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Synergy Between Geomatics and Artificial Intelligence for Optimizing Forest Fire Risk Management.
Case of Study: Theniat El Had Tissemsilt

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To my dear parents who always trusted me .

To my dear brothers.

To my dear sisters.

To my friend " YAHI Mohamed" and my other friends.

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Table of contents

Acknowledgements	*ii*
Dedications	*iii*
Table of contents	*v*
List of figures	*ix*
List tables	*xii*
General Introduction	1

Chapiter I: FOREST FIRES

1. Introduction	5
2. Definition	5
2.1 The fuel	6
2.2 The oxidizer	6
2.3 The heat	6
3. Different types of forest fires	6
3.1 Ground Fires	7
3.2 Surface Fires	7
3.3 Crown fires	7
4. Origins of Forest Fires	8
4.1 Natural origins	8
4.2 Human Origins	8
4.2.1 Accidental	8
4.2.2 Deliberate	8
5. Factors Affecting Forest Fire Spread	9
5.1.1 Meteorological factor	9
5.1.2 Temperature	9
5.1.3 Wind	9
5.1.4 Humidity	9
5.1.5 Precipitations	10
5.2 Topographical factors	10
5.2.1 Slope steepness	10
5.2.2 Slope aspect	10
5.2.3 Terrain elevation	11
6. Advantages and disadvantages of forest fires	11
6.1 Advantages	11
6.2 Disadvantages	11
7. Fighting forest fires	12
7.1 Curative measures	12

7.2 Extinguishing 12
7.3 Preventive Measures 12
8. Historical Analysis 13
8.1 The Importance of Historical Analysis 13
8.2 Forest fires in Algeria 13
9. Conclusion 13

Chapter II: MAPPING FIRE RISK

1. Introduction 18
2. Risk index calculation models 18
2.1 DUCHE and DAGORNE model 18
2.1.1 Topomorphological Index (TI) 19
2.1.2 Combustibility Index (CI) 19
2.1.3 Human index (HI) 20
2.2 The 'Turque' fire risk mapping model 21
3. Analytical Hierarchy Process (AHP) 21
3.1 Key Steps of AHP 21
3.2 AHP, a Mathematical Approach to Decision Making 22
3.2.1 Pairwise comparison 22
4. Conclusion 25

Chapitre III: GENETIC ALGORITHMS

1. Introduction 27
2. Genetic Algorithm (GA) 28
3. Description of a GA.. 29
4. Basic Evolutionary Tools 30
4.1 Encoding 30
4.2 Selection 30
4.3 Elitism 32
4.4 Crossover 32
4.5 Mutation 32
4.6 Parameterization of a GA 33
5. Conclusion 34

Chapitre IV: GENERAL PRESENTATION OF THE STUDY AREA

1. Introduction 36
2. Geographical and administrative situation 37
3. Presentation of the forest massif Thénia El Had 37
3.1 Road 37
4. Physical characteristics 39

4.1 Relief 39
4.1.1 Slope 39
4.1.2 Aspect 39
4.1.3 Altitude 40
4.2 Hydrography 41
5 Climatology 41
5.1 Precipitation 42
5.2 Temperature 42
5.3 Humidity 43
5.4 Wind 44
6. Vegetation 46
7. Infrastructure 46
8. History of forest fires 47
9. Conclusion 50
Chapitre V : APPLICATION AND RESULTS
1. Introduction 52
2. Means used 52
2.1. Data used 52
2.2. Hardware used 52
2.3. Software used 53
3. Methodological approach adopted 54
3.1 Data acquisition 55
3.1.1 Georeferencing 55
3.1.2 Digitization 55
3.2 Digital Elevation Model 55
3.3. Calculation of the Topomorphological Index 56
3.3.1 Slope map 56
3.3.2. Aspect map 57
3.3.4. Topomorphological map 58
3.3.5 Topomorphological index (IM) 58
3.4 Combustibility index 59
3.4.1 Carte de l'Indice de Végétation Normalisé (NDVI) 60
3.4.2 Combustibility index (IC) 61
3.5 Calcuation of Human Index (HI) 62
3.5.1 Map of Road structurs 63
3.5.2 Agglomeration map 63
3.5.3. Human Index Map (HI) 64
3.6. Wildfire Risk Index Map (IR) 64
4. Calculating fire risk using the AHP method 65
4.1.Handling the criteria used AHP 9 cretiria 66
4.2. Handling the criteria used AHP 11 cretiria 67
5. Calculating fire risk using GA 72

5.1 Individual encoding 72
5.2 Initial population 73
5.3 Implemented crossover 74
5.4 Implemented mutation 74
5.5 Training and validation dataset 75
5.6 Evaluation process and proposed fitness 78
5.7 Experimentation and results 80
6. Conclusion 83

Conclusion et Perspectives 84
Références Bibliographiques 86

Liste of figure

Number of figure	Title	Page
1. 1	Fire triangle	05
1. 2	Different types of fires	07
1. 3	fires and embers	08
1. 4	The main forest species in Algeria	14
1. 5	The main forest species in Algeria	14
1. 6	Areas affected by forest fires during the period from 1963 to 2013 (Algeria) (GDF 2013)	15
1. 7	Number of fires in the study area between 1999 and 2023 (Algeria) (GDF)	16
2. 1	General hierarchy of the AHP method	22
3. 1	RWS	31
3. 2	Crossover	32
3. 3	Mutation	33
4.1	Location map of the study area	37
4.2	Forest cantons map	38
4.3	Road network map	38
4.4	Slope map	39
4.5	Aspect map	40
4.6	Elevation map	40
4.7	Hydrological network map	41
4.8	Precipitation map	42

4.9	LST map	43
4.10	Humidity map	44
4.11	Wind speed map	45
4.12	Ndvi map	45
4.13	Infrastructure map	46
4.14	Number of fires	47
4.15	Burned area	48
4.16	Percentage of burned area	49
4.17	Map of forest fire occurrences	49
5.1	The overall organizational chart	54
5.2	Digital Elevation Model (DEM)	56
5.3	Slope map	57
5.4	Aspect map	57
5.5	Topomorphological map	58
5.6	Topomorphological index	59
5.7	Biovolume map	60
5.8	NDVI map	60
5.9	Combustibility notes of the main dominant vegetation species Mediterranean (Source CEMAGREF)	61
5.10	Combustibility Index.	62
5.11	Road map	63
5.12	Agglomeration map	63
5.13	Humain index map	64
5.14	vulnerable areas using classic method	65

5.15	The general structure of designing a sensitivity map using AHP 09 cretiria	66
5.16	Criteria weights for AHP 09 criteria	66
5.17	The general structure of designing a sensitivity map using AHP 11 cretiria	67
5.18	Criteria weights for AHP 11 criteria	67
5.19	map of vulnerable using ahp (11 criteria)	68
5.20	map of vulnerable using ahp (11 criteria)	69
5.21	Adopted approach	72
5.22	necessary libraries	73
5.23	Generating Initial population	73
5.24	Crossover and selection	74
5.25	mutation	74
5.26	Mask function	76
5.27	NBR index	76
5.28	The selected points	77
5.29	Partitioning of Selected Points for Training and Validation	77
5.30	Map of selected points	78
5.31	Evolution of classification accuracy as a function of population size (IND) and number of generations (GEN)	80
5.32	Evolution of classification accuracy over generations	81
5.33	Risk image for 7-parameter classification	82
5.34	Risk image of 8-parameter classification	82
5.35	Risk image with all criteria	83

Liste of Table

Number of table	**title**	**page**
2. 1	9-point intensity of relative importance scale	23
2. 2	Random Inconsistency indices (RI) for n = 10	24
4.1	Forest species	37
5.1	Individual encoding	72
5.2	reparttion of Selected Points between Training and Validation	77

Abstract :

This work focuses on the contribution of Geomatics and Artificial Intelligence to forest fire protection, recognized as a major threat to forest ecosystems. We utilized the Analytic Hierarchy Process (AHP) and Genetic Algorithms (GAs) to map the fire risk in the Théniat el Had forest, located in the Wilaya of Tissemssilt Province. Integrating the historical fire data of the area into our analysis was crucial in enhancing our understanding of the risks involved.

The results obtained with genetic algorithms are promising and urge us to refine our approach to produce more accurate risk maps. These maps could then be effectively used as tools for fire prevention.

Key words: AHP, GA, Forest Fires, Fire History

الملخص:

تركز هذه الدراسة على إسهام الجيوماتيك والذكاء الاصطناعي في حماية الغابات من الحرائق، التي تُعتبر تهديدًا كبيرًا لنظم الغابات البيئية. لقد استخدمنا عملية التسلسل الهرمي التحليلي (AHP) والخوارزميات الجينية (GAs) لرسم خرائط لمخاطر الحرائق في غابة تينية الحد، الموجودة في ولاية تسيمسيلت. كان دمج بيانات تاريخ الحرائق للمنطقة في تحليلنا أمرًا حاسمًا في تعزيز فهمنا للمخاطر المتضمنة.

النتائج التي حصلنا عليها باستخدام الخوارزميات الجينية واعدة وتحثنا على تحسين منهجيتنا لإنتاج خرائط مخاطر أكثر دقة. يمكن استخدام هذه الخرائط بفعالية كأدوات للوقاية من الحرائق.

.

الكلمات المفتاحية : التسلسل الهرمي التحليلي , لخوارزميات الجينية , حرائق الغابات, تاريخ الحرائق

GENERAL INTRODUCTION

Considered the lung of the Earth, the forest is a treasure trove of biodiversity, a laboratory where humans can search for new medicines, a space for leisure and relaxation, and a true factory for purifying air, soil, and water.

This natural wealth, covering 1% of the national territory, is now subject to multiple aggressions, both of climatic and anthropogenic origins. However, undoubtedly the most devastating factor for forests is fire, which benefits from favourable physical and natural conditions for its outbreak and spread.

The world as a whole, and Algeria specifically, has recently experienced a significant increase in the number of fires, attributed to both natural and human factors. This rise in fires is driven by a combination of climate change, which leads to hotter and drier conditions, and human activities. These activities include deforestation, agricultural practices, and accidental ignitions, further exacerbating the natural susceptibility of forests to ignite. Urban expansion into wildland areas also increases the likelihood of fire initiation and spread, posing greater risks to both human lives and natural ecosystems. To combat this scourge, prevention alone is imperative as an effective means of fighting it.

Prevention through traditional means remains inadequate given the complexity and diversity of forest ecosystems. To address this challenge, interactive mapping plays a crucial role, especially with modern and fast tools such as remote sensing and Geographic Information Systems (GIS). These technologies enable proactive management of fire risks by providing accurate data for mapping high-risk areas and facilitating the planning of preventive interventions.

Geomatics, which encompasses remote sensing and GIS, provides an integrated approach to forest fire risk management. Remote sensing technology, through satellites and drones, can monitor vast forest areas in real-time, detecting changes in vegetation health, moisture levels, and temperature anomalies, enabling the identification of areas at increased risk of fire. GIS, on the other hand, facilitates spatial analysis and scenario modeling, helping managers make informed decisions for fire prevention and suppression. This combination of geospatial technologies enables proactive and effective management of natural resources while enhancing ecosystem resilience against environmental threats.

Therefore, Geomaticians manage extensive geospatial datasets, including maps and images covering vast areas, crucial for understanding and modelling risks related to forest fires and other complex environmental phenomena. The integration of artificial intelligence (AI) in this field is crucial for optimizing risk management. Machine learning techniques efficiently analyze these massive datasets. For instance, AI algorithms can monitor real-time changes in vegetation cover, assess weather conditions conducive to fires, and predict high-risk areas. This ability to perform sophisticated multi-criteria analysis, considering factors such as topography and land use, allows for precise assessment of environmental risks. By integrating AI with geospatial big data, geomaticians can develop advanced solutions to effectively prevent and manage forest fires.

Among these machine learning techniques, Genetic Algorithms (GAs) stand out as powerful optimization methods. GAs can handle multi-criteria and multi-objective problems, making them particularly suitable for complex scenarios such as forest fire risk management. Process By simulating the of natural evolution, GAs explore a wide range of potential solutions, iteratively improving them based on defined criteria. This approach enables the identification of optimal strategies for fire prevention and response, tailored to the unique characteristics of each geographical area. The potential of GAs in this context remains to be fully explored, promising significant advancements in the precision and effectiveness of forest fire management strategies.

The synergy between Geomatics and AI is evident in our exploration of using GA to manipulate various criteria and geospatial information. We utilize Geomatic tools such as GIS and remote sensing to compute and integrate complex data. The goal is to establish a forest fire risk map by precisely analyzing environmental factors and predicting areas with high risk. C'est dans ce contexte que s'inscrit la présente étude.

The methodology of this study is divided into two main parts: In the first part, we calculate the risk map using a statistical model, then apply a multi-criteria approach using the AHP method. This approach integrates the historical data of fires (frequency and burnt areas) into the AHP analysis. The resulting maps are then compared and serve as the basis for validating the evolutionary approach discussed in the second part of the study. This latter part involves implementing an application using Genetic Algorithms to compute a risk map, based on the different parameters calculated in the previous part.

This work is structured into five chapters:

- ✓ The first chapter deals with forest fires, addressing their causes, propagation factors, and focusing on the situation of forest fires in Algeria.
- ✓ The second chapter explores risk mapping methods, such as classical approaches, and introduces the principles of AHP (Analytic Hierarchy Process).
- ✓ The third chapter examines Genetic Algorithms.
- ✓ The fourth chapter presents an overview of the study area, highlighting its relevant geographical and environmental characteristics.
- ✓ The final chapter details the methodological approach adopted to generate forest fire risk maps, discussing the results obtained. The chapter concludes with a summary of findings and future perspectives.

CHAPTER I

FOREST FIRES

Abstract

This chapter focuses on forest fires by exploring their origins, propagation factors, as well as the associated advantages and disadvantages, while also examining the increasing intensity of fires in Algeria in recent years.

1. Introduction

Each year, wildfires ravage extensive areas of Algeria's forested areas, posing a threat to numerous forests. Indeed, Algerian forests annually record alarming figures of burned hectares, representing a serious threat to biodiversity, natural resources, and local communities.

This chapter explores the origins and propagation factors of wildfires, as well as the advantages and challenges associated with their management. We will also examine the recent increase in forest fires incidence in Algeria, emphasizing the importance of mitigating their effects and protecting fragile forest habitats.

2. Definition

Forest fires result from the uncontrolled spread of fire in a forested area. They cause combustion of the vegetation (trees, scrubs, grasslands and croplands) and they can be originated by natural or human causes (Plana et al, 2016). For a forest fire to ignite, three fundamental parameters must be present simultaneously: fuel, oxidizer, and source of heat, if any one of these elements is absent, the combustion reaction cannot initiate, or the fire is immediately extinguished. The association of these three elements is symbolically represented in a diagram called *the fire triangle* (figure 1.1).

Several factors contribute to the spread and the severity of forest fires once ignited, such as fuel type (dense vegetation), weather conditions (temperature, wind), and topography (slope).

Figure 1. 1: Fire triangle

2.1 the fuel

It is a substance capable of burning (flammable material). All elements that constitute the forest, from the forest floor to the tree canopy, are combustible materials. Within forested areas, vegetation is categorized into four layers:

- *Leaf litter*: Refers to the accumulation of dead leaves and decomposing plant debris covering the forest floor. Highly flammable, it often initiates numerous fires starts that are difficult to detect because it burns slowly

- *The herbaceous layer*: consists of grasses, which are highly flammable during dry periods

- *The lower woody layer*: includes maquis and garrigue, which are abundant in the Mediterranean region. This layer exhibits moderate flammability and facilitates rapid fire spread to the upper layers.
- *Upper woody*: layer: Comprised of tall trees. While it rarely starts fires, it facilitates the spread of flames once ignited.

2.2 The oxidizer

In the case of a forest fire, the oxidizer refers to the oxygen in the air. A deficiency of oxygen generally leads to slow combustion without flame formation. Wind plays a crucial role in fire propagation, primarily by ensuring oxygen renewal.

2.3 The heat

Refers to the energy needed to start a fire. Dry grass can ignite with minimal energy, while igniting wood requires significantly more. Heat generated during a fire sustains its own continuation.

3. Different types of forest fires

Three types of forest fires are distinguished (figure 1.2):

Surface fires Crown fires Ground fires

Figure 1. 2: Different types of fires

3.1 Ground Fires

These fires Burn organic matter in litter, spreading slowly. However, this type of fire is highly destructive as it attacks underground systems (tree roots) and can smolder deeply, making detection (no flames) and thus complete extinction more difficult.
Even if the flames are not visible, the fire can remain active for long periods (Johann, SD). This type of fire requires a lot of water to achieve complete extinction, as it smolders deep down (Colin et al., 2001).

3.2 Surface Fires

These fires burn the lower layers of vegetation, including the upper part of the litter, the herbaceous layer, and low shrubs. The spread of this type of fire can be rapid when it develops freely, especially under conditions that facilitate propagation such as wind and terrain (Colin et al., 2001)

3.3 Crown fires

These fires burn the upper parts of trees (tall shrubs) and form a crown of fire. They generally release large amounts of energy and spread very quickly. They are especially intense and difficult to control when the wind is strong and the fuel is dry.
In Figure (Figure 2.2), it is illustrated that ember fires can occur. Embers are produced by crown fires or under specific wind and topographical conditions. These embers can be carried over long distances and can ignite secondary fires. Such fires are very challenging to control, and their rapid spread is highly unpredictable (Marguerit, 1998).

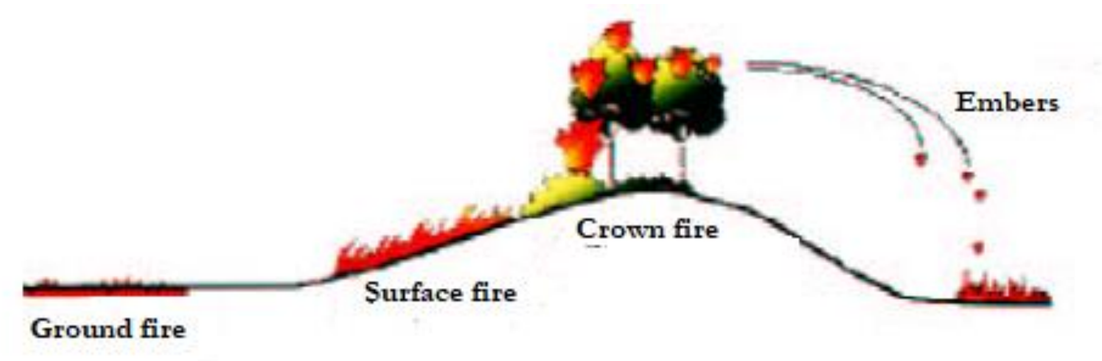


Figure 1. 3: fires and embers

4. Origins of Forest Fires

There are two main categories of causes for the start of fires

4.1 Natural origins

Spontaneous ignition of vegetation is improbable, and the primary natural cause of forest fires is lightning. However, it remains a rare event (2 to 3% of cases) in Mediterranean regions. The most effective risk reduction strategy is to protect installations located in forests that could attract lightning strikes, such as pylons and power lines (Khalfa and Ziani, 2010)

4.2 Human Origins

They constitute the primary causes of forest fires, whether accidental or deliberate.

4.2.1 Accidental

Negligence-related carelessness regarding fire risks includes agricultural activities (such as honey harvesting by smoking, garden burning, cigarette smoking), camping, barbecuing, etc. Accidents may also result from malfunctions of agricultural or forestry machinery, traffic incidents, and power lines.

4.2.2 Deliberate

Fires can be caused for various reasons:

- *Security measures*: Preventive actions by the military.
- *Illegal land clearing*: Removing Forest to occupy the land.
- *Economic motives*: Reducing the cost of wood.
- *Personal motives*: Arson driven by personal satisfaction or by pyromaniacs.

5. Factors Affecting Forest Fire Spread

When a fire breaks out, it is not necessarily dangerous, as its impact depends on its intensity and area of spread. The propagation of the fire will be determined by several factors:

5. 1 Meteorological factor

5.1.1 Temperature

The main heat source is the sun; fuels exposed to the sun warm up more quickly than those under forest cover. Temperature can have a direct influence (by warming or cooling materials) or an indirect influence (by altering atmospheric humidity content)

5.1.2 Wind

Wind enhances combustion and fire spread by:

- Increasing oxygen supply;
- Drying out fuels;
- Facilitating the heating of fuels ahead of the fire;
- Influencing the direction of fire spread;
- Transporting sparks or other ignited materials over long distances.

5.1.3 Humidity

It is the proportion, expressed as a percentage, between the actual water vapor content in the air and the air's capacity to absorb moisture at a given temperature. It does not directly affect the occurrence of fires, but it conditions the moisture content of fuels.

Changes in relative humidity significantly affect combustible materials. High air moisture content causes fuels to become moist and less easily ignitable. Conversely, dry air increases the rate of moisture evaporation from fuels, thereby enhancing forest flammability (ZOUAIDIA , 2006).

In technical jargon we refer to the "*three thirties*" to indicate the conditions favorable to the development of large forest fires or high intensity fires: temperatures above 30° C, wind speed faster than 30 km/h and relative humidity below 30%. The closer the weather conditions to these values, the higher the fire risk.

5.1.4 Precipitations

The effect of precipitation on forest fires depends on two parameters: the amount of water and the duration of the precipitation. Small fuels react quickly to small amounts of precipitation, while the duration of precipitation is crucial for larger fuels, which react more slowly to rain. A small amount of water over a long period is preferable to a large amount of water in a short time.

5.2 Topographical factors

Generally, the influence of topography varies depending on slope steepness, aspect, and elevation of the terrain.

5.2.1 Slope steepness

The slope percentage directly influences forest fire behavior. Generally, fire spread rate increases with steeper slopes, and fires burn more rapidly on steep gradients.

5.2.2 Slope aspect

Slope aspect affects:

- The amount of heat received by fuels depending on solar exposure
- Local winds

- The quantity and type of fuel

5.2.3 Terrain elevation

Elevation above sea level affects the behavior of forest fires by altering weather patterns and vegetation. Higher terrain exposes fuels to more sunlight and intense winds, making them drier and fires burn faster as a result.

6. Advantages and disadvantages of forest fires

6.1 Advantages

- *Ecosystem Renewal*: Fire removes old plants, creating space for new growth.
- *Soil Enrichment*: Ash from fires enriches the soil with minerals and nutrients, enhancing its fertility.
- *Pest Control*: Fires can eliminate harmful insects and pests, thereby contributing to forest health.
- *Risk Reduction*: Small, controlled fires reduce the amount of dry vegetation, decreasing the risk of larger future destructive fires.

6.2 Disadvantages

- *Threat to Life*: Fires pose a threat to human and animal life.
- *Air Quality*: Smoke from fires affects air quality, causing health problems.
- *Biodiversity Loss*: Large fires can destroy plant and animal species.
- *Environmental Degradation*: Loss of vegetation cover significantly contributes to other disasters like desertification and drought.
- *Water Impact*: The removal of vegetation can negatively affect water flow and quality, increasing the likelihood of floods.

7. Fighting forest fires

Fire prevention plans define the actions and equipment for prevention, extinguishing, and reforestation (post-fire) to be implemented spatially and temporally to minimize damage caused by fires.

There are two main forms of combating fires: prevention and active firefighting (extinguishing)

7.1 Curative Measures

Active firefighting methods, both human and material, vary globally. In Algeria, these methods involve voluntary, professional, and military firefighters, supported by resources from various organizations such as national parks and civil protection.

7.2 Extinguishing

Fire control strategies include direct attack for localized fires, parallel attack to establish fire lines, and indirect attack to burn fuels at a distance. Effective extinguishing relies on timely detection, prioritization, rapid mobilization of firefighting resources, and expertise in disrupting the fire triangle through cooling, smothering, isolating, and inhibiting.

7.3 Preventive Measures

Prevention encompasses proactive measures to mitigate fire risks and restrict fire spread, such as managing fuels by clearing dead vegetation and creating defensible spaces, educating the public on fire safety practices, establishing firebreaks through controlled burns or mechanical clearing, implementing early detection systems, and enforcing regulations on outdoor activities that could pose fire hazards. These efforts aim to reduce the occurrence of fires and minimize their impact on communities and ecosystems.

8. Historical Analysis

8.1 The Importance of Historical Analysis in Understanding and Mitigating fire forest Impacts

Understanding the comprehensive impact of current and future forest fires on any study area begins with reviewing the history of fires in this region. Analyzing historical fire patterns is not merely an academic exercise but a crucial tool to uncover the root causes of fires, assess their diverse impacts, and identify environmental and social changes that have emerged over time due to these fires.

Studying fire history allows us to identify periods of increased or decreased frequency and intensity of fires, linking them to climatic factors and human activities that may have contributed. For instance, Algeria, in general, and the study area specifically, have experienced significant challenges during the "Black Decade."

Historical review can also elucidate the environmental impacts of fires, such as changes in vegetation cover and wildlife diversity, as well as economic ramifications like damage to infrastructure and losses in natural resources. Socially, we can understand how fires affect local communities, including displacement and property loss, and how these communities have interacted with and responded to disasters over time.

Analyzing historical patterns also provides insight into the effectiveness of firefighting strategies adopted over the years. We can evaluate whether past preventive measures and emergency responses succeeded in mitigating fire damage or if further improvements are needed.

Ultimately, historical understanding helps in developing more efficient future strategies to deal with fires. Knowing what has succeeded and what has not in the past can guide current policies and enhance our preparedness to face future challenges, thereby reducing the negative impacts of fires on both the environment and society.

8.2 Forest fires in Algeria

Algeria's forests, covering approximately 4.100.000 hectares, play a crucial role in maintaining environmental balance and preserving biodiversity. However, these forests have faced severe degradation in recent years due to recurrent fires, which annually affect around 36. 000 hectares of land.

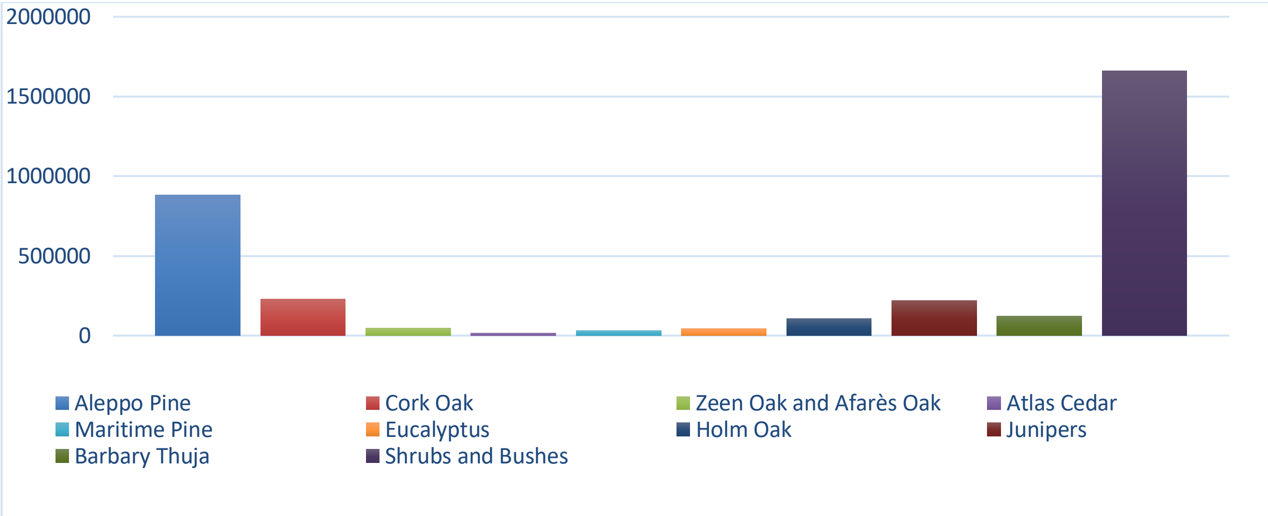


Figure 1. 4: The main forest species in Algeria

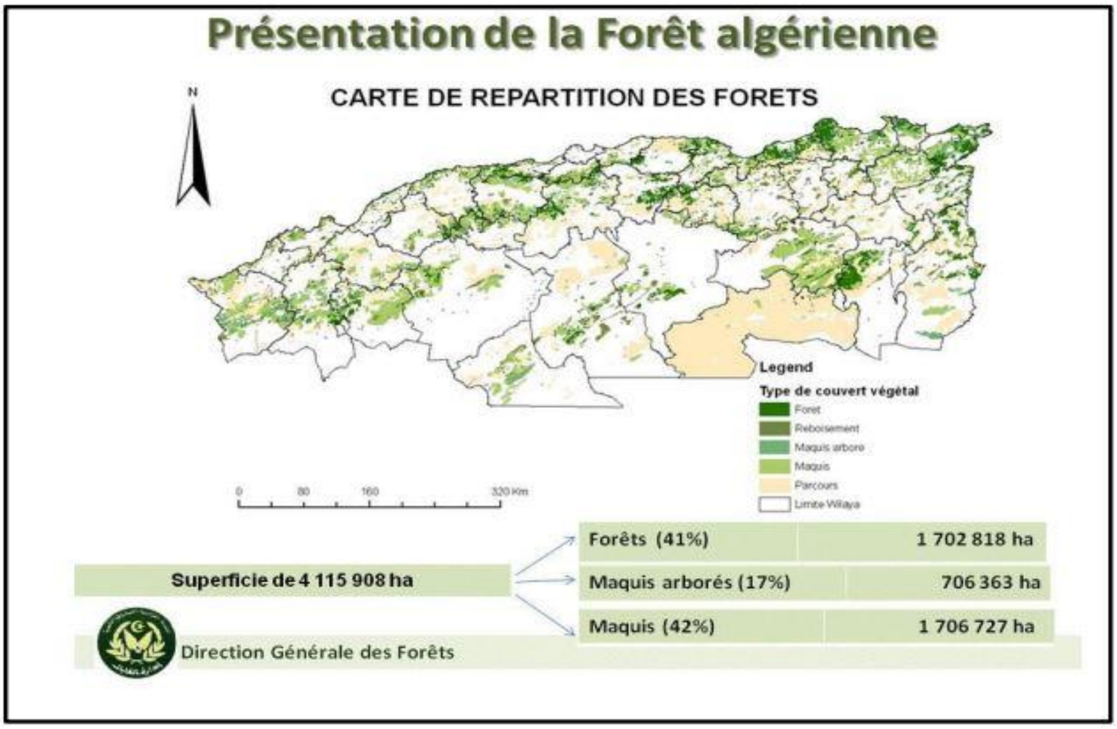


Figure 1. 5: The main forest species in Algeria

Figure (figure 1.4) illustrates the areas affected by forest fires during the period from 1963 to 2013. It can be observed that in certain years, the Algerian forest was affected by large and harmful fires, significantly surpassing the average for the period 1963-2013, notably the two catastrophic years 1983 and 1994, with 221.367 Ha and 271.598 Ha respectively.

In recent years, fires have been increasingly widespread, in 2017 fires consumed more than 43.414 hectares, highlighting the acute threat posed by this phenomenon. Human activities significantly contribute to this problem, with over 80% of fires attributed to anthropogenic causes.

According to figures published on the Ministry of Interior's Facebook page, the fires of 2021 and 2022 resulted in 150 deaths and caused more than 17 billion dinars in losses. The heaviest toll was undoubtedly in 2021. That year, significant fires affected several provinces in the central and eastern regions of the country, particularly in Kabylie and in the province of Khenchela. These fires led to 103 deaths and hundreds of injuries. They also caused substantial material losses in terms of animal and agricultural wealth, not to mention the homes destroyed by the flames, amounting to losses estimated at 15.65 billion dinars. Additionally, more than 100 000 hectares of forested areas were burned by 1 631 fire outbreaks.

The summer of 2022, though less severe than the previous year, also recorded losses, particularly due to fires affecting the eastern provinces of the country, notably in El-Tarf and Souk-Ahras. These fires resulted in the deaths of 47 people and hundreds of injuries. Material damages were estimated at 1.5 billion dinars, with 28,000 hectares of forests burned [1]. According to [2], an area of 41.000 hectares spread across 37 wilayas was destroyed by fires recorded between January 1st and October 31st, 2023.

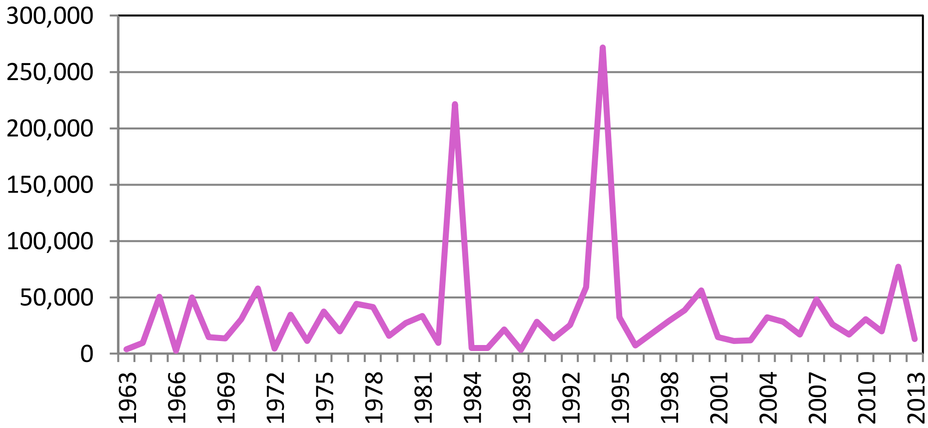


Figure 1. 6: Areas affected by forest fires during the period from 1963 to 2013 (Algeria) (GDF 2013)

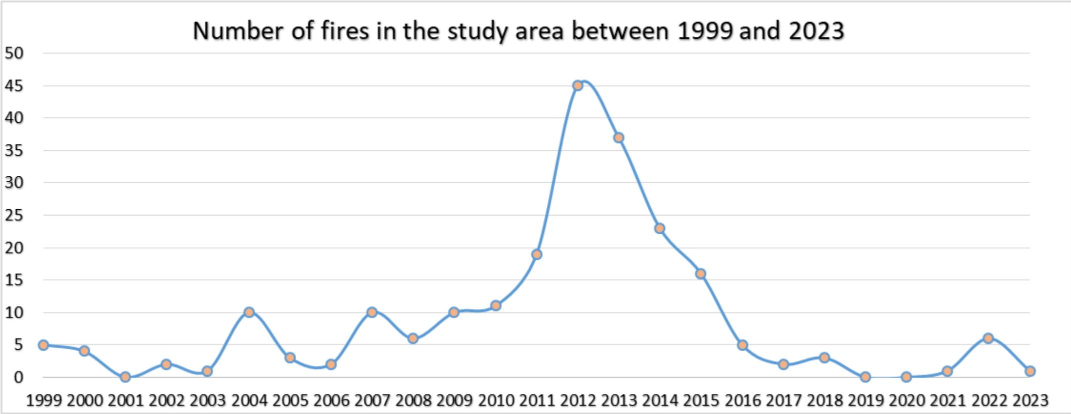


Figure 1. 7: Number of fires in the study area between 1999 and 2023 (Algeria) (GDF)

9. Conclusion

Forests represent a valuable natural resource for our country. Despite their critical importance, they are increasingly degraded due to wildfires, which pose serious threats to forest ecosystems and surrounding communities. To address these challenges, an integrated approach to prevention, firefighting, and restoration is essential. The next chapter will explore a crucial tool for anticipating and managing these risks: wildfire risk mapping. This cartographic methodology will enable the analysis of risk zones, identification of vulnerabilities, and development of effective prevention and intervention strategies.

CHAPTER II

MAPPING FIRE RISK

Abstract

This chapter focuses on presenting the main methods used to forest fire risk mapping, with an emphasis on the AHP method.

1. Introduction

Fire risk mapping aims to protect fire-prone areas in forests. This approach is not new, having been proposed as early as the 1930s in California by Frederick Law Olmsted Jr. as a means to mitigate fire damage in Malibu.

In terms of prevention, these maps can serve as a guide for future placement of water points, new trails, or firebreaks, and for identifying high-risk areas. In detection efforts, they are valuable for strategically locating lookout towers and increasing surveillance patrols in high-risk zones.

Thus, the primary goal of fire risk mapping is to enhance the anticipation of interventions by pre-positioning response teams in proximity to areas prone to fire outbreaks, based on anticipated intervention complexities.

Establishing a fire risk map indeed employs several methods, such as applying risk index calculation models, multicriteria analysis methods. These approaches integrate various factors such as topography, vegetation, weather conditions, and other relevant variables to assess and map high-risk fire areas.

2. Risk index calculation models

The literature offers several applications with different statistical models, such as

2.1 DUCHE and DAGORNE model

This model was used in Algeria in several studies, for instance, in the state forest of Kounteidat located in the wilaya of Sidi Bel Abbés (Missoumi et al. 2003), in the Bainem forest in Algiers (Belhadj-Aissa et al, 2003) , and in the Nesmouth forest located southeast of Mascara (khader, 2009).

The creation of the forest fire risk map utilizes a model developed by Dagorne Y. Duche (1994) and tested on the forested areas of the Mediterranean region. This model involves three main factors for assessing the risk of forest fires: Topomorphology, Fuel and

Human activity, which acts both as a factor and as a vulnerable element. The model is based on the following formula:

$$RI = 5 \times CI + 2 \times HI + TI \tag{2.1}$$

Where:

- RI: Fire Risk Index.
- CI: Combustibility Index.
- HI: Human Occupation Index.
- TI : Topomorphological Index.

The characterization of this index is based on the spatial variability of fire risk, which is determined by the physical and human parameters involved in the chosen model.

2.1.1 Topomorphological Index (TI)

Three topographical parameters are involved in the model: Slope, Aspect, and Elevation. All these parameters are derived from the Digital Terrain Model (DEM) of the region. This index is expressed by the following formula:

$$TI = 3 \times S + (T \times A) \tag{2.2}$$

Where:

- S: Slope
- T: Topomorphology
- A: Aspect

2.1.2 Combustibility Index (CI)

Vegetation is characterized by its combustibility, which represents its ability to propagate fire while burning. This indicates how it burns, releasing varying amounts of heat. Combustibility depends on the structure and dominant species of the forest and is correlated with the amount of combustible biomass (BV) related to the fuel's structure and composition.

To evaluate the combustibility index (CI), *MARIEL (1995)* proposed the following method:

$$CI = 39 + 0{,}23BV \times (E1 + E2 - 7{,}18) \quad (2.3)$$

- *BV*: Represents the biovolume of the vegetative formation.
- *E1*: Represents the combustibility ratings for the most dominant high woody plants.
- *E2*: Represents the combustibility ratings for the most dominant low woody plants or herbaceous plants.

2.1.3 Human index (HI) (Ali et al, 2012)

This index depends on human occupation of space and its activities. To analyze the human activity component, we proposed an approach involving two aspects: the source of fire starts and associated stakes.

- The first parameter (IV) is based on anthropogenic impact on the nearby forest environment. We assume that humans exert pressure on their immediate forest surroundings.
- The second parameter (ID) considers road infrastructures (roads, tracks, trails). However, fire outbreaks are much more frequent near roads and forest paths.

The human occupation index will therefore be expressed as a linear combination of these two indices:

$$HI = IV + 2 \times ID \quad (2.4)$$

Where:

IV: neighborhood index

ID: human presence index

2.2 The 'Turque' fire risk mapping model

Developed by Turkish academics, this model was used in different studies on forest fires in Algeria, for example the work of **(Hachemi , 2014)** for studying the fire forest risk of Ain el Hdjer in Saida

This model is based on the following formula:

$$RI = 7 \times Tveg + 5 \times (S + A) + 3 \times (Dr + Da) \quad (2.5)$$

- Tveg: Type of vegetation.
- S: Slope
- A: Slope Aspect
- Dr : Distance from Roads
- Da : Distance from Agglomération.

3. Analytical Hierarchy Process (AHP)

Developed by Thomas L. Saaty in the Saaty (1980), the Analytic Hierarchy Process (AHP) is a valuable tool based on a hierarchical structure for managing both qualitative and quantitative multi-criteria elements in decision-making. This method allows for a range of decision options and enables the application of sensitivity analysis to the resulting criteria and benchmarks. It simplifies judgments and calculations through paired comparisons. Additionally, it highlights the compatibility and incompatibility of decisions, which is a key advantage of multi-criteria decision making. One of the strengths of AHP is its versatility, as it can be adapted to a wide range of decision-making contexts, including risk management. Several studies, particularly recent ones, in the field of risk management show its growing application and have already proven its effectiveness, especially for forest fire risks(Demir, 2024) (Rahmani,2019) , (Taibi, 2020).

3.1 Key Steps of AHP

The principal keys of an AHP process are:

- *Define the Goal and Structure the Hierarchy*: Clearly state the decision problem and identify the goal, decompose the problem into a hierarchy of goal, criteria, and alternatives (Taherdoost , 2017)

- *Construct Pairwise Comparisons*: Create pairwise comparison matrices to evaluate the relative importance of criteria and the performance of alternatives against each criterion.
- *Calculate Priority Weights*: Derive the priority weights (eigenvectors) from the pairwise comparison matrices, ensure consistency in judgments using the Consistency Ratio (CR).
- *Aggregate and Synthesize Results*: Combine the priority weights to determine the overall ranking of alternatives, make the final decision based on the highest-ranking alternative.

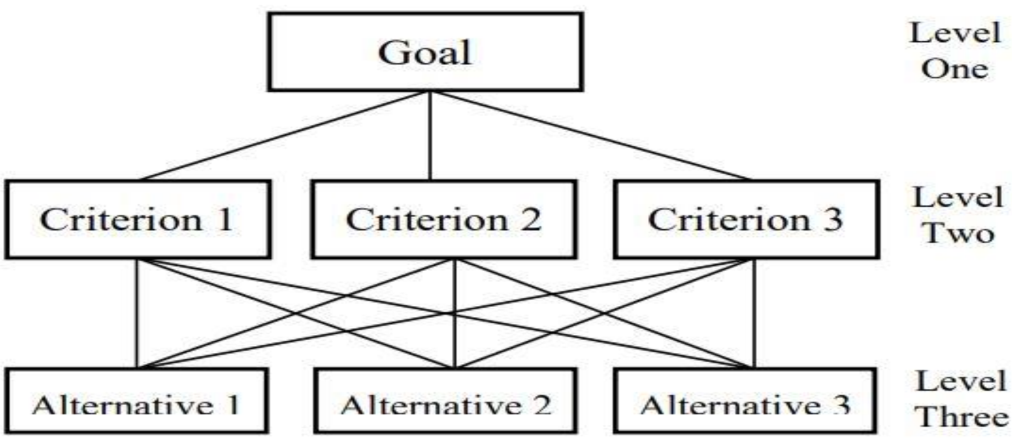


Figure 2. 1: General hierarchy of the AHP method

3.2 AHP, a Mathematical Approach to Decision Making

3.2.1 Pairwise comparison

Each pair of elements in each level are compared with respect to the corresponding elements in the level above them. This is done in terms of their importance. The comparisons can then be represented by multiple square matrices C (Yap et al, 2018).

$$C = \begin{pmatrix} c_{11} & \cdots & c_{1n} \\ \vdots & \ddots & \vdots \\ c_{n1} & \cdots & c_{nn} \end{pmatrix}$$

The matrix has reciprocal properties, which are:

$$C = \begin{pmatrix} \frac{1}{c_{11}} & \cdots & \frac{1}{c_{1n}} \\ \vdots & \ddots & \vdots \\ \frac{1}{c_{n1}} & \cdots & \frac{1}{c_{nn}} \end{pmatrix}$$

In AHP, Satty (1980) recommended a scale of relative importance from 1 to 9 for making subjective pairwise comparisons (table 2.1)

Importance	***Definition***	***Explanation***
1	Equal importance	Two activities contribute equally to objective 1
3	Moderate importance of one over another	Experience and judgment slightly favor one activity over another.
5	Essential or strong importance	Experience and judgment strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored, and its dominance is demonstrated in practice.
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When a compromise is needed.

Table 2. 1: 9-point intensity of relative importance scale

Ater all pairwise comparison matrices are formed, the vector of weights, $W = [w_1, w_2, \ldots, w_n]$, is computed on the basis of Saaty's eigenvector procedure. The computation of the weights involves two steps (Chen, 2006):

1) Normalizing the pairwise matrix: Each element in the matrix C will be divided by the sum of its column:

$$C_{ij}^{*} = \frac{c_{ij}}{\sum_{j=1}^{n} c_{ij}} \quad (2.6)$$

2) Creating a weighted matrix:

$$w_i = \frac{\sum_{j=1}^{n} C_{ij}^{*}}{n} \quad (2.7)$$

3.2.2 Consistency check

According to (Chen, 2006) there is a correlation between the weight vector W, and the pairwise comparison matrix C, as expressed in equation (2. 8).

$$CW = \lambda_{max} W \quad (2.8)$$

Where λ_{max} represents the maximum eigenvalue of the comparison matrix. To derive

The consistency index, CI, is calculated as follows:

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (2.9)$$

Additionally, the consistency ratio (CR) is given by:

$$CR = \frac{CI}{RI} \quad (2.10)$$

A randomly generated pairwise comparison matrix is employed to determine the random consistency index, RI. The values of RI for matrices of order 1 to 10 are detailed in Table 2.2. If the value of CR exceeds 0.1 the pairwise comparisons necessitate reevaluation, prompting a review.

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.46	1.49

Table 2. 2: Random Inconsistency indices (RI) for n = 10

4. Conclusion

Forests are one of the natural riches of the country. Despite their crucial importance, they are increasingly degraded due to forest fires. To protect this resource and mitigate fire risks, it is crucial to adopt appropriate methods, particularly through fire risk mapping.

Various techniques are described in the literature for evaluating and mapping this risk. Statistical models, such as the one by Duche and Dagorne, primarily rely on three factors: human presence, vegetation, and topography. Another widely used method is Analytic Hierarchy Process (AHP) due to its multicriteria nature, well-suited for such problems.

Furthermore, this thesis proposes an approach utilizing genetic algorithms for fire risk mapping. Accordingly, Genetic Algorithms will be the focus of the upcoming chapter.

CHAPTER III

GENETIC ALGORITHMS

Résumé

In this chapter, we explore Genetic Algorithms (GA), which are a class of Artificial Intelligence techniques inspired by the process of natural selection observed in living organisms. They are used to solve complex optimization problems that are difficult to optimize by traditional methods. The growing use of AGs reflects their potential to improve decision processes and system performance in various sectors.

1. Introduction

Artificial Intelligence (AI), in its broadest sense, is intelligence exhibited by machines, particularly computer systems. It is a field of research in computer science that develops and studies methods and software that enable machines to perceive their environment and uses learning and intelligence to take actions that maximize their chances of achieving defined goals. Such machines may be called Ais [Wikipedia].

The goal of AI is to develop systems that can perform tasks like pattern recognition, decision-making, in a way that mimics human intelligence. Unlike humans, however, these systems can process vast amounts of data at unprecedented speeds and scales. This unique ability enables AI to analyze and interpret information with exceptional efficiency, leading to innovative applications and significant advancements across various domains.

Machine learning (ML) is a discipline of AI that provides machines with the ability to automatically learn from data and past experiences while identifying patterns to make predictions with minimal human intervention [3]. ML focuses on algorithms that give computers the capability to learn and act as humans do. If a computer is given input data with the corresponding output data, it can learn the algorithm itself and, therefore, continue to predict the right output data. This is called supervised learning. Alternatively, if a computer is given a complex set of input data with no corresponding output data, the machine identifies the relationships in the data to provide valuable insights for decision-makers. This is called unsupervised learning [4].

Bioinspired approaches are among the techniques generating significant interest in AI and ML, they draw inspiration from biological processes and behaviors observed in nature to design algorithms and computational models. They exploit evolutionary mechanisms, animal behavior strategies, and other biological phenomena to tackle complex problems. For instance, Artificial Neural Networks can be structured similarly to the human brain for advanced data processing. Evolutionary methods replicate natural selection to optimize solutions, while other bio-inspired approaches may utilize models based on collective insect behavior or animal communication systems to address optimization and information processing challenges.

Genetic Algorithm (GA) is a part of Evolutionary Computing, which is a rapidly growing area of AI (Haldar et al, 2014). GAs are one of the most well-known natural-inspired algorithms (Hamad et al, 2023). They have been successfully used in various fields, including optimization, pattern recognition, and image processing (Hamad et al, 2023) (Holland, 1992), they have demonstrated their effectiveness in exploring large and complex solution spaces, enabling the discovery of solutions that may be challenging to attain using traditional methods.

2. Genetic Algorithm (GA)

GAs are stochastic search techniques based on the mechanism of natural selection and natural genetics (Gen and Chen, 1997). They abstract the problem space as a population of individuals, and try to explore the fittest individual by producing generations iteratively. GA evolves a population of initial individuals to a population of high-quality individuals, where each individual represents a solution of the problem to be solved (Haldurai et al, 2016) . GA is one of the most well-regarded evolutionary algorithms in the history (Mirjalili et al 2020).

The beginning was in 1859, with the publication of the book "The Origin of Species" written by the biologist Charles Darwin, where he presented his theory of evolution based on two simple postulates:

- In each environment, only the best-adapted species endure over time, while the others are doomed to disappear.
- Within each species, population renewal is primarily driven by the fittest individuals.

In the early 1960s, Professor J. Holland, along with his colleagues and students at the University of Michigan, initiated an extensive study. Their research had two main objectives: Highlight and rigorously explain the adaptation processes of natural systems, develop artificial systems that possess important properties of natural systems. In 1975, J. Holland presented the results of his research in his book "*Adaptation in Natural and Artificial Systems*," where he explained the foundations of Gas based on Darwinian principles and theoretically demonstrated their robustness in exploring complex spaces. These works sparked an increasingly strong interest among mathematicians, including

KOZA, who rigorously validated their mechanisms. Since their introduction by John Holland, GAs have come a long way as powerful and versatile tools for solving complex problems, continuing to attract significant interest in the scientific and industrial community so far.

3. Description of a GA

GA is an optimization method that simulates the evolutionary process of species, based on the idea that the fittest individuals have better longevity and offspring. Initially, a population of individuals or chromosomes is defined, selected randomly and uniformly distributed throughout the search space if possible. Each chromosome consists of a set of elements called genes, which can take multiple values (alleles), according to the appropriate coding. In the basic algorithm (as defined by J. Holland), possible alleles are 0 and 1, making the chromosome a binary string. The population evolves through successive iterations (generations). Each generation results in a new population with the same number of individuals. Each individual is evaluated using a measurement function (the Fitness function). To generate a new population, the GA evaluates individuals and selects chromosomes based on their fitness function, it then recombines selected individuals using genetic operators such as mutation and crossover. Over generations, individuals converge towards the optimum of the fitness function. Algorithm 1 illustrates the general structure of a genetic algorithm.

Algorithm 1: Pseudo code of a classical GA

```
BEGIN
Iteration←1
Generate initial population
Evaluation (initial population)
While not (stopping criterion) do
   Select the best individuals for reproduction
   New population=crossover (population)
   New population=mutation (New population)
   Evaluation (New population)
   population=New population
   Iteration=Iteration+1
End while
END
```

4. Basic Evolutionary Tools

The principal elements of a standard Genetic Algorithm are:

4.1 Encoding

Coding solutions into chromosomes is a fundamental question in a GA. The coding step assigns a data structure to each individual. Historically, binary coding was the first to be used because it allows for the creation of simple genetic operators and the encoding of diverse types of objects such as real numbers, integers, and character strings. This simply requires the use of a coding/decoding function to switch between representations. It was also using this coding that the first results of theoretical convergence were obtained. individual encoding in a GA is determined by the characteristics of the data used to represent solutions to the problem. This encoding is not restricted to binary; it can vary based on the specific attributes of the problem's variables. For example, real-valued data can be encoded using floating-point numbers, whereas more complex data may necessitate specialized encoding for efficient representation within the search space.

4.2 Selection

The selection operation involves choosing elite individuals from the current population to serve as parents, resulting in the generation of offspring. Fitness values are used as criteria to judge whether individuals are elitist (Haldurai et al, 2016). Choosing elite individuals involves giving those with higher fitness values a greater probability of contributing to the next generation by producing at least one offspring. This process statistically identifies the best individuals in a population and eliminates the less fit ones. It is an artificial version of natural concept of survival of the fittest. In nature, adaptation is determined by the ability of organisms to overcome various obstacles to reach adulthood and reproductive age. In genetic algorithms, the optimization function determines the survival or elimination of each individual.

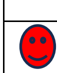
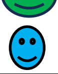
Different technical approaches can be employed for the selection process such Rank Selection, Tournament Selection and Roulette Wheel Selection (RWS). Rank selection first sorts the population by fitness and then every chromosome receives fitness from this ranking. The worst will have fitness 1, second worst 2 etc. and the best will have fitness N (number of chromosomes in population). After this, all the chromosomes have a chance to be selected. The probability that a chromosome will be selected is then proportional to its rank in this sorted list, rather than its fitness (Haldurai et al, 2016). In Tournament Selection, n individuals are chosen at random from the entire population. These individuals compete against each other. The individual with the highest fitness value wins and gets selected for further processing of Genetic Algorithm (Shukla et al , 2015).

RWS assigns to each individual i of the current generation a probability $p(i)$ proportional to its fitness $f(i)$, calculated as follows:

$$p(i) = \frac{f(i)}{\sum_{j=1}^{n} f(j)} \tag{3.1}$$

Where n denotes the number of individuals (the population size).

A circle is then drawn and divided into n sectors (n is the number of individuals in the population), where each individual i occupies a portion proportional to its probability $p(i)$, this guarantees that the sectors of greater size are occupied by the higher-quality chromosomes. Then, spin the wheel n number of times. When the roulette stops, the sector on which the pointer point corresponds to the individual being selected (Shukla et al, 2015). It can be seen that individuals with high selection probability are more likely to be selected (Lin and Zhang, 2020).

i	$F(i)$	$P(i)$
	0.1	0.08
	0.5	0.39
	0.29	0.23
	0.39	0.30

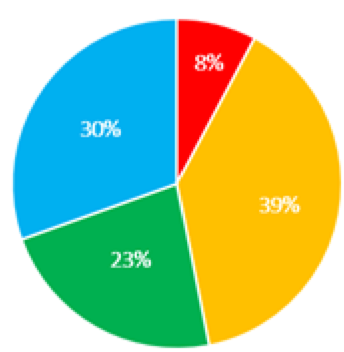


Figure 3. 1: RWS

4.3 Elitism

Elitism in GAs ensures that the best individuals in a population are preserved and passed on to the next generation. A certain percentage of the top-performing individuals from the current population is retained and transferred to the new generation. For instance, the top 10% are directly copied into the new population. Another approach found in the literature involves replacing the least-fit individuals in the new population with the best individuals from the previous generation after generating a new population using genetic operators. This method effectively keeps track of the best solutions identified up to the current generation.

4.4 Crossover

Crossover is the main genetic operator. It operates on two chromosomes at a time and generate offspring by combining both chromosomes' feature (Gen and Chen, 1997). Figure 2 illustrates various crossing techniques which are employed to perform genetic recombination between two individuals.

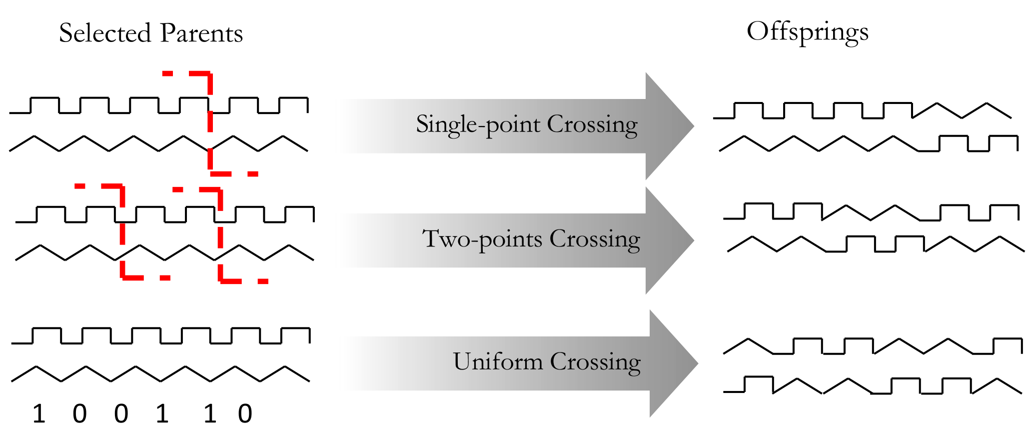


Figure 3. 2: Crossover

4.5 Mutation

Mutation is often performed after crossover (Haldurai et al, 2016). Mutation is an operator that maintains the genetic diversity from one population to the next population

(Katoch et al, 2020). This genetic operator randomly alters a portion of the population to explore the search space, the size of this portion is determined by a significantly lower mutation probability compared to the crossover probability. Figure 3 shows a simple mutation example applied to a randomly chosen individual from the new population.

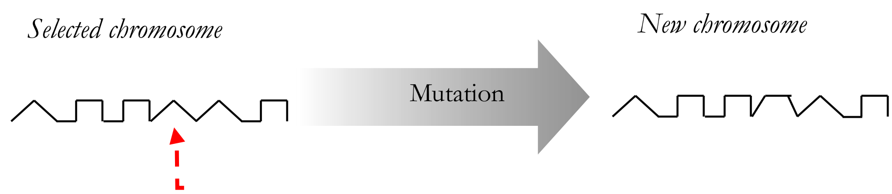


Figure 3. 3: Mutation

4.6 Parameterization of a GA

Despite the seemingly simple nature of GAs, creating an effective one is challenging due to their sensitivity to algorithmic and parametric choices. They require significant creativity in representation choices. Three key parameters are crucial for the successful operation of a GA:

- *The population size and its initialization:* Are critical aspects of GAs. Determining the optimal number of individuals often requires multiple trials, as it directly impacts the algorithm's performance. Similarly, the random initialization of the population plays a crucial role in the convergence of the GA, as it defines the starting points for searching optimal solutions.
- *Termination criteria:* It is crucial to determine the optimal moment to stop the process. A common method involves setting a maximum number of iterations. The process can also stop when the maximum fitness value is reached or when stagnation in the evolution of the population is detected over several generations.
- *The probability of applying genetic operators:* determines the choice of mutation and crossover rates. The crossover rate is typically high, ranging between 70% and 95% of the total population, while the mutation rate is generally low, varying between 0.5% and 1% of the total population.

This setting is not universal, as it may not be suitable for solving all problems, but it can serve as a starting point to initiate a search for solutions to a given problem.

5. Conclusion

Genetic algorithms, as part of nature-inspired AI techniques, use evolutionary mechanisms to solve complex problems. After presenting the main elements of a genetic algorithm, the next chapter will provide a detailed analysis of their application in a supervised learning framework for calculating a wildfire risk map. This approach will DEMONSTRATE THE EFFECTIVENESS and relevance of genetic algorithms in addressing significant environmental challenges.

CHAPTER IV

GENERAL PRESENTATION OF THE STUDY AREA

Abstract

In this chapter, we present the geographical and administrative location of the *Thénia El Had* state forest, as well as some characteristics of this forest area (terrain, climate, vegetation cover, etc.).

1. Introduction

The wilaya of Tissemsilt is one of the wilayas (provinces) of Algeria, located in the central Tell region, approximately 220 km southwest of the capital. It is situated in the Tell Atlas mountains, between the Ouarsenis range to the west and the Blida Atlas to the east. It is bordered by the wilayas of Tiaret and Djelfa to the south, Relizane to the west, Chlef and Ain Defla to the north and Médéa to the east.

This region is characterized by its rich forest resources. The area of interest in this study is the *Thénia El Had* forest.

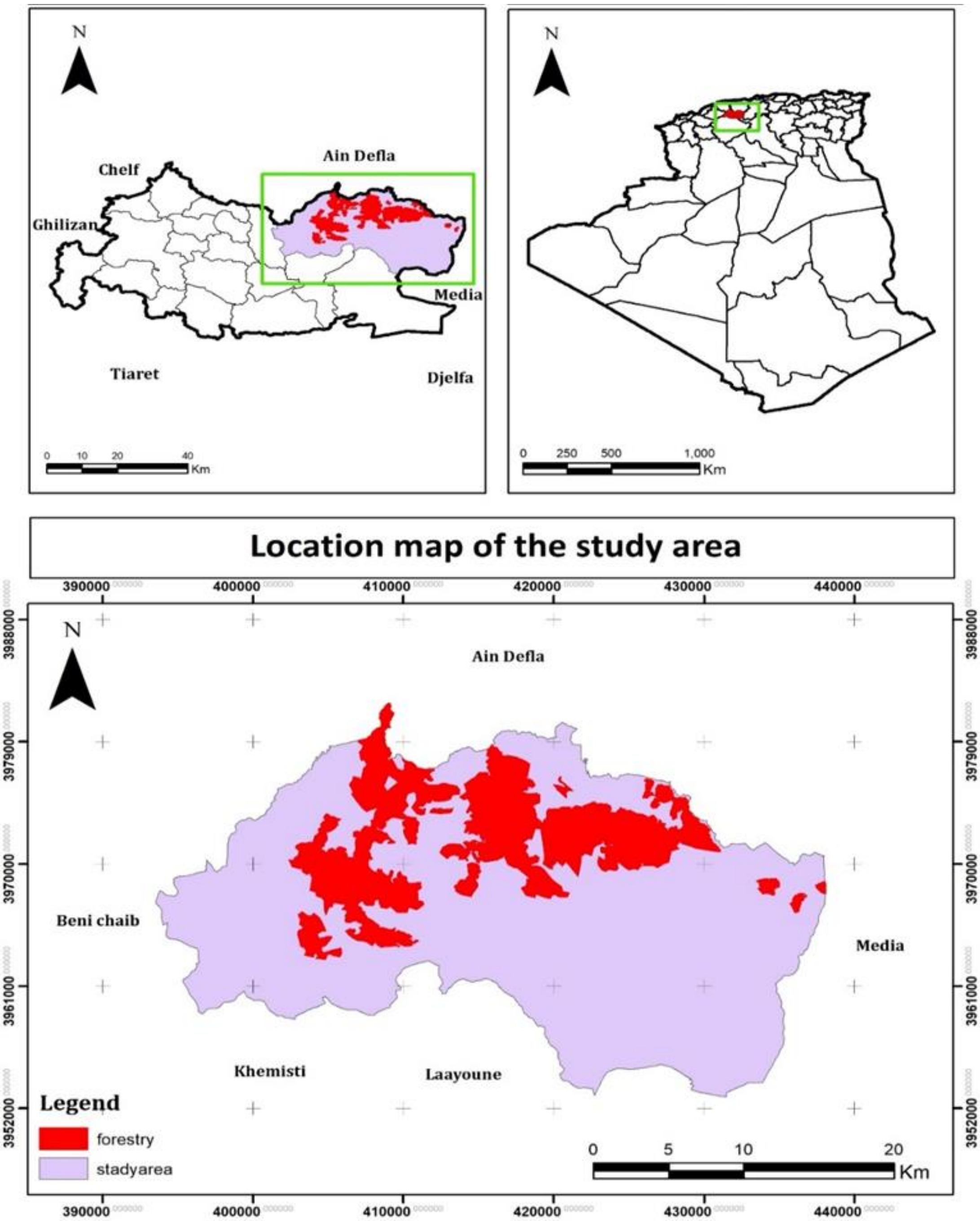


Figure 4.1: Location map of the study area

2. Geographical and administrative situation

The *Thénia El Had* district is located about 46 km northeast of Tissemsilt. It consists of four municipalities: Thénia El Had, Bordj Emir Abdelkader, El Youssoufia and Sidi Boutchent. The district is made up of ten forests divided into several sections, characterized by the presence of various types of trees, including Atlas cedar, oak, and pine.

3. Presentation of the forest massif Thénia El Had

3.1 types of vegetation

The study area is distinguished by its diverse plant life, encompassing a range of species from trees and shrubs to various other types of vegetation.

Trees	Shrubs	Other Plants
Green oak, Cork oak, Atlas cedar, Aleppo pine, Cypress, Zeen oak, Olive tree.	Juniper Prickly juniper Dense Mediterranean shrubs	Esparto grass Brushwood Dry grasses and shrubs

Tableau 4.1: Forest species

The Thénia El Had area is divided into 40 cantons spread across ten forests, covering a total area of [14000ha]. This area is distinguished by the presence of the Madagh National Reserve, established on August 3, 1923, spanning 3,460 hectares. It is characterized by Atlas cedar trees covering a third of its area, alongside various other types of forests such as oak and pine. The region is considered one of the most important tourist destinations due to its stunning natural beauty and picturesque landscapes. (Figure3)

3.1 Road:

The road network (Figure4) in Thénia El Had is considered the lifeline of the area, with three national roads (National Road No. 14, 60, and 65) passing through it, in addition to provincial roads (Provincial Road No. 19 and 5). The area also has several forest trails that cover the entire forested region, facilitating access to its various parts.

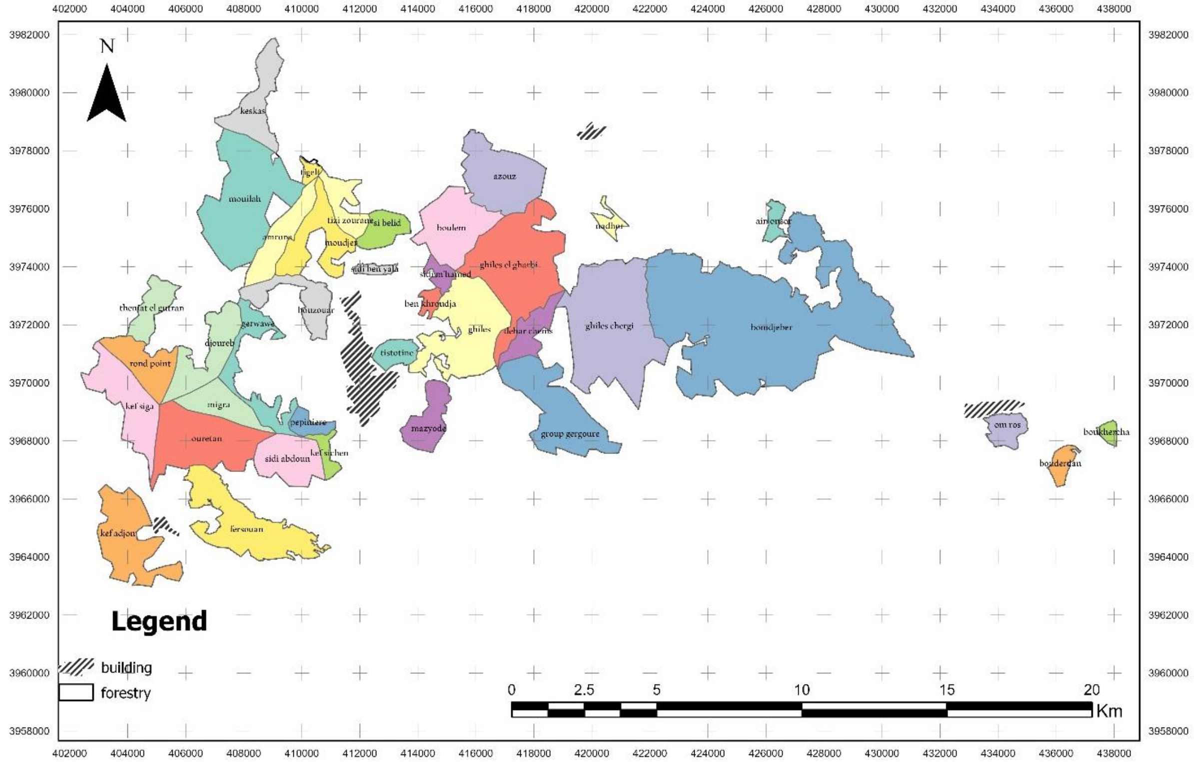


Figure 4.2: Forest cantons map

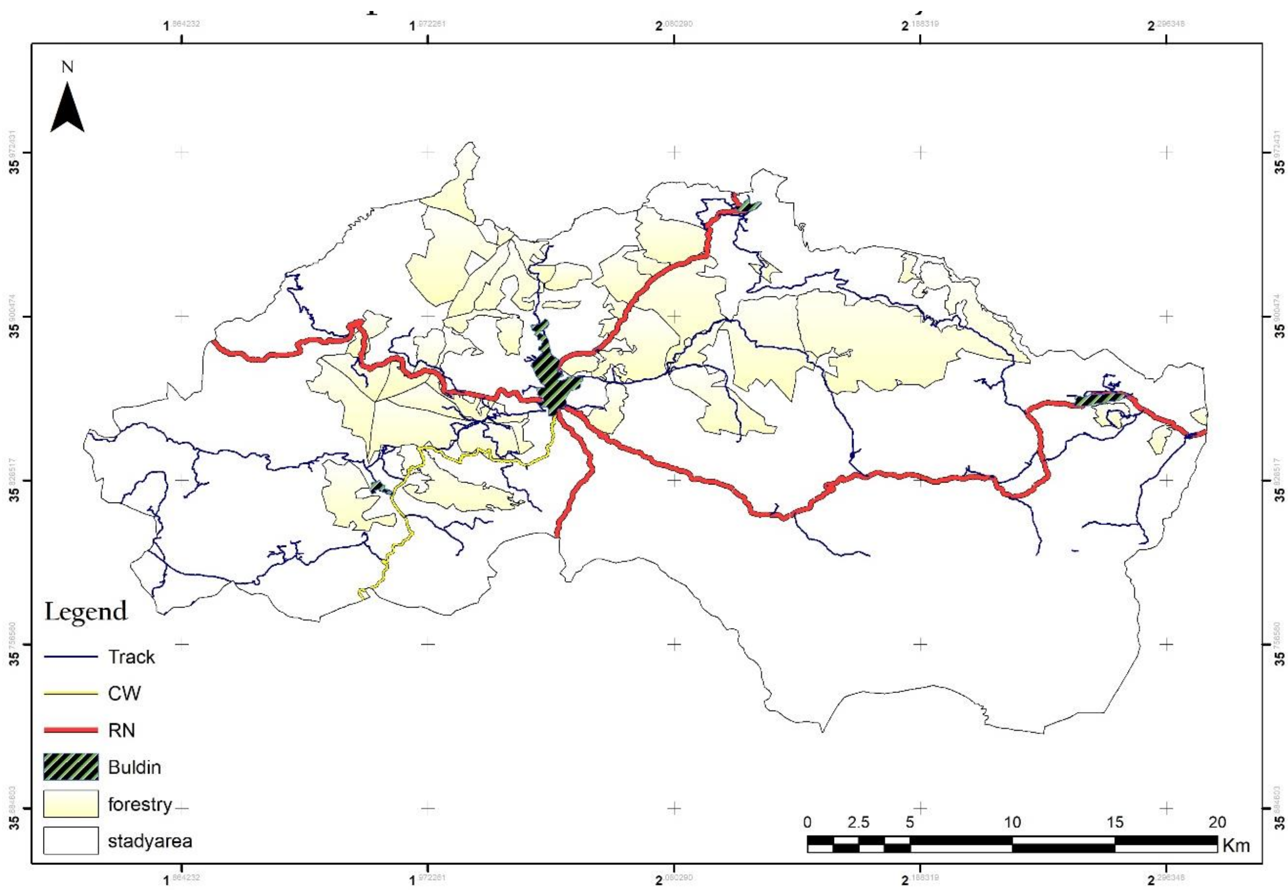


Figure 4.3: Road network map

4. Physical characteristics

4.1 Relief

In general, the study area is characterized by very rugged terrain, crossed by several seasonal streams distributed throughout the forest, with numerous ridgelines present.

4.1.1 Slope:

The significant variability in slope indicates higher elevation changes in specific regions, with steeper slopes (represented in red and orange) suggesting more rugged terrain. These areas are more prone to erosion and landslides.

Gentler slopes (0-20 degrees), on the other hand, are more suitable for agricultural activities, urban development.

Ecologically, slope impacts vegetation types and density, with steeper areas potentially having less dense vegetation due to soil instability. This data guides reforestation or conservation efforts by identifying areas prone to erosion that would benefit from increased vegetation cover.

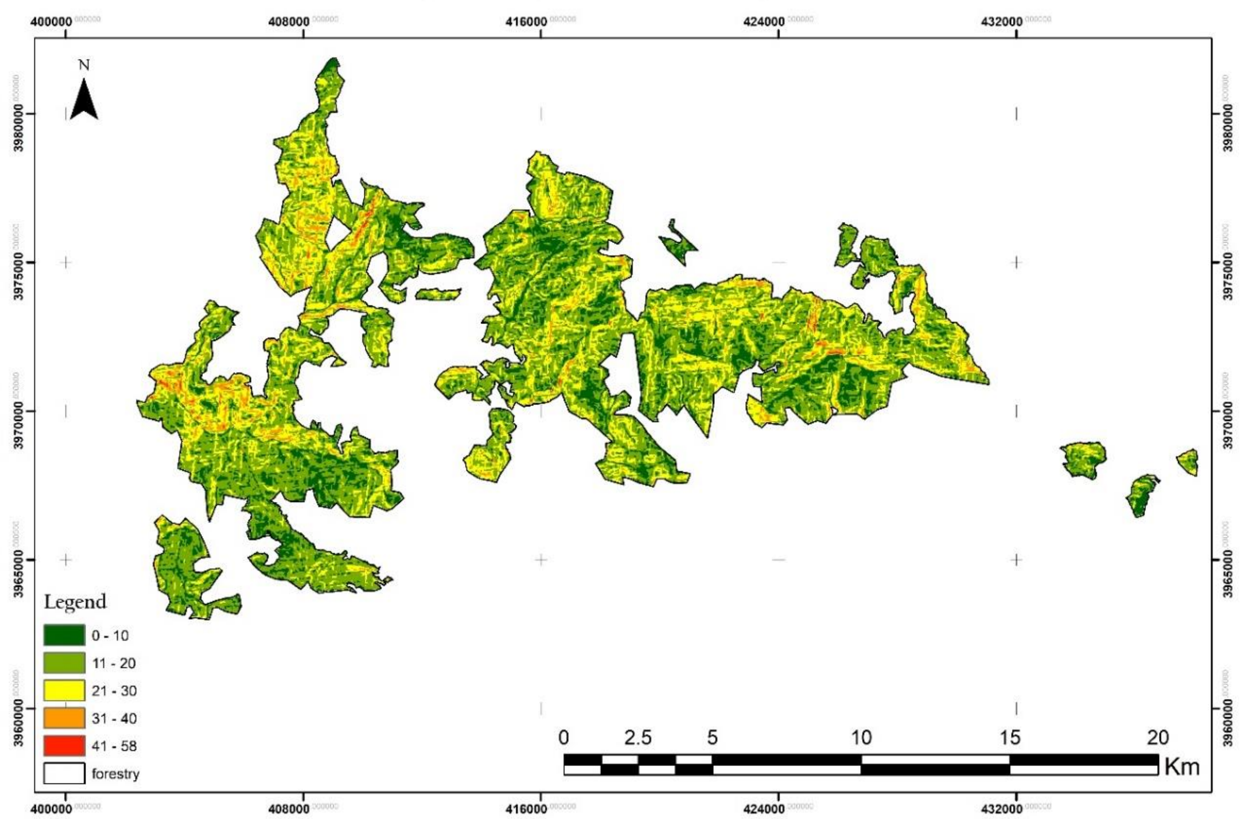


Figure 4.4: Slope map

4.1.2 Aspect

The aspect map reveals considerable variability in slope orientation, indicating diverse microenvironments within the study area. North-facing slopes (represented in red) typically receive less solar radiation, making them cooler and more humid compared to south-facing slopes (cyan), which receive more sunlight and are warmer and drier.

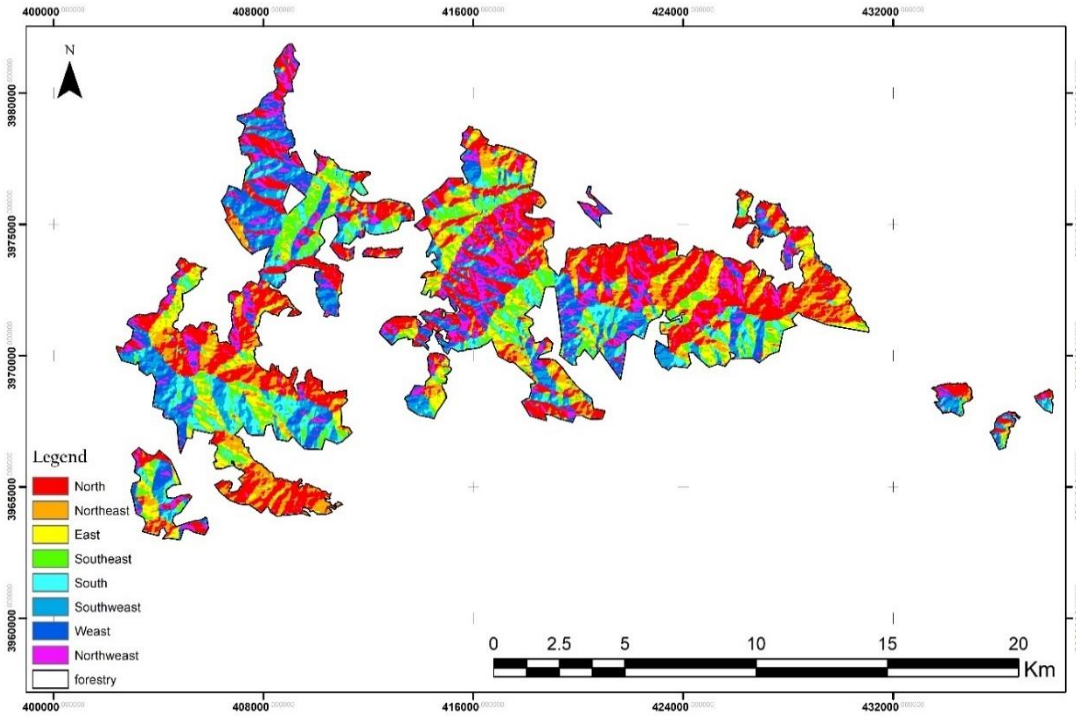


Fig06 : Aspect map

4.1.3 Altitude

The elevation map shows significant topographic diversity in the area, with elevations ranging from 714 meters at the lowest point to 1782 meters at the highest point.

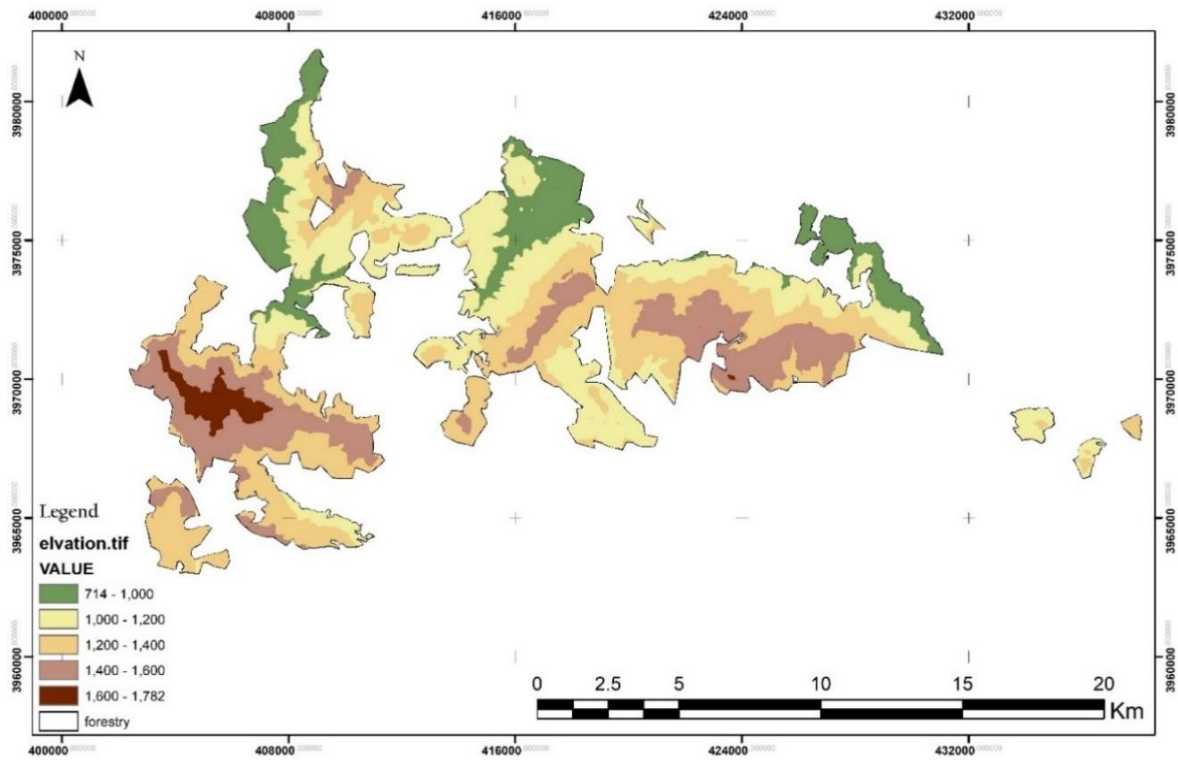


Figure 4.6: Elevation map

The highest elevations are concentrated in the western part of the study area, while the lowest elevations are found in the eastern part.

4.2 Hydrography:

The hydrological network includes all water components in the area. Some key features of the hydrological network can be observed from the map:

- Distribution: Most valleys are concentrated in the western part of the study area, where elevations are higher.
- Flow: Valleys generally flow from west to east.
- Density: The density of the hydrological network increases in the western part of the study area, where elevations are higher and rainfall is more frequent.
- Diversity: The hydrological network includes a variety of water components.

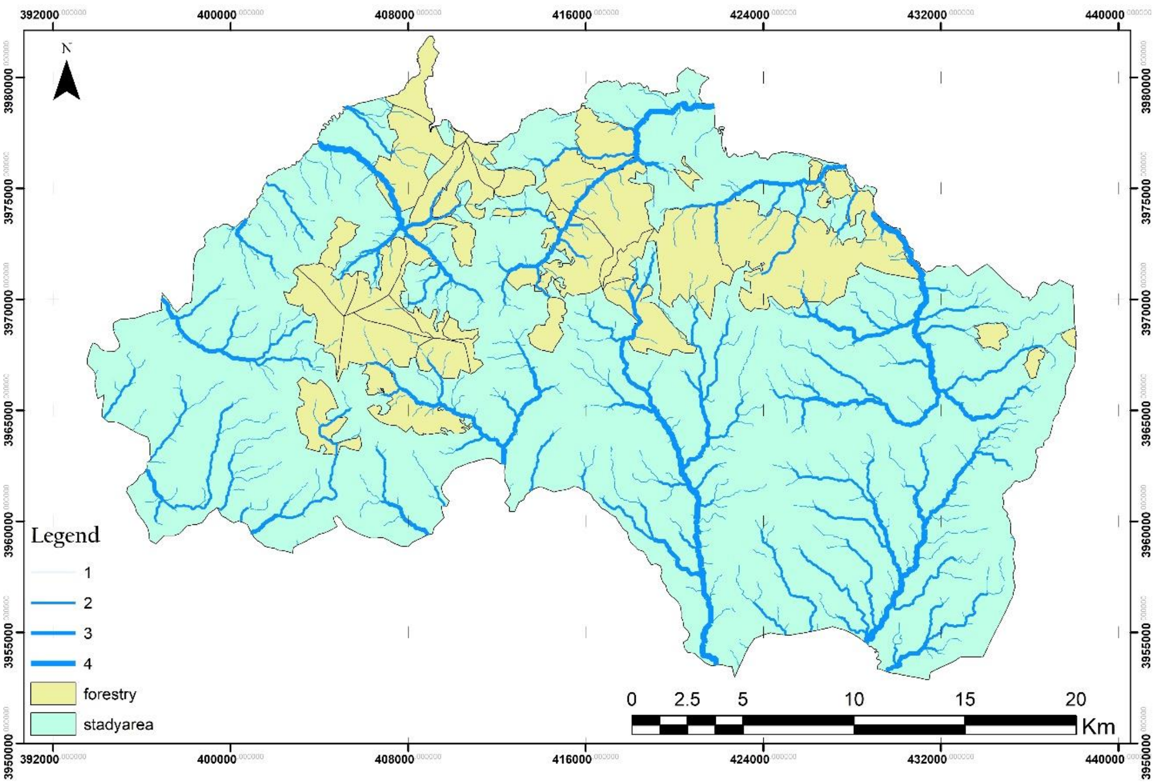


Figure 4.7: Hydrological network map

5 Climatology

Understanding the climatic conditions of a region requires long series of climatic data (rainfall, temperature, winds, etc.), as they allow for monitoring the climate's evolution in the region and managing fluctuations observed during climate changes and their potential effects. The study of local climate necessitates climatic data, but due to the absence of meteorological stations in Thénia El Had, extrapolations need to be made relative to a reference station.

5.1 Precipitation

The downloaded data shows that:

- The distribution of precipitation in the Thénia El Had massif is irregular.
- The maximum rainfall occurs in December and January.
- The months of July and August receive only small amounts of rain.

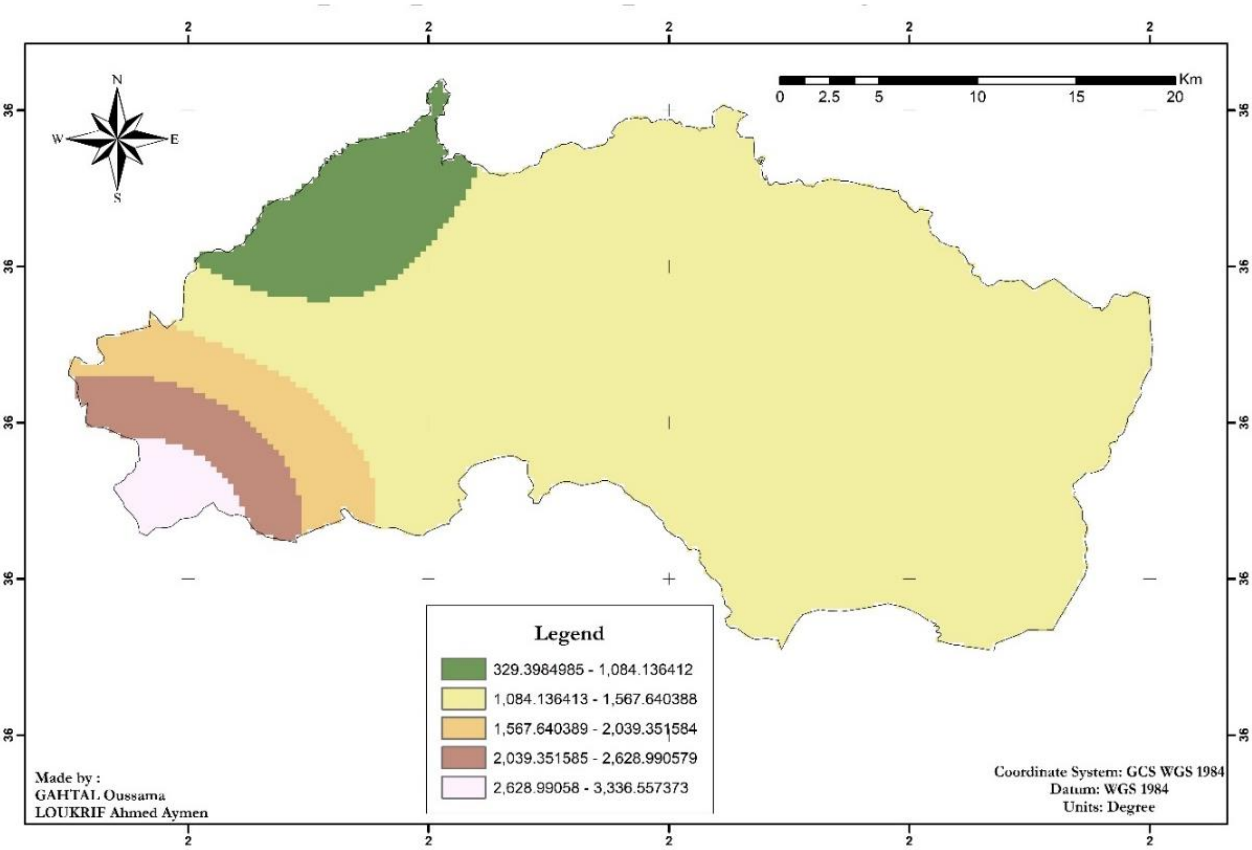


Figure 4.8: Precipitation map

5.2 Temperature

The downloaded data shows that recorded temperatures exhibit a positive correlation with biomass: moderate temperatures are observed where biomass is high, while higher temperatures are recorded where vegetation is low.

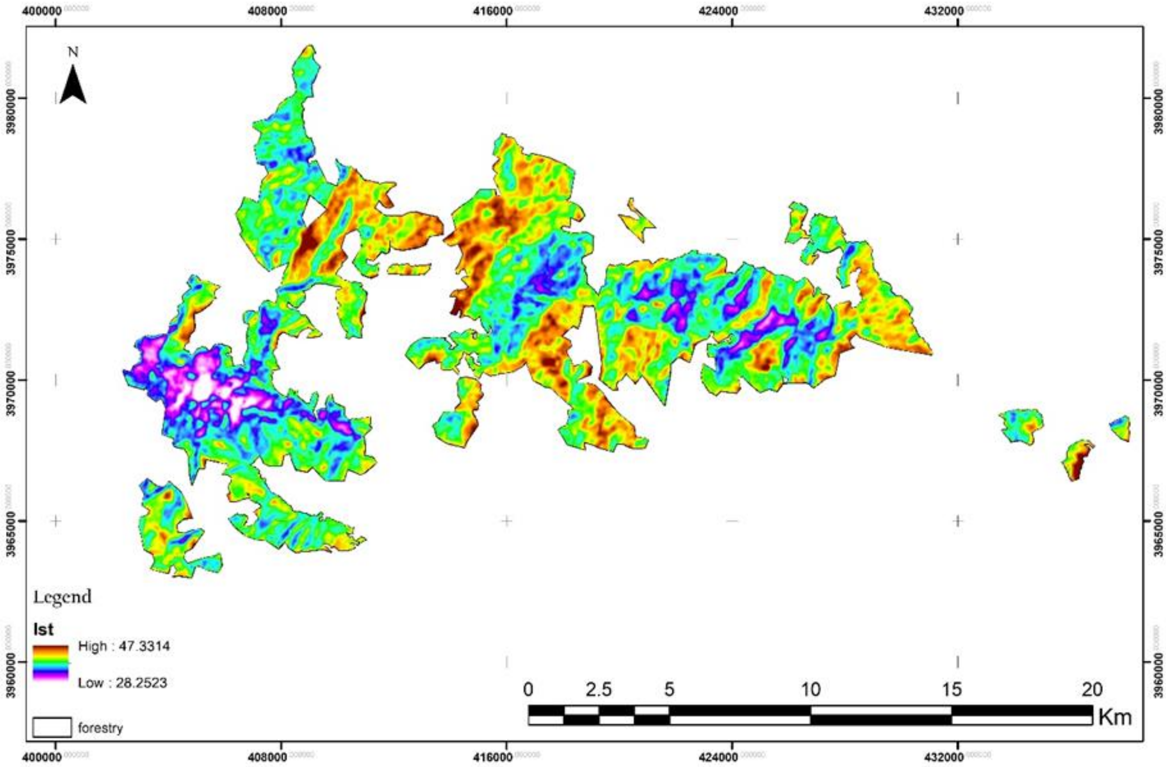


Figure 4.9: LST map

5.3 Humidity

The humidity index in the study area ranges approximately between 0.17 and 0.214.

From this map, we observe the following:

The National Park M'dad has areas with high humidity, especially in the sections of rond point and migra.

The sections of azouz, boulem, amrona, and tigelt exhibit low humidity levels.

The differences in humidity levels can be attributed to the following factors:

- Soil type
- Density of vegetation cover in some areas and its scarcity in others
- Variances in elevation
- Sun exposure

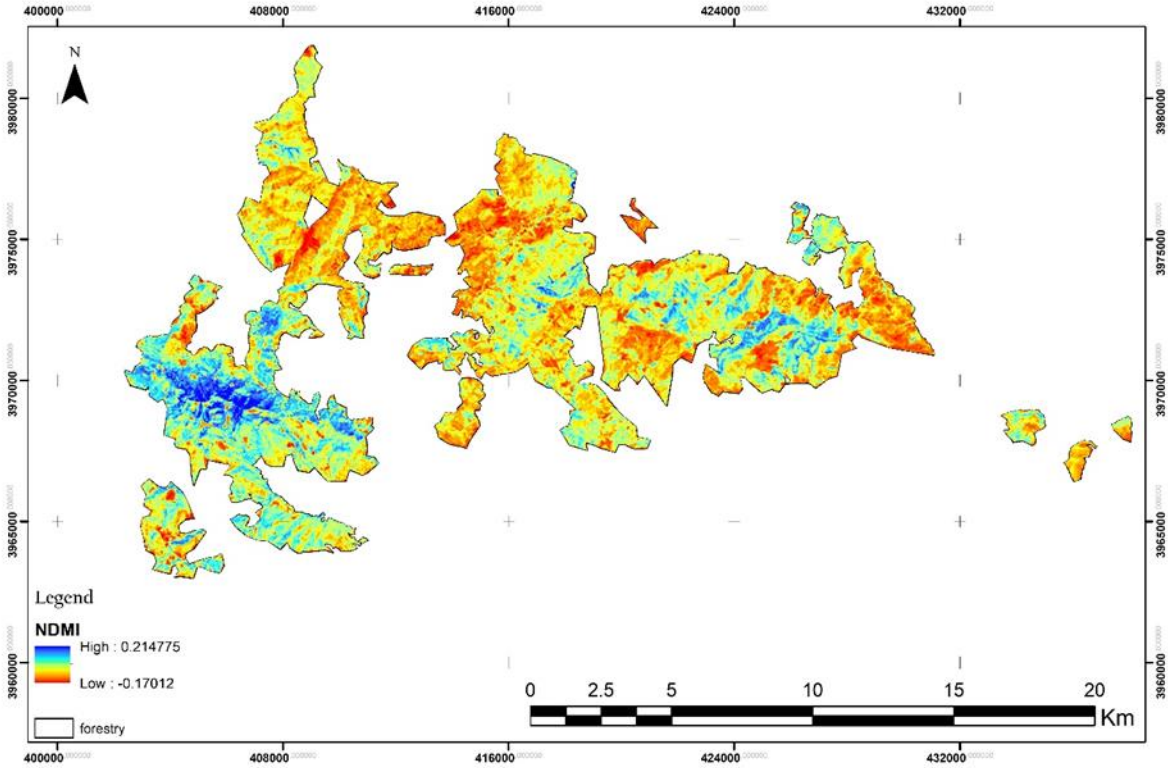


Figure 4.10: Humidity map

5.4 Wind

Wind is one of the most important parameters influencing the spread of fires. Therefore, its study is of paramount importance, requiring knowledge of its directions, frequency, and intensity.

Wind Speed Map:

- Areas with High Wind Speed: The highest wind speeds are concentrated in the western part of the study area, where elevations are higher.
- Areas with Low Wind Speed: Lower wind speeds are found in the eastern part of the study area, where elevations are lower.

Distribution: Wind speeds vary unevenly throughout the study area, with a significant concentration in the western part.

Direction: Winds generally blow from west to east.

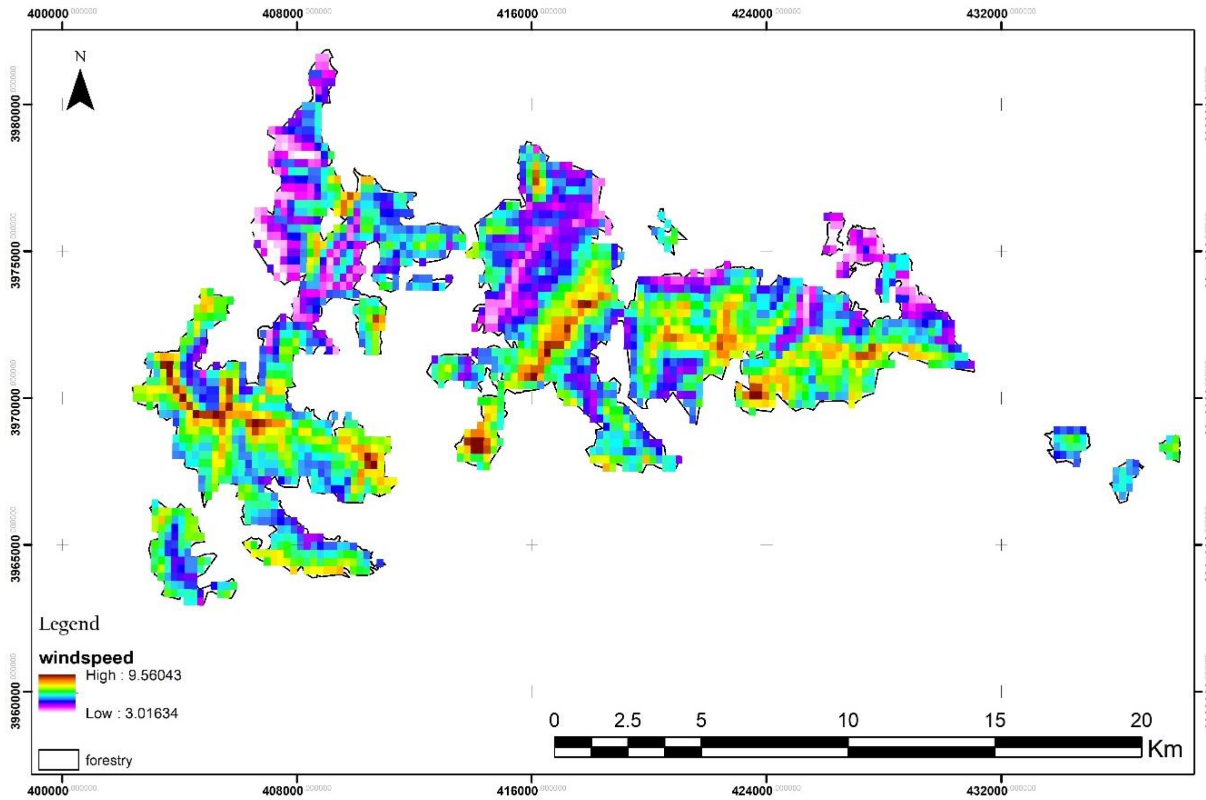


Figure 4.11: Wind speed map

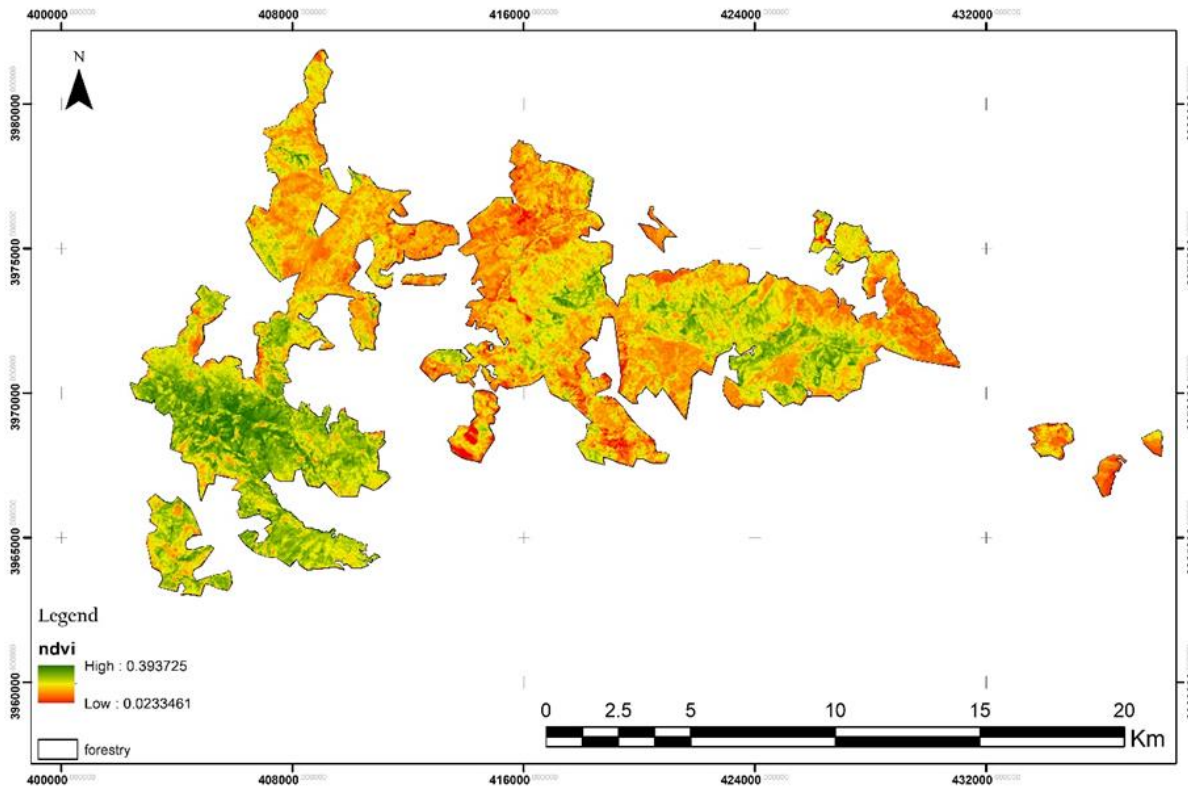


Figure 4.12: Ndvi map

6. Vegetation

The vegetation index values in the study area range approximately from 0.02 to 0.4. Here are the observations:

- There is dense vegetation cover in the section corresponding to the M'dad National Park.
- In contrast, the central section has moderately dense vegetation cover.
- Additionally, the eastern and the northern parts, specifically the sections of Amrona, Azouz, and Boulem, exhibit very low vegetation density.

The variation in vegetation index can be attributed to several factors, whether climatic or human-induced.

7. Infrastructure

The study area includes several water points, approximately ten in total, mostly concentrated within the National Park M'dad. Additionally, there are two monitoring centers, one located within the National Park and the other in the municipality of Bordj Emir Abdelkader. It is noticeable that the distribution of water points is not well spread throughout the entire forested area.

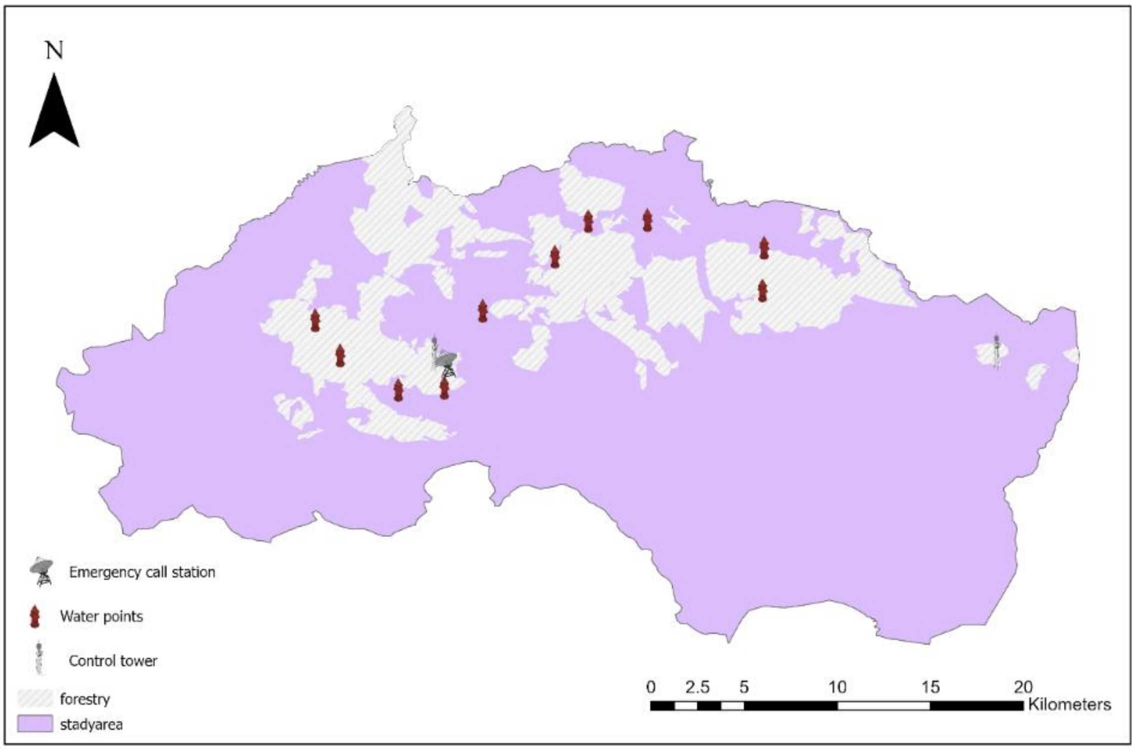


Figure 4.13: Infrastructure map

8. History of forest fires

By examining historical trends, experts can identify seasonal or cyclical patterns in the occurrence of fires. This helps to better understand the times of year or meteorological conditions conducive to fires.

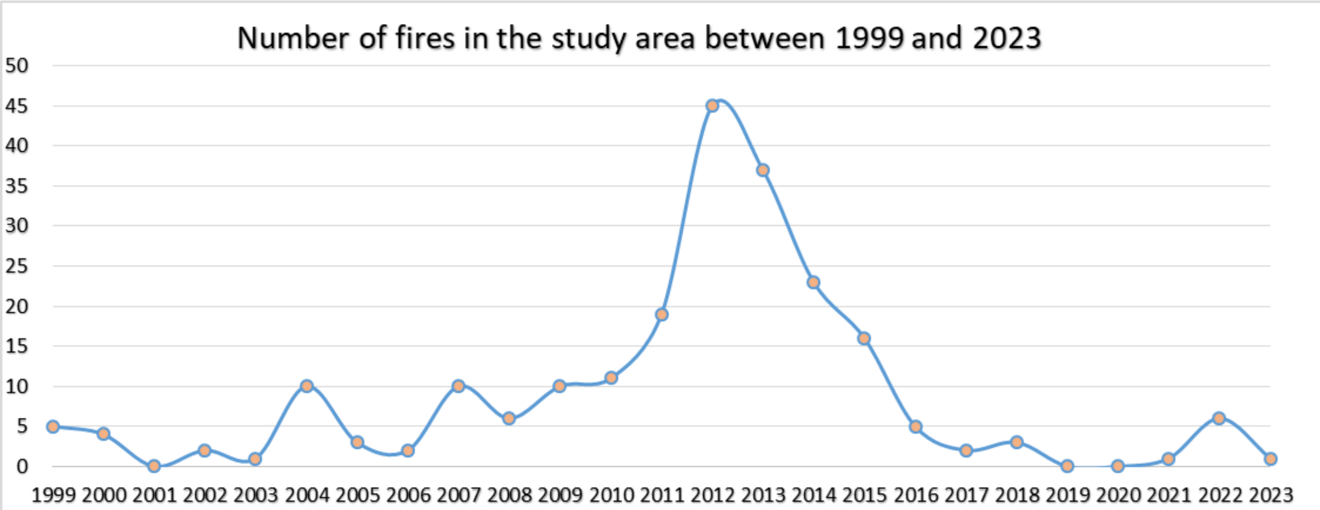


Figure 4.14: Number of fires

The graph shows changes in the number of fires in the study area between 1999 and 2023. Based on the provided data, several key trends can be observed:

Period from 1999 to 2009: This period experienced slight fluctuations in the number of fires, ranging between 2 and 10 fires annually.

A notable increase was observed in 2005, where the number of fires reached its first peak at around 11 fires.

Period from 2010 to 2015: This period saw a sharp increase in the number of fires starting in 2010, with a significant rise leading to a peak in 2012 at approximately 46 fires. After the peak in 2012, the number of fires began to gradually decline but remained relatively high until 2015.

Period from 2016 to 2023: This period witnessed a continuous decrease in the number of fires, dropping to much lower levels compared to the peak in the previous period.

From 2017 to 2020, there was relative stability in the number of fires, ranging between 1 and 3 fires annually.

In 2021, the number of fires rose again to about 6 fires, but it decreased in the following years.

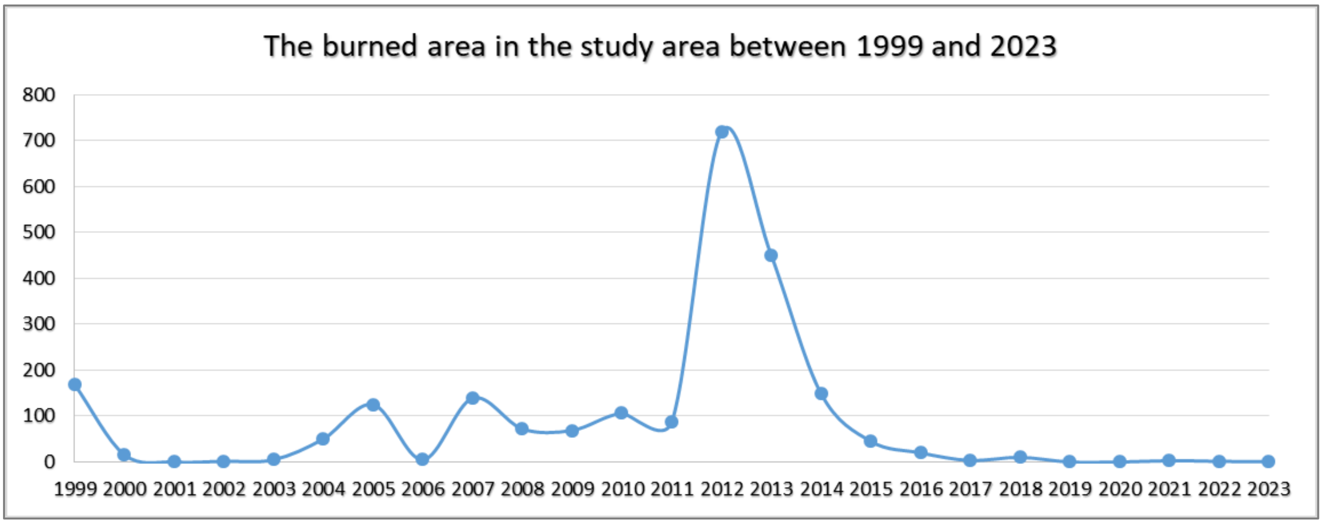


Figure 4.15: Burned area

This graph illustrates the burned area in the study region between 1999 and 2023. Below is an analysis of the key trends in the provided data:

Period from 1999 to 2009:

This period experienced slight fluctuations in the burned area, ranging between 50 and 200 hectares annually.

There were notable increases in the years 1999, 2005, and 2008, where the burned area reached approximately 100 to 200 hectares.

Period from 2010 to 2015:

This period saw a sharp increase in the burned area, especially in 2012, where it peaked at around 750 hectares.

After the peak in 2012, the burned area began to gradually decline, but remained relatively high until 2015.

Period from 2016 to 2023:

This period witnessed a significant and continuous decrease in the burned area, dropping to very low levels compared to the peak in the previous period.

From 2017 to 2023, there was relative stability in the burned area, ranging between 0 and 20 hectares annually.

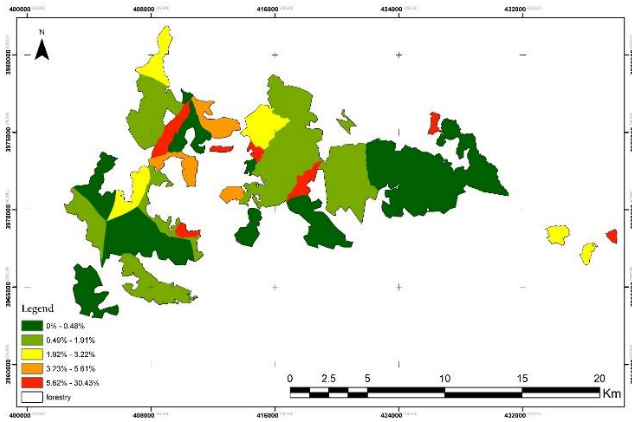


Figure 4.16: Percentage of burned area

The attached map shows the percentage of burned areas in each canton. We notice that:

The Amrona canton recorded the highest percentage of burned areas, indicating the severity and impact of large fires in this region.

Some areas belonging to the El-Medad National Park and Bomdjeber recorded the lowest percentage of burned areas, suggesting that these areas experience less impact from fires, possibly due to better protection, more fire-resistant environmental conditions, or swift intervention when fires occur.

The majority of cantons did not burn completely (the percentage of burned area is low).

The areas with the highest percentages of burned area are scattered and not concentrated in one place.

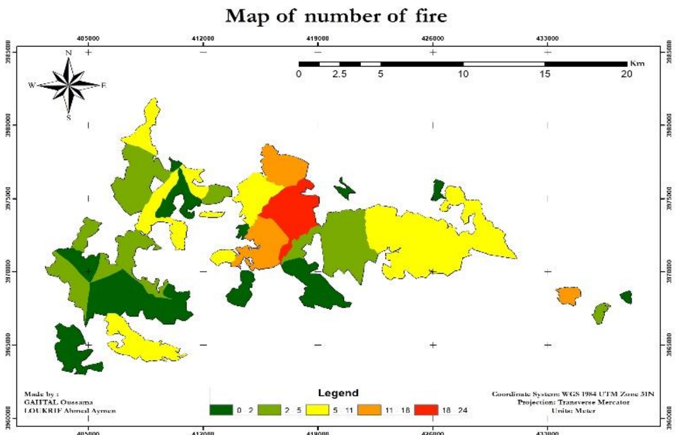


Figure 4.17: Map of forest fire occurrences

The attached map illustrates the number of fires in each section from the year 1999 to 2023. Several observations can be made:

- The section "Ghliss Chegri" has experienced the highest number of fires, indicating a high fire risk in this area.
- Areas within the El-Medad National Park recorded the lowest number of fires, suggesting a higher level of protection or environmental factors less prone to fires.

9. Conclusion

Based on the results obtained from the analysis of climatic data in the study area during the period 1999-2023, it can be said that the local climate of the forest is Mediterranean, with a humid winter season and a dry summer season. There is also irregularity in the distribution of rainfall throughout the year.

The Thénia El Had forest is primarily composed of dominant forest formations: Evergreen oak, Atlas cedar, and Aleppo pine. According to environmental factors, these species are in their semi-arid and sub-humid bioclimatic zones. These species are of Mediterranean origin and are very common in Algeria. The Evergreen oak, along with Aleppo pine, forms the majority of the woodlands in the Tell region and occupies extensive areas in pure stands.

The analysis of the flammability and combustibility of the dominant forest formations in Thénia El Had reveals a high sensitivity to the risk of fire.

CHAPTER V

APPLICATION AND RESULTS

Abstract

In this chapter, we present the methodological approach adopted to calculate the fire risk index map for the Thénia El Had forest using three different methods. This approach utilizes remote sensing data and Geographic Information Systems (GIS).

1. Introduction

The methodological approach adopted to develop a fire risk map is based on various cartographic information. It involves calculating different factors (topography, human presence, vegetation combustibility in the region, climate, incorporating information on fire history over the past 25 years) using various types of data (satellite images, maps, field data, etc.).

2. Means used

2.1. Data used

- Satellite imagery:

We used satellite images from Landsat 7, 8, and 9 satellites, acquired from 1999 to the present day, with a resolution of 30 meters, along with Google Earth images for reconnaissance.

- Maps and plans

We have topographic maps of the study area as well as several forest plans provided by the General Directorate of Forests of *Tissemsilet* at various scales.

2.2. Hardware used

HP EliteBook 840 G5 I5-8350U

Samsung M13 64/04

2.3. Software used

ArcGIS (Map 10.8/Pro): Is a Geographic Information System (GIS) tool used to manipulate (store, process, analyze, manage, and present) all types of spatial and geographic data.

***Envi* (v5.3)**: used for satellite image processing. It includes a library of algorithms with data transformation functions, filtering functions, classification functions, etc.

Google Earth: is a software developed by Google that allows users to explore the Earth using satellite and aerial imagery. It enables visualization of images from various parts of the world, including 3D views, geographical data, maps, and other geospatial information.

Google Earth Engine: is a geospatial processing service. You can perform large-scale geospatial processing powered by Google Cloud Platform. The purpose of Earth Engine is to provide an interactive platform for developing large-scale geospatial algorithms.

Pydroid 3: is a Python IDE for Android devices. It allows users to write and run Python code directly on their Android smartphones or tablets. Pydroid 3 provides features such as code editing, debugging capabilities, and access to Python libraries, making it a convenient tool for programming on mobile devices.

Spyder (v5.4): is typically known as an integrated development environment (IDE) primarily used for scientific programming in Python.

3. Methodological approach adopted

The different stages of the methodology used throughout this work are represented in the following flowchart:

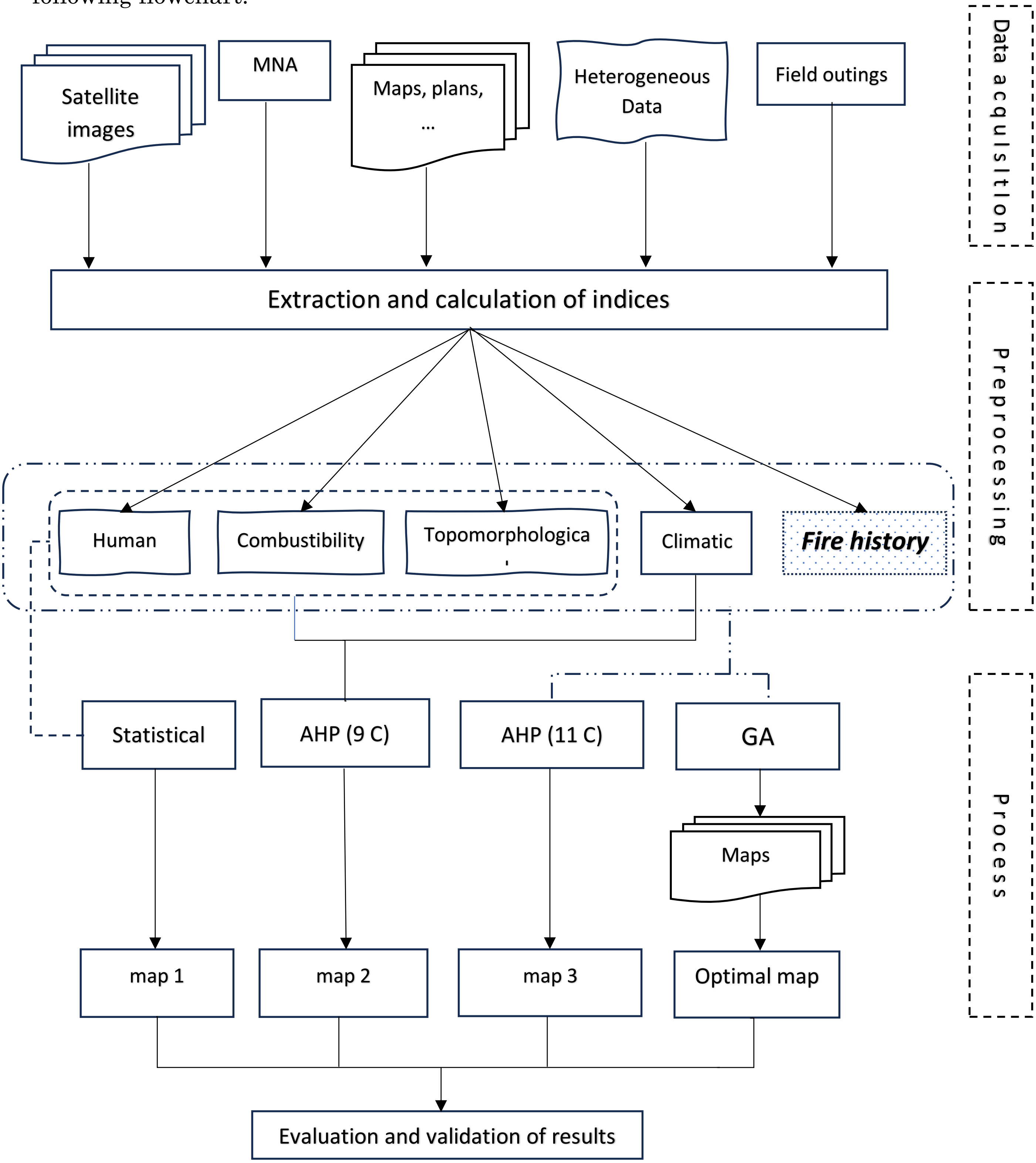


Figure 5.1: The overall organizational chart

3.1 Data acquisition

To carry out our study effectively, we collected, recorded, and retrieved all relevant data concerning our theme. This includes satellite images, digital elevation models (DEMs), topographic and thematic maps, forest plans, Sonelgaz plans, civil protection statistics, fire reports, etc.

3.1.1 Georeferencing

we proceeded with georeferencing, which is a critical step ensuring accurate alignment of all layers of information (satellite images, plans, maps, overlays, etc.). This registration process is performed in the universal geodetic system WGS 1984, using the Universal Transverse Mercator projection zone 31 (UTM31).

3.1.2 Digitization

Once the maps were georeferenced, we proceeded with digitizing all relevant geometric information for our study, including forests, points, and linear and zonal structures present within the study area.

3.2 Digital Elevation Model

The Digital Elevation Model (DEM) allows for the derivation of *slope*, *aspect*, and the *topomorphology* of the study area. These products are used to calculate parameters that will be employed in our methodological approach: the Topomorphological Index. The Digital Elevation Model of our study region is depicted in the figure 5.2.

Elevation Class	Vulnerability	Code
714-1000	Very low	5
1000-1200	Low	4
1200-1400	Moderate	3
1400-1600	Strong	2
1600-1782	Very strong	1

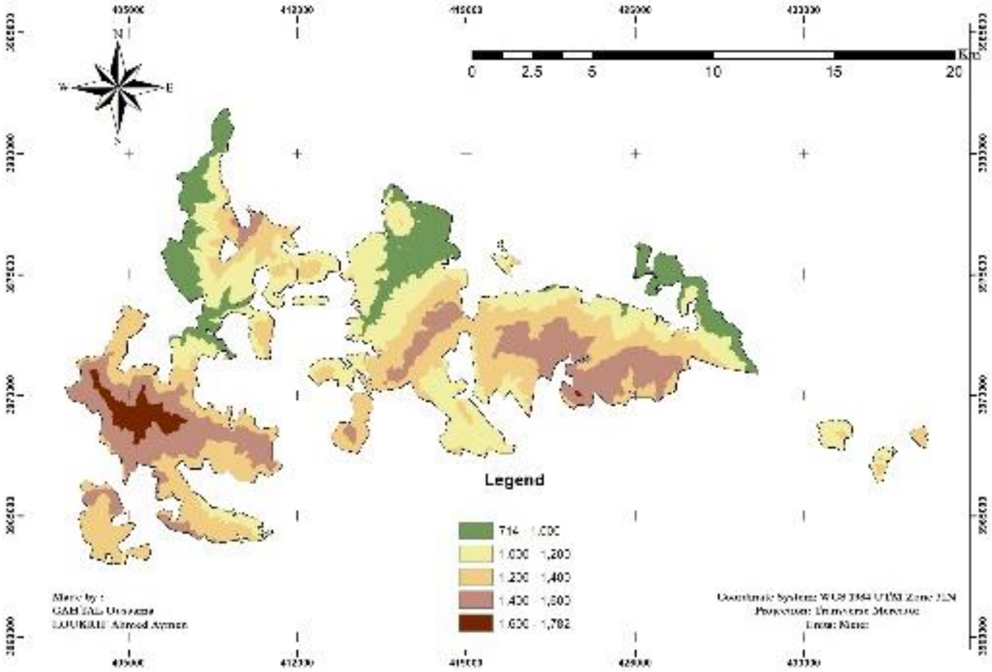


Figure 5.2: The Digital Elevation Model (DEM)

3.3. Calculation of the Topomorphological Index

3.3.1 Slope map

After generating the map, we proceeded with reclassifying the slope classes into five (5) classes, according to the adapted model. The slope map allows us to estimate the relative inclination of flames to the ground, indicating upward spread. Fires spread more rapidly uphill on steep slopes.

Slope Class	vulnerability	code
0-10	Very low	5
11-20	Low	4
21-30	Moderate	3
31-40	Strong	2
40-58	Very strong	1

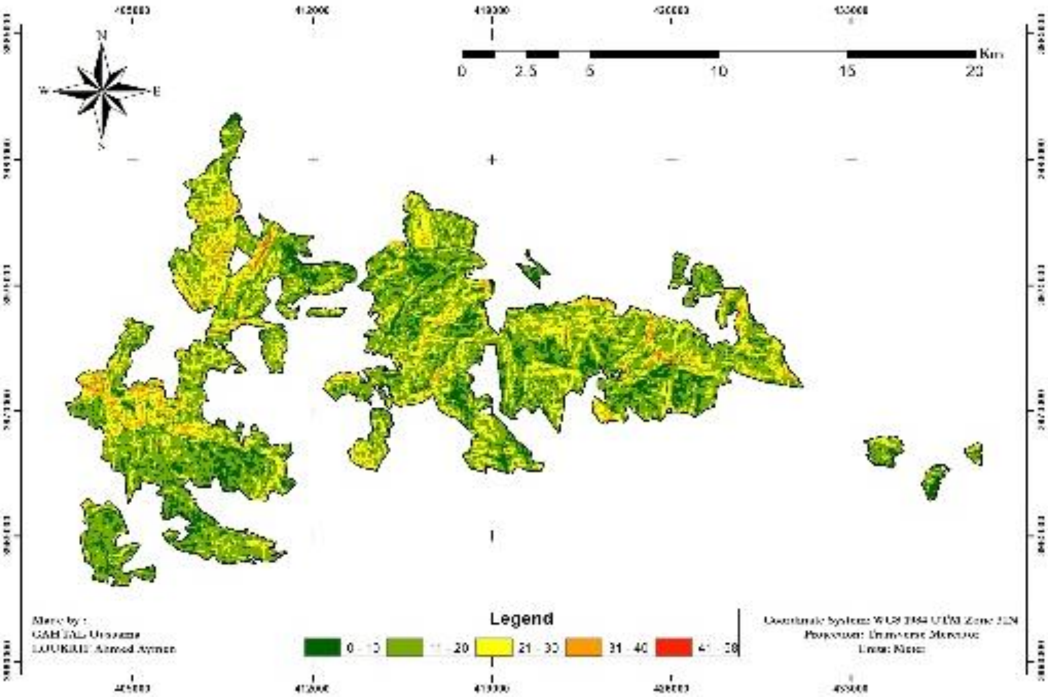


Figure 5.3: Slope map.

The class of moderate slope is the most dominant in the forest, leading us to conclude that the terrain relief in the study area is rugged.

3.3.2. Aspect map

After generating the exposure map, we reclassified the classes into five categories.

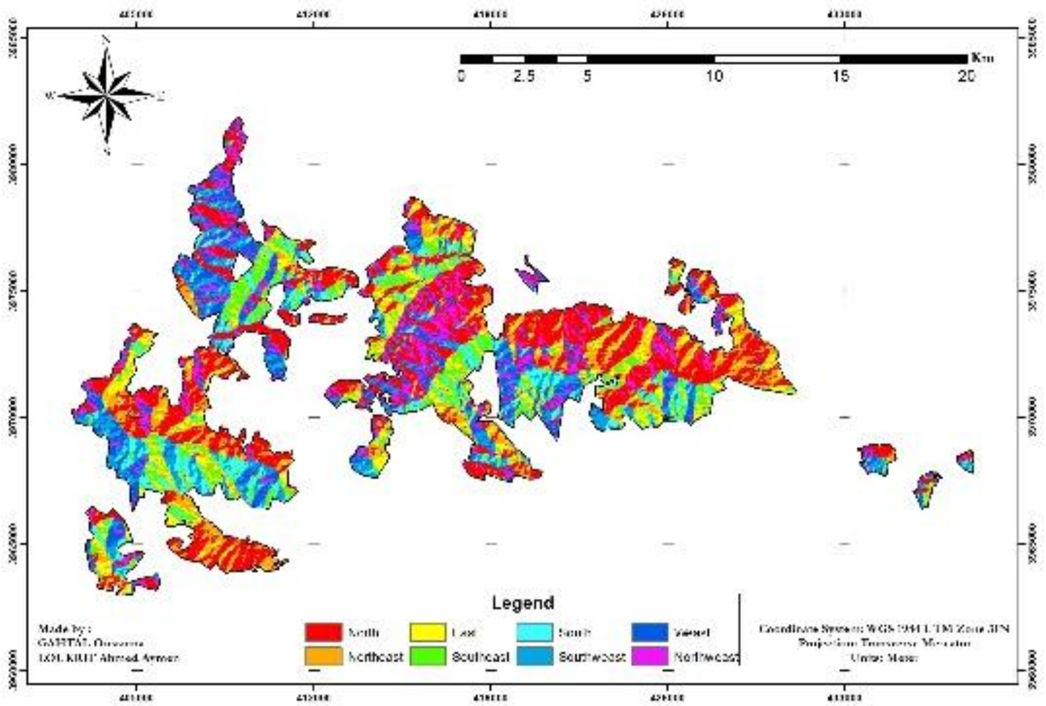
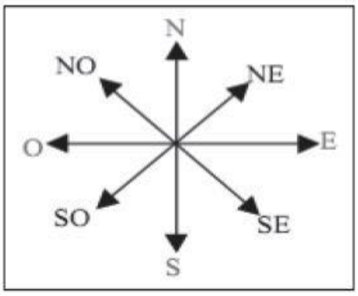


Figure 5.4: Aspect map

Aspect Classe	vulnerability	Code
S	Very low	5
SW-W	Low	4
E_SE	Moderate	3
N-NW	Strong	2
NE	Very strong	1



3.3.4. Topomorphological map

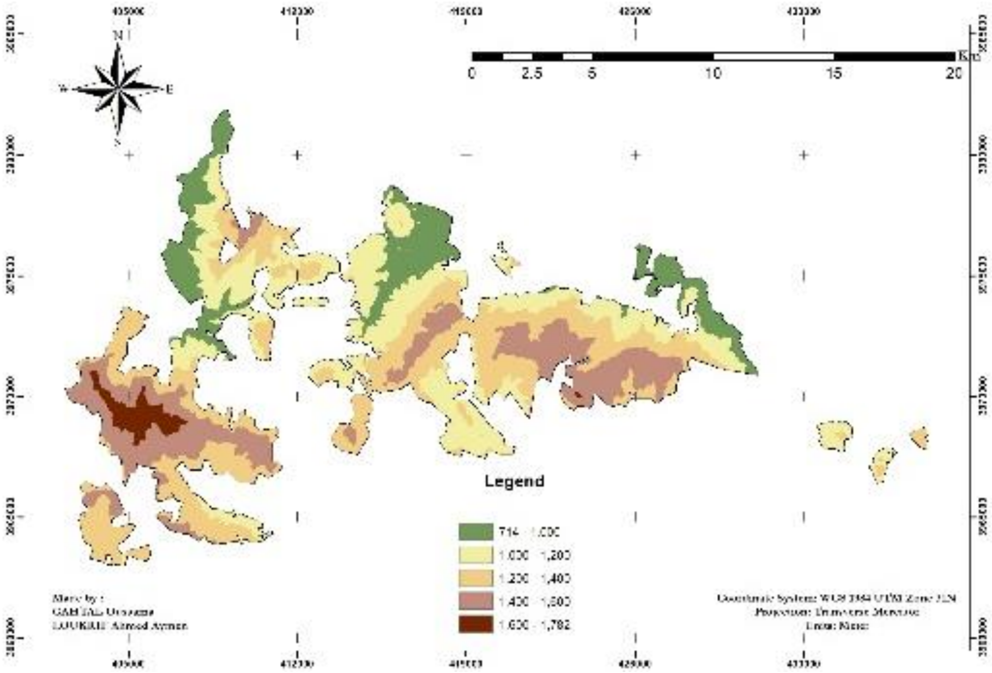


Figure 5.5 : Topomorphological map.

The position on the slope or the topomorphology "m" weights the intensity of the fire based on its position on the terrain relief.

The topomorphology map reflects that approximately 70% of the studied area consists of mountains and high foothills, whereas plains and low foothills represent a small percentage (30%) of the total area studied.

3.3.5 Topomorphological index (IM)

The topomorphological index map is the result of combining the slope map, the exposure map, and the topomorphology map, applying the formula mentioned earlier. The calculated map is shown in the figure. After reclassification, we obtained five topomorphological classes, summarized according to their significance.

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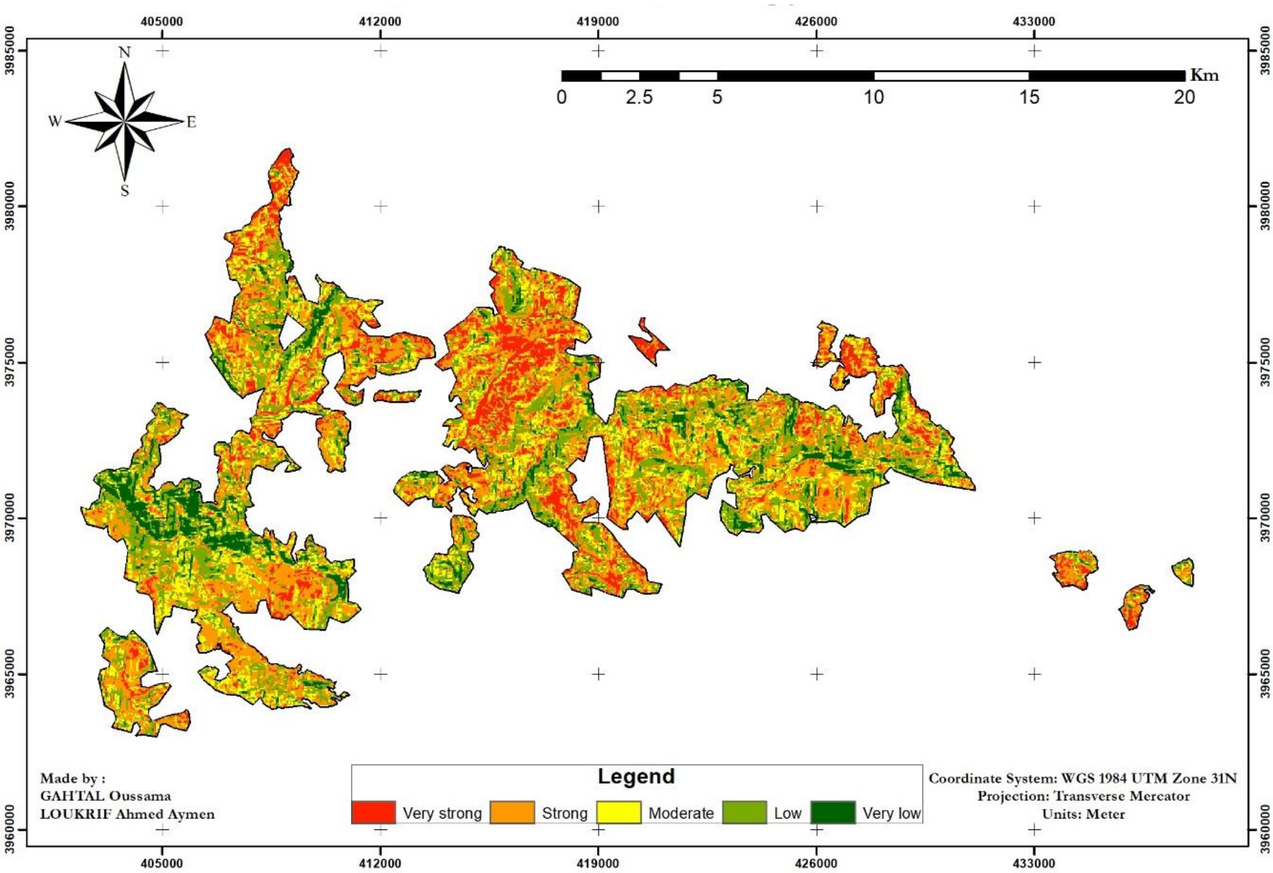


Figure 5.6 : Topomorphological index

Over 55% of the forest area is found under topomorphological conditions that are favorable to highly favorable for fire intensification.

3.4 Combustibility index

The calculation of the combustibility index results from the intersection of two factors: the quantity of fuel (derived from the NDVI) and its quality (the type of forest species). You can refer to the species classification table for more details. The formula used is as follows:

$$\mathbf{CI = 39 + 0{,}23\ BV\ (E1 + E2 - 7{,}18)}$$

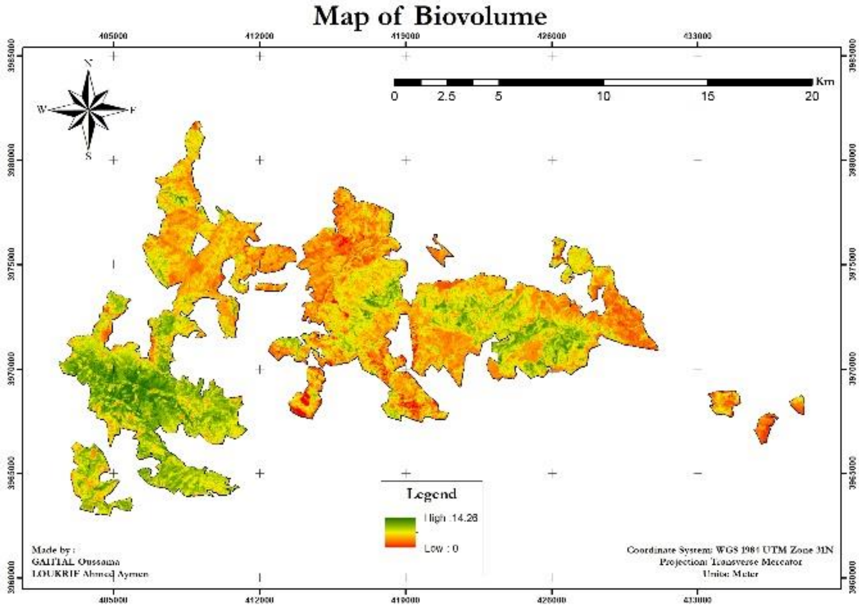


Figure 5.7 : Biovolume map.

3.4.1 Carte de l'Indice de Végétation Normalisé (NDVI)

The vegetation index allows for the calculation of the biovolume of dominant forest species. The NDVI map was created using ENVI software and then exported to ArcGIS to overlay it with other maps.

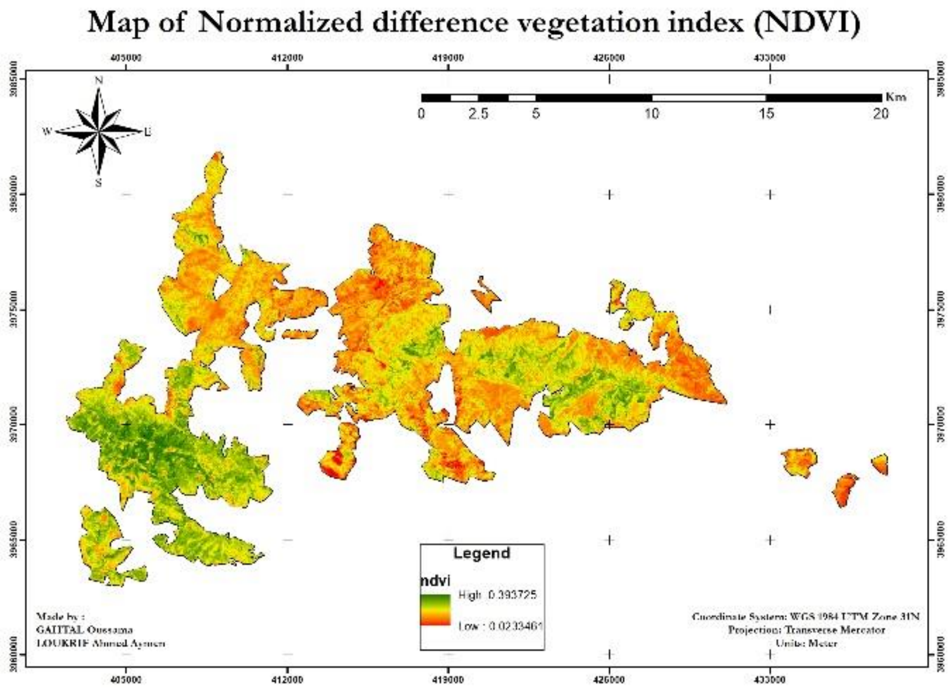


Figure 5.8 : NDVI map.

LIGNEUX HAUT			
Arbousier (Arbutus unedo) 5	Châtaignier (Castanea Sativa) 5	Cèdre (Cedrus atlantica) 6	Cyprès (Cupressus macrocarpa) 6
Chêne vert (Quercus ilex) 7	Erable (Acer palmatum) 5	Epicéa (Picea abies) 6	Noisetier (Corylus avellana). 2
Hêtre (Fagus ylvatica) 2	Peuplier (Populus nigra, poplar). 2	Chêne pubescent (Quercus pubesscens) 5	Pin d'Alep (Pinus halepensis) 7
Ome 2	Pin noir (Pinus nigra Arn.) 7	Douglas (- Pseudotsuga menziesii) 6	Pin pignon (Pinus pinea) 7
Pin maritime (Pinus pinaster) 7	Pin de salzman (Pinus salzmanni) 7	Frêne (*Fraxinus* spp.) 2	Robinier (Robinia pseudoacacia) 2
Pin sylvestre (Pinus sylvestris) 7	Saule (Salix alba, Willow). 2	Olivier (Olea europea) 5	Sapin (épicéa) 6

LIGNEUX BAS			
Ajonc épineux (*Ulex europaeus*) 8	Amélanchier (*Amelanchier laevis*) 3	Bruyère arborescente (*Erica arborea*) 8	Bruyère multiflore (Erica multiflora L.) 6
Bruyère cendrée (Erica cinerea L) 6	Bruyère à balais (Erica scoparia) 7	Buis (Buxus sempervirens) 5	Canne de Provence (arundo donax) 5
Callune (Calluna vulgaris) 6	Ciste blanc (CISTUS albidus) 6	Ciste à f. de sauge cistus salvifolius) 3	Epine du christ (Paliurus spina-christi) 3
Eglantine (Rosa canina L) 5	Genet à balais (Cytisus scoparius L.) 5	Genet d'Espagne (Spartium junceum) 5	Genet purgatif (Cytisus purgans) 7
Genet scorpion (Genista scorpius). 8	Genévrier commun (Juniperus communis) 7	Genévrier oxycèdre (Juniperus oxycedrus) 7	Lavande stéchade (Lavandula stoechas) 5
Lavande à large f. (Lavandula litifolia.) 5	Chêne kermès (Quercus coccifera) 8	Pistachier lentisque (Pistacia lentiscus) 4	Prunellier (Eriogaster catax) 4
Romarin (Rosmarinus officinalis) 5	Ciste de Montpellier (Cistus monspeliensis) 3	Ronces (Rubus fructicosus) 6	Staeheline (Staehelina dubia) 3
Térébinthe (Pistacia terebinthus) 4	Filaria (*Phillyrea latifolia*) 5	Thym (Thymus vulgaris) 4	

HERBACEES			
Agrostis 1	Anthyllide (Anthyllis vulneraria) 1	Aphyllanthe (Aphyllanthes) 1	Avoine (Avena sativa,) 1
Brachypode des bois (Brachypodium sylvaticum) 1	Brachypode penné (Brachypodium pinnatum) 1	Brachypode rameux (Brachypodium ramosum) 1	Brome érigé (Bromus erectus) 1
Canche flexueuse (Deschampsia flexuosa) 1	Dactyle (Dactylis glomerata) 1	Fétuques (Festuca) 1	Fougère aigle (Pteridium aquilinum) 2
Fromental (Arrhenatherum elatius) 1	Inule visqueuse (Inula viscosa) 1		

Figure 5.9: Combustibility notes of the main dominant vegetation species Mediterranean (Source CEMAGREF)

3.4.2 Combustibility index (IC)

La carte de l'indice de combustibilité est le résultat du croisement de la couche de l'indice de végétation et la couche de la classification supervisée en appliquant la formule (IV.3) citée précédemment dans ce chapitre.

La carte résultante a été donc reclassifiée en cinq classes selon le modèle adopté dans les travaux cités ci-dessus.

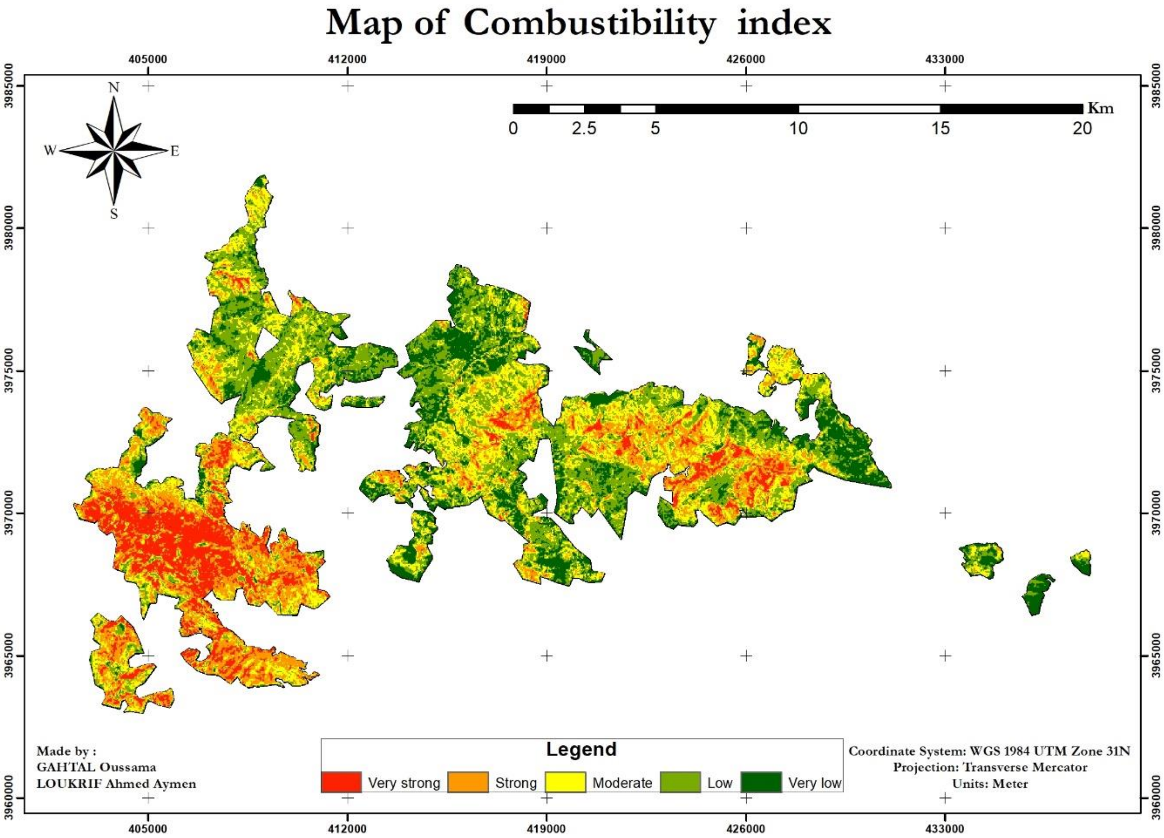


Figure 5.10 : Combustibility Index.

The combustibility index map shows that:

- 33% of the area of Thénia El Had forest is in the very high-risk category,
- 17% of the forest area is in the high-risk category,
- 21%, 16%, and 12% of the study area are in the medium, low, and very low-risk categories, respectively.

3.5 Calcul de l'indice humain (IH)

As detailed in the methodology section earlier, the Human Occupation Index is composed of two indices: the Neighborhood Index and the Road Network Index. We created the map of the Road Network Index (ID) and the Human Activity Index (IV) by digitizing roads, tracks, built structures, and human activity areas (cultivated lands) from a satellite image downloaded from Google Earth.

3.5.1 Carte de présence de structures routières

The influence zones relative to the paved road were categorized according to the degree of human influence: very high, high, moderate, low, and very low.

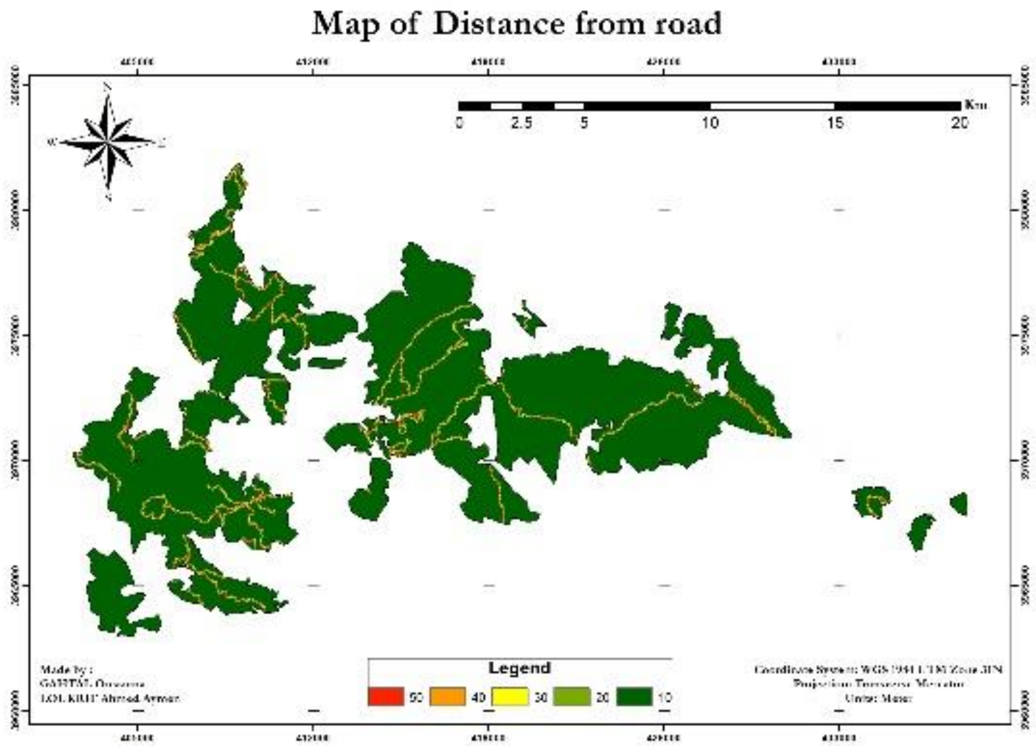


Figure 5.11 : Road map.

3.5.2 Agglomeration map

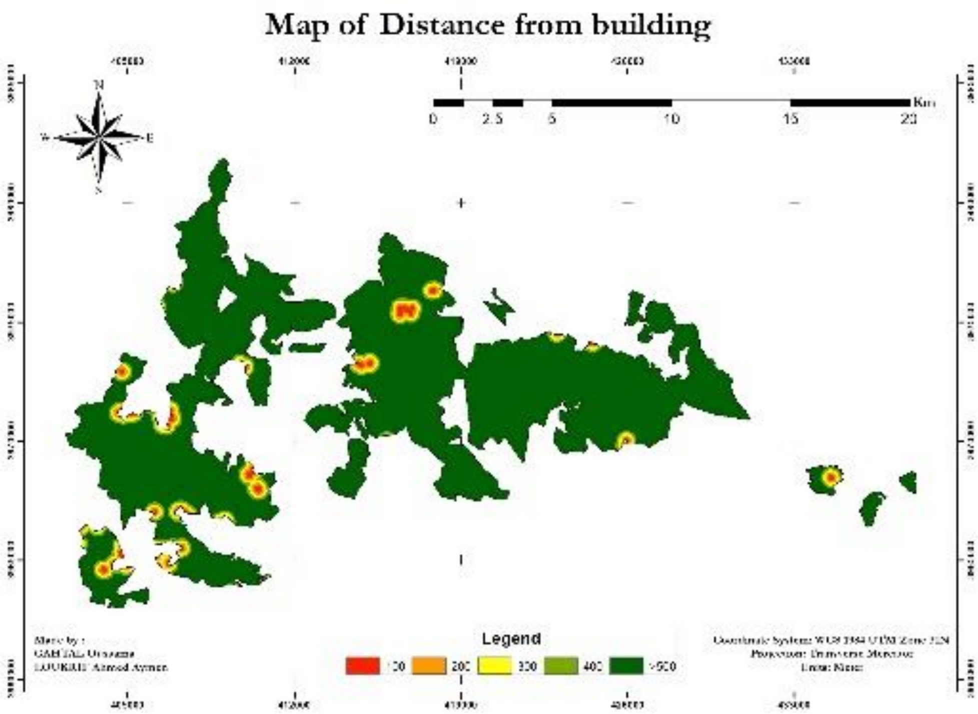


Figure 5.12: Agglomeration map

3.5.3. Carte d'indice humain (IH)

The human index map results from the intersection of the layer showing the presence of road structures and the layer showing built structures (buildings).

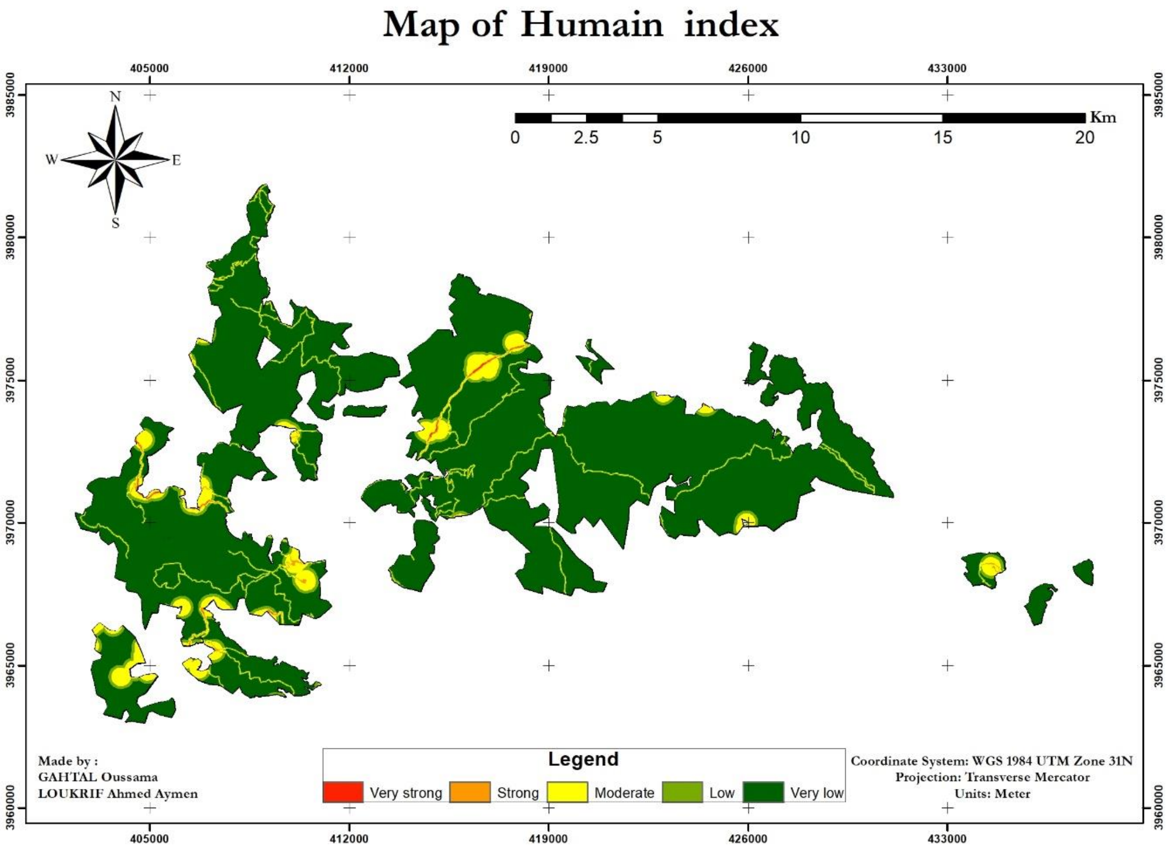


Figure 5.13: Humain index map.

3.6. Wildfire Risk Index Map (IR)

The calculated indices—the combustibility index, the topomorphological index, and the human activity index—will be overlaid to compute the wildfire risk index map, following the formula which we remind below:

$$IR = 5 \times IC + 2 \times IH + IM$$

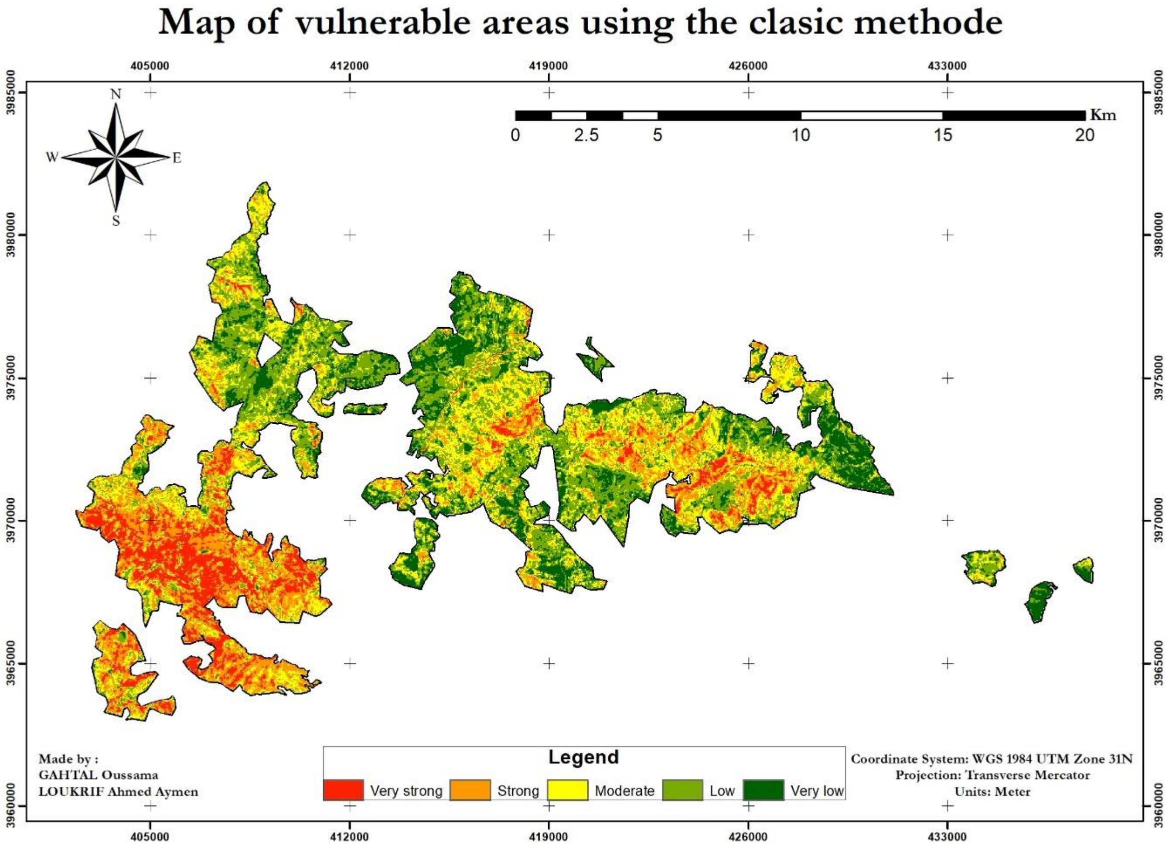


Figure 5.14: vulnerable areas using classic method.

4. Calculating fire risk using the AHP method

Calculating fire risk using the Analytic Hierarchy Process (AHP) involves a structured approach to assess and prioritize the risk factors associated with forest fires. Here is a general overview of the process:

- Criteria Identification
- Criteria Hierarchy
- Comparison Matrix
- Weight Calculation
- Risk Assessment
- Risk Mapping

The AHP process enables a systematic and structured approach to evaluate fire risk by integrating multiple factors and providing a rational basis for decision-making in forest fire management.

4.1. Handling the criteria used AHP 9 cretiria

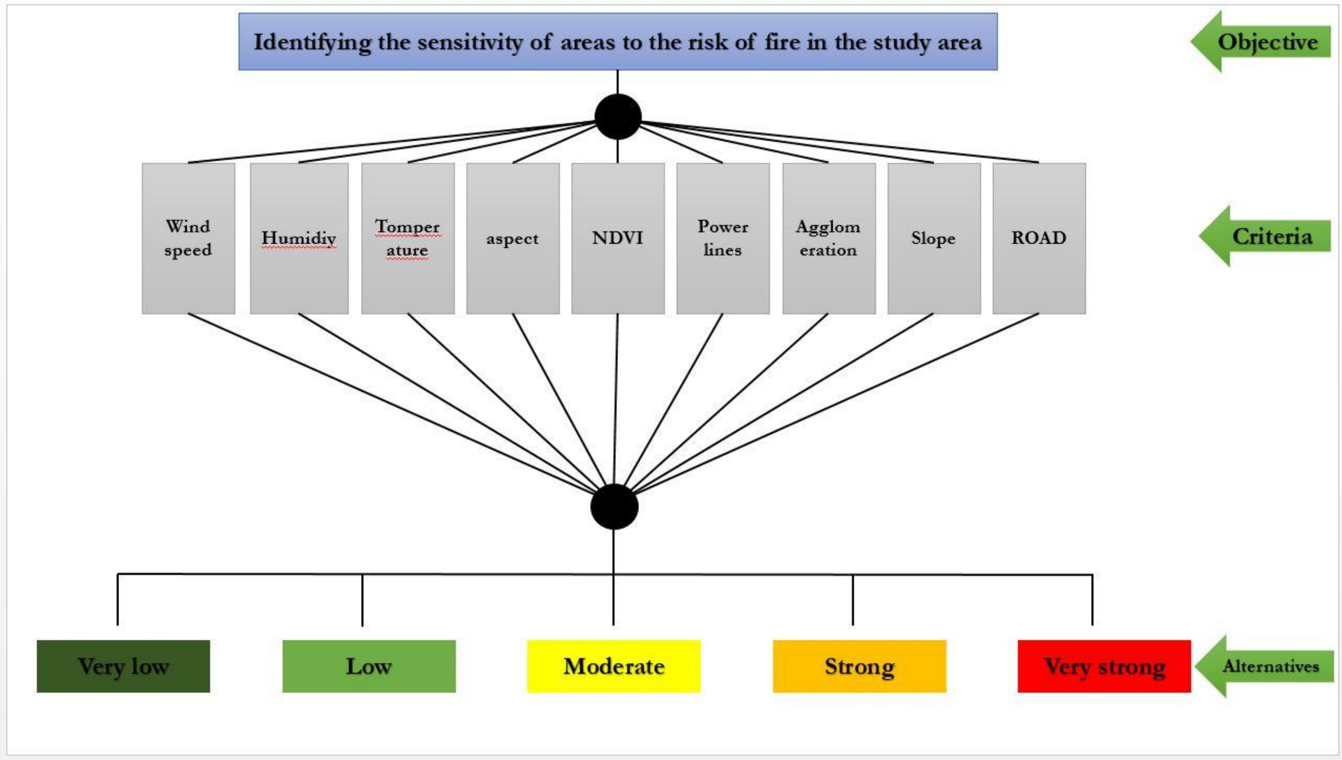


Figure 5.15: The general structure of designing a sensitivity map using AHP 09 cretiria

Resulting Priorities

Priorities

These are the resulting weights for the criteria based on your pairwise comparisons:

Cat	Priority	Rank	(+)	(-)
1 Ndvi	32.2%	1	15.5%	15.5%
2 Road	24.2%	2	13.2%	13.2%
3 Agglomeration	15.2%	3	6.5%	6.5%
4 Power lines	10.7%	4	4.8%	4.8%
5 Aspects	6.4%	5	2.6%	2.6%
6 Temperature	4.4%	6	1.5%	1.5%
7 Humidity	3.2%	7	1.6%	1.6%
8 Slope	2.3%	8	1.0%	1.0%
9 Wind speed	1.5%	9	0.9%	0.9%

Decision Matrix

The resulting weights are based on the principal eigenvector of the decision matrix:

	1	2	3	4	5	6	7	8	9
1	1	3.00	3.00	4.00	5.00	7.00	9.00	9.00	9.00
2	0.33	1	3.00	5.00	5.00	5.00	7.00	7.00	9.00
3	0.33	0.33	1	3.00	3.00	4.00	7.00	6.00	8.00
4	0.25	0.20	0.33	1	3.00	3.00	6.00	6.00	8.00
5	0.20	0.20	0.33	0.33	1	3.00	3.00	3.00	5.00
6	0.14	0.20	0.25	0.33	0.33	1	2.00	3.00	5.00
7	0.11	0.14	0.14	0.17	0.33	0.50	1	3.00	4.00
8	0.11	0.14	0.17	0.17	0.33	0.33	0.33	1	3.00
9	0.11	0.11	0.12	0.12	0.20	0.20	0.25	0.33	1

Number of comparisons = 36
Consistency Ratio CR = 7.8%

Principal eigen value = 9.909
Eigenvector solution: 7 iterations, delta = 5.4E-9

Figure 5.16 : Criteria weights for AHP 09 criteria

4.2. Handling the criteria used AHP 11 cretiria

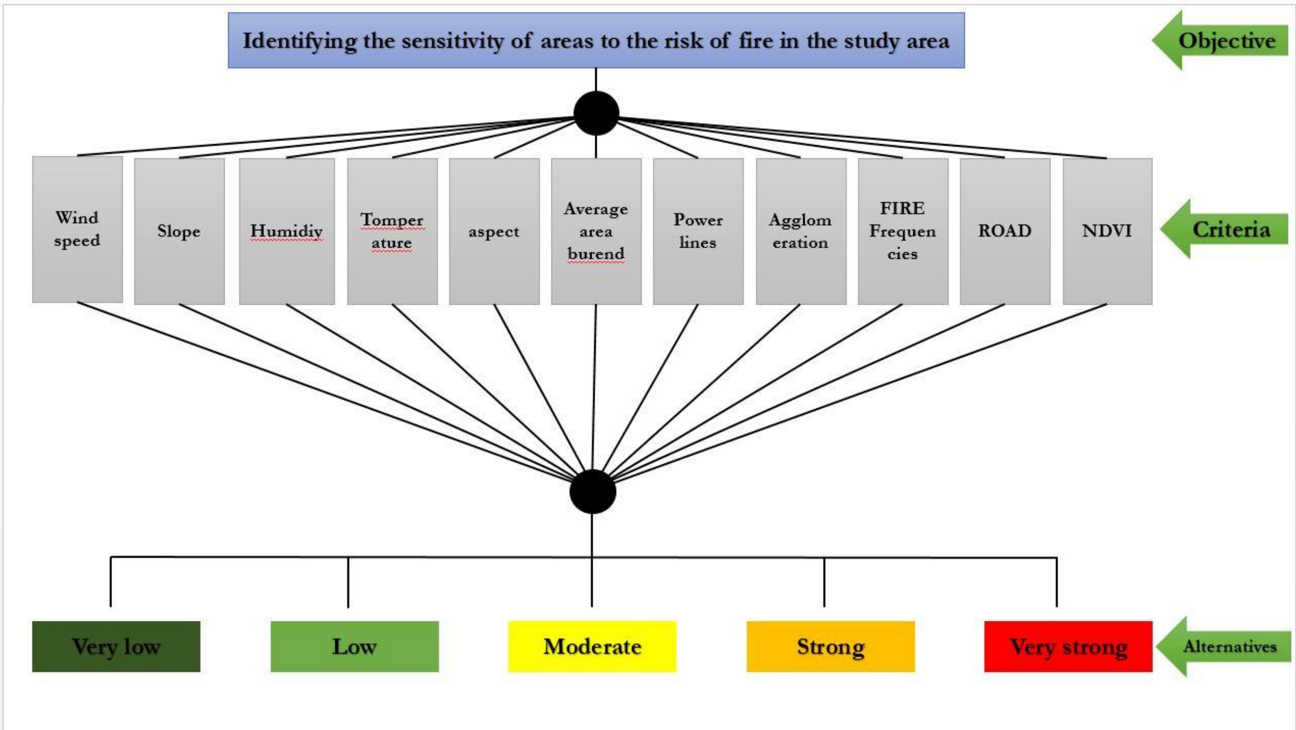


Figure 5.17: The general structure of designing a sensitivity map using AHP 11 cretiria

Resulting Priorities

Priorities

These are the resulting weights for the criteria based on your pairwise comparisons:

	Cat	Priority	Rank	(+)	(-)
1	Ndvi	26.5%	1	11.9%	11.9%
2	Road	19.0%	2	7.0%	7.0%
3	Fire frequencies	17.1%	3	7.4%	7.4%
4	Agglomeration	11.3%	4	4.3%	4.3%
5	Power lines	3.6%	8	1.4%	1.4%
6	Average area burned	6.9%	5	4.6%	4.6%
7	Aspects	5.1%	6	2.5%	2.5%
8	Temperature	3.7%	7	2.0%	2.0%
9	Humidity	2.8%	9	1.8%	1.8%
10	Slope	2.1%	10	1.2%	1.2%
11	Wind speed	1.9%	11	1.6%	1.6%

Number of comparisons = 55
Consistency Ratio CR = 9.7%

Decision Matrix

The resulting weights are based on the principal eigenvector of the decision matrix:

	1	2	3	4	5	6	7	8	9	10	11
1	1	3.00	3.00	3.00	4.00	5.00	5.00	7.00	9.00	9.00	9.00
2	0.33	1	2.00	3.00	5.00	4.00	5.00	5.00	7.00	7.00	9.00
3	0.33	0.50	1	3.00	4.00	5.00	4.00	6.00	7.00	8.00	8.00
4	0.33	0.33	0.33	1	3.00	3.00	3.00	4.00	7.00	6.00	8.00
5	0.25	0.20	0.25	0.33	1	1.00	1.00	1.00	1.00	1.00	1.00
6	0.20	0.25	0.20	0.33	1.00	1	3.00	3.00	6.00	6.00	1.00
7	0.20	0.20	0.25	0.33	1.00	0.33	1	3.00	3.00	3.00	5.00
8	0.14	0.20	0.17	0.25	1.00	0.33	0.33	1	2.00	3.00	5.00
9	0.11	0.14	0.14	0.14	1.00	0.17	0.33	0.50	1	3.00	4.00
10	0.11	0.14	0.12	0.17	1.00	0.17	0.33	0.33	0.33	1	3.00
11	0.11	0.11	0.12	0.12	1.00	1.00	0.20	0.20	0.25	0.33	1

Principal eigen value = 12.460
Eigenvector solution: 7 iterations, delta = 4.6E-9

Figure 5.18 : Criteria weights for AHP 11 criteria

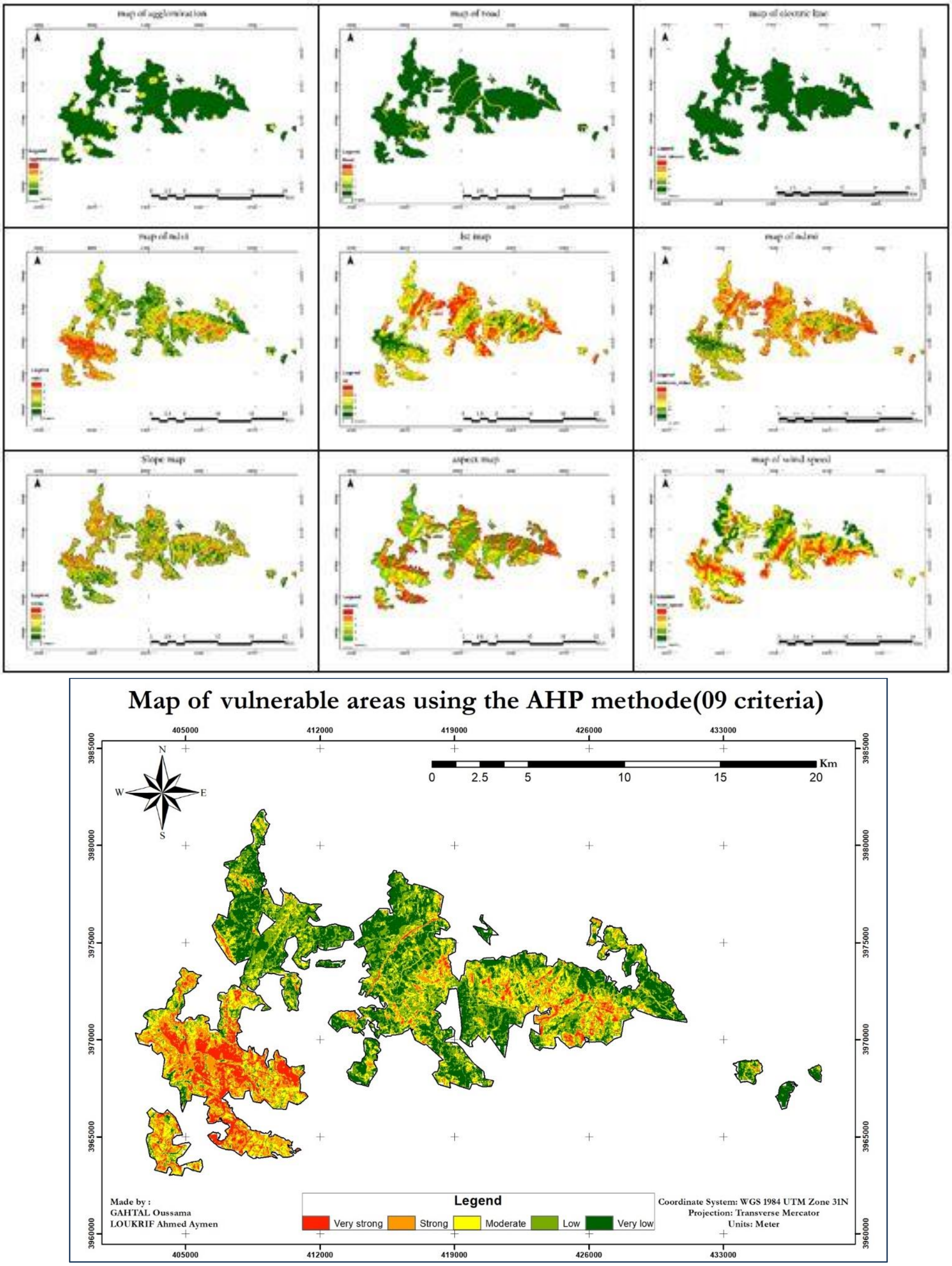
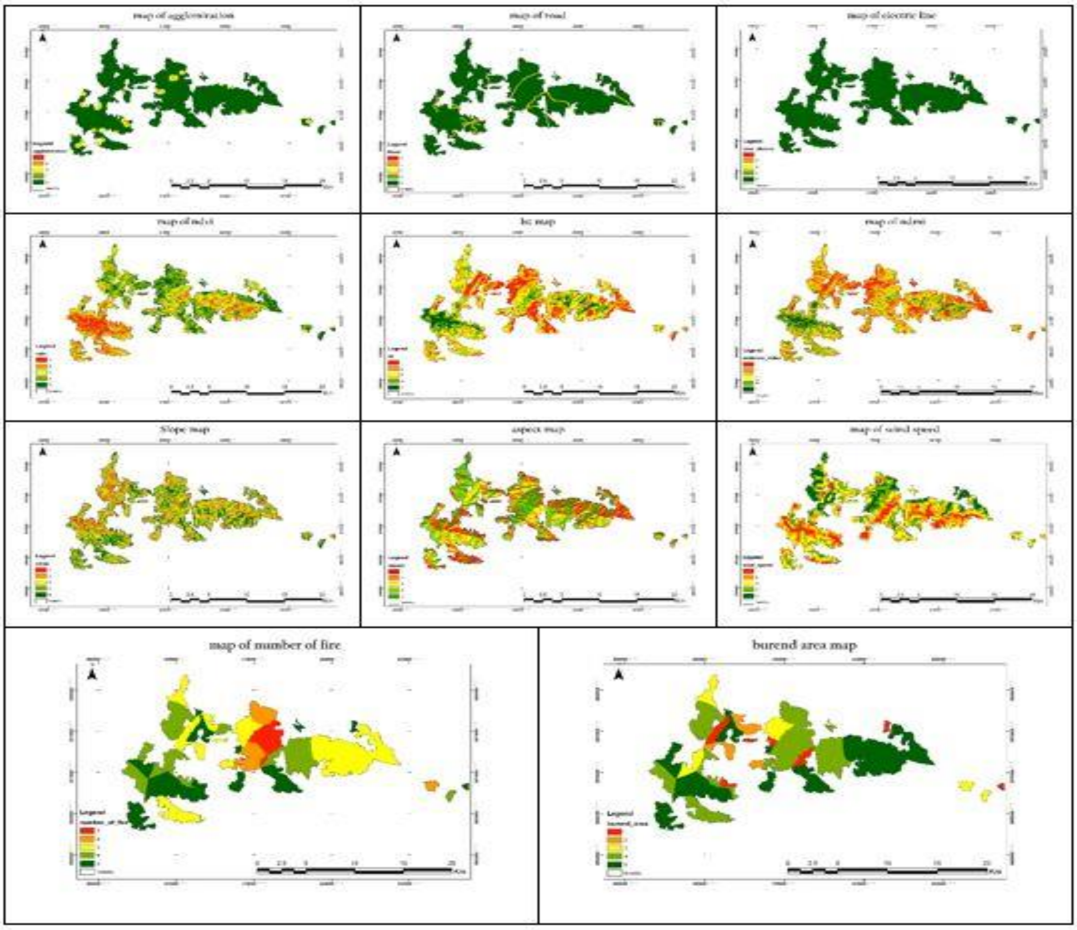


Figure 5.19 : map of vulnerable using ahp (11 criteria)



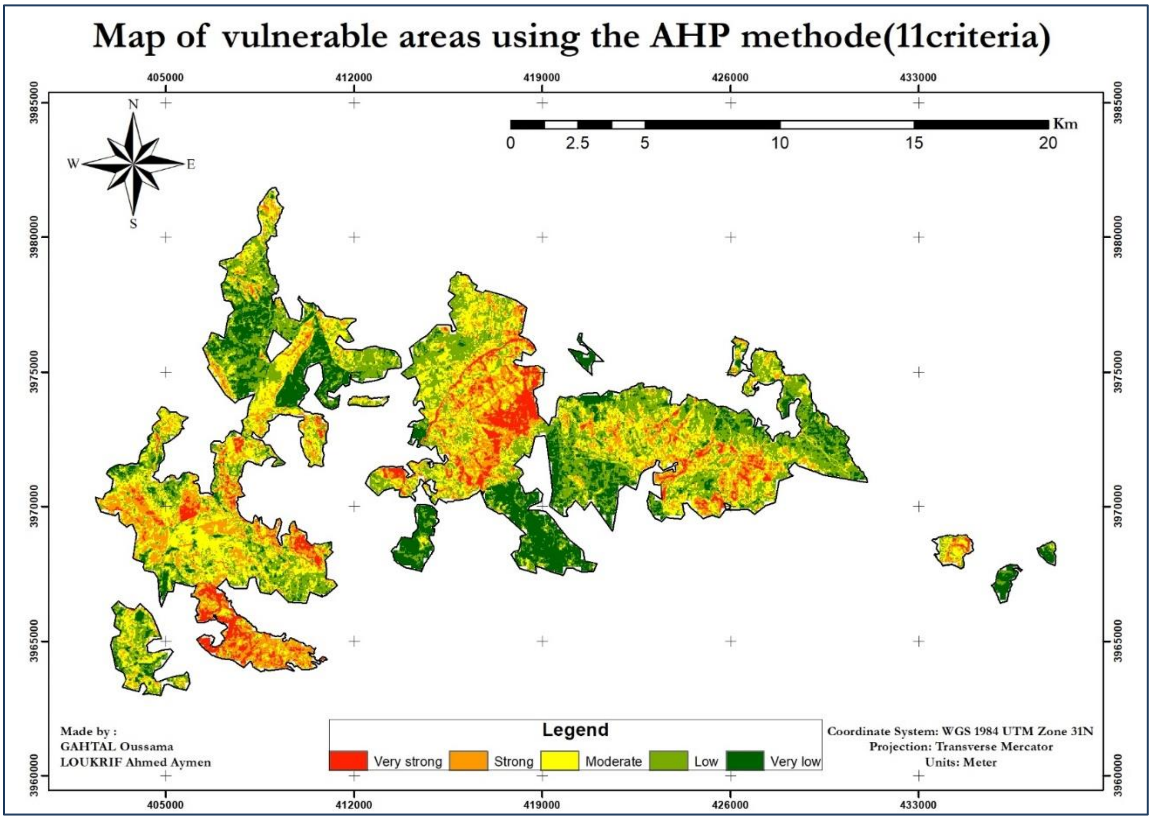
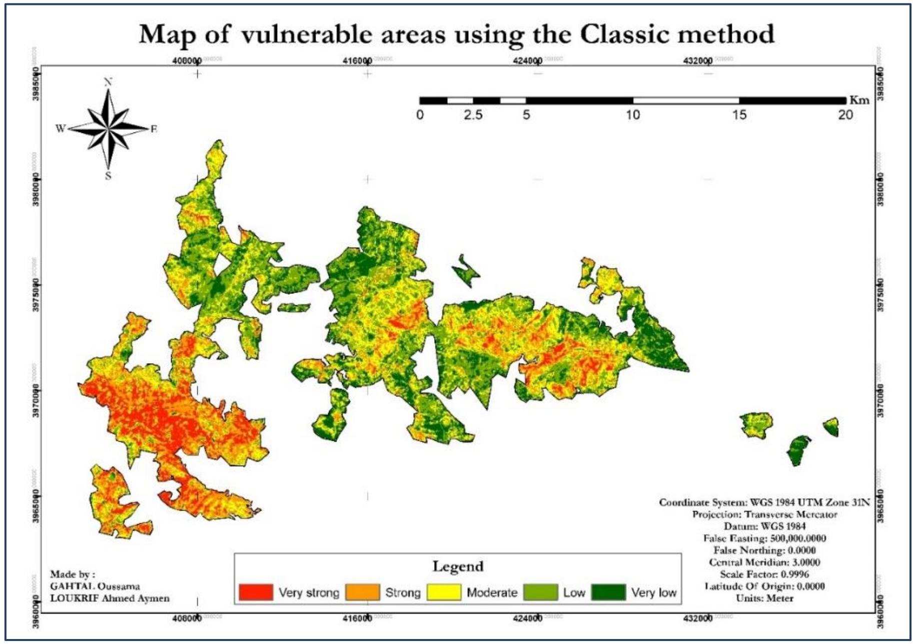
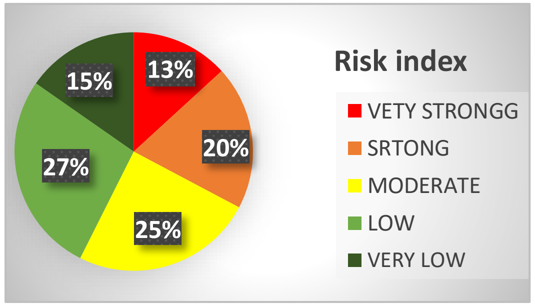
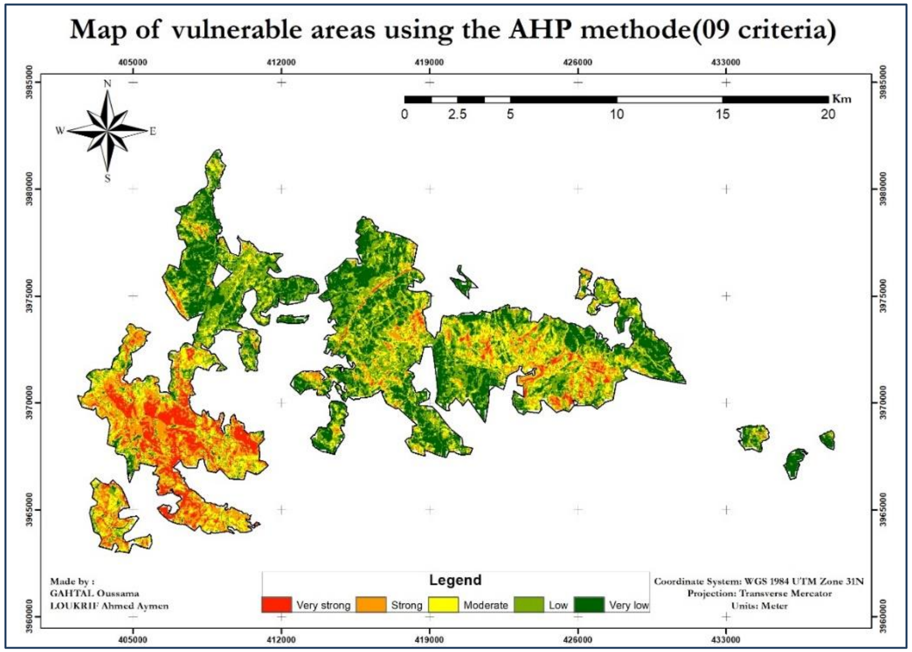


Figure 5.20 : map of vulnerable using ahp (11 criteria)

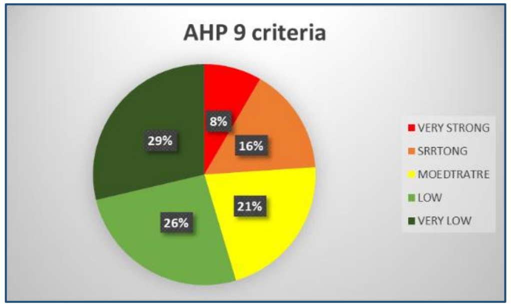


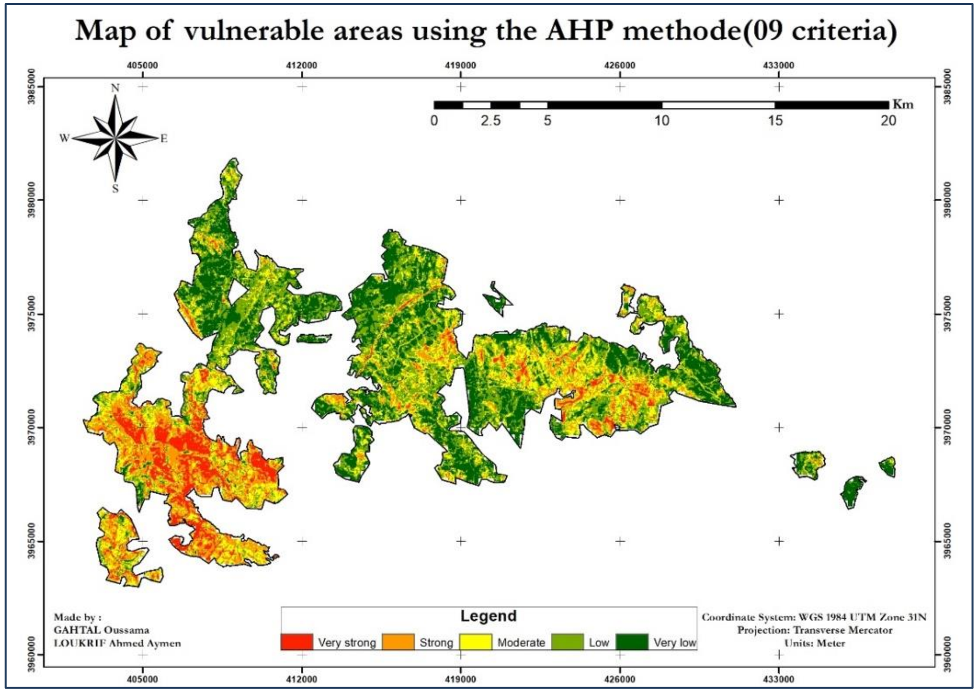
The classical method primarily relies on the combustibility index, which constitutes 62.5% of the overall risk index. The risk level is extremely high in the southwestern and southeastern parts (Medad Forest, Boumajber Forest). In the central and northern regions, there is a mix of high and medium vulnerabilities (Ain Onser Forest, Beni Mahrez, Beni Soumer). Areas with low and very low vulnerabilities are scattered and not prevalent





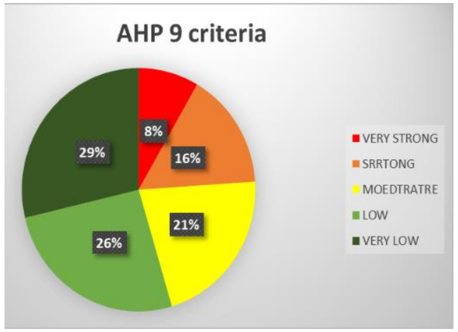
The AHP allows for controlling the weights of criteria according to each region, unlike the classical method, which assigns fixed weights to criteria. It also enables adjusting the number of criteria used. Compared to the classical method, the distribution of areas with "very strong" vulnerability is more spread out. There is a more detailed and precise distribution of vulnerabilities across the region. Areas of "moderate" and "low" vulnerability were identified more frequently, and "very low" vulnerability areas were more common in specific regions



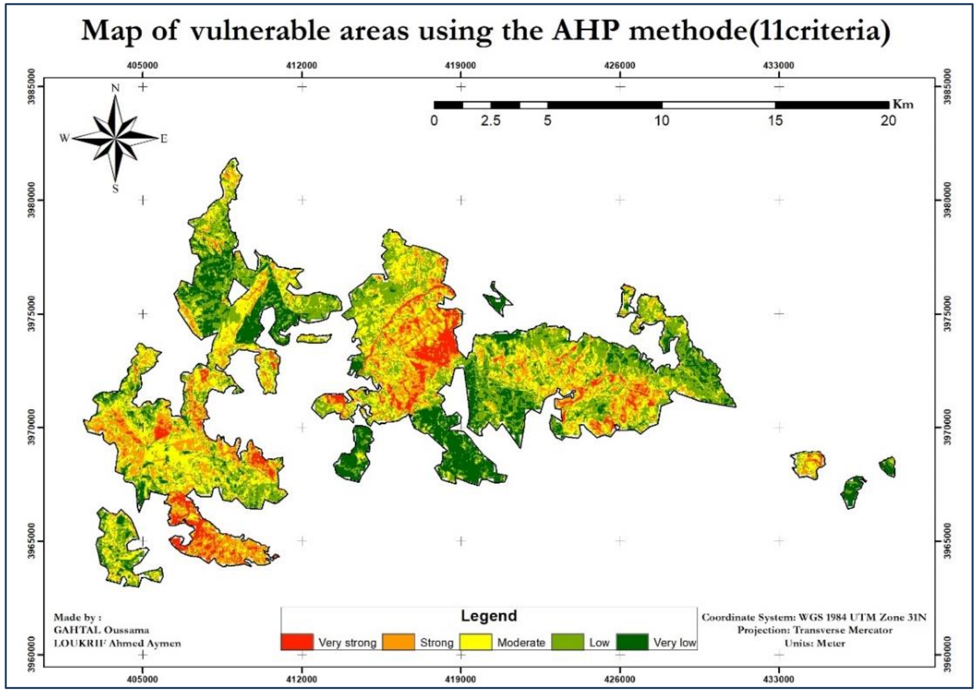


This map showed that the El Medad National Park is at slightly elevated risk of fire. However, historical data indicate that this area has experienced few fires due to the presence of a military barracks, which reduces the risk of deliberate fires.

In contrast, Contan Ghilas appeared to have a low sensitivity, which contradicts historical data indicating frequent fires.

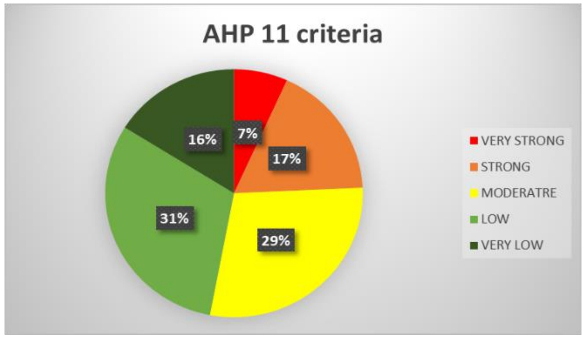


The map with 11 criteria shows a broader distribution of risk zones compared to the map with 9 criteria. This is due to the significant contribution of information provided by adding fire history.



This map showed a decrease in the fire hazard sensitivity of the El Medad National Park, which is consistent with historical data and reflects the mitigating effect of the military barracks.

Contan Ghilas appeared to have high sensitivity, which aligns better with the historical fire data for this area.



5. Calculating fire risk using GA

This section is focused on the genetic approach adopted to generate a risk map (figure5.21), leveraging the index maps calculated in the previous step. These maps, along with data related to the fire history of the region, will serve as inputs to our evolutionary process. From this dataset, the algorithm computes, in the supervised learning step, the optimal representative of classes, upon which the system will base its determination of the risk class for each point in the study area, thereby generating a risk map. Most of the code was implemented on a smartphone using Pydroid 3. We used Spyder 5.4.3 as well for part of the implementation and tests.

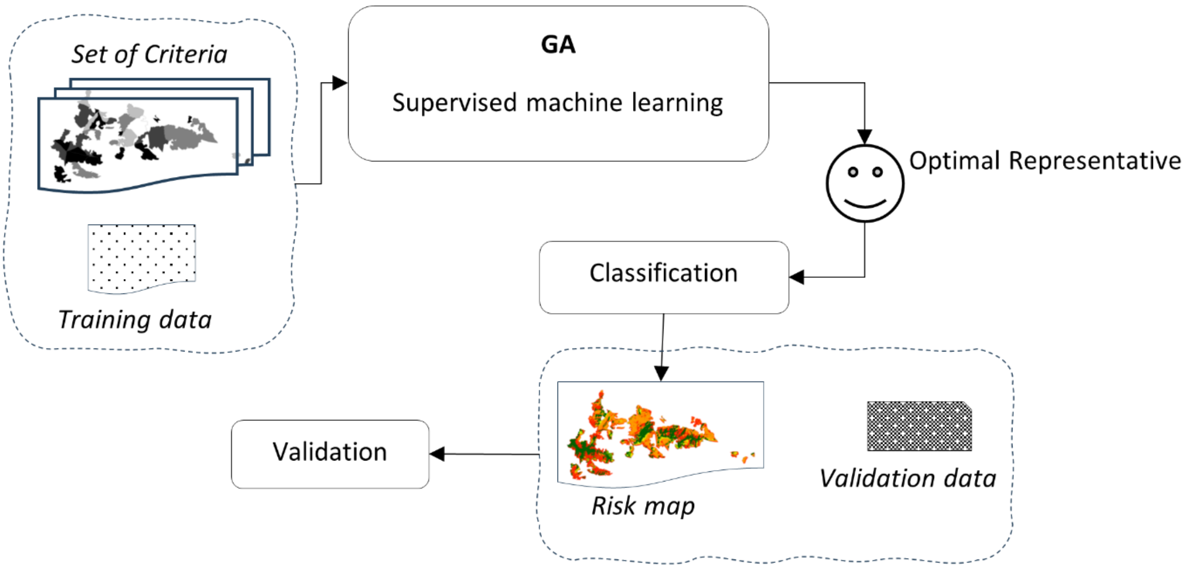


Figure 5. 21: Adopted approach

5.1 Individual encoding

As illustrated in Table 5.1, an individuals is defined by k disjunctions of grayscale level intervals (subclasses) noted Int_{jk}^{i} , in each image j (criteria j) and for each class C_i. The number k is among the parameters to initialize in the implemented GA.

☺	Criterion j
C_1	$Int_{j1}^{1} \cup Int_{j2}^{1} \cup \ldots \cup Int_{jk}^{1}$
C_2	$Int_{j1}^{2} \cup Int_{j2}^{2} \cup \ldots \cup Int_{jk}^{2}$
$\vdots$	$\vdots$
C_n	$Int_{j1}^{n} \cup Int_{j2}^{n} \cup \ldots\ Int_{jk}^{n}$

Tableau 5.1 Individual encoding

5.2 Initial population

Unlike the two previously used methods, our approach does not assign weights to the criteria. Instead, we prioritize the frequency of fires occurrence, as the allocation of selected points depends on their position within the frequency class.

The generation of the initial population occurs in two steps:

- Determine the class membership for each pixel in the training dataset. For each class sample, the script computes the extreme values (minimum and maximum) for each index (criterion).
- Subsequently, it randomly generates intervals (individuals) whose values must lie between the calculated minimum and maximum values.

Figure 5.23, shows a code snippet written to generate the initial population, after importing the necessary libraries (figure 5. 22)

```
import random
import numpy as np
from PIL import Image
from numpy import asarray
import pandas as pd


```

Figure5. 22: necessary libraries

```
def gin(tab):
    tabgin = np.zeros((nc,ncr,5,2))
    for i in range(nc):
        for j in range(ncr):
            for k in range(5):
                for p in range(2):
                    tabgin[i][j][k][p]=random.uniform(tab[i][j][0],tab[i][j
                tabgin[i][j][k]=tri(tabgin[i][j][k])
    return tabgin
```

Figure 5. 23 Generating Initial population

5.3 Implemented crossover

The GA operates within a single population for all risk classes. Initially, after selecting the two parents, the process involves choosing the crossover class number. Subsequently, the algorithm arbitrarily generates the criterion and interval numbers where the crossover between the two parents will take place. Parent selection employs the Roulette Wheel Selection (RWS) method, of this thesis.

```
#Selection and Generation Function.
def select(pop,T1,T2):
    tab1 = random.choices(pop,weights=tab_f(pop,T1,T2),k=2)
    a = tab1[0]
    b = tab1[1]
    tab2 = crossover(a,b)
    return tab2
```

```
#crossover function.
def crossover(g1,g2):
    tab_crossover = []
    child1 = np.copy(g1)
    child2 = np.copy(g2)
    for i in range(nc):
        a = random.randint(0,ncr)
```

Figure 5. 24: Crossover and selection

5.4 Implemented mutation

The mutation process operates as follows: a position of an individual is randomly selected, and the individual at this position is either replaced with a newly generated individual.

```
def Mutation(pop,data,T1,T2):
    b = len(pop)//10
    a = random.randint(b,len(pop)-1)
    gin_nouveau = gin(data)
    pop[a] = gin_nouveau
    pop = Tri(pop,T1,T2)
    return pop
```

Figure 5. 25: mutation

Observation

The crossing-over rate is 89%. Each generation experiences a mutation rate of 1% among individuals, while the top 10% of individuals are selected for reproduction.
Assigning pixels to a class is done by calculating the distance between the pixel data vector, which consists of the grayscale levels of the pixel in question for each criterion used, and the intervals that make up the selected individual during the learning stage. Subsequently, the pixel is assigned to the nearest class.

5.5 Training and validation dataset

To accurately assess fire occurrences in the region, we employed remote sensing tools utilizing satellite imagery from Landsat 7, 8, and 9 spanning the period from 2000 to 2023. This approach was essential due to the limited historical fire data provided by the Directorate General of Forests (DGF), which included only 34 fire points with coordinates covering the period from 2017 to 2023.
For this analysis, we utilized the Normalized Burn Ratio (NBR) index, widely recognized in the literature for detecting forest changes (Boulghobra et al., 2022).

$$NBR = \frac{NIR-SWIR2}{NIR+SWIR2} \tag{5.1}$$

NIR (Near Infrared) corresponds to Landsat band 5, and SWIR2 (Short wave Infrared 2) corresponds to band 7.
Given the large number of satellite images involved and the constraints of ArcGIS software in processing multiple images simultaneously, we developed two Python scripts within ArcGIS: the first applies the *Extract* by *Mask function to* the study area, while the second calculates the *NBR index* (Figure 5.26 and figure 5.27) respectively.
In addition to the points calculated by remote sensing and those provided by the DGF, the dataset was enriched by adding other points identified through specific expertise. These points are distributed as shown in Figure 5.8 and Table 5.2.

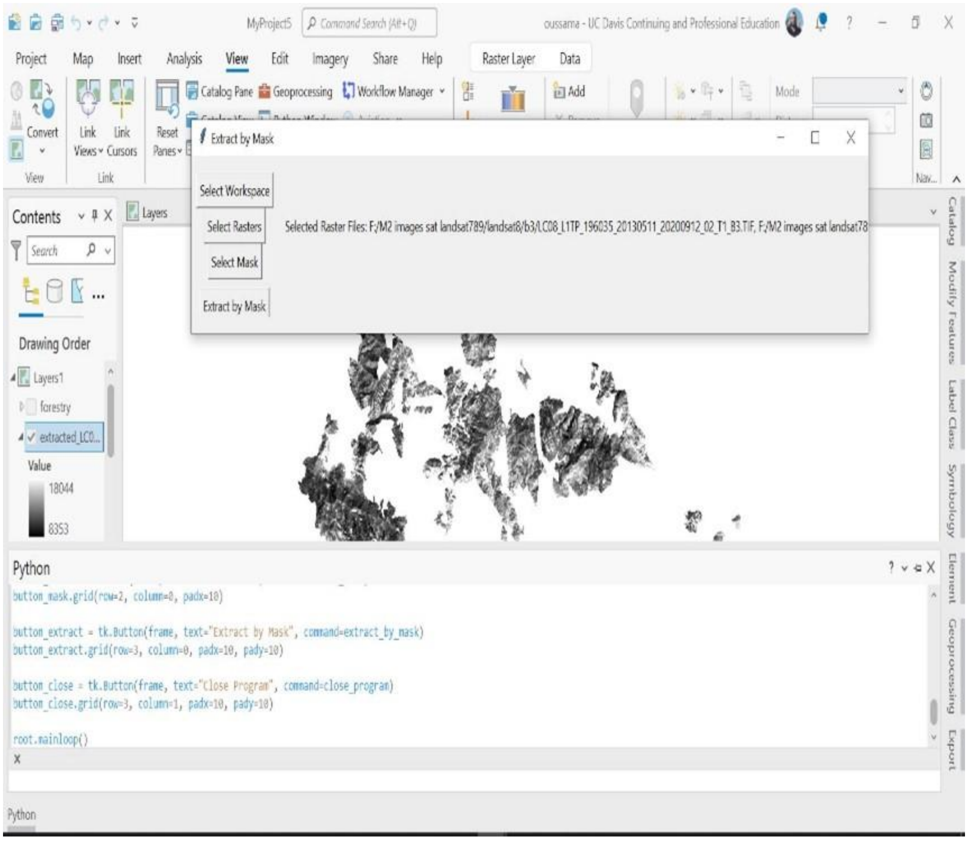


Figure 5. 26 Mask function

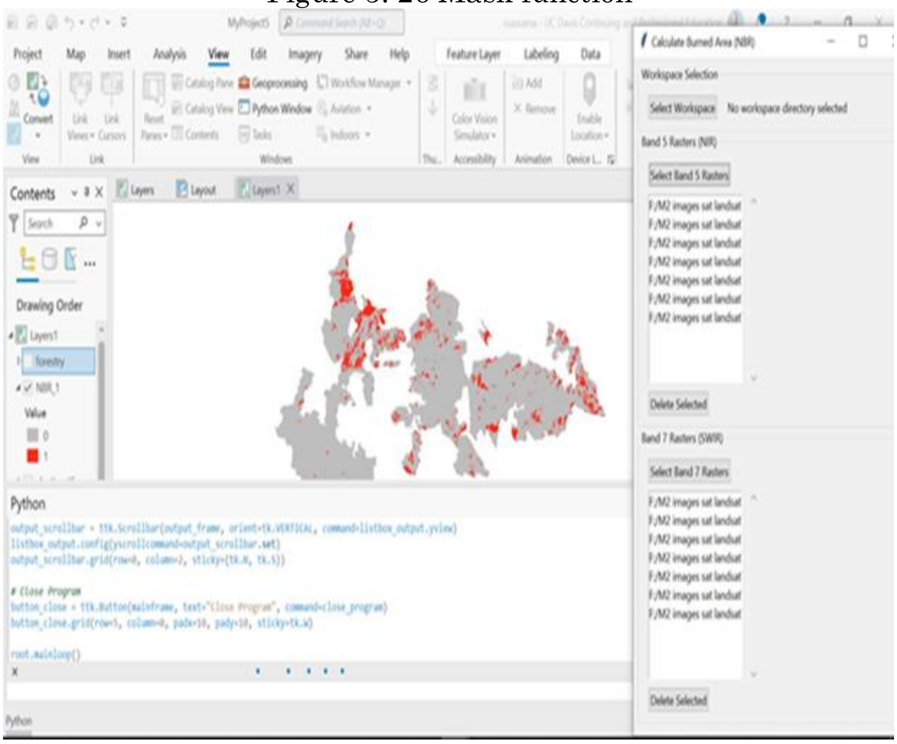


Figure 5. 27 NBR index

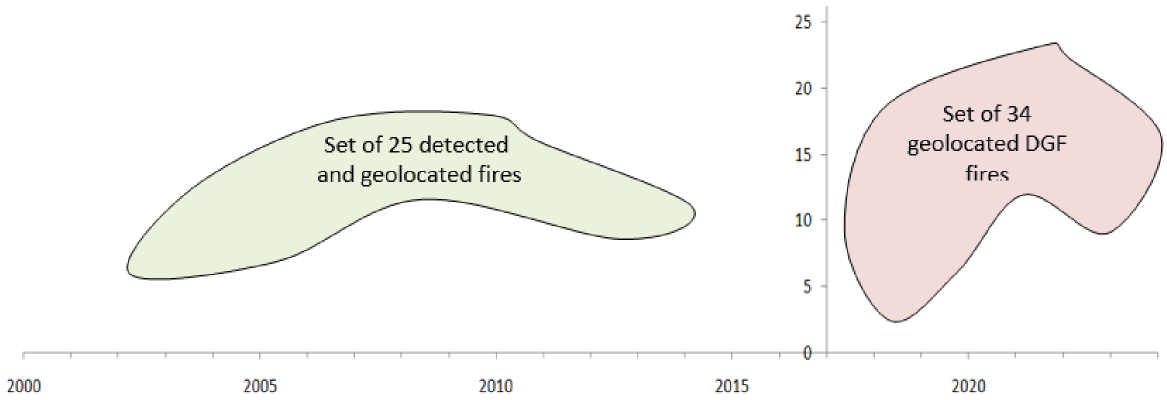


Figure 5. 28 The selected points

Type of points	Number of fires	Training	Validation
Fires DGF	34	24	10
		24/34 = 0.706	10/34 = 0.294
Fires identified by remote sensing	25	17	8
		17/25 = 0.68	8/25 = 0.32
Fires identified based on expertise	10	7	3
		7/10 = 0.70	3/10 = 0.30
Total	69	48	21
		48/69 = 0.696	21/69 = 0.304

Table 5.2 repartion of Selected Points between Training and Validation

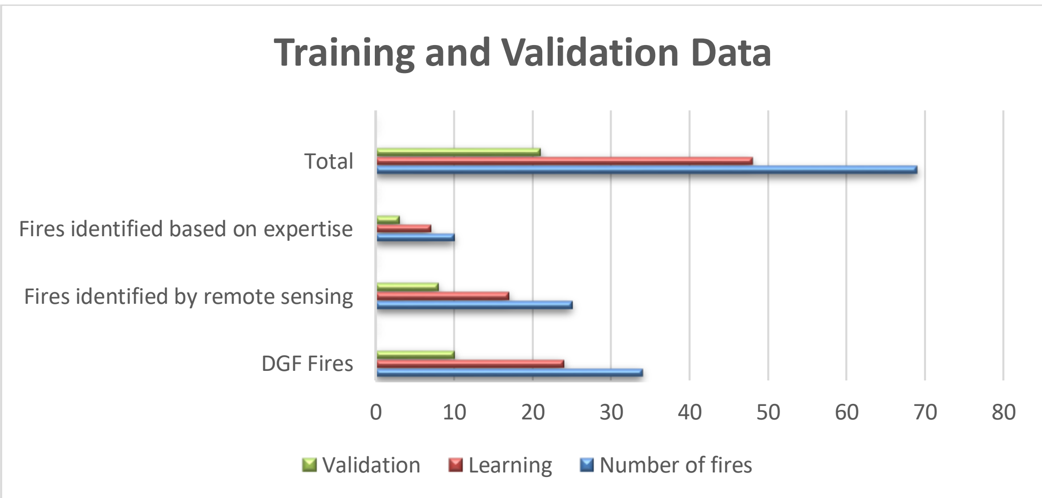


Figure 5. 29 Partitioning of Selected Points for Training and Validation

Figure 5.30 illustrates the distribution of points across the area.

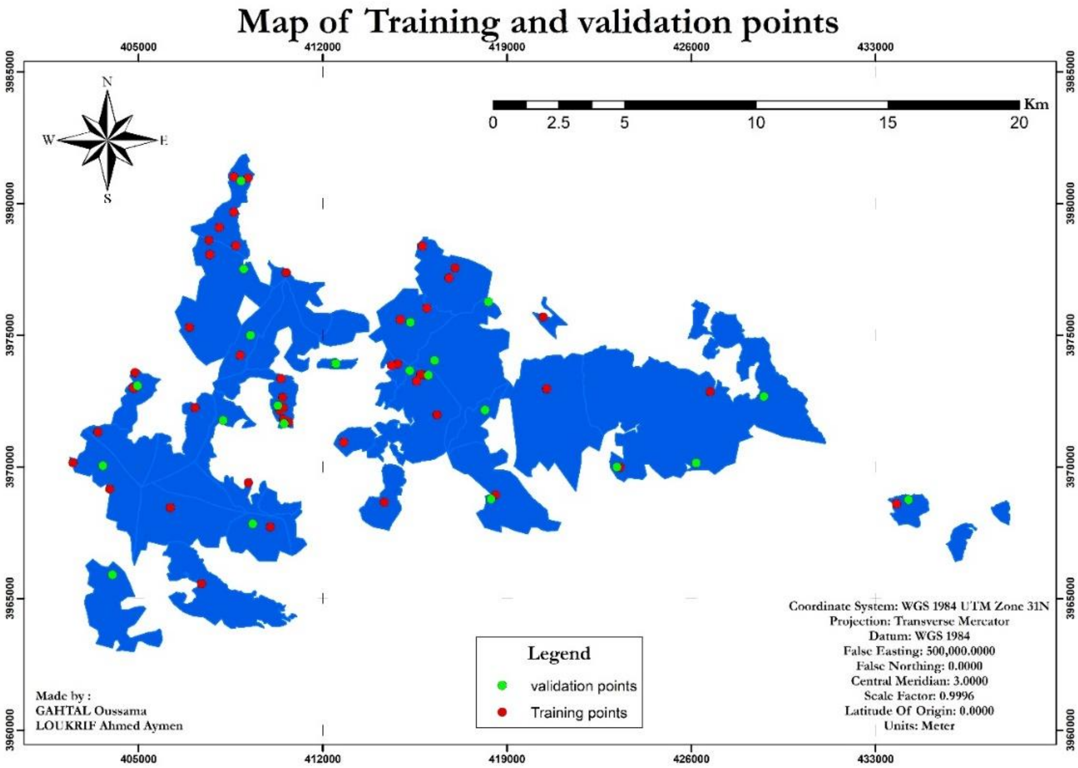


Figure 5. 30 Map of selected points

Given that chromosomes are represented by value intervals, samples must be representative and rich in information. The implemented application did not consider isolated pixels but rather samples in the form of polygons around pixels positioned on the map.

5.6 Evaluation process and proposed fitness

The proposed fitness assesses the potential classification accuracy of the currently evaluated individual. It uses the F1 score function calculated from the training samples. We opted to determine class membership of points based (training and validation) on the frequency map of fire occurrences in the region. We maintained the same risk class legend for consistency with methods used in the initial stages of this work.

Once training is completed, the individual with the best fitness is considered capable of producing the most accurate risk map. The algorithm then computes the F1 score on the validation set to decide whether to select the current individual or initiate another training process. The function F1 score is given by the following formula:

$$F1score = 2 \times \frac{precision \times recall}{precision + recall}$$

$$recall = \frac{TP}{TP + FN}$$

$$precision = \frac{TP}{TP + FP}$$

Where:

- TP: True Positives (number of pixels correctly classified as positive).
- FN: False Negatives (number of pixels incorrectly classified as negative).
- FP: False Positives (number of pixels incorrectly classified as positive).

Algorithm 2 Evaluation Process

```
BEGIN
Initialiser F1score, F1 score individual, TP, FN and FP individual à 0
for count class=1 to number of classes do
    for pixel=1 to number of pixels in the count class do
      C= Calculate the eventual class of pixel by the current evaluated individual
      if C== count class then
          TP (count class) = TP (count class) +1
      else
          FP (C) = FP (C) +1
          FN (count class) = FN (count class) +1
      end if
    end for
   Precision (count class) = TP (count class) / (TP (count class) + FP (count class))
   Recall (count class) =TP (count class) / (TP (count class) +FN (count class))
   F1score (count class) = 2*Precision*Recall / (Precision + recall)
   F1score individual=F1score individual +F1score (count class)
end for
F1score individual= F1score individual / number of classes
Return F1 score
END
```

5.7 Experimentation and results

Several experiments were conducted to evaluate our approach. The results are depicted on the graph in Figure 5, illustrating the evolution of the fitness function across five separate tests based on the number of generations and population size. The best outcome was achieved using a population of 30 individuals evolving over 50 generations, with a maximum accuracy of 80% for the training samples and only 40% for the validation set (Figure 5.31). Based on these findings, subsequent tests were conducted using these parameters: a population of 30 individuals evolving over 50 generations.

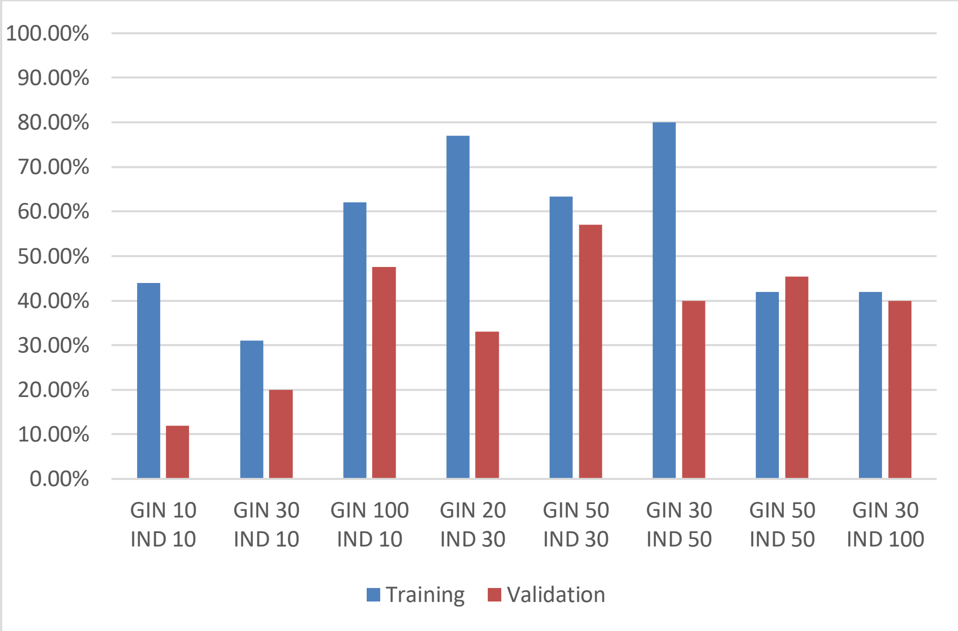


Figure 5. 31 Evolution of classification accuracy as a function of population size (IND) and number of generations (GEN).

Several experiments were conducted to evaluate our approach. The results are depicted on the graph in Figure 5, illustrating the evolution of the fitness function across five separate tests based on the number of generations and population size. The best outcome was achieved using a population of 30 individuals evolving over 50 generations, with a maximum accuracy of 80% for the training samples and only 40% for the validation set (Figure 5. 32). Based on these findings, subsequent tests were conducted using these parameters: a population of 30 individuals evolving over 50 generations

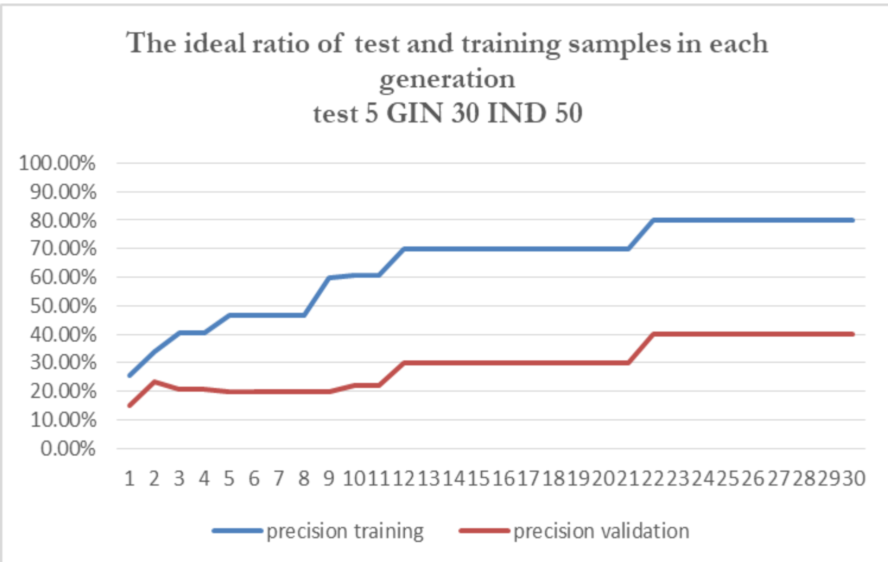


Figure 5.32 Evolution of classification accuracy over generations.

In light of the previous tests, we proceeded with the fusion of certain criteria. Given that the chosen information modelling manipulates gray level intervals generated from the different extreme values of the criteria, the matrix of the road and track map, the map of power lines, and the agglomeration were superimposed to form a single map: the human occupation map. Since these images, when considered individually, represent sparse matrices, the representative values of the gray Level intervals of the population remain similar, making the processing lengthy and reducing the accuracy of the results.
The frequency map is not directly included among the program's inputs, as the class membership of the training and validation pixels was determined from this map.
Several tests were conducted to determine the optimal number of features to use. The highest achieved rates were 80% for the training samples and 60% for the validation samples. These results were obtained using 9 criteria, considering the prior use of historical fire maps for sample classification. The highest quality image obtained is depicted in Figure 5.33.

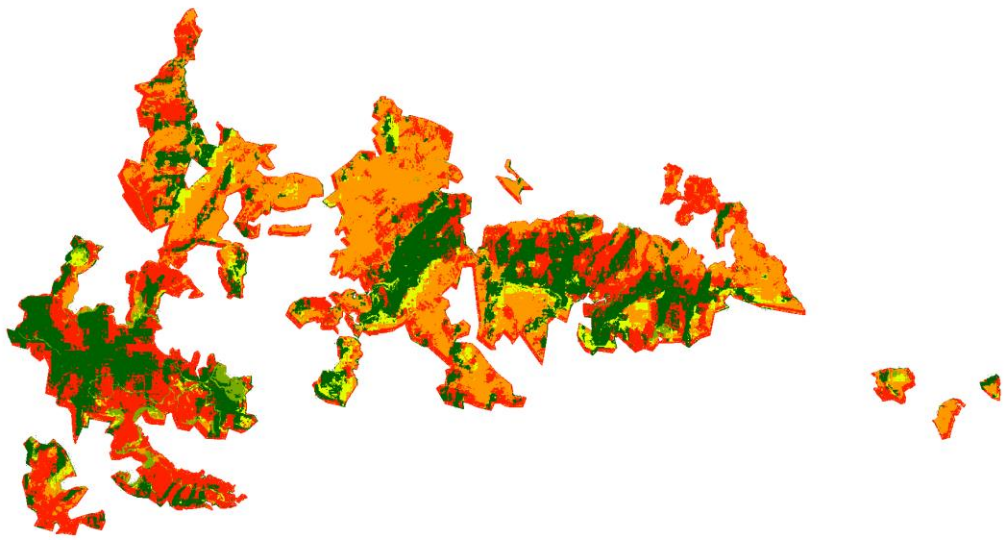


Figure 5. 33 Risk image for 7-parameter classification. Among 11 criteria, human index replaces 3 maps (roads, power lines, tracks); frequency and burned surface maps not included as inputs.

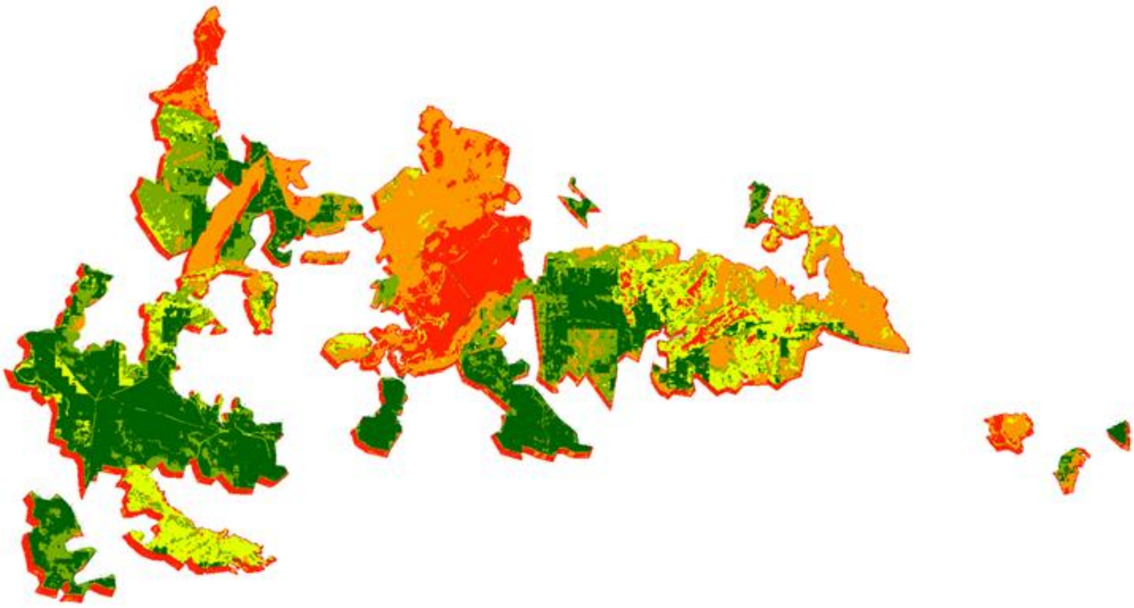


Figure 5.34 Risk image of 8-parameter classification. Among 11 criteria, human index replaces 3 maps (roads, power lines, tracks); frequency map included as input.

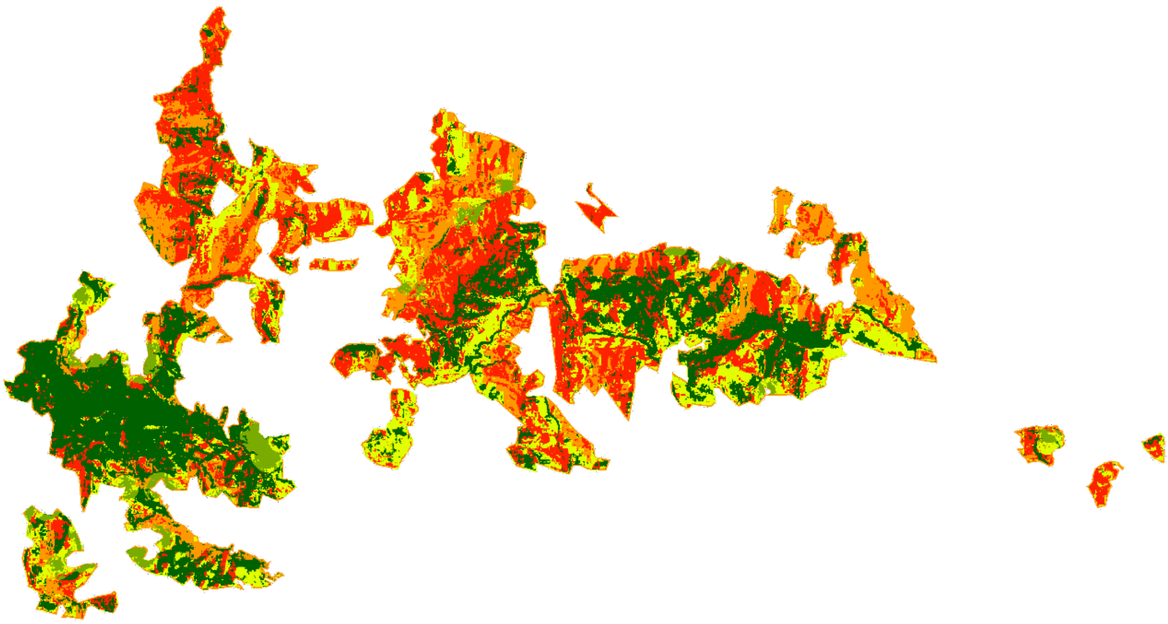


Figure 5.35 Risk image with all criteria.

6. Conclusion

The results obtained so far by the implemented GA are encouraging and promising; 80% of the training samples and 60% of the validation samples were correctly assigned to their respective classes. Performance varies depending on the criteria used in the classification process. Conducting additional tests with fewer parameters remains to be explored.

Genetic approach, unlike AHP, does not assign weights to criteria but relies on pixel similarity in terms of topomorphological, climatological, and human presence characteristics, as well as class characteristics. Each pixel is assigned to the class that most closely resembles it based on these criteria.

Forest fires can only be minimized through prevention, which relies on risk assessment. Studying fire risks in the *Thénia El Had* forest using remote sensing and Geographic Information Systems (GIS) enables the creation of a wildfire risk map by overlaying multiple layers of information.

The wildfire risk map is a preventive measure against forest fires. It will enable forest managers to implement prevention strategies and acquire suitable equipment for more effective firefighting efforts.

General conclusion

This study explored various crucial aspects of forest fire risk management using an integrated approach of Geomatics and Artificial Intelligence. Through the analysis of causes and factors contributing to forest fires in Algeria, we highlighted the importance of risk mapping methods, particularly the application of AHP and GA. The combination of these approaches enabled the generation of risk maps, taking into account the specific geographical and environmental characteristics of the study area.

Integrating forest fire history as a crucial element in our analysis is of paramount importance for several reasons. Firstly, this historical data provides valuable insights into past fire patterns and trends, thereby establishing a robust foundation for understanding risk dynamics in the study area. By leveraging this data in our approach using AHP or GAs, we were able to not only assess current risk factors but also anticipate potential high-risk areas in the future.

The GA approach proves particularly promising in this regard. By employing multi-criteria optimization techniques, GAs enabled us to effectively integrate complex geospatial data such as topography, vegetation, and weather conditions to develop precise and detailed risk maps. This methodology not only strengthens fire prevention efforts by identifying the most vulnerable areas but also enhances the planning of rapid intervention measures and post-fire management strategies.

In conclusion, the integration of forest fire history and the application of GAs in our study represent significant advancements towards proactive and sustainable fire risk management. This work opens up new avenues for enhancing the resilience of forest ecosystems and effectively protecting communities against the increasing threats posed by forest fires.

The implemented application marks the beginning of an in-depth exploration into the use of GA in forest fire risk management, requiring further extensive testing and the exploration of multiple criteria combinations.

Studying the correlation between parameters is crucial to eliminate redundant and irrelevant information from our process, thereby enhancing result accuracy.

The promising results of this approach encourage us to explore alternative similarity measures to replace Euclidean distance in the pixel classification process.

BIBLIOGRAPHIC REFERENCES

(Ali et al, 2012) F. Ali, EH. Lakhouaja, A. Sadiki, J. CHAAOUAN, "SIG, Télédétection et évaluation du risque d'incendie de forêts «Exemple du massif forestier Khezana (Province de CHAOUENE, Maroc)". Papeles de Geografía, volume n. 55-56, pp. 37-48, January 2012. https://www.researchgate.net/publication/274720813.

(Belhadj-Aissa et al, 2003) M. Belhadj-Aissa, A. Belhadj-Aissa and Y Smara: "Application Du Sig Et De La Télédétection Dans La Gestion Des Feux De Forêts En Algérie". 2nd FIG Regional Conference Marrakech, Morocco, December 2-5, 2003.

(Boulghobra et al, 2021) N. Boulghobra, S. Merdas and Ahmed Benmalek, " Evaluation Et Cartographie Des Feux De Forêts Généralisés D'août 2021 À Bejaia Et Tizi Ouzou : Approche Géomatique". Algerian Journal of Arid Regions Journal Algérien des Régions Arides JARA. Volume 14, n. 2, pp. 60–67 https://www.researchgate.net/publication/361738642.

(Chen, 2006) C.-F. Chen, "Applying the Analytical Hierarchy Process (AHP) Approach to Convention Site Selection. Journal of Travel Research, volume n. 35, pp. 167- 174, November 2006. doi: 10.1177/0047287506291593.

(Dogson et al, 2009) JF Dogson, M Spackman, Aln D. Pearman and Lawrence D. Philips multicriteria analysis: Manual. Departement for Communiities and Local Government. London. January 2009. http://researchgate.net/ publication.

(Demir et al, 2024) A. Demin, A .E. Akay, " Forest Fire Mapping Using GIS Base Anlytical Hierarchy Orocess Approach". European Journal of Forest Engineering, volume 10, n. 20 pp. 15-28, 2024. https://doi.org/10.33904/ejfe.1400233.

(Gen and Chen, 1997) M. Gen and R. Cheng, "Genetic Algorithms & Engineering Design". A Wiley-Interscience Publication, John Wiley and Sons, INC, 1997.

(Girard and Girard, 2010) J.C Girard and M. Girard, "Traitement des données de latélédétection , Environnement et ressources naturelles", 2nd edition, DUNOD., June 2010.

(Haldar et al, 2014) A. Haldar, S. Biswas and S. De, "A Review on Genetic Algorithm", International Journal of Engineering Sciences & Research Technology IJESRT, Vol. 3, pp. 369–372. January 2014.

(Haldurai et al, 2016) L. Haldurai, T. Madhubala and R. Rajalakshmi, “A Study on Genetic Algorithm and its Applications”. International Journal of Computer Sciences and Engineering, Vol. 4, Num. 10, pp.139–143, 2016

(Holland , 1992) J.H. Holland, “Adaptation in Natural and Artificial Systems: an Introductory Analysis with Applications to Biology, Control, and Artificial Intelligence”, MIT press, 1992.

(Khalfa and Ziani, 2010) AF Khalfa and M.C ziani: “Mise au point d’outils pour la délimitation et la quantification des feux de forêt à partir des images satellites. Application à la région de Tlemcen” (2010).

(Katoch et al, 2020) ,S. Katoch, S.S. Chauhan and V. Kumar, “A review on genetic algorithm: past, present, and future”. Multimedia Tools and Applications, Vol. 80, pp. 8091–8126. October 2020. https://doi.org/10.1007/s11042-020-10139-6

(Lin and Zhang, 2020) Z. Lin and G. Zhang, “Genetic algorithm-based parameter optimization for EO-1 Hyperion remote sensing image classification”, European Journal of Remote Sensing, Vol. 53, pp. 124–131, April 2020.
https://doi.org/10.1080/22797254.2020.1747949.

(Mirjalili et all, 2020) S. Mirjalili, J. Dong and A. Lewis, “ Nature-Inspired Optimizers Theories, Literature Reviews and Applications”, Studies in Computational IntelMligence, Vol. 811, Springer, Poland, 2020. https://doi.org/10.1007/978-3-030-12127-3

(Missoumi et al, 2003) A. MISSOUMI et K. TADJROUNI : SIG et imagerie Alsat 1 pour la cartographie du risque d’incendie de forêt, 2nd FIG Regional Conference Marrakech, Morocco, December 2-5, 2003.

(Plana et al, 2016) E., Font, M., Serra, M., 2016. FOREST FIRES, Guideline for Communicator and journalists. eFIRECOM Project. CTFC Editions. 32pp. https://efirecom.ctfc.cat/docs/efirecomperiodistes_en.pdf.

(Shukla et al , 2015) A. Shukla, H.M. Pandey and D. Mehrotra, “Comparative Review of Selection Techniques in Genetic Algorithm”. International Conference on Futuristic Trends on Computational Analysis and Knowledge Management (ABLAZE), Greater Noida, India, pp. 515-519, March 2015.

(Zouaidia, 2006) H. Zouaidia, “ Bbilan des incendies de forêt dans l’est algérien cas Mila, Constantine, Guelma et Souk Aras” . Mémoire de Magistère en écologie et environnement. Université de Constantine, 2006.

Webography

[1] https://lasentinelle.dz/index.php/2023/06/24/bilan-des-incendies-de-forets-en-2021-et-2022-150-morts-et-17-milliards-de-dinars-de-pertes/

[2] https://www.aps.dz/regions/162534-feux-de-foret-destruction-de-plus-de-41-000-hectares-jusqu-au-31-octobre-dernier

[3] https://www.spiceworks.com/tech/artificial-intelligence/articles/what-is-ml/

[4] https://www.hcltech.com/blogs/artificial-intelligence-defined-simple-terms
/