 1

Data and tools

Data	Description	Source
LC08_L1TP_194035_20190802_20200827_02_T1	Landsat 8 Imagery satellite	UGS 2023
LC08_L2SP_194035_20200430_20200820_02_T1	Landsat 8 Imagery satellite	
LC08_L1TP_193037_20200813_20200814_01_RT	Landsat 8 Imagery satellite (Used to validate our model after a fire happened on 09/08/2020)	
LC08_L1TP_197035_20200809_20200809_01_RT	Landsat 8 Imagery satellite (Used to validate our model after a fire happened on 04/08/2020)	
Fire.shp	Recorded fire on the park	Collected from different sources
Trees.shp	Trees applied of dendrochronology	
National_park_limit	Belezma park limit.	Google Earth
extAHP 2.0	AHP tool for ArcGIS	Spatial Autocorrelation 2021; ArcGis 2023

Results

The vulnerability to forest fire in Belezma Park decreases relative to altitude. For instance, the areas below 1000 m a.s.l. have the greatest LST values (47°C), whereas the areas above 1800 m a.s.l. have just 27°C, which is insufficient to start a fire naturally. In the same NDVI pattern, with the lowest altitude regions, we recorded the loudest NDVI values (NDVI=0.16). These values indicate a dry grassland that emerges in the spring; the majority of the plants are seasonal spiky plants and grains. We notice the same pattern distribution for NDWI values, with the greatest value, NDWI=0.7, found in the regions over 1800 metres above sea level is high. The fire triangle rule clearly indicates that the NDVI (grassland) and LST indices have the highest priority and weights when looking at the AHP analysis results. Forest fire danger is likewise influenced by NDWI and NDBI (Fig. 4).

The final equation of the vulnerability map will be:
fire vulnerability:
= 41.12% NDVI,
+40.55% LST,
+9.39% NDWI,
+4.92% NDBI.

Based on the preceding AHP equation (Fig. 5), depicts Belezma Park's vulnerability to forest fires. It is evident that the low area (see Fig. 1) is more sensitive than the mountain peak and than the grassland located in the low area.

The effect of drought stress on the drying of combustible seasonal vegetation (combustibility) was assessed by comparing the regional patterns of NDVI in May of the same year and August of the same year. Due to drought stress, the pre-fire NDVI circumstances for August constituted a more favourable and optimal condition than the NDVI values for May.

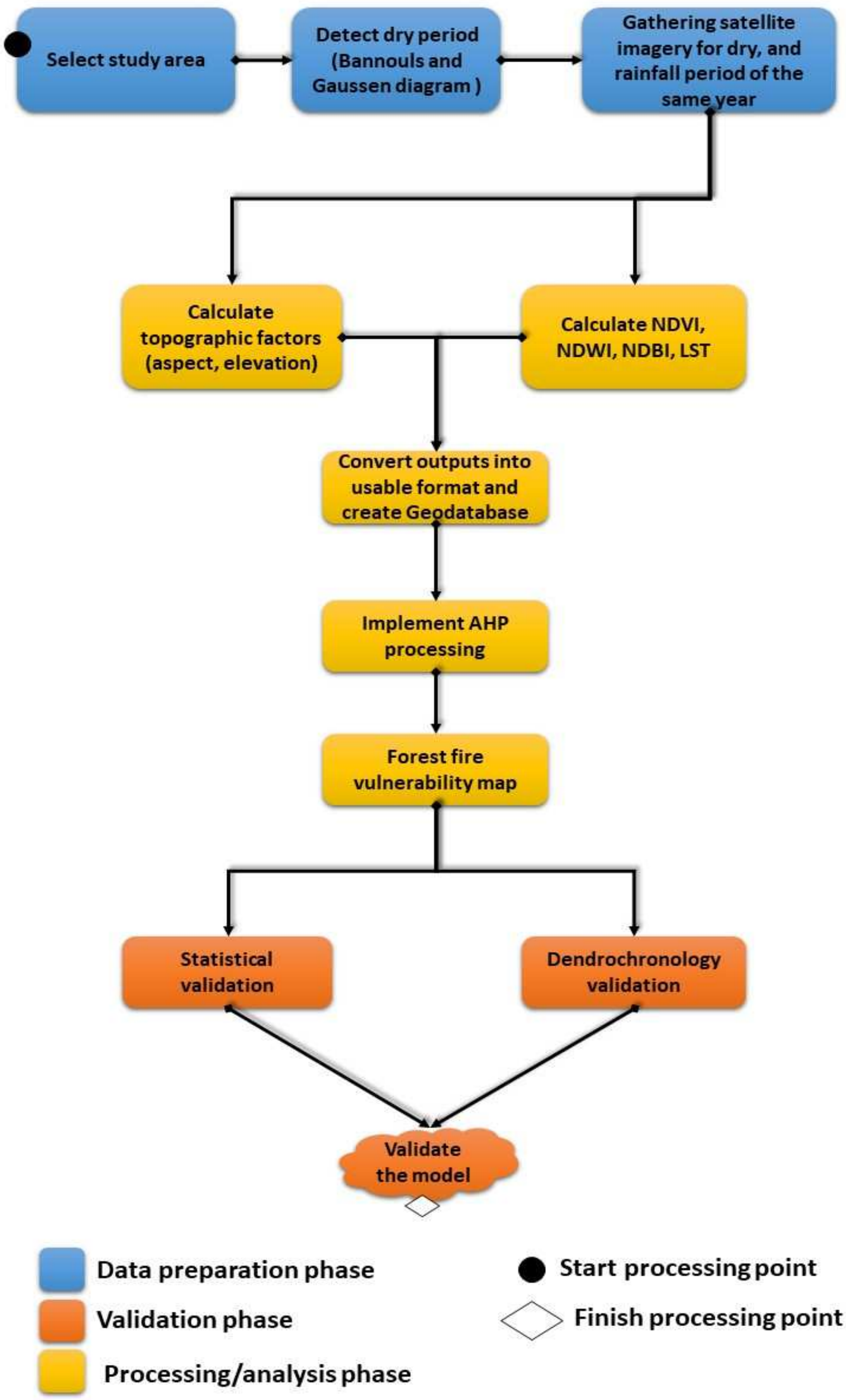

Fig. 4. Forest fire methodological data processing diagram

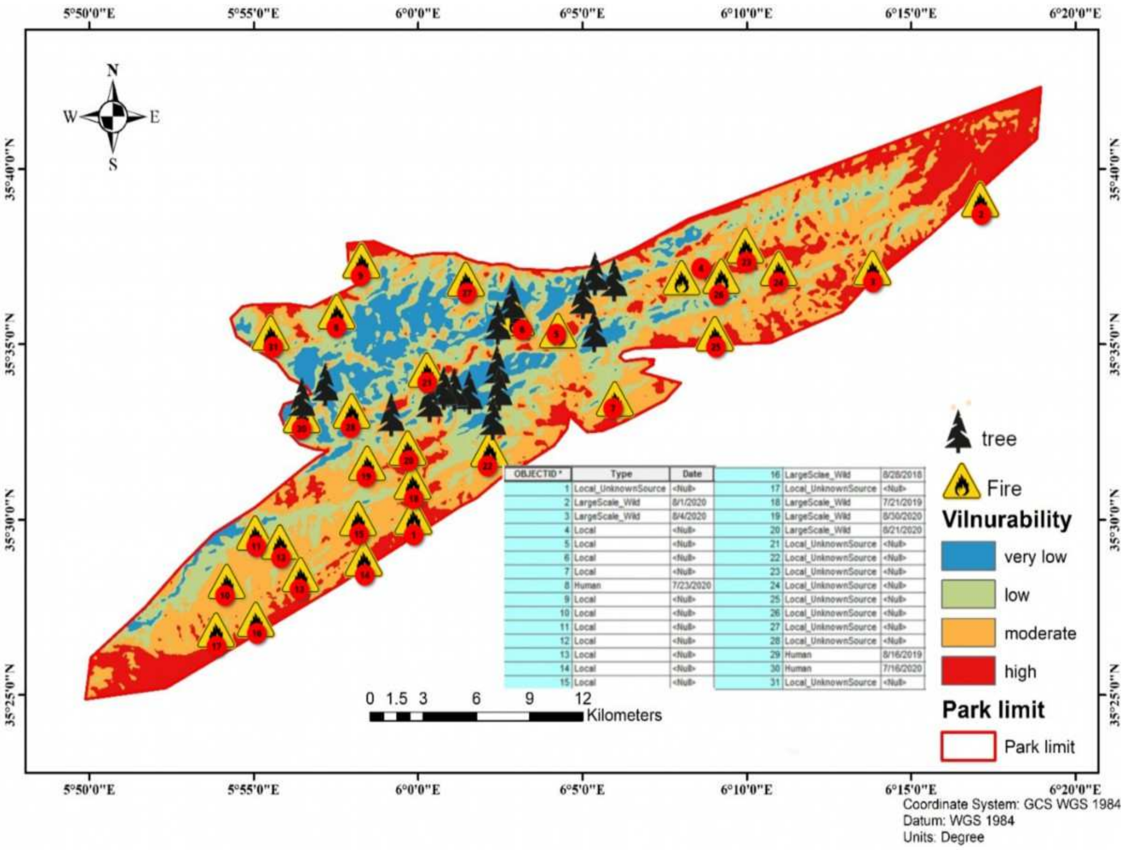

Fig. 5. Forest fire vulnerability map to in Belezma park

The precipitation in the spring contributes to the growth of seasonal plants, which increases the degree of probability of forest fire in summer, the same observations for NDWI and LST, whereas the measured values of LST in the wet period (April–May) recorded 15°C to 20°C as maximum which is not enough to trigger a fire; after that, the LST increased to 40°C in July and reached its maximum value 58°C by August. *Vice versa*, the NDWI values are higher in the April–May period (NDWI=0.7) due to the precipitation; on the other hand, in the July–August period, NDWI=-0.2, which helps in the forest fire. Figure 4 summarises the timeline and spatial vulnerability.

Validation

Fire location validation

In this research stage, we located all possible recorded fires in past years; this sort of data is not available officially. However, we selected every possible recorded fire from different sources, including the environment department, the forestry service, the local Algerian Civil Defence and the field in a way that does not affect the scientific approach of our result work. To validate data, every single recorded fire datum is re-checked from different sources, using Google image satellite and confirmed by local citizen reports and declarations (Fig. 2).

Dendrochronology validation

The attached map summarizes the location of unburned trees (a sample that was processed in the laboratory using dendrochronology, and the results were edited to serve the research paper) and the fire's locations with available attribute data (i.e., date, type – human or natural, scale), using the vulnerability as a base map, and this is for the sake of comparison between the outputs (i.e., unburned trees, fire's locations, and vulnerability) as follows:

1. low vulnerability area: represents areas with altitudes over 1900 m a.s.l. where the existence of old, non-burned trees and almost non-significant fires is recorded;
2. moderate vulnerability: it is noted that there are some limited fires in areas with an average altitude of approximately 1300–1900 m a.s.l.;

the recorded fires are widelyl dispersed throughout the study area, with significant impacts on the grassland and the absence of trees;
3. high-vulnerability areas: These are the lowest altitude areas in the study area. We highlighted the recording of frequent fires that, with the complete absence of trees.

Discussion

In the Mediterranean basin, many papers and research papers are focused on semi-arid areas such as Algeria. Comparing our proposed model with Fekir *et al.* (2022), involved seven factors being responsible for forest fire ignition (i.e., slope, elevation, aspect, road distances, proximity to settlements, farms distances, and NDVI), which are divided into three major criteria (natural topographical factors, vegetation, and human factors) and seven sub-criteria. Its model confirms that vegetation (fuel) has the most important factor with 52.5% of the total factors (i.e., represent NDVI) which is the same as our model (45.11%), secondly, the topography (slope, aspect, and elevation) weight was 14.2%, and human index (Roads, settlements and farms) are given a weight of 33.4%. Compared to Fekir *et al.* (2022) model, we add the LST index as a significant factor in the fire triangle, so our final model will include it. In addition, Curt *et al.* (2020) confirm our model, whereas most fires occur in summer after the high rainfalls from autumn to spring that promote fuel growth (timeline factor), since it is maximal in the high-fuelled (productive) oak forests of northern Algeria with high annual rainfall amount, whereas it is fuel-limited in the south by semi-arid conditions. The paper results compared with Fire Hotspots and Burned Areas (MODIS) where NBF is the number of fires per 3×3 km pixel, it found that NBF in the humid bioclimatic zone is 1.07 with NDVI index of 0.56, subhumid NBF=0.53, and NDVI=0.4, and in the subarid (as Belezma Park) the NBF=0.01 with NDVI=0.23.

Also, Boulghobra (2021) found that the dry climate, slope and aspect played an important role in forest fire within North Khenchela, Aurès region, Algeria which has the same climate conditions as Belezma Park.

Furthermore, Mokhtari (2018) and Rahmani, Benmassoud (2019) used Vegetation Type, NDVI, NDBI, topography, and distance to improve that Aures is a region of high forest fire risk. A full list of forest fire models in Algeria can be found in the work of Lebiar (2023).

Conclusions

Forest fire is triggered because of natural or anthropogenic factors (Barbache *et al.* 2018). In this paper, we use pre-tested factors to identify zones that are vulnerable to forest fires by analysing pre-fire circumstances using the AHP approach to monitor and forecast forest fires. Additionally, the validation was verified by first using historical fire records and then by using the dendrochronology method. Consequently, we have two categories of vulnerabilities:

- spatial vulnerability is based on physical and natural characteristics like elevation, altitudinal zonation, climate, temperature and vegetation type (frost and grassland);
- timeline vulnerability contains the dry period (June–September).

Several pre-fire conditions can be controlled using remote sensing; the first one is related to the fuel type, which can be mapped, like classical vegetation mapping, grasslands and fuel moisture. Second, the ignition of the spread of wildfires depends on weather conditions and high temperatures.

The incorporation of multi-criterion analysis methods such as AHP has significantly improved its efficacy. The obtained results were consistent with and closer to those obtained from other research papers and in on-field validation (Civil defence report), whereas most forest fires occur in the semi-arid region due to the presence of fuel (dry grassland) at less than 1000 m a.s.l. that grows in the spring (>350mm) and dry up in the summer to create a combustible fuel. As a second factor, in the summer, the temperature reaches +37°C, affecting the LST directly; for this, we make a statistical correlation between LST and station temperature. Also, we can confirm our prediction factors are the rainfall above 250 mm in May–April in the height vulnerability zone and the recorded temperature above (38°C) in the summer, which are pre-fire conditions.

This research paper contributes to forest fire revention programs in Algeria, especially in regions with similar natural, climatic and physical characteristics to Belezma Park. However, we should note that the proposed approach has not been tested (yet) in a large-scale area or another country's forest. Because Algeria is the largest country in Africa (over 2 million square kilo-metres) and has at least four main climate zones (arid, desert, steppe, Mediterranean), so too every region has its own climate and natural characteristics.

As a final word, we could propose the following recommendations:

- one of the best ways to stop a fire is to cut off the fuel (trees, grass, etc.);
- monitor local activities during the dry period, educate farmers and involve them efficiently in prevention programmes;
- during the fire season, observation stations should be set up at mountain peaks, supported by teams to intervene in real time;
- to create more efficient prediction tools, it is necessary to update information and adjust the proposed model by field experience and review from year to year.

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