EARTH SCIENCES
RESEARCH JOURNAL
Earth Sci. Res. J. Vol. 29, No. 4 (December, 2025): 485-496

UNIVERSIDAD
NACIONAL
DE COLOMBIA

ENVIRONMENTAL GEOLOGY

A Multi-Criteria GIS–AHP Framework for Wildfire Risk Assessment in Northern Algeria: Integrating Environmental and Anthropogenic Factors

Salim Dehimi[1]*, Malika Ouzir[1], Hanane Boutaghane[1], Halima Madani[1], Ibrahim Djouani[2]

1. City, Environment, Hydraulic and Sustainable Development Laboratory (VEHDD), Department of City and Urbanism, Institute of Urban Technology Management, University of Mohamed Boudiaf of M'Sila, University Scientific Pole, Bordj Bou Arreridj Road, M'Sila 28000, Algeria

2. City, Environment, Hydraulic and Sustainable Development Laboratory (VEHDD), Faculty of Civil Engineering and Architecture, Hassiba Ben Bouali University of Chlef, B.P. 78C, Ouled Fares, 02180, Chlef, Algeria.

*Corresponding author. Email: salim.dehimi@univ-msila.dz

ABSTRACT

Forest fires represent a significant and escalating environmental threat in Northern Algeria, impacting biodiversity, ecosystem services, regional climate stability, and socioeconomic systems. In recent years, the frequency and intensity of wildfires have increased due to prolonged droughts, rising temperatures, and intensified human activities. This study aims to model and assess wildfire risk by integrating Geographic Information Systems (GIS) with the Analytic Hierarchy Process (AHP), thereby providing a robust spatial decision-support framework for wildfire management. Ten environmental and anthropogenic factors were evaluated: wind speed, temperature, proximity to rivers, solar radiation, proximity to buildings, precipitation, Land Cover/Land Use (LCLU), elevation, proximity to roads, and the Normalized Difference Vegetation Index (NDVI). Each factor was assigned a weight using the AHP method to quantify its influence, and spatial overlay analysis in ArcGIS was applied to generate a comprehensive forest fire risk map. The study area was classified into three risk zones: low (34%), medium (46%), and high (20%), emphasizing the need for targeted interventions in vulnerable regions. Wind speed (0.244) and temperature (0.152) were identified as the most influential factors, while NDVI (0.037) and proximity to roads (0.054) had minimal impact. Despite its relatively low weight, NDVI remains ecologically significant due to its role in influencing vegetation density and fire propagation. The findings highlight the necessity for site-specific prevention strategies, enhanced vegetation management, and continuous monitoring. Furthermore, the study recommends extending the GIS–AHP framework to other regions of Algeria and integrating machine learning techniques to improve predictive accuracy and adaptive wildfire risk management.

Keywords: wildfire risk; GIS; AHP; Northern Algeria; fire risk; spatial modeling; environmental factors; fire risk modeling; climate change; risk mapping.

Marco SIG-AHP Multicriterio para la Evaluación del Riesgo de Incendios Forestales en el Norte de Argelia: Integración de Factores Ambientales y Antrópicos

RESUMEN

Los incendios forestales representan una amenaza ambiental significativa y en aumento en el norte de Argelia que afectan la biodiversidad, los servicios ecosistémicos, la estabilidad climática regional y los sistemas socioeconómicos. En los últimos años, la frecuencia y la intensidad de los incendios forestales han aumentado debido a las sequías prolongadas, el incremento de las temperaturas y la intensificación de las actividades humanas. Este estudio tiene como objetivo modelar y evaluar el riesgo de incendios forestales mediante la integración de los Sistemas de Información Geográfica (SIG) con el Proceso de Jerarquía Analítica (AHP), con el fin de proporcionar un marco robusto de apoyo espacial para la toma de decisiones en la gestión de incendios. Con este fin se evaluaron diez factores ambientales y antropogénicos: velocidad del viento, temperatura, proximidad a ríos, radiación solar, proximidad a edificaciones, precipitación, cobertura y uso del suelo (LCLU), altitud, proximidad a carreteras e índice de vegetación de diferencia normalizada (NDVI). A cada factor se le asignó un peso utilizando el método AHP para cuantificar su influencia, y se aplicó un análisis de superposición espacial en ArcGIS para generar un mapa integral de riesgo de incendios forestales. El área de estudio se clasificó en tres zonas de riesgo: bajo (34%), medio (46%) y alto (20%), con énfasis en la necesidad de intervenciones específicas en las regiones vulnerables. La velocidad del viento (0,244) y la temperatura (0,152) fueron identificadas como los factores más influyentes, mientras que el NDVI (0,037) y la proximidad a carreteras (0,054) tuvieron un impacto mínimo. A pesar de su peso relativamente bajo, el NDVI sigue siendo ecológicamente significativo porque influye en la densidad de la vegetación y la propagación del fuego. Los hallazgos resaltan la necesidad de estrategias de prevención específicas para cada sitio, una mejor gestión de la vegetación y una monitorización continua. Además, el estudio recomienda extender el marco SIG-AHP a otras regiones de Argelia e integrar técnicas de aprendizaje automático para mejorar la precisión predictiva y la gestión adaptativa del riesgo de incendios forestales.

Palabras clave: riesgo de incendio forestal; Sistema de Información Geográfica; Proceso de Jerarquía Analítica; norte de Argelia; riesgo de incendio; modelamiento espacial; factores ambientales; modelamiento del riesgo de incendio; cambio climático; mapeo de riesgos.

Record
Manuscript received: 02/04/2025
Accepted for publication: 04/11/2025

How to cite this item:
Dehimi, S., Ouzir, M., Boutaghane, H., Madani, H., & Djouani. I. (2025). A Multi-Criteria GIS–AHP Framework for Wildfire Risk Assessment in Northern Algeria: Integrating Environmental and Anthropogenic Factors. *Earth Sciences Research Journal,* 29(4), 485-496. https://doi.org/10.15446/esrj.v29n4.119634

1. Introduction

Wildfires have become a critical global environmental concern, particularly in Mediterranean regions such as Northern Algeria, where climatic stressors and anthropogenic pressures intersect. These fires contribute to severe biodiversity loss, soil degradation, and increased greenhouse gas emissions, thereby accelerating climate change (Flannigan et al., 2009; Wang et al., 2025). In Algeria, wildfire risk has intensified due to prolonged droughts, rising temperatures, and rapid land-use changes. Recent global studies have emphasized the evolving nature of wildfire regimes under the combined influence of climate variability and anthropogenic pressures (Shen et al., 2025). According to Global Forest Watch (2024), Algeria lost approximately 1.53 million hectares of natural forest in 2020, representing 0.66% of its land area. In 2024 alone, the country lost 4.820 thousand hectares of natural forest, corresponding to approximately 994 kilotons of CO_2 emissions.

Between 2001 and 2023, Algeria experienced a cumulative loss of 168 thousand hectares of tree cover due to fires, accounting for 74% of total forest loss during that period. The year 2017 was particularly devastating, with 41.7 thousand hectares lost to fires, which represented 91% of that year's total forest loss. These figures underscore the increasing hazard level and ecological impact of wildfires in the region.

Local assessments, such as those by Djabri et al. (2024) and Rahmani & Benmassoud (2019), have highlighted the vulnerability of Eastern Algerian forests, emphasizing the role of topography and human activity in fire propagation. Given the growing complexity of wildfire dynamics, spatially explicit modeling frameworks have become essential to support proactive risk assessment and mitigation. In response to these challenges, integrated modeling approaches have gained prominence, particularly those combining Geographic Information Systems (GIS) with Multi-Criteria Decision Analysis (MCDA) techniques like the Analytic Hierarchy Process (AHP). GIS facilitates spatial analysis and visualization, while AHP enables systematic weighting of diverse environmental and anthropogenic factors (Lahmar & Akakba, 2024). International applications of GIS–AHP frameworks have demonstrated high predictive accuracy in wildfire risk mapping (Kumar et al., 2025).

Despite its proven effectiveness, the GIS–AHP framework remains underutilized in Algeria, with limited applications in landslide risk (Seddiki & Dehimi, 2022) and a few localized fire studies (Bentekhici et al., 2020; Fekir et al., 2022). A comprehensive, region-specific wildfire risk model is urgently needed, especially for NORTHERN Algeria. This gap is further complicated by limited access to historical fire data, inconsistent data quality, and insufficient collaboration Among stakeholders.

This study, conducted in 2024, addresses these limitations by integrating GIS and AHP to develop a comprehensive wildfire risk map for Northern Algeria. Using spatial, climatic, and anthropogenic data from 2018 to 2023—including elevation, slope, temperature, wind speed (MODIS), land use, and urban expansion (Landsat) — the model assigns weights to each factor through AHP and applies spatial overlay techniques in ArcGIS to identify high-risk zones. The ultimate goal is to support decision-makers in implementing targeted prevention strategies, optimizing resource allocation, and enhancing long-term forest sustainability. Additionally, the study advocates extending the GIS–AHP framework to other Algerian regions and integrating machine learning algorithms to improve predictive accuracy and adaptive fire management.

2. Literature Review

Forest fires are increasingly recognized as a major environmental hazard, particularly in Mediterranean and semi-arid regions where climatic variability and human pressures converge. The growing frequency and hazard level of wildfires have prompted researchers to adopt advanced spatial and decision-support tools for risk assessment. Among these, the integration of Geographic Information Systems (GIS) with Multi-Criteria Decision Analysis (MCDA) techniques, especially the Analytic Hierarchy Process (AHP) has gained prominence due to its ability to model complex environmental interactions and support structured decision-making (Akay & Şahin, 2019).

Internationally, GIS–AHP frameworks have demonstrated high predictive accuracy. For instance, Ersoy et al. (2025) developed the Forest Fire Danger Assessment System (FoFiDAS) for Turkiye's Mediterranean coast, integrating GIS, AHP, and machine learning with an AUC > 0.91. In North Africa, El Mazi et al. (2024) applied GIS–AHP to model fire risk in Morocco's Rif forests, confirming regional applicability. In Iran, Nejatiyanpour et al. (2025) assessed fire vulnerability in the Hyrcanian forests using 30 biophysical and socioeconomic indicators, emphasizing the importance of integrating environmental and human dimensions.

In the Algerian context, applications remain limited. Soualah et al. (2024) used fuzzy logic and GIS to evaluate fire risk in the Djebel El Ouahch Massif, highlighting the influence of topography and proximity to settlements. However, few studies have systematically applied GIS–AHP to wildfire risk assessment in Algeria. This gap is particularly evident in northern regions, where fire frequency is high but spatial modeling remains underdeveloped.

Bibliometric analyses by Moazeni & Artemi (2025) reveal a significant rise in GIS–AHP applications in wildfire research over the past decade, reflecting a global shift toward spatially explicit, multi-criteria approaches. These methods offer robust tools for hazard mapping, scenario planning, and resource prioritization.

Bibliometric analyses by Moazeni & Artemi (2025) reveal a significant rise in GIS–AHP applications in wildfire research over the past decade, reflecting a global shift toward spatially explicit, multi-criteria approaches. These methods offer robust tools for hazard mapping, scenario planning, and resource prioritization.

3. Materials and methods

This study employs an integrated approach combining the Analytic Hierarchy Process (AHP) and Geographic Information Systems (GIS) to develop a forest fire risk map. This approach has been successfully applied in previous studies (e.g., Eskandari et al., 2015; Novo et al., 2020; Zakari et al., 2025; Abd El Karim & Awawdeh, 2020). The overall methodological framework is illustrated in the flowchart in Figure 1.

3.1 Study area

The study area includes eight wilayas in Northern Algeria, a region historically affected by frequent forest fires. Geographically, it is situated between latitudes 35° 50′ and 37° 50′ N, and longitudes 2° 30′ and 7° 30′ E. The total forested area is approximately 835,534 hectares. Dominant tree species include pine, wild olive, and oak. Pine trees are particularly vulnerable to fire due to their chemical composition and the presence of volatile oils, which facilitate ignition.

Between 2001 and 2023, Algeria lost 168,000 hectares of tree cover due to wildfires, with an additional 59,000 hectares lost to other causes. Notably, in 2017 alone, 41,700 hectares were destroyed by fire, representing 91% of that year's total tree cover loss (Global Forest Watch, 2024). This region was selected as a case study due to its high frequency of fire events and increased susceptibility. Human activities such as agriculture and grazing further exacerbate fire risk by increasing fuel availability. According to the Köppen climate classification, the area falls within the hot-summer Mediterranean climate zone (Beck et al., 2018), which contributes to prolonged dry seasons and elevated fire potential.

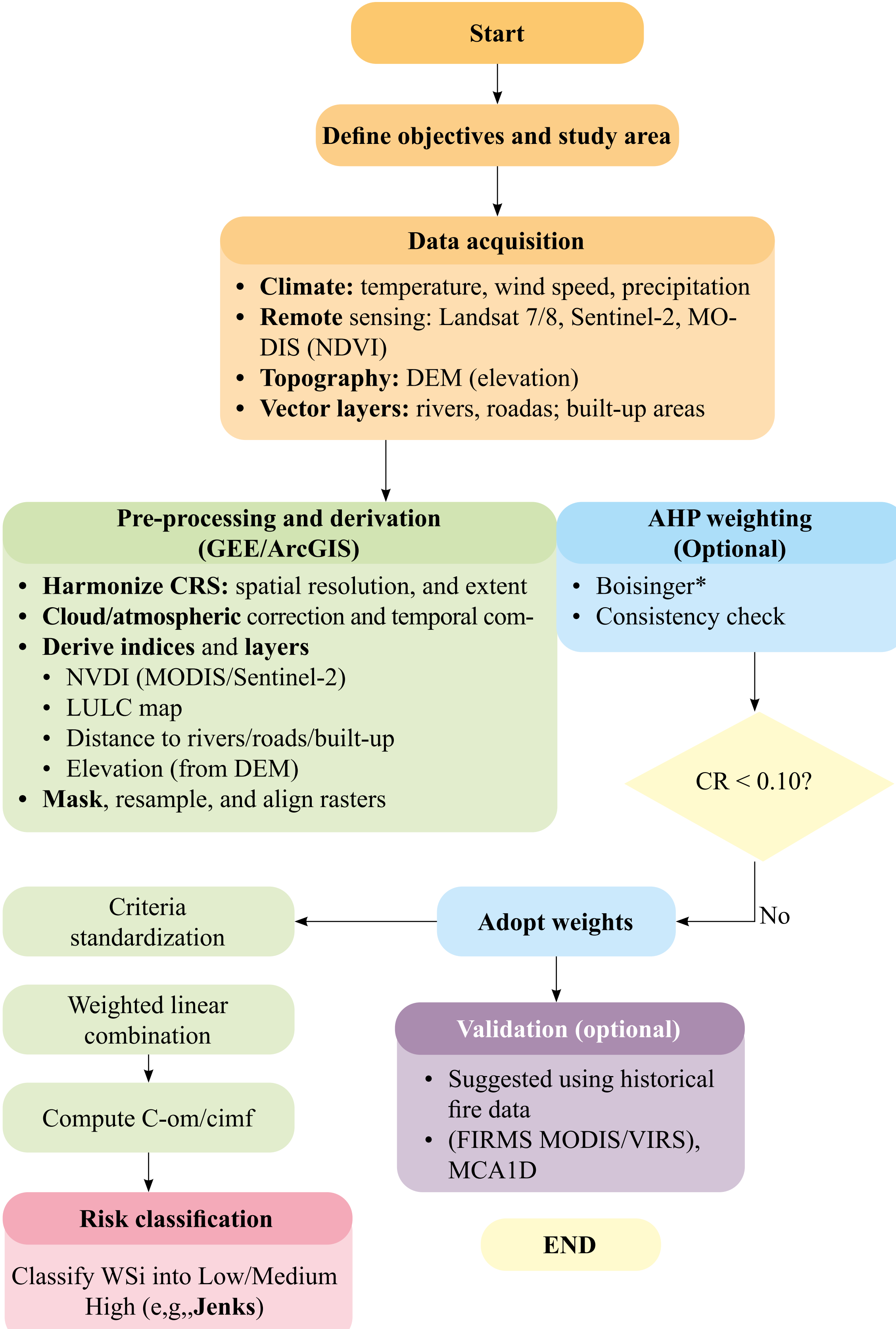


Figure 1. Flowchart of the AHP–GIS integration methodology for fire risk assessment

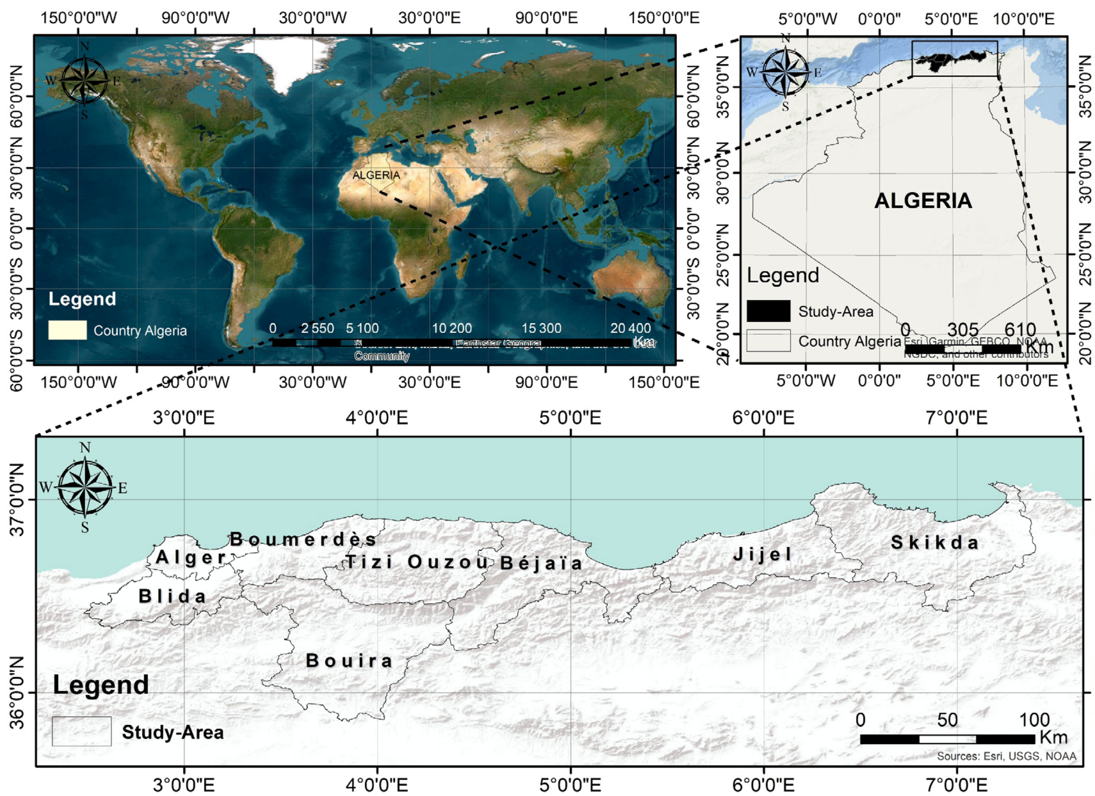


Figure 2. Study Area Location

3.2 Data Acquisition and Factor Selection

Ten key environmental and anthropogenic factors influencing wildfire risk were selected based on a comprehensive literature review and data availability. All datasets were processed into raster layers with a uniform spatial resolution of 30 meters. The selected factors include:

1. **Wind Speed:** Wind speed is a primary weather factor that greatly affects fire spread. Strong winds can carry burning embers to new areas, accelerating fire expansion and making it more difficult to control.
2. **Temperature:** High temperatures are an important factor contributing to the dryness of plants and reducing soil moisture, making the environment more conducive to fire spread (Flannigan, et al., 2009).
3. **Distance from rivers:** Rivers provide a natural source of moisture, helping to keep the soil and plants moist. Thus, the distance from rivers affects the likelihood of fire, as the probability is lower in areas near rivers compared to those far from them (Boyer et al., 2022).
4. **Solar Radiation:** Solar radiation contributes to the drying of plants, which increases their flammability. Areas exposed to high levels of solar radiation are more prone to fires as a result of increased drought (Sánchez, et al., 2021; Boyer et al., 2022).
5. **Distance from buildings:** Proximity to buildings reflects frequent human activity, such as smoking or starting fires, which increases the likelihood of fires. Therefore, areas near buildings are more vulnerable to forest fires (Mercer & Prestemon, 2005; Soualah et al., 2024).
6. **Precipitation:** Rain contributes to increasing soil and plant moisture, reducing the chance of fires. Areas with low precipitation are more prone to fires due to persistent drought (Beck et al., 2018).
7. **Land Cover Type and Land Use (LCLU):** Some land cover types, such as thickets and dense shrubs, are more susceptible to ignition compared to urban or agricultural areas. Therefore, land cover type analysis is an important factor in risk assessment (Chuvieco et al., 2016; Fekir et al., 2022).
8. **Elevation:** Altitude affects the distribution of temperature and humidity, which contributes to the varying nature of plant life. Some elevated and dry areas may be more prone to fires (Bao et al., 2024; KABOOSI & MAJIDI, 2018; Moghim & Mehrabi, 2024; Zhai et al., 2023; Zikiou et al., 2024).
9. **Distance from Roads:** Proximity to roads increases the likelihood of human activities that may lead to fires. The greater the distance from the roads, the less likely fires are to be caused by human activities.
10. **Normalized Difference Vegetation Index (NDVI):** NDVI is a basic criterion for measuring vegetation cover density. Low values of this indicator reflect a high percentage of dry plants, which are more susceptible to ignition (Fensholt & Proud, 2012).

These factors were combined to produce a wildfire risk map using an approach that integrates AHP and GIS. AHP was applied to determine the relative weights of each of the ten factors, where the factors are evaluated according to their relative importance and impact on risk. The AHP equation, which includes a pairwise comparison matrix, was used to determine the weights, providing accurate estimates of wildfire risk. ArcGIS was then used to combine data from AHP and GIS to create an integrated wildfire risk map.

The effectiveness of this approach has been tested in several previous studies, including one conducted in Hua Sai Province, Thailand, which experienced environmental stress due to frequent wildfire events. The results indicate that combining GIS and AHP can be a powerful tool to support fire risk management, making this approach suitable for application in our study. This research aims to: Model and map wildfire risk in Northern Algeria by integrating AHP and GIS techniques and leveraging various satellite data. In this context, the work relies on various data sources, including climate, terrain, and remote sensing data.

3.3 Data collection:

- **Climate Data:** Collected from national weather stations, this includes data such as average temperatures, wind speed, and precipitation over a decade.

- **Remote Sensing Data:** Topographic and botanical data were obtained using the following satellites:
  - » **Landsat 7 and Landsat 8:** Data from NASA were used to monitor changes in LCLU, uploaded and processed using Google Earth Engine.
  - » **Sentinel-2:** Data from the European Space Agency (ESA) allow for high-accuracy identification of vegetation patterns, up to 10 meters, and are highly effective for advanced applications such as machine learning-based burned area detection (Roodsarabi et al., 2024).
  - » **MODIS:** Data from NASA were used to provide the NDVI, which is useful in estimating plant density and identifying dry areas (Chen et al., 2024).
  - » **Data Processing:** Satellite imagery is processed to remove noise and correct for atmospheric reflections using Google Earth Engine tools. Geographic correction and consolidation of data into a unified spatiotemporal format are also performed to prepare it for analysis.

Topographic Data: This includes elevation and distance from rivers and roads, obtained from Digital Elevation Maps (DEM) from the U.S. Geological Survey (USGS) through Google Earth Engine.

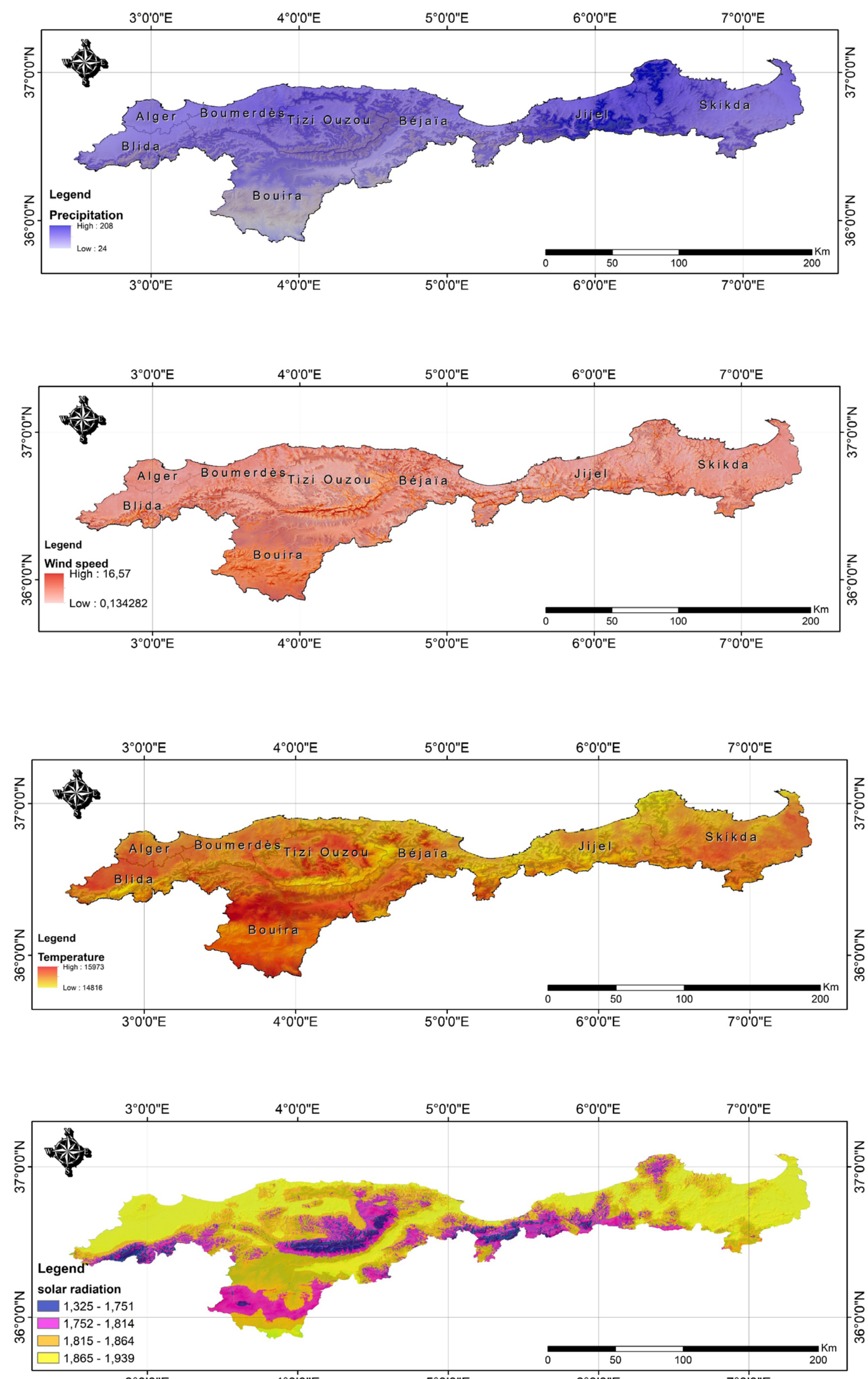


Figure 3. Precipitation (A), temperature (B), wind speed (C), solar radiation (D).

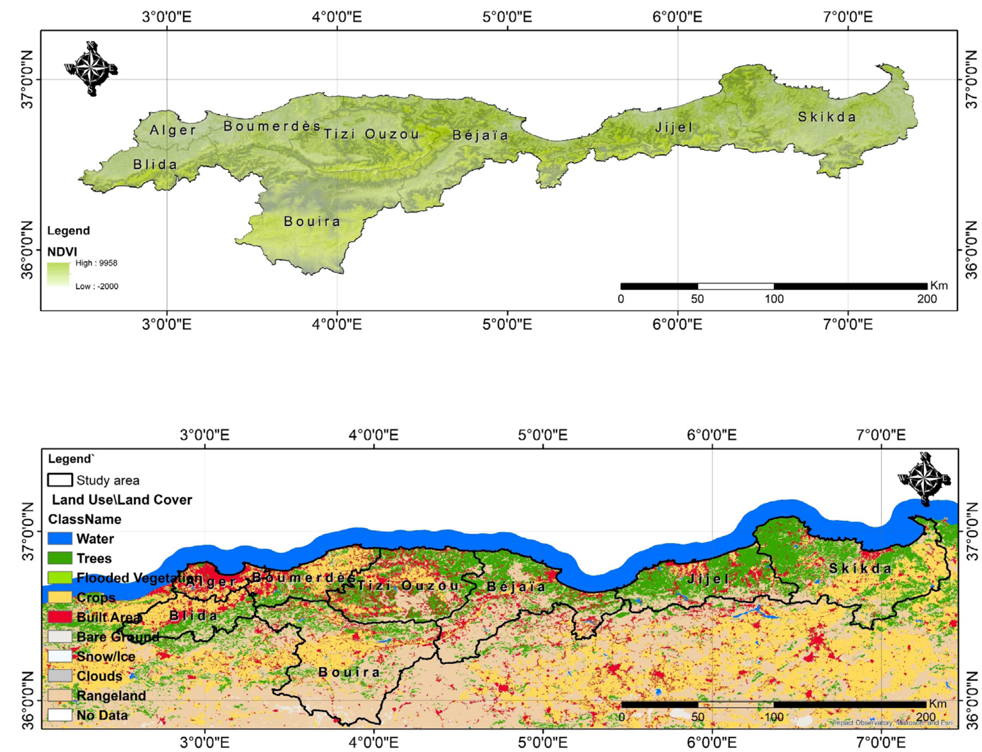


Figure 4. NDVI (E)and Land Cover Maps from MODIS and Sentinel-2 (F).

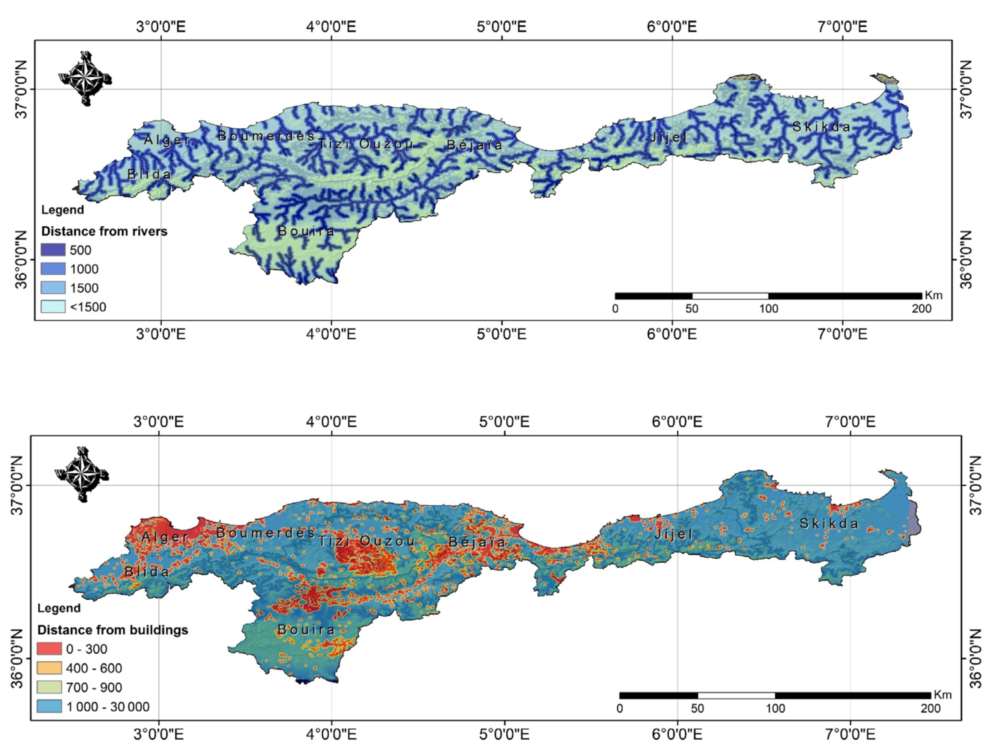
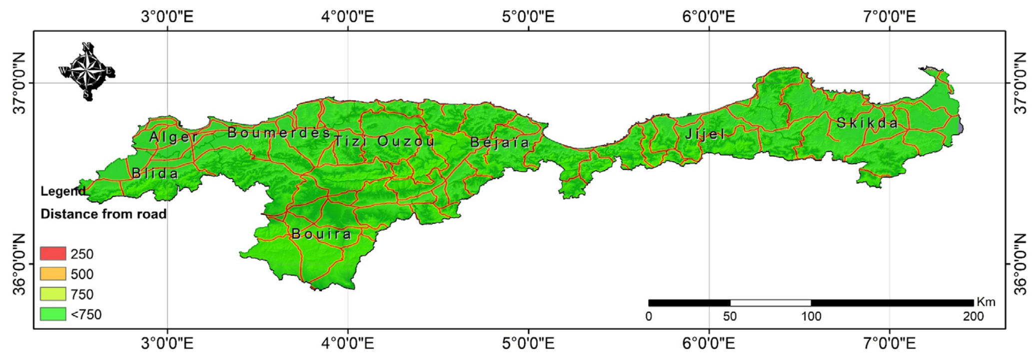


Figure 5. Distance from Rivers (G), Buildings (H), Elevation (I), and Roads (J).



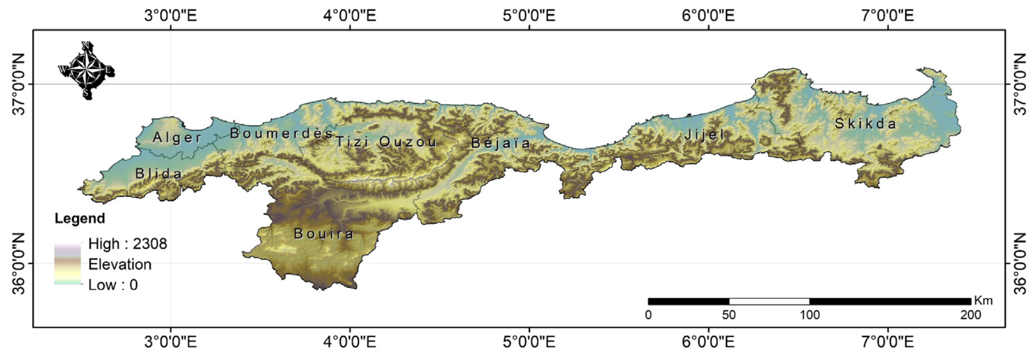


Figure 5. Distance from Rivers (G), Buildings (H), Elevation (I), and Roads (J).

3.4 Data Analysis:

Spatial analysis was conducted using ArcGIS to integrate and examine climatic, topographic, and vegetation-related datasets. The analysis involved several geoprocessing steps, including raster reclassification, weighted overlay, and spatial correlation assessment. Each factor was standardized to a common scale to ensure comparability, and AHP-derived weights were applied to generate a composite wildfire susceptibility index. This approach enabled the identification of spatial patterns and the delineation of zones with varying fire risk levels across the study area. The resulting maps provide a visual representation of fire-prone regions, supporting targeted mitigation strategies and resource allocation.

3.5 The Integrated GIS–AHP Framework

The integration of the Analytic Hierarchy Process (AHP) within a Geographic Information System (GIS) environment forms a robust Multi-Criteria Decision Analysis (MCDA) framework for spatial risk assessment (Akay & Erdoğan, 2017). This hybrid approach is particularly effective for addressing complex spatial decision-making problems, as it combines the structured weighting capabilities of AHP with the spatial visualization and analysis power of GIS.

In the Algerian context, this methodology has been successfully applied to various environmental and urban planning challenges, such as optimal landfill site selection (Magoura et al., 2023) and the evaluation of urban infrastructure efficiency (Djouani et al., 2022). By assigning relative weights to multiple criteria and integrating them into spatial layers, the GIS–AHP framework enables the generation of susceptibility maps that support informed decision-making. Its adaptability and precision make it a suitable tool for wildfire risk modeling, especially in regions with complex environmental and socioeconomic dynamics.

3.6 Analytic Hierarchy Process (AHP)

The Analytic Hierarchy Process (AHP) is a structured multi-criteria decision-making technique that facilitates the evaluation of complex problems by decomposing them into a hierarchy of criteria and sub-criteria. Among the various methods available for wildfire susceptibility modeling, including fuzzy logic and statistical approaches, AHP stands out for its ability to incorporate expert judgment in a systematic and quantifiable manner (Sinha et al., 2023; Saaty, 2008).

Construction of Pairwise Comparison Matrix

To prepare wildfire susceptibility maps, various methods such as fuzzy logic, statistical techniques, and AHP can be used. AHP is an indirect, qualitative, heuristic method widely adopted by researchers globally. The AHP method involves a matrix-based pairwise comparison of the influence of each factor. A detailed explanation of AHP is provided by (Saaty, 2008). Each factor is compared against another by assigning a relative importance value ranging from 1 to 9. These values and their definitions are listed in Table 1.

Table 1. Fundamental scale for pair-wise comparisons (Saaty, 1980)

Importance	Definition of Scale
1	Equal Importance
3	Moderate prevalence of one over another
5	Strong or essential prevalence
7	Very strong or demonstrated prevalence
9	Extremely high prevalence
2,4,6,8	Intermediate values

To establish a pair-wise comparison matrix (C), factors of each level and their weights are shown as: $c_1, c_2, \ldots, c_n$ and $w_1, w_2, \ldots, w_n$. The relative importance of c_i and c_j is shown as c_{ij}. The pair-wise comparison matrix of factors $c_1, c_2, \ldots, c_n$ as $C = [c_{ij}]$ is expressed as:

$$C = \begin{bmatrix} 1 & c_{12} & \cdots & c_{1n} \\ 1/c_{12} & 1 & \cdots & c_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/c_{1n} & 1/c_{2n} & \cdots & 1 \end{bmatrix}$$ eq. 01 (Dehimi, 2021.)

In this matrix, the element, $c_{ij} = 1/c_{ji}$ and thus, when i = j, $c_{ij}=1$.

In AHP, for checking consistency of matrix, consistency ratio is used, which depends on the number of parameters. The consistency ratio (CR) is obtained by comparing the consistency index (CI) with average random consistency index (RI). The consistency ratio is defined as:

$$CR = \frac{CI}{RI}$$ eq. 02 (Boutaghane, et al., 2022.)

The consistency index of a matrix of comparisons is given by Consistency Index (CI)

$$CI = \frac{\lambda_{max} - n}{n-1}$$ eq. 03 (Saaty, 1990.)

And the average random consistency index (R.I.) is derived from a sample of randomly generated reciprocal matrices using the scales 1/9, 1/8, …, 8 and 9 (see Table 2).

Table 2. Average random consistency index (R.I.) (Dehimi & Hadjab, 2019).

N (Number of factors)	1	2	3	4	5	6	7	8	9	10
RI	0.00	0.00	0.52	0.89	1.11	1.25	1.35	1.40	1.45	1.49

For these matrices, the consistency ratio (CR) must be less than 0.10 (Saaty, 2008).

GIS: Integration and Mapping

The Geographic Information System (GIS) component plays a pivotal role in spatial data processing and the integration of reclassified thematic layers with the weights derived from the Analytic Hierarchy Process (AHP) (Akay & Erdoğan, 2017). This integration enables the construction of a spatially explicit wildfire susceptibility model.

a. **Spatial Reclassification**

Each thematic layer, such as elevation, land cover/land use (LCLU), and temperature, was reclassified into a standardized scale (e.g., 1 to 5 or 1 to 9) using GIS tools. This step ensures that higher values correspond to greater fire susceptibility. The reclassification process was guided by expert knowledge and literature benchmarks, and implemented using the "Raster Reclassify" and "Raster Calculator" functions in ArcGIS (Pham et al., 2020).

b. **Weighted Overlay and Susceptibility Index (WSI)**

Following reclassification, the Weighted Overlay method was applied to integrate all criteria layers based on their respective AHP-derived weights. The final wildfire susceptibility score for each pixel was calculated using the following equation:

$$(iC + iW) = \sum_{i=1}^{n} \text{WSI}$$ eq. 04

Where:

- WSI: Wildfire Susceptibility Index.
- ***i***W: Weight of criterion ***i.***
- ***i***C: Reclassified value of criterion ***i.***
- ***n:*** The total number of criteria used in the model.

This spatial modeling approach facilitates the identification of high-risk zones, thereby supporting strategic planning and resource prioritization for wildfire prevention and mitigation (Pham et al., 2020).

3.7 Data modeling using AHP and GIS:

- **AHP Method for Determining Relative Weights:** AHP was applied to calculate the relative weights of the ten selected factors through the following steps:
  - » A pairwise comparison matrix was constructed using Saaty's fundamental scale (1–9), where 1 indicates equal importance and 9 indicates extreme importance of one factor over another (Table 1 provides the scale).
  - » The values for these pairwise comparisons were primarily informed by a systematic literature review of recent Q1 publications focusing on wildfire driving factors in Mediterranean ecosystems, and were further refined through expert elicitation involving five specialists in forest fire management to ensure regional relevance.
- **Consistency check:** Relative weights were derived from the principal eigenvector of the comparison matrix. The Consistency Ratio (CR) was calculated as CR = 0.086, using the Random Index (RI = 1.49 for n = 10; Saaty, 1980). This value confirms that the pairwise comparisons were within the acceptable threshold (CR < 0.1), ensuring logical consistency of judgments.
- **GIS Integration:** After determining the weights, the spatial datasets were integrated in ArcGIS using weighted overlay analysis. The steps include:
  - » **Spatial Overlay:** Various factors are combined with Spatial Overlay tools to identify high, medium and low risk areas.
  - » The resulting composite map was symbolized with graduated color anges, clearly distinguishing low, medium, and high fire risk zones.

4. Results and discussion

Environmental data influencing forest fire risk in Northern Algeria were collected and analyzed. The results reveal varying degrees of correlation between the selected factors and the fire hazard level. Similar GIS–AHP-based assessments have been conducted in Central India, confirming the method's robustness (Khan et al., 2024). A detailed summary is presented in Table 3.

Wind Speed: The results showed that wind speed is the most influential factor in the outbreak of fires, with the highest relative weight (0.244). Increased wind speed leads to a rapid spread of fire, which increases the risk.

Temperature: Temperature came in second (0.152), indicating its crucial role in creating conditions for fires. High temperatures are directly related to an increased likelihood of fires, especially in dry areas.

Distance from rivers: The results showed that distance from rivers (0.131) also plays an important role. Areas near rivers may be less prone to fires due to the presence of moisture, which reduces the risk of ignition.

Solar radiation: Solar radiation obtained a relative weight of 0.127, which indicates its effect on heating the environment and increasing drought, thus increasing the likelihood of fires.

Distance from buildings: The results showed that distance from buildings (0.079) also affects the spread of fires, as the proximity of buildings can lead to increased risk due to flammable materials.

Precipitation: The relative weight of precipitation was 0.066, which indicates that it is an influencing factor, as a lack of rain increases drought and the likelihood of fires.

Land Cover/Land Use (LCLU): Although LCLU had a lower weight (0.059), it remains significant, as land-use patterns can affect how fires ignite and spread.

Elevation: The altitude has a relative weight (0.050), indicating that areas of different heights may suffer from different fire hazards.

Distance from Roads: Distance from roads had the least impact (0.054), but still suggests that proximity to roads may increase the risk of wildfires due to human activity.

Normalized Difference Vegetation Index (NDVI): NDVI (0.037) was the least influential factor, suggesting that while vegetation cover is important, other climatic and topographic variables play a more dominant role in this context.

Based on the analysis carried out using GIS and AHP, and the results of the spatial modeling map of forest fires, the regions of Northern Algeria were classified into three categories based on the hazard level of potential fires and the areas affected by them, as shown in Table 4.

Table 3. AHP comparison between standards

Standard	Wind Speed	Temperature	Distance from Rivers	Solar Radiation	Distance from Buildings	Precipitation	LCLU	Elevation	Distance from Roads	NDVI	Relative weight	Rank
Wind Speed	1	3	4	2	4	3	3	3	3	7	0.244	1
Temperature	1/3	1	1	3	3	2	3	3	2	5	0.152	2
Distance from Rivers	1/4	1	1	2	3	2	3	2	2	4	0.131	3
Solar Radiation	1/2	1/3	1/2	1	3	4	3	2	3	3	0.127	4
Distance from Buildings	1/4	1/3	1/3	1/3	1	2	3	2	2	2	0.079	5
Precipitation	1/3	1/2	1/2	1/4	1/2	1	2	3	1	1	0.066	6
LCLU	1/3	1/3	1/3	1/3	1/3	1/2	1	3	2	1	0.059	7
Elevation	1/3	1/3	1/2	1/2	1/2	1/3	1/3	1	2	1	0.050	9
Distance from Roads	1/3	1/2	1/2	1/3	1/2	1	1/2	1/2	1	3	0.054	8
NDVI	1/7	1/5	1/4	1/3	1/2	1	1	1	1/3	1	0.037	10
λmax=11.158 CI= 0.128 RI= 1.49 CR = 0.086												

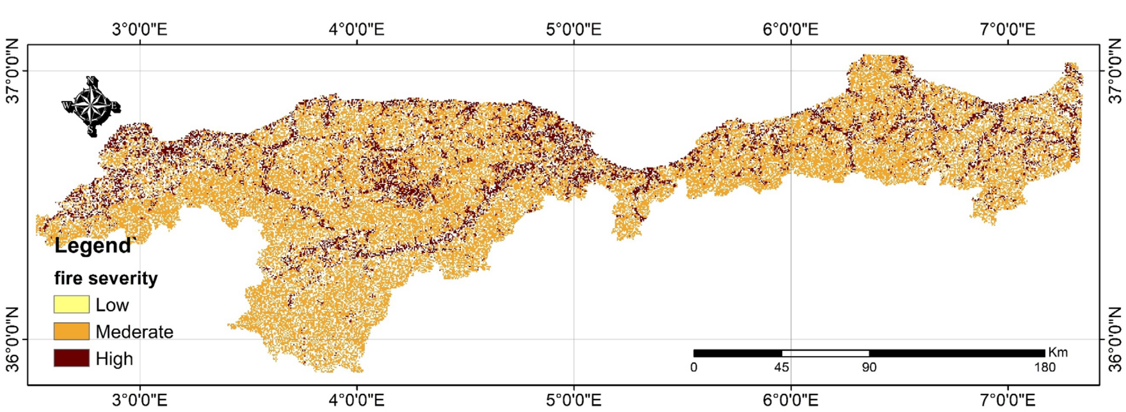


Figure 6. Wildfire Hazard/Risk Map in Northern Algeria

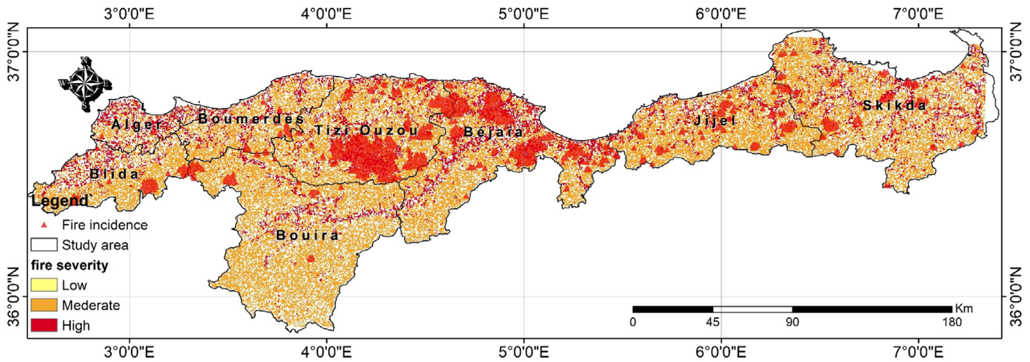


Figure 7. Fire Risk Zones and Fire Incidence Map

Table 4. Classification of Forest Fire Hazard and Risk Levels

Fire Hazard/Risk Level	Fire area in hectares	Percentage
High	421,430.26	20%
Medium	961,650.08	46%
Low	708,558.97	34%

Analysis of Fire Hazard Levels and Distribution:

By reading the results of Table 4, we find that:

» The medium hazard/risk level is the most widespread, covering 961,650.08 hectares and representing approximately 46% of the total area. In contrast, low and high hazard/risk areas account for smaller proportions. This indicates that most wildfire-prone zones are characterized by moderate fire conditions, highlighting the need for targeted preventive measures in these areas to reduce the likelihood of escalation into severe fires.

» Low hazard/risk areas rank second, accounting for 34% of the total area (708,558.97 hectares). This suggests that although a large portion of the territory is at low risk, preventive actions remain essential to avoid potential fire aggravation under unfavorable conditions.

» The high hazard/risk level, representing 20% of the total area (421,430.26 hectares), poses a significant challenge. These areas require enhanced protection measures, including resource allocation, continuous monitoring, and rapid response strategies to prevent the spread and intensification of wildfires.

4.1 Interpreting Forest Fire Modeling Results

The resulting fire risk map highlights zones with varying levels of susceptibility, providing practical insights for decision-makers. It can guide the prioritization of fuel management, the establishment of buffer zones around settlements, and the implementation of early warning systems based on meteorological thresholds.

The relative weights indicate that wind speed (0.244) and temperature (0.152) are the most critical factors influencing fire risk, reflecting the dominant role of climatic variables. By contrast, NDVI (0.037) and distance from roads (0.054) were the least influential, suggesting that vegetation variation and accessibility play secondary roles in this region.

The GIS–AHP vulnerability map provides actionable guidance for fire management in Northern Algeria. The predominant influence of wind speed and temperature suggests that prevention policies should be adapted to climatic forecasts to allocate resources efficiently and dynamically. Moreover, the role of land cover and land use (LCLU) highlights the necessity of zoning regulations and fuel management programs (e.g., prescribed burning, thinning) in high-risk zones. By contrast, the minimal impact of NDVI and distance from roads indicates that investments should focus on vegetation management and early warning systems rather than road infrastructure. Such targeted actions support a transition from reactive suppression to proactive risk mitigation.

These findings align with recent regional research emphasizing the utility of AHP–GIS frameworks for continuous fire risk monitoring in semi-arid Mediterranean contexts (Lahmar & Akakba, 2024; Bentekhici et al., 2020). They further reinforce the broader trend toward proactive, data-driven fire management policies tailored to evolving climatic and spatial conditions.

Areas with High Fire Hazard/Risk (Red)

- **Geographical Location:** Highly concentrated in northeastern Algeria, especially in the Wilayas of Tizi Ouzou, Bejaia, Jijel, and Skikda.
- **Hazards:** These areas indicate a high risk of fire, and these risks can be attributed to several factors:
  » **Dry Vegetation:** The presence of a high density of dry plants provides easily flammable fuel.
  » **Mountainous Terrain:** The nature of the mountainous area contributes to the rapid spread of fire.
  » **Human Activity:** Proximity to human settlements increases the likelihood of fires resulting from human activities, such as starting fires and discarding cigarette butts.

Areas with Medium Fire Hazard/Risk (Orange)

- **Geographical Location:** These areas cover a large part of Northern Algeria and include most of the study area.
- **Hazards:** Indicates a medium probability of wildfires:
  » **Mixed Vegetation:** These areas contain a mix of plants, including both dry and wet types.
  » **Topographic** Diversity: These areas vary in terms of terrain, making it more difficult to predict fire behavior.

Areas with Low Fire Hazard/Risk (Yellow)

- **Geographical Location:** Mainly located in the western part of Northern Algeria, and the Wilaya of Blida.
- **Risk:** Indicates a lower likelihood of fires, due to:
  » **Proximity to water sources:** The presence of these areas near plains and valleys contributes to higher humidity.
  » **Lack of vegetation:** Vegetation in these areas can be less dense, reducing the amount of available fuel.

5. Conclusion

This study presents a comprehensive analysis of forest fire risk in Northern Algeria by integrating Geographic Information Systems (GIS) and the Analytic Hierarchy Process (AHP) within a multi-criteria decision-making framework. It enhances the understanding of wildfire dynamics and supports local authorities in identifying high-risk areas. Furthermore, it contributes to the development of targeted strategies for risk mitigation and improved future fire management.

The results clearly demonstrate the importance of targeted prevention strategies and continuous monitoring in high-risk zones. The findings underscore the necessity of strengthening collaboration between authorities and local communities, as well as promoting public engagement in preventive measures and early response initiatives. Based on the findings, this study recommends prioritizing preventive efforts in the identified high-risk zones.

Nevertheless, limitations such as data availability and the inherent subjectivity of the AHP method should be acknowledged. Future studies are encouraged to validate the model in other regions of Algeria and to explore the integration of machine learning algorithms to enhance predictive performance. Although robust, the AHP framework relies heavily on expert judgment, introducing subjectivity into weight assignment. Moreover, the model is static and does not account for the dynamic nature of fire behavior.

To address these limitations, future research should incorporate machine learning algorithms to enhance predictive performance. Recent comparative analyses have demonstrated the superior performance of models like Random Forest (RF) and CART for susceptibility mapping, with RF often providing more nuanced and accurate risk classification in ecologically sensitive areas (Sheriff et al., 2025). Implementing these models will enhance predictive accuracy and broaden the applicability of the framework to other regions in Algeria. Furthermore, such techniques are versatile and have proven effective in post-event analysis, such as using Sentinel-2 imagery for precise burned area detection (Roodsarabi et al., 2024). This data-driven approach should be supported by advanced monitoring systems, including satellite imagery and surveillance technologies, to enable proactive fire management (Novkovic et al., 2024; Guiop-Servan et al. 2025; Pallikarakis & Konstantopoulou, 2024; Zagalikis, 2023). Ultimately, integrating these advanced technologies into policy is essential for effective wildfire risk management in the era of climate change (Synolakis & Karagiannis, 2024).

Implementing the findings of this study in future forest fire management policies in Algeria could significantly reduce fire risk and contribute to the preservation of forests and natural resources.

References

Abd El Karim, A., & Awawdeh, M. M. (2020). Integrating GIS accessibility and location-allocation models with multicriteria decision analysis for evaluating quality of life in Buraidah city, KSA. *Sustainability*, 12(4), 1412. https://doi.org/10.3390/su12041412

Akay, A. E., & Erdoğan, A. (2017). GIS-based multi-criteria decision analysis for forest fire risk mapping in Turkey. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* 25–30. https://doi.org/10.5194/isprs-annals-IV-4-W4-25-2017

Akay, A. E., & Şahin, H. (2019). Forest Fire Risk Mapping by using GIS Techniques and AHP Method: A Case Study in Bodrum (Turkey). *European Journal of Forest Engineering,* 5(1), 25-35. https://doi.org/10.33904/ejfe.579075

Bao, M., Zhang, Y., Liu, H., Wang, J., & Chen, L. (2024). Research trends in wildland fire prediction amidst climate change: A comprehensive bibliometric analysis. *Fire*, 7(7), 1197. https://doi.org/10.3390/fire15071197

Beck, H. E., Zimmermann, N. E., McVicar, T. R., Vergopolan, N., Berg, A., & Wood, E. F. (2018). Present and future Köppen-Geiger climate classification maps at 1-km resolution. *Scientific Data,* 5(1), 180214. https://doi.org/10.1038/sdata.2018.214

Bentekhici, N., Bellal, S., & Zegrar, A. (2020). Contribution of remote sensing and GIS to mapping the fire risk of Mediterranean forest: Case of the forest massif of Tlemcen, North-West Algeria. *Natural Hazards*, 104(1), 811–831. https://doi.org/10.1007/s11069-020-04191-6

Boutaghane, H., Boudjemaa, K., & Dehimi, S. (2022). Geospatial modelling of the future urban expansion map using AHP and GIS in Bordj Bou Arreridj, Algeria. *Journal of Degraded and Mining Lands Management,* 9(4), 3645-3656. https://doi.org/10.15243/jdmlm.2022.094.3733

Boyer, E. W., Wagenbrenner, J. W., & Zhang, L. (2022). Wildfire and hydrological processes. *Hydrological Processes*, 36(7), e14640. https://doi.org/10.1002/hyp.14640

Chen, X., Zhang, Y., Wang, S., Zhao, Z., Liu, C., & Wen, J. (2024). Comparative study of machine learning methods for mapping forest fire areas using Sentinel-1B and 2A imagery. *Frontiers in Remote Sensing*, 5. https://doi.org/10.3389/frsen.2024.1446641

Chuvieco, E., Yue, C., Heil, A., Mouillot, F., Alonso-Canas, I., Padilla, M., Pereira, J. M., Oom, D., & Tansey, K. (2016). A new global burned area product for climate assessment of fire impacts. *Global Ecology and Biogeography*, 25(5), 619–629. https://doi.org/10.1111/geb.12440

Dehimi, S., & Hadjab, M. (2019). Evaluating the quality of life in urban area by using the Delphi Method: A case study of M'Sila City, Algeria. *Romanian Journal of Geography,* 63(2), 193–202. Available at: https://rjgeo.ro/vol63/2019/art5 (Accessed: November, 2024)

Dehimi, S. (2021). The use of new techniques in spatial modeling and analysis of urban quality of life: Multiple-criteria decision analysis and GIS. *GeoJournal of Tourism and Geosites*, 35(2), 355–363. https://doi.org/10.30892/gtg.35213-659

Dehimi, S., Seddiki, A., Hadjab, M., Allal, A., & Bediar, A. (2022). Urban upgrading scenarios, an approach to urban development and the well-being of the population. *Acta Geographica Universitatis Comenianae,* 66(1), 25–46. Available at: https://actageographica.sk/archive/2022-vol66-iss1/ (Accessed: November 2024)

Djabri, A. D., Bouhata, R., Guellouh, S., & Bensekhria, A. (2024). Wildfire vulnerability assessment and mapping using remote sensing, GIS and weighted overlay method in the Eastern Aures in Khenchela, Algeria. *Geoadria*. https://doi.org/10.15291/geoadria.4218

Djouani, I., Dehimi, S., & Redjem, A. (2022). Evaluation of the efficiency and quality of the tram route of Setif city, Algeria: Combining AHP and GIS approaches. *Journal of the Geographical Institute "Jovan Cvijic", SASA,* 72(1), 85–102. https://doi.org/10.2298/IJGI2201085D

El Mazi, M., Boutallaka, M., Saber, E., Chanyour, Y., & Bouhlal, A. (2024). Forest fire risk modeling in Mediterranean forests using GIS and AHP method: Case of the high Rif Forest massif (Morocco). *Euro-Mediterranean Journal for Environmental Integration,* 9, 1109–1123. https://doi.org/10.1007/s41207-024-00591-3

Ersoy, İ., Ünsal, E., & Gürsoy, Ö. (2025). A multi-criteria forest fire danger assessment system on GIS using literature-based model and analytical hierarchy process model for Mediterranean coast of Manavgat, Türkiye. *Sustainability*, 17(5), 1971. https://doi.org/10.3390/su17051971

Eskandari, S., & Chuvieco, E. (2015). Fire danger assessment in Iran based on geospatial information. *International Journal of Applied Earth Observation and Geoinformation*, 42, 57-64. https://doi.org/10.1016/j.jag.2015.05.006

Fekir, Y., Hamadouche, M. A., & Anteur, D. (2022). Integrated approach for the assessment of forest fire risk and burn severity mapping using GIS, AHP method, and Google Earth Engine in Western Algeria. *Euro-Mediterranean Journal for Environmental Integration,* 7(4), 531–544. https://doi.org/10.1007/s41207-022-00338-y

Fensholt, R., & Proud, S. R. (2012). Evaluation of Earth Observation based global long term vegetation trends — Comparing GIMMS and MODIS global NDVI time series. *Remote Sensing of Environment,* 119, 131–147. https://doi.org/10.1016/j.rse.2011.12.015

Flannigan, M., Stocks, B., Turetsky, M., & Wotton, M. (2009). Impacts of climate change on fire activity and fire management in the circumboreal forest. *Global Change Biology*, 15(3), 549–560. https://doi.org/10.1111/j.1365-2486.2008.01660.x

Global forest monitoring. (2024). Algeria fires painting, Global Forest Watch. https://www.globalforestwatch.org/dashboards/country/DZA/?category=fires (last accessed November, 2024)

Guiop-Servan, R. E., Martinez, J., Lopez, M., & Torres, A. (2025). Remote sensing for wildfire mapping: A comprehensive review of advances, platforms, and algorithms. *Fire*, 8(8), 316. https://doi.org/10.3390/fire8080316

Kabosi, K., & Majidi, O. (2018). Zoning of forest fire risk based on environment, human and land factors (case study: Golestan Province, Iran). *Asian Journal of Water, Environment and Pollution*, 15(2), 99-106. https://doi.org/10.3233/AJW-180022

Khan, M. A., Gupta, A., Sharma, P., & Roy, A. (2024). Investigation of wildfire risk and its mapping using GIS-integrated AHP method: A case study over Hoshangabad Forest Division in Central India. *Environment, Development and Sustainability.* https://doi.org/10.1007/s10668-024-05225-w

Kumar, R., Singh, A., Patel, V., & Mehta, S. (2025). Forest fire consequences under the influence of changing climate: A systematic review with bibliometric analysis in the context of sustainable development goals. *Discover Sustainability*, 6, Article 541. https://doi.org/10.1007/s43621-025-00801-0

Lahmar, B., & Akakba, A. (2024). Forest fire detection based on earlier pre-fire conditions using analysis hierarchic process (AHP) in a semi-arid climate: a case study of Belezma National Park, Algeria. *Acta Geographica Lodziensia*, 114, 35–48. https://doi.org/10.26485/AGL/2024/114/3

Magoura, A., Dehimi, S., & Redjem, A. (2023). A GIS-based multi-criteria evaluation of landfill site selection in the region of Hodna, Algeria. *Journal of Degraded and Mining Lands Management*, 10(4), 4709-4720. https://doi.org/10.15243/jdmlm.2023.104.4709

Mercer, D. E. & Prestemon, J. P. (2005). Comparing production function models for wildfire risk analysis in the wildland–urban interface. *Forest Policy and Economics,* 7(5), 782-795. https://doi.org/10.1016/j.forpol.2005.03.003

Moazeni-Noghondar, S., & Cerdà, A. (2025). A comprehensive bibliometric review of forest fires in Iran. *Environmental Development,* 54, 101160. https://doi.org/10.1016/j.envdev.2025.101160

Moghim, S., & Mehrabi, M. (2024). Wildfire assessment using machine learning algorithms in different regions. *Fire Ecology,* 20, Article 104. https://doi.org/10.1186/s42408-024-00335-2

Nejatiyanpour, E., Ghorbanzadeh, O., Strobl, J., Yousefpour, R., Daneshvar Kakhki, M., Amirnejad, H., Gholamnia, K., & Sabouhi Sabouni, M. (2025). Assessing Hyrcanian Forest fire vulnerability: Socioeconomic and environmental perspectives. *Journal of Forestry Research*, 36, 35. https://doi.org/10.1007/s11676-025-01832-z

Novo, A., Fariñas-Álvarez, N., Martínez-Sánchez, J., González-Jorge, H., Fernández-Alonso, J. M., & Lorenzo, H. (2020). Mapping forest fire risk—A case study in Galicia (Spain). *Remote Sensing,* 12(22), 3705. https://doi.org/10.3390/rs12223705

Pallikarakis, A., & Konstantopoulou, F. (2024). Multi-criteria wildfire risk hazard assessment in GIS environment: Projection for the future and impact on RES projects. *Journal of Geoscience and Environment Protection,* 12(5), 242-265. https://doi.org/10.4236/gep.2024.125014

Pham, B. T., Prakash, I., Singh, S. K., Shirzadi, A., & Tien Bui, D. (2020). A comparative study of multi-criteria decision-making methods for landslide susceptibility mapping using GIS. *Geocarto International,* 35(3), 341–372. https://doi.org/10.1080/10106049.2018.1520924

Rahmani, S., & Benmassoud, H. (2019). Modeling and mapping forest fire risk in the region of Aures (Algeria). *Geoadria*, 24(2). https://doi.org/10.15291/geoadria.2846

Roodsarabi, Z., Farhadi, H., Ebadi, H., & Kiani, A. (2025). Machine learning-based burned area detection using Sentinel-2 imagery and spectral indices. *Environmental Monitoring and Assessment*, 197, Article 905. https://doi.org/10.1007/s10661-025-14332-8

Saaty, T. L. (1980). *The Analytic Hierarchy Process.* McGraw-Hill. https://link.springer.com/chapter/10.1007/978-1-4613-2805-6_12

Saaty, T. L. (1990). Decision making for leaders: The analytic hierarchy process for decisions in a complex world. *RWS Publications*. https://doi.org/10.1016/0377-2217(90)90057-I

Saaty, T. L. (2008). Decision making with the analytic hierarchy process. *International Journal of Services Sciences,* 1(1), 83–98. https://www.rafikulislam.com/uploads/resourses/197245512559a37aadea6d.pdf

Sánchez, J. R., Manzanera, J. A., & Palacios, J. J. (2021). The role of solar radiation in forest fire occurrence: A meta-analysis. *Forest Ecology and Management,* 494, 119330. https://doi.org/10.1016/j.foreco.2021.119330

Seddiki, A., & Dehimi, S. (2022). Using GIS combined with AHP for mapping landslide susceptibility in Mila, Algeria. *International Journal of Design & Nature and Ecodynamics,* 17(2), 169–175. https://doi.org/10.18280/ijdne.170202

Shen, Z., Liu, Y., Wang, H., & Zhang, T. (2025). Novel wildfire regimes under climate change and human activity: Patterns, driving mechanisms and ecological impacts. *Philosophical Transactions of the Royal Society B,* 380, 20230446. https://doi.org/10.1098/rstb.2023.0446

Sheriff, R., Patel, N., & Ghosh, S. (2025). Machine learning-based forest fire susceptibility mapping using random forest and CART models. *Rangeland Ecology & Management,* 102(1), 96–109. https://doi.org/10.1016/j.rama.2025.06.004

Sinha, A., Verma, R., & Joshi, M. (2023). Wildfire risk zone mapping in contrasting climatic conditions: An approach employing AHP and F-AHP models. *Fire*, 6(2), 44. https://doi.org/10.3390/fire6020044

Soualah, L., Abdelhafid, B., & Haroun, C. (2024). Hoping the best, expecting the worst: Forecasting Forest fire risk in Algeria using fuzzy logic and GIS. *Trees, Forests and People*, 17, 100614. https://doi.org/10.1016/j.tfp.2024.100614

Synolakis, C. E. & Karagiannis, G. M. (2024). Wildfire risk management in the era of climate change. PNAS Nexus, 3(5), pgae151. https://doi.org/10.1093/pnasnexus/pgae151

Wang, D., Yang, S., Yao, Q., Zhang, W., Liu, Z., Pei, Y., & Zuo, F. (2025). Fire carbon cycle research is on the rise: A bibliometric analysis from 1989–2023. *Fire*, 8(1), 4. https://doi.org/10.3390/fire8010004

Zagalikis, G. (2023). Remote sensing and GIS applications in wildfires. In Geographic Information Systems – Data Science Approach. *IntechOpen*. https://doi.org/10.5772/intechopen.111616

Zakari, R. Y., Malik, O. A., & Ong, W.-H. (2025). Machine learning-driven wildfire susceptibility mapping in New South Wales, Australia using remote sensing and explainable artificial intelligence. *Natural Hazards,* 121, 15331–15357. https://doi.org/10.1007/s11069-025-07395-w

Zhai, J., Ning, Z., Dahal, R., & Yang, S. (2023). Wildfire susceptibility of land use and topographic features in the western United States: Implications for the landscape management. *Forests*, 14(4), 807. https://doi.org/10.3390/f14040807

Zikiou, N., Rushmeier, H., Capel, M. I., Kandakji, T., Rios, N., & Lahdir, M. (2024). Remote sensing and machine learning for accurate fire severity mapping in Northern Algeria. *Remote Sensing,* 16(9), 1517. https://doi.org/10.3390/rs16091517