DOI: 10.2478/jlecol-2025-0031 Journal of Landscape Ecology (2025), Vol: 18 / No. 4

# SPATIO-TEMPORAL ASSESSMENT OF VEGETATION DYNAMICS IN THE ZOUAGHA FOREST, NORTHEASTERN ALGERIA (2000-2020)

NORHANE CHOUITER*[1], MAYA BENOUMELDJADJ[2], AND MALIKA RACHED-KANOUNI[2]

[1]*Laboratory of Functional Ecology and Environment, Department of Nature and Life Sciences, Faculty of Exact Sciences, Nature and Life Sciences, University of Larbi Ben M'hidi, Oum El Bouaghi. 1st November 1954 Street, Oum El Bouaghi 04000, Algeria.*
[2]*AUTES Research Laboratory, Faculty of Architecture and Urban Planning, Department of Architecture, University of Salah Boubnider. El Khroub Road, Ali Mendjeli New City, Constantine 25000, Algeria.*
**Corresponding author email: chouiter.norhane@univ-oeb.dz*

**Received:** 6th March 2025, **Accepted:** 6th May 2025

## ABSTRACT

This study aims to assess the spatio-temporal dynamics of vegetation in the Zouagha Forest, located in northeastern Algeria, over the period 2000-2020, taking into account the degradation induced by the complex interactions between biotic, abiotic, and anthropogenic factors. The analysis of vegetation indices, notably the NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), and SAVI (Soil-Adjusted Vegetation Index), for the years 2000, 2010, and 2020 reveals divergent trends. The NDVI shows a slight increase, rising from 0.20 in 2000 to 0.33 in 2020, suggesting a moderate regeneration of the vegetation cover. In contrast, the EVI records a notable decline, dropping from 0.38 in 2000 to 0.30 in 2020, indicating a continuous degradation in vegetation quality. Additionally, the SAVI shifts from -0.10 to 0.07, reflecting a modest improvement, yet the vegetation remains weak in terms of density and quality. This divergence between the indices suggests a spatial variation in vegetation conditions, indicating a growing heterogeneity in vegetation distribution across the forest. This phenomenon is exacerbated by unfavorable climatic conditions, such as reduced rainfall and rising temperatures. These changes, combined with anthropogenic pressures such as deforestation, greatly limit the forest's natural regeneration capacity. Moreover, pest attacks, particularly by (*Lymantria dispar*) and (*Tortrix viridana*), contribute to uneven degradation of the forest ecosystem. These findings highlight the urgency of developing sustainable management strategies, incorporating soil restoration and water resource management, to strengthen the ecological resilience of the Zouagha Forest in the face of growing challenges posed by climate change and human pressures.

**Keywords**: Zouagha Forest, degradation, NDVI, EVI, SAVI, vegetation indices.

## INTRODUCTION

The degradation of Algerian forests, a major ecological challenge, is marked by a continuous decline and significant loss of biodiversity (Encinas-Valero *et al.*, 2022; Gentilesca *et al.*, 2017; Quezel & Barbero, 1990). According to data from the Ministry of Land Planning and Environment, over 1,030,000 hectares of forests were destroyed between 1955 and 2000, representing an average annual loss of 24,523 hectares (Chouiter *et al.*, 2023). This degradation is the result of multiple factors, including fires, overgrazing, increasing demographic pressure, deforestation, illegal logging, insect attacks, and institutional deficiencies. Consequently, forests are often replaced by shrublands or reforestation efforts that show signs of recent degradation (Belote *et al.*, 2011; Abdourhamane *et al.*, 2013).

These degradation processes are exacerbated by climate change, which has become a major concern over the past decades. The Mediterranean region, in particular, is undergoing significant climatic changes that profoundly disrupt forest ecosystems (Cao *et al.*, 2019; Frolking *et al.*, 2009). These changes manifest through thermal anomalies, shifts in precipitation patterns, and an increase in the frequency of extreme events, such as prolonged droughts. These ecophysiological disturbances lead to increased water stress, a decrease in photosynthesis, and reduced tree growth, directly impacting forest productivity (Roula *et al.*, 2020). As a result, forest areas are shrinking, and the biogeographical ranges of plant species are shifting, sometimes toward less favorable zones, further weakening ecosystems (Getzin *et al.*, 2012). This dynamic contributes to increased forest degradation, compromising their ability to regenerate and fulfill essential ecological functions such as carbon sequestration, soil protection, and the regulation of hydrological cycles (Hrůza *et al.*, 2016). To understand the interaction between these degradation factors and climate impacts, the application of remote sensing is an effective and economical method. This technique allows for regular monitoring, precise mapping, and temporal analysis of changes at various spatial scales (Aricak, 2015; Balenović *et al.*, 2017). Data from Landsat satellites, particularly those from Landsat-5and 8, stand out for their high spectral resolution and free accessibility, making them a valuable tool for vegetation research at the global, continental, regional, and national levels (Baumann *et al.*, 2014; Coulter *et al.*, 2013; Giannetti *et al.*, 2018).

Remote sensing, based on the interaction between radiative energy and matter, facilitates continuous and repeated monitoring of vegetation cover. It allows for the detection of temporal variations, the analysis of time series, and the revelation of patterns related to phenology, vegetation growth, seasonal fluctuations, and long-term trends (Jurjević *et al.*, 2021). This information is crucial for understanding ecosystem dynamics, detecting disturbances, and assessing the impacts of climate change (Ji & Perters, 2003; Babamaaji & Lee, 2014).

In this context, the present study focuses on the detailed mapping of vegetation cover in the Zouagha forest, located in northeastern Algeria, over a twenty-year period from 2000 to 2020. The objective is to document the spatio-temporal changes in forest cover using advanced vegetation indices, such as NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), and SAVI (Soil Adjusted Vegetation Index). The NDVI (Normalized Difference Vegetation Index) is a key indicator for assessing vegetation density and vitality. This index helps quantify above-ground biomass and estimate plant health, making it a valuable tool for monitoring ecosystems on a global scale. The SAVI (Soil-Adjusted Vegetation Index) is an improved version of the NDVI that corrects for soil influences, which is particularly useful in areas where vegetation cover is sparse or the soil is visible, providing more accurate estimates of vegetation density. The EVI (Enhanced Vegetation Index) further adjusts for atmospheric effects and improves sensitivity in high biomass areas, making it more effective than the NDVI for monitoring dense forests and tropical ecosystems.

Integrating these indices into the analysis of multispectral remote sensing data allows for a detailed assessment of the health, density, and structural characteristics of the vegetation, providing a deep understanding of the ecological dynamics of the Zouagha forest. This approach aims to inform forest management and conservation strategies essential for the preservation of this region.

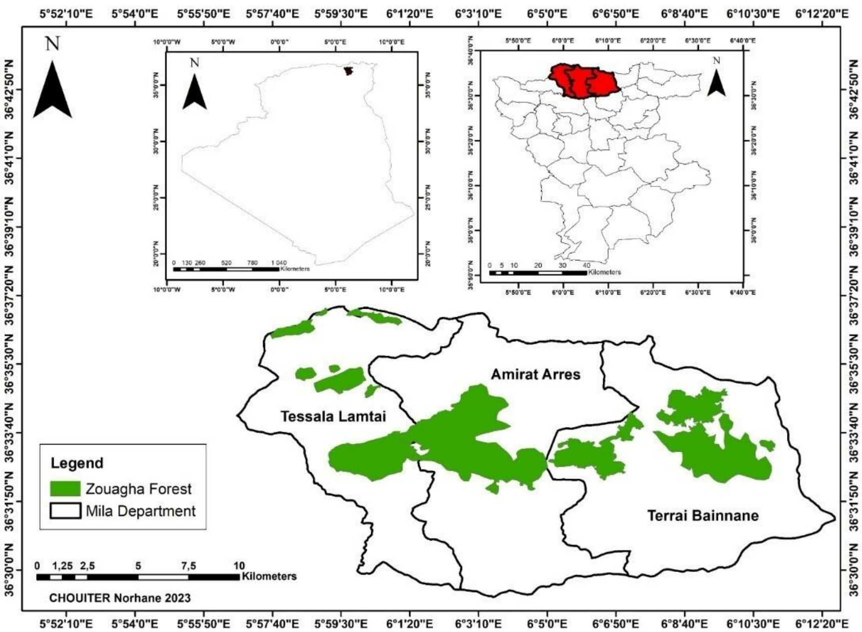
In addition to this spatio-temporal analysis, a central objective of the study is to explore the relationships between the three vegetation indices (NDVI, SAVI, and EVI). A key aspect of this approach involves conducting a correlation analysis to assess how these indices evolve together or differently in response to environmental conditions. This effort aims to better understand their complementarity, individual sensitivity, and relevance in monitoring long-term vegetation dynamics.

## MATERIALS AND METHODS

### Study Area

This research was conducted in the Zouagha forest (Fig. 1), located in the high plateaus of eastern Algeria, northeast of the Mila region. The forest spans the geographical coordinates: 36°34'38.90" N latitude and 6°9'15.52" E longitude, covering a total area of 3,915.52 hectares. It is bordered by the Oued El Kabir to the south, by the localities of Chigara, Terrai Bainen, Arres, and Tassala Lemtai, upstream of the Béni Haroune lake (Grarem Gouga). To the north, it borders the Wilaya of Jijel and is divided into five distinct sectors, the main ones being "El Bahloul, Beni Afek, Bouzourane, Djbel Arres, and Meguelet."

**Fig.1: Geographical location of the Zouagha forest (Northeast Algeria)**



**Climatic Characteristics**

Summer temperatures average between 25°C and 30°C, while winter temperatures range from 8°C to 12°C. The region receives an average of 700 mm of annual rainfall, concentrated mainly during autumn and winter. The months of November, December, and January are the wettest, often marked by heavy rainfall episodes (DGF, 2010).

**Floristic Composition**

The Zouagha forest is home to a diversity of native species such as *Juniperus phoenicea*, *Juniperus oxycedrus*, *Pistacia atlantica*, and *Olea europaea*. The planted stands mainly consist of oak species, namely cork oak (*Quercus suber* L.), zeen oak (*Quercus canariensis* Wild.), and afares oak (*Quercus afares* Pomel). These oaks are accompanied by a rich undergrowth including species such as: Rockrose (*Cistus sp),* Lavender (*Lavandula sp)*, Thyme *(Thymus sp)*, and Rosemary (*Rosmarinus officinalis)* (Chouiter *et al*., 2022).

**Acquisition and Preprocessing of Satellite Data**

In this study, remote sensing was conducted using Landsat satellite imagery. Specifically, Landsat 5 images were used for the year 2000, and Landsat 7 images for the years 2010 and 2020. The image acquisition periods for each year extended from January 1 to December 31 (i.e., from 01/01/2000 to 31/12/2000, from 01/01/2010 to 31/12/2010, and from 01/01/2020 to 31/12/2020, respectively), ensuring a comprehensive temporal coverage of each year. These satellites provide high-resolution data with multiple spectral bands, which is essential for a detailed analysis of vegetation dynamics. Landsat 5 offers seven spectral bands, while Landsat 7 provides eight, both with a spatial resolution of 30 meters. This 20-year period allows for an in-depth analysis of long-term vegetation trends in the studied region (Meera *et al*., 2015; Hyyppä *et al*., 2020). The satellite images were downloaded from Google Earth Engine, a platform that provides easy access to a vast collection of freely available satellite data. The use of these high-resolution images enables the detection and quantification of subtle vegetation variations (De Vivo *et al*., 2021).

**Vegetation Index Analysis**

*Normalized Difference Vegetation Index (NDVI)*

The Normalized Difference Vegetation Index (NDVI) is a key indicator of vegetation health, based on the ratio between the near-infrared (NIR) and red reflectance.

It is calculated using the following equation:

$$\textbf{NDVI}= \frac{(\mathrm{NIR+Red})}{(NIR-Red)} \qquad \textbf{(Eq.1)}$$

Where :

NIR represents the near-infrared band.

Red represents the red band of the Landsat.

NDVI values range from -1 to +1, with higher positive values indicating denser and healthier vegetation (Fayech &Tarhouni, 2021).

*Soil-Adjusted Vegetation Index (SAVI)*

The Soil-Adjusted Vegetation Index (SAVI) is designed to improve the accuracy of vegetation cover measurements by minimizing the influence of soil brightness. Unlike NDVI, SAVI introduces an "adjustment factor" (L) to correct for soil effects, particularly in areas with low vegetation cover.

SAVI values range from -1 to +1, with higher positive values indicating denser and healthier vegetation.
It is calculated using the following equation:

$$\textbf{SAVI}=\frac{(NIR-Red)}{(NIR+Red+L)}\times(1+L) \qquad \textbf{(Eq.2)}$$

Where :
NIR represents the near-infrared band.
Red represents the red band.
L is the soil brightness adjustment factor.

The soil brightness adjustment factor L is an empirical parameter introduced to reduce the influence of soil reflectance in areas with sparse vegetation cover. In environments with low vegetation density, exposed soil contributes significantly to the spectral signal, which can distort vegetation indices like NDVI (Rondeaux *et al*., 1996, Xue & Su, 2017). SAVI corrects for this by introducing L into the equation. The value of L depends on vegetation density:

L ≈ 0 for dense vegetation
L ≈ 1 for bare soil

L = 0.5 is commonly used as a standard value for intermediate vegetation cover (Huete, 1988).
In this study, we used L = 0.5 to account for the mixed soil-vegetation conditions in the Zouagha Forest.

*Enhanced Vegetation Index (EVI)*
The Enhanced Vegetation Index (EVI) was developed to increase the sensitivity of remote sensing to vegetation conditions, particularly in areas with dense vegetation. EVI is more responsive to variations in vegetation biomass compared to NDVI, and it addresses some of the issues related to atmospheric reflectance and soil influence. The value of EVI ranges from 0 to 1, with higher values close to 1 indicating denser and healthier vegetation.
It is calculated using the following equation:

$$\textbf{EVI}=\textbf{G}\times \frac{(NIR-Red)}{(NIR+C1\times Red-C2\times Blue+L)} \qquad \textbf{(Eq.3)}$$

Where :

- NIR represents the near-infrared band.
- Red represents the red band.
- Blue represents the blue band.
- G is a gain factor, set at 2.5.
- C1 and C2 are coefficients to correct atmospheric influences, set at 6 and 7.5 respectively.

L is a soil adjustment factor, set at 1. (Bento *et al*., 2018; Mushtaq & Asima, 2016).

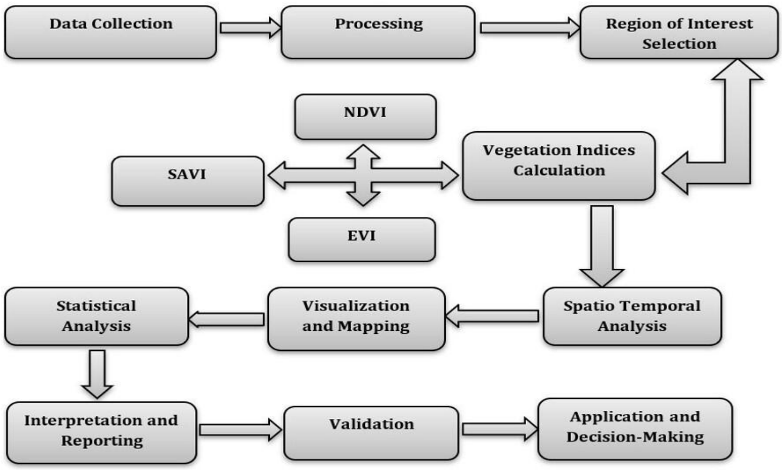
**Statistical Analysis of Vegetation Indices**
The analysis of vegetation indices in this study was conducted using Python, employing the libraries Matplotlib, Seaborn, and Pandas to process and visualize the data. The main

objective was to explore the relationships between different vegetation indices: NDVI, SAVI, and EVI.

A key aspect of this analysis was the examination of correlation, which measures how two variables change together. We used Pearson's correlation coefficient to quantify this relationship. This coefficient ranges from -1 to 1 (Benoumeldj *et al.*, 2023) a value close to 1 indicates that both variables increase together (positive correlation), a value close to -1 shows that they move in opposite directions (negative correlation), and a value close to 0 means there is no linear relationship between them.

An ANOVA (Analysis of Variance) test was performed to assess significant differences between multiple groups of data based on the vegetation indices (Blanca *et al.*, 2017; Blanca *et al.*, 2018; Kim, 2015). To refine this analysis and specifically identify which groups stand out, a Tukey HSD post-hoc test was conducted to determine which years exhibit significant differences for each index (Ruxton & Beauchamp, 2008).

**Fig. 2: Steps of Remote Sensing and Statistical Analysis in the Study**




### Acquisition and Preprocessing of Climatic Data

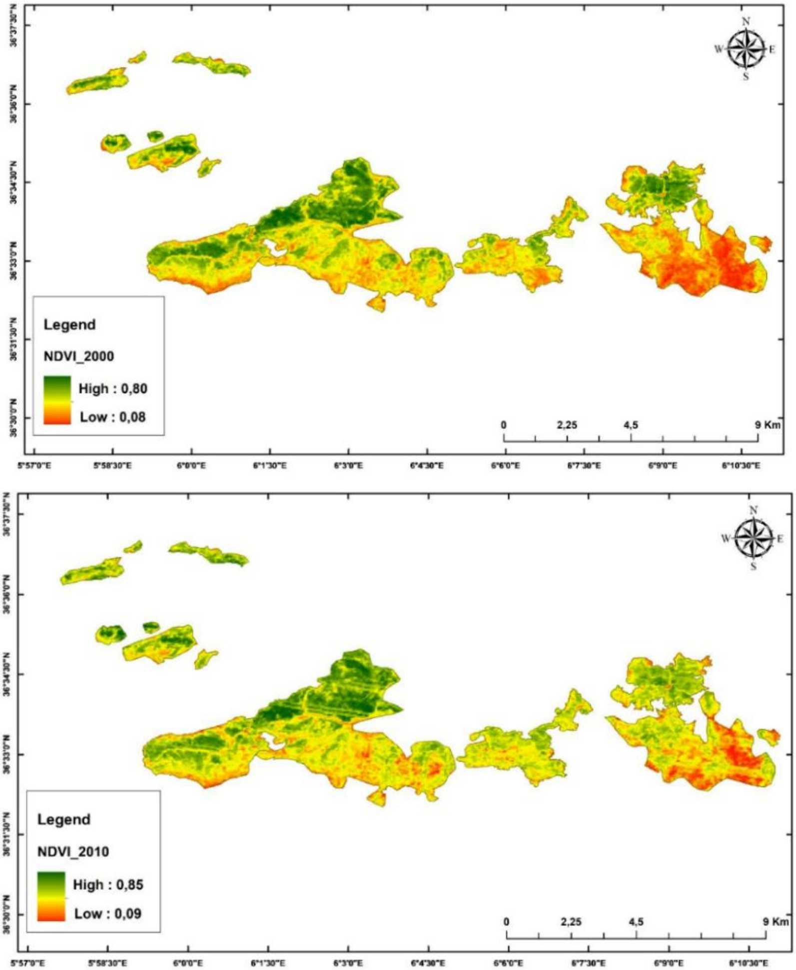
The climatic data used in this study, including monthly precipitation and average monthly temperatures, were obtained from the Aïn Tine meteorological station, located in Mila Province near the Zouagha Forest. This station provides the official climatic records for the study area. Data were collected for the years 2000, 2010 and 2020, enabling a temporal comparison of climatic variability over two decades. These data were used to assess changes in summer weather conditions, particularly in terms of minimum precipitation, maximum temperatures, and their potential impact on vegetation cover dynamics.

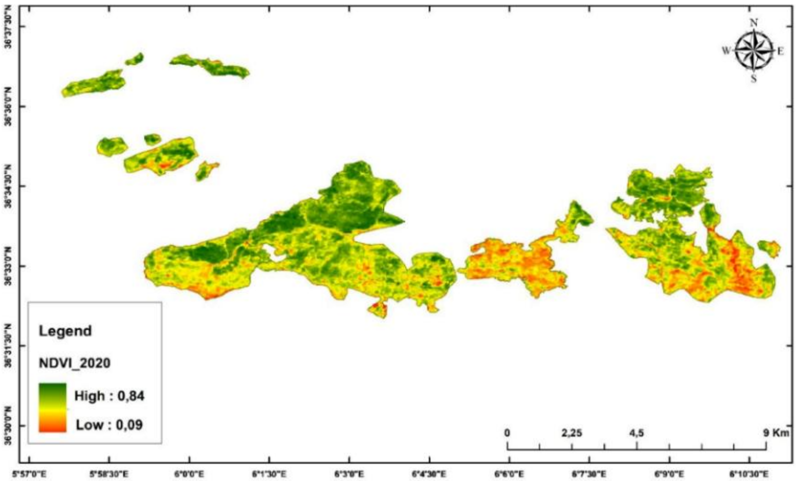
## RESULTS

**Spatio-temporal analysis of vegetation dynamics in the Zouagha forest using NDVI, SAVI, and EVI indices (2000-2010-2020)**

Figs. 3, 4, and 5 illustrate a spatio-temporal analysis of vegetation in the the Zouagha forest across three distinct periods (2000-2010-2020).

**Fig. 3: Normalized Difference Vegetation Index (2000-2010-2020)**

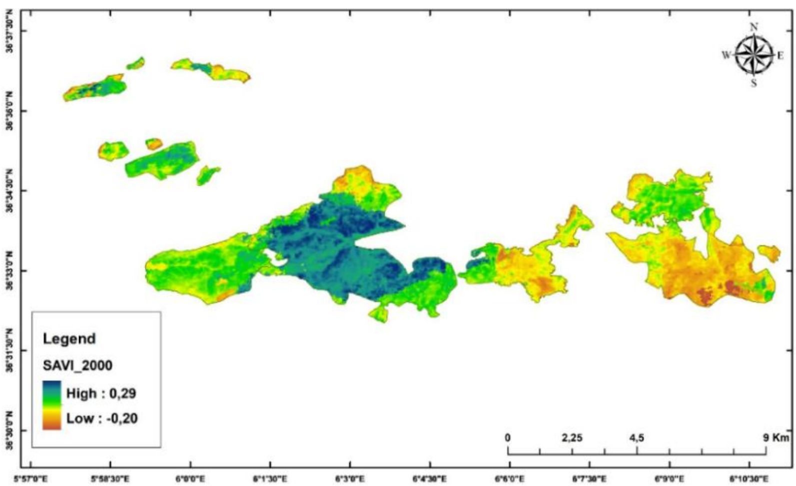


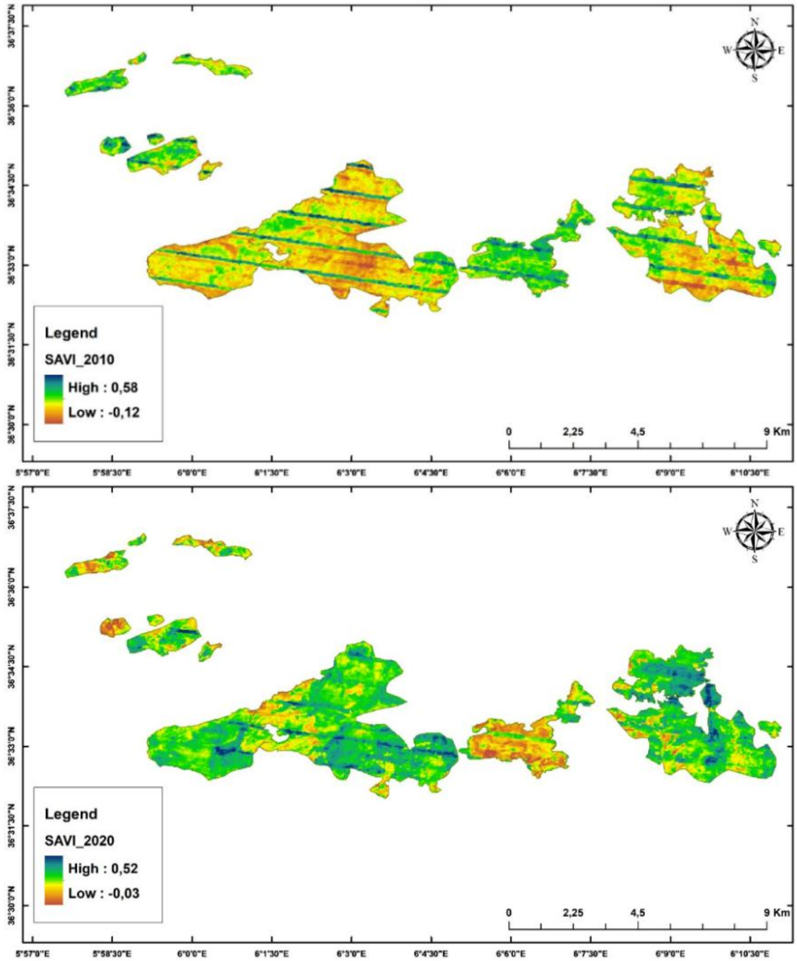



**NDVI (Normalized Difference Vegetation Index)**

In 2000, the NDVI map reveals an uneven distribution of vegetation, with dense coverage mainly concentrated in the central and western areas. Values range from 0, 08 to 0, 80, indicating moderately dense vegetation, but also highlighting areas of ecological stress. In 2010, an improvement compared to the year 2000 is observed, with maximum values increasing to 0, 85. This improvement indicates some recovery of vegetation, although degraded areas persist, reflecting ongoing environmental challenges. However, in 2020, a slight decrease in maximum values compared to 2010, reaching 0, 84, suggests moderate degradation. Despite this, areas of dense vegetation remain, demonstrating a certain ecological resilience in the face of environmental pressures.

**Fig. 4: Soil Adjusted Vegetation Index (2000-2010-2020).**

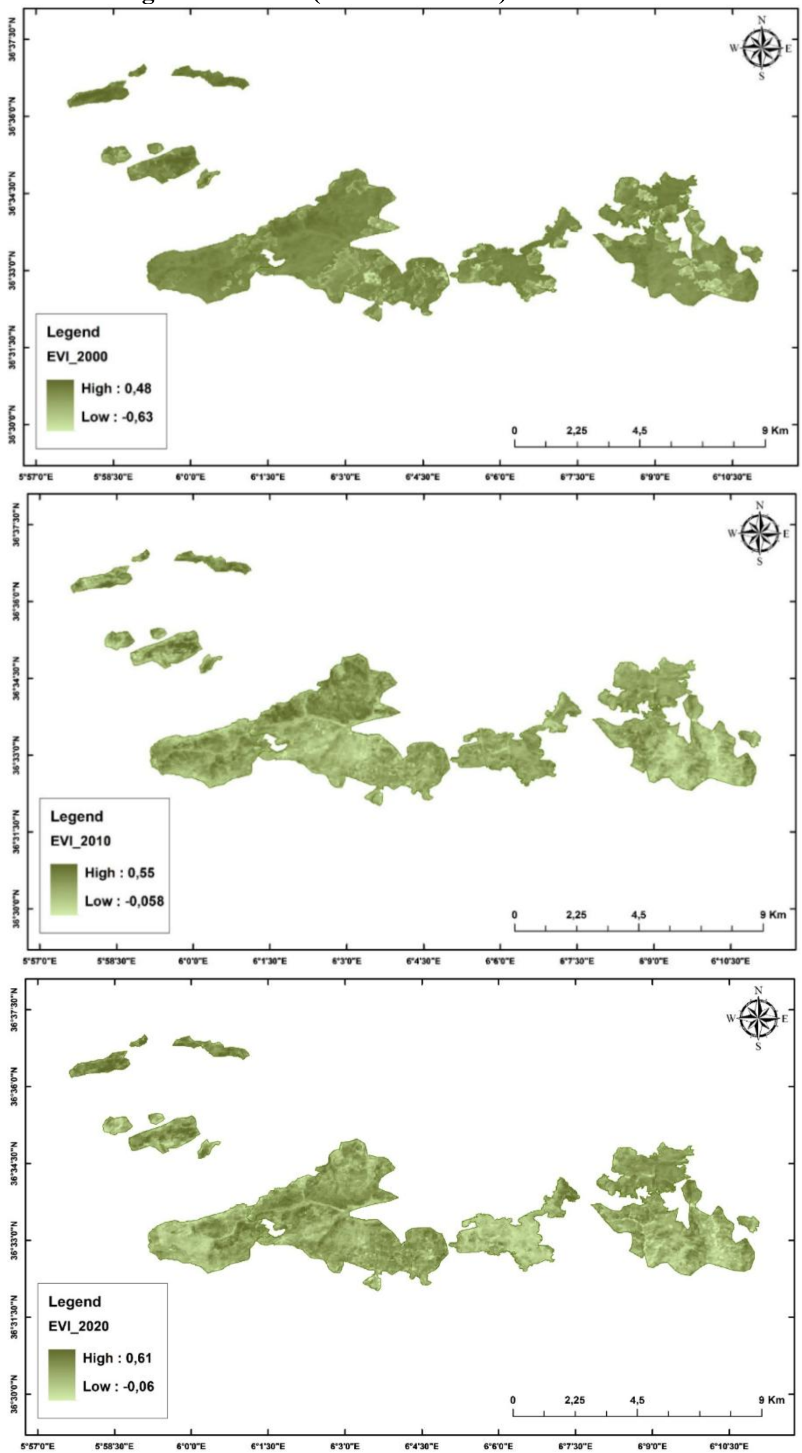





**SAVI (Soil Adjusted Vegetation Index)**

In 2000, the SAVI reveals dense vegetation in the central areas, with values ranging from -0.20 to 0, 29, reflecting significant variability in soil and vegetation conditions. In 2010, a notable improvement compared to 2000 is observed, with maximum values increasing to 0, 58. This indicates a moderate improvement in vegetation cover. However, in 2020, compared to 2010, a decrease in maximum values to 0, 52 is noted, suggesting moderate degradation of vegetation cover. This degradation is accompanied by marked spatial variations, highlighting differences in ecological conditions across the region.

**Fig. 5: Enhanced Vegetation Index (2000-2010-2020)**

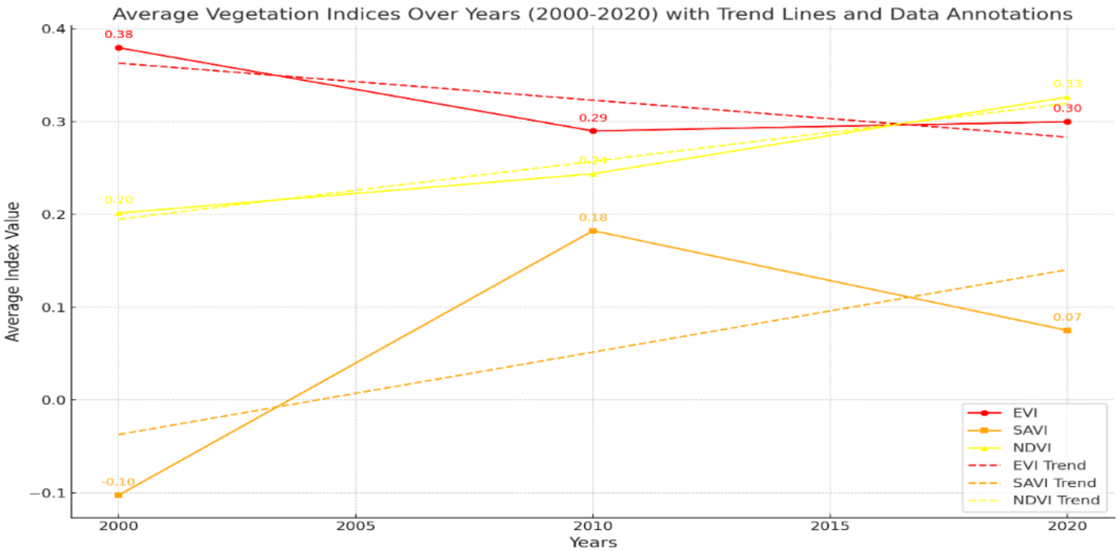


**Enhanced Vegetation Index (EVI)**

In 2000, EVI values are mainly concentrated around 0, 48, indicating modest vegetation in the most productive areas. However, negative values close to -0, 63 reveal the presence of bare soil or areas without vegetation. In 2010, compared to 2000, a notable improvement in vegetation density is observed, with values reaching 0, 55. Despite this progress, some areas still show a reduction in vegetation density, indicating uneven resilience in certain parts. Although in 2020, compared to 2010, maximum values increase further, reaching 0, 61. This indicates moderate vegetation in several areas, despite environmental pressures. However, a large portion with low EVI values highlights ecological decline in certain regions, suggesting areas vulnerable to degradation.

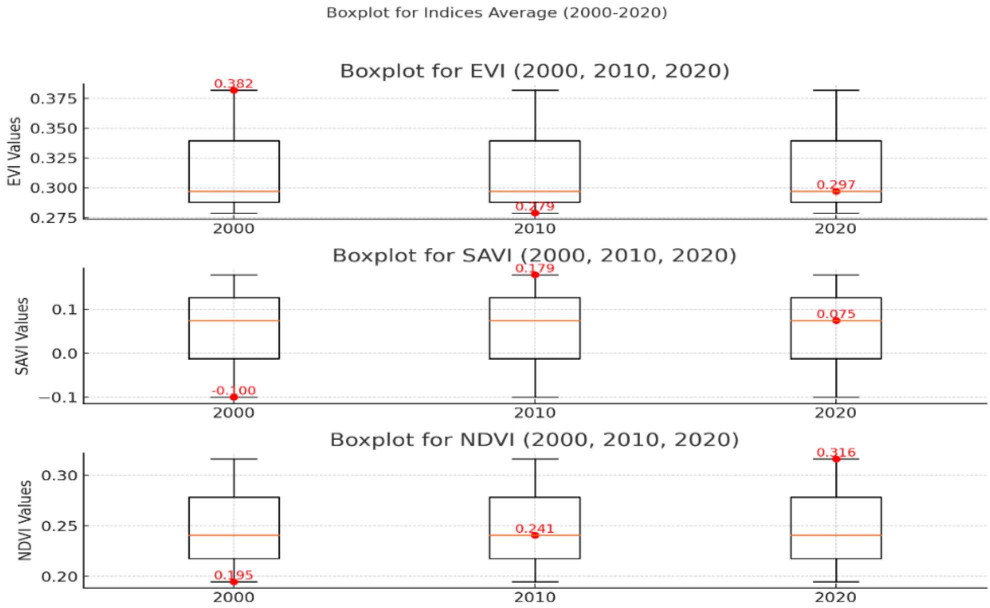
Figs. 6 and 7 provide graphical representations showing the evolution of the average vegetation indices (EVI, SAVI, NDVI) over the years (2000- 2010- 2020).

**Fig. 6: Average Vegetation Indices Over Years (2000-2010-2020)**




The analysis of EVI, SAVI, and NDVI indices over the years 2000, 2010, and 2020 highlights varied dynamics in vegetation cover. EVI shows a decrease in the average, dropping from 0.38 in 2000 to 0.27 in 2010, followed by a slight increase to 0.29 in 2020. The increase in standard deviations, reaching 0.06 in 2010 and 0.05 in 2020 compared to 0.03 in 2000, suggests a growing heterogeneity in vegetation vigor over time. SAVI, on the other hand, shows an increase in the average, rising from -0.10 in 2000 to 0.18 in 2010, before declining to 0.07 in 2020. The standard deviations show a slight increase in 2010 and remain stable at 0.02 in 2020, indicating moderate variability but a progressive decline in uniformity. Finally, NDVI shows a steady increase in the average, from 0.20 in 2000 to 0.24 in 2010, and then to 0.32 in 2020. The increase in standard deviations, notably reaching 0.13 in 2020, reflects greater diversification and increased heterogeneity in vegetation cover.

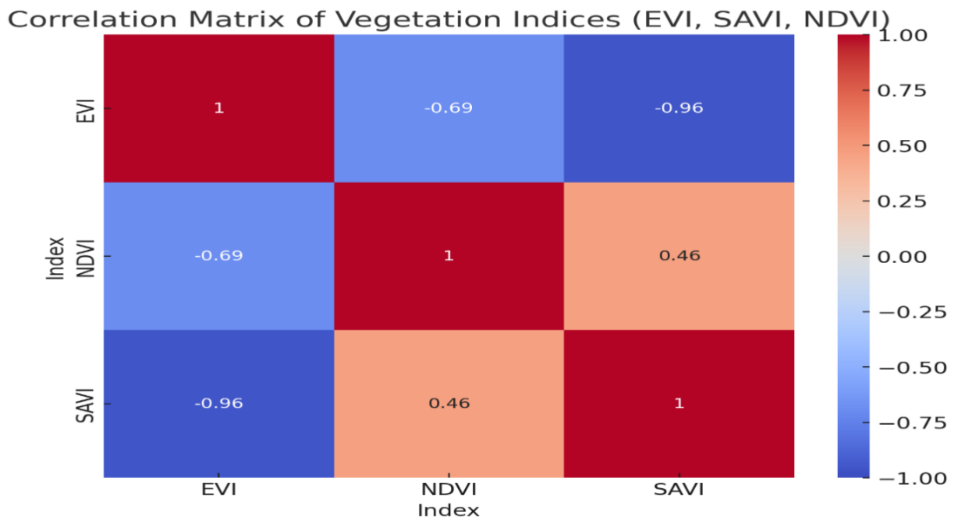
**Fig. 7: Boxplot for Indices Average (2000-2010-2020)**




**Correlation between Vegetation Indices**

Fig. 8 shows the correlation between the indices. This correlation matrix highlights the relationships between three vegetation indices: EVI, NDVI, and SAVI.

**Fig. 8: Correlation Matrix of Vegetation Indices (EVI, SAVI, NDVI)**




EVI and SAVI (-0.96): The strong negative correlation suggests that an increase in EVI is almost always accompanied by a decrease in SAVI. This can be explained by the different sensitivities of these indices: EVI is more responsive to dense vegetation and less influenced by soil effects, whereas SAVI explicitly incorporates this effect, leading to inverse variations between the two indices.

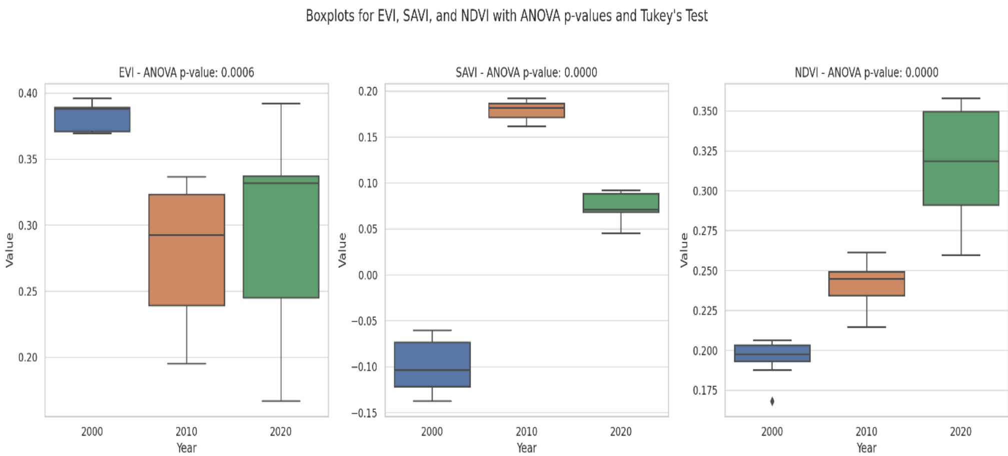
EVI and NDVI (-0.69): The moderately strong negative correlation indicates that although both indices are designed to measure vegetation, they react differently to certain environmental factors. This divergence could be attributed to the NDVI's tendency to saturate more quickly in areas of very dense vegetation, while EVI, designed to reduce this effect, continues to provide distinct values.

NDVI and SAVI (0.46): The moderate positive correlation between these two indices shows that they tend to evolve in the same direction under certain conditions. However, the adjustment made by SAVI to compensate for soil effects creates a notable difference in how these indices respond to variations in vegetation cover. Although all these indices are used to assess vegetation, their differences in responding to environmental conditions make them complementary tools for a more precise analysis of vegetation in various contexts.

**Analysis of Temporal Variations in Vegetation Indices Using ANOVA and Tukey's Post-Hoc Test**

Figure 9 illustrates boxplots comparing the values of the vegetation indices EVI, SAVI, and NDVI for three distinct years, along with the p-values obtained from the ANOVA and Tukey post-hoc tests. The p-values, all below 0.05, indicate the presence of statistically significant differences between the group means for each index over the studied years. The Tukey HSD post-hoc test reveals that the largest variations for the EVI index occurred between 2000 and 2010, with a notable decrease in vegetation between these two periods. In contrast, for the NDVI index, the most significant differences occurred between 2010 and 2020, with a major improvement in vegetation density during this period. Regarding the SAVI index, fluctuations were observed throughout the studied periods, with significant differences between each pair of years, suggesting variations in soil and vegetation conditions.

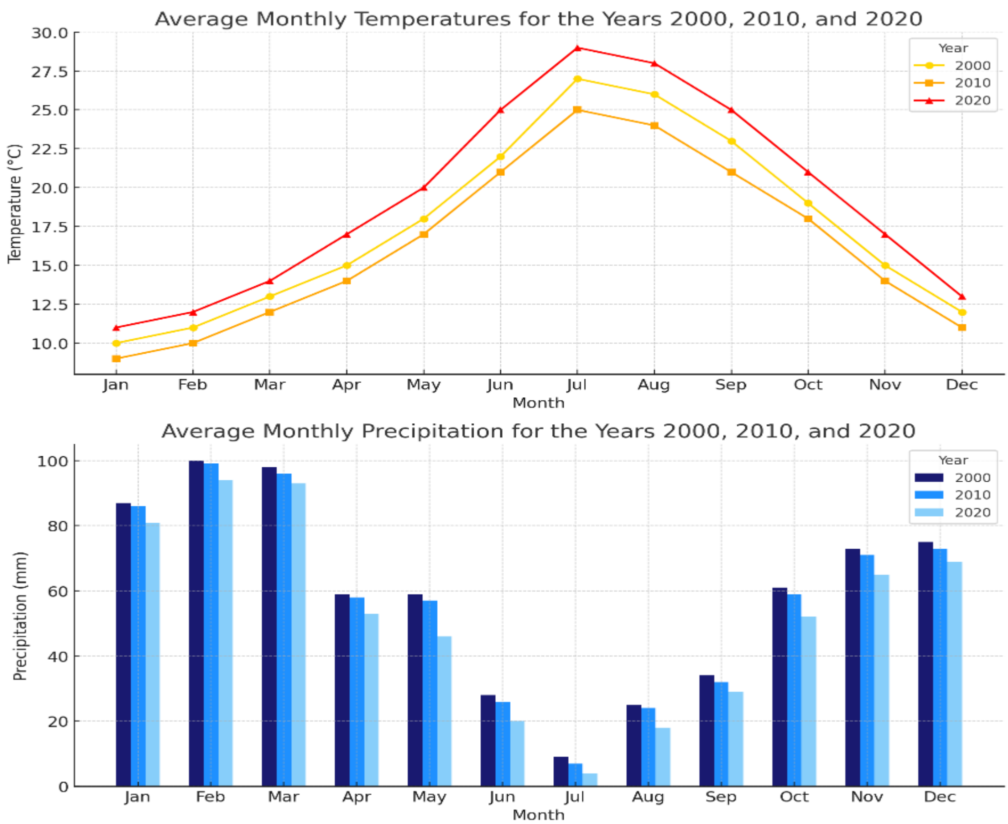
**Fig. 9: Analysis of Temporal Variations in Vegetation Indices Using ANOVA and Tukey's Post-Hoc Test**



**Variation in Precipitation and Temperature (Comparative Analysis between 2000, 2010, and 2020)**

The climatic data over the years presented in Figure 10 show a significant shift towards hotter summers and drier periods. Regarding precipitation, the year 2000 recorded a peak of 100 mm in February, with a minimum of 9 mm in July. In 2010, the maximum precipitation remained close to that of 2000, reaching 99 mm in February, while the minimum dropped to 7 mm in July. However, in 2020, a notable decrease was observed, with a maximum peak of only 94 mm in February and an extremely low minimum of 4 mm in July, reflecting an intensification of summer drought conditions. As for temperatures, there is a consistent upward trend. In 2000, the maximum temperature was around 26°C in July, with the lowest being 10°C in January. In 2010, the maximum temperature climbed to 28°C in July, while maintaining a similar winter low of 11°C. The year 2020 shows an even more marked increase, with temperatures reaching about 29°C in July and a minimum of 12°C in January.

**Fig. 10: Variation in Precipitation and Temperature (2000-2010-2020)**



## DISCUSSION

The Zouagha forest, located in the northeast of Algeria, is a striking example of the complexity of ecological dynamics where the interactions between biotic, abiotic, and anthropogenic factors lead to an accelerated degradation of this ecosystem. The analysis of NDVI, EVI, and SAVI vegetation indices over the periods 2000, 2010, and 2020 reveals contradictory trends, illustrating an underlying degradation that is not immediately visible through a simple increase in vegetation cover. Indeed, although NDVI shows an overall upward trend, rising from 0.20 in 2000 to 0.33 in 2020, indicating an apparent regeneration of vegetation cover. EVI, which measures the density and vigor of vegetation, shows a significant decline, dropping from 0.38 in 2000 to 0.30 in 2020, while SAVI, an indicator of soil quality, rises from -0.10 in 2000 to 0.07 in 2020 after a temporary peak in 2010. These trends reflect a reduction in both the density and quality of vegetation. The divergences between the indices can be better understood by analyzing the correlations between them. The strong negative correlation between EVI and SAVI (-0.96) indicates that when EVI increases, SAVI tends to decrease, and vice versa (Alademomi *et al.*, 2020). EVI is designed to reduce the influence of soils on vegetation measurements, making it particularly suitable for areas with dense vegetation. On the other hand, SAVI explicitly integrates soil conditions into its calculation, making it more sensitive to environments where the soil has a significant impact, such as in areas with sparse vegetation. This opposite behavior explains the strong negative correlation between the two indices, showing that they capture different aspects of vegetation conditions. The moderate negative correlation (-0.69) between EVI and NDVI can be explained by the fact that NDVI saturates quickly in high biomass environments, losing its ability to differentiate subtle levels of vegetation density (Zou *et al.*, 2022; Rahimi *et al.*, 2025a ; Mersha *et al.*, 2024). EVI, however, was developed to overcome this saturation problem, providing more distinct values in such conditions. This means that in areas with dense vegetation, EVI can still detect fine variations that NDVI does not capture, resulting in a moderate negative relationship between the two indices. The moderate positive correlation (0.46) between NDVI and SAVI indicates that, in certain conditions, especially in environments with less dense vegetation and a more marked soil influence, these indices tend to evolve in the same direction. NDVI does not directly take into account the impact of soil, but in low vegetation cover environments, SAVI adjusts the measurements by considering soil reflectance, allowing for a better representation of vegetation in these contexts (Baret & Guyot, 1991; Rahimi *et al.*, 2025b ). This explains why the two indices show similar trends, even though SAVI introduces subtle adjustments that differentiate it from NDVI. The analysis of the correlations between these indices highlights their complementarity and the importance of a multi-index approach for a more comprehensive and accurate analysis of vegetation and its interaction with soil and climate (Catry *et al.*, 2012a; Alves *et al.*, 2010). The results of the ANOVA and Tukey Post-Hoc statistical tests confirm these observations, revealing statistically significant differences between the indices across the studied years. P-values lower than 0.05 indicate that the observed variations in the indices are not due to chance but reflect real changes in environmental and anthropogenic conditions. These statistical results highlight the importance of an in-depth analysis of the underlying factors influencing these variations. Indeed, to better understand the complexity of the dynamics and the real changes in environmental conditions affecting the Zouagha Forest, it is essential to establish a link between the climatic, biotic, and anthropogenic factors contributing to its degradation. Among these factors, climate change plays a major role in the forest's degradation, particularly through the reduction of summer rainfall and the increase in temperatures. The reduction in summer precipitation has direct effects on the survival of young plants, increasing water stress and making the ecosystem more vulnerable to drought

(Chouiter *et al.*, 2024a), thereby contributing to the regression of vegetation cover. This trend is clearly illustrated by the climatic data recorded over the years 2000, 2010, and 2020. A gradual and worrying decrease in summer rainfall is observed, with minimum precipitation dropping from 9 mm in July 2000 to only 4 mm in July 2020. At the same time, the average maximum temperatures rose from 26°C in 2000 to 29°C in 2020. These combined changes reflect an intensification of summer drought conditions and a shift towards a hotter and drier climate. Such conditions drastically increase evapotranspiration, exacerbate soil dryness, and reduce the water use efficiency of plants, particularly during the growing season (De la Cruz *et al.*, 2014; Catry *et al.*, 2017). The sustained thermal stress and lower soil moisture availability directly contribute to the decline in vegetation vigor and regeneration potential, especially in a semi-arid Mediterranean context like that of the Zouagha forest (Barbati *et al.*, 2012; Catry *et al.*, 2012b; Boucif *et al.*, 2024). These climatic constraints are reflected in the vegetation indices, particularly in the drop of EVI values, which are sensitive to vegetation density and health. Although higher temperatures can sometimes extend the growing season, they can also accelerate plant senescence and increase the risk of forest fires, thereby compromising the stability of ecosystems (Bouget *et al.*, 2023; Moreira *et al.*, 2009). Climatic variations, such as decreased precipitation and increased temperatures, are indicators of climate change that negatively affect vegetation dynamics. However, these unfavorable climatic conditions are only part of the pressures faced by the forest. The declines observed in vegetation quality and density suggest that, in addition to climate change, other stress factors, particularly biological ones, such as pests like *Lymantria dispar* and *Tortrix viridana* (DGF, 2020), have played a key role in this degradation. Their epidemic cycles cause massive defoliation, which compromises photosynthesis and weakens the trees, making them more vulnerable to other environmental stresses (Castro *et al.*, 2012; Tiberi *et al.*, 2016; Gidey *et al.*, 2018). This situation is exacerbated by the presence of pathogenic fungi like *Biscogniauxia mediterranea*, responsible for internal wood decay and the formation of necrotizing stromata, thereby increasing tree mortality (Sanchez-Gonzalez *et al.*, 2010; Nadezhdina *et al.*, 2010). Anthropogenic pressures, such as intensive deforestation for agriculture, urbanization, overgrazing, and human-caused forest fires, have also contributed to increased habitat fragmentation and a drastic reduction in forest area. Between 2000 and 2020, over 240 hectares of forest were destroyed, worsening biodiversity loss and further weakening the ecosystem (DGF, 2022; Chouiter *et al.*, 2024b). Although legislative frameworks exist for forest protection, their implementation is often insufficient to counter the multiple pressures faced by the Zouagha forest.

## CONCLUSION

This study analyzed the spatio-temporal dynamics of vegetation in the Zouagha Forest over a twenty-year period (2000-2020) using vegetation indices (NDVI, EVI, SAVI) to better understand the ecological changes and anthropogenic pressures on this ecosystem. The results reveal divergent trends: although the NDVI indicates a moderate improvement in vegetation cover, this masks a deeper degradation in the quality and density of vegetation, as highlighted by the significant decline in the EVI. Similarly, while the SAVI shows slight progress in soil quality, it points to persistent challenges related to land resource degradation. These observations highlight an increasing heterogeneity in vegetation conditions across the forest, driven by climatic pressures and anthropogenic influences. These findings underscore the urgency of adopting sustainable and integrated management strategies to strengthen the ecological resilience of the Zouagha Forest. Targeted actions for soil restoration, water resource management, and effective measures to protect against human and biological pressures are essential to prevent further degradation of the ecosystem. Moreover, strict enforcement of existing legislation, combined with the development of more tailored policies, is essential to ensure the long-term sustainability of this ecosystem in the face of climate change challenges.

## ACKNOWLEDGMENTS

This work was supported and supervised by the General Directorate of Forests (DGF) of the Mila Wilaya. We express our deep gratitude for their support and guidance throughout this study.

## CONFLICTS OF INTEREST

The authors declare no conflict of interest

## REFERENCES

Abdourhamane, H., Morou, B., Rabiou, H., & Mahamane, A. (2013). Caractéristiques floristiques, diversité et structure de la végétation ligneuse dans le Centre-Sud du Niger : cas du complexe des forêts classées de Dan Kada Dodo-Dan Gado. *International Journal of Biological and Chemical Sciences, 7*(3), 1048-1068. https://doi.org/10.4314/ijbcs.v7i3.13

Alademomi, A. S., Okolie, C. J., Daramola, O. E., Agboola, R. O., & Salami, T. J. (2020). Assessing the relationship of LST, NDVI and EVI with land cover changes in the Lagos Lagoon. *Geographicae Environment, 39*(3), 87-109. https://doi.org/10.2478/quageo-2020-0025

Alves, L. F., Vieira, S. A., Scaranello, M. A., Camargo, P. B., Santos, F. A. M., Joly, C. A., & Martinelli, L. A. (2010). Forest structure and live aboveground biomass variation along an elevational gradient of tropical Atlantic moist forest (Brazil). *Forest Ecology and Management, 260*(5), 679-691. https://doi.org/10.1016/j.foreco.2010.05.023

Aricak, B. (2015). Using remote sensing data to predict road fill areas and areas affected by fill erosion with planned forest road construction: A case study in Kastamonu Regional Forest Directorate (Turkey). *Environmental Monitoring and Assessment, 187*(7), 1-10. https://doi.org/10.1007/s10661-015-4663-7

Babamaaji, R. A., & Lee, J. (2014). Land use/land cover classification of the vicinity of Lake Chad using NigeriaSat-1 and Landsat data. *Environmental Earth Sciences, 71*, 4309-4317. https://doi.org/10.1007/s12665-013-2825-x

Balenović, I., Šimić Milas, A., & Marjanović, H. (2017). A comparison of stand-level volume estimates from image-based canopy height models of different spatial resolutions. *Remote Sensing, 9*(3), 205. https://doi.org/10.3390/rs9030205

Barbati, A., Salvati, R., Ferrari, B., Di Santo, D., Quatrini, A., Portoghesi, L., Travaglini, D., Iovino, F., & Nocentini, S. (2012). Assessing and promoting old-growthness of forest stands: Lessons from research in Italy. *Plant Biosystems, 146*(1), 167-174. https://doi.org/10.1080/11263504.2011.650730

Barbeito, I., Collet, C., & Ningre, F. (2014). Crown responses to neighbour density and species identity in a young mixed deciduous stand. *Trees, 28*(6), 1751-1765.

https://doi.org/10.1007/s00468-014-1082-2

Baret, F., & Guyot, G. (1991). Potentials and limits of vegetation indices for LAI and APAR assessment. *Remote Sensing of Environment, 35*, 161-173. https://doi.org/10.1016/0034-4257(91)90009-U

Baumann, M., Ozdoga, M., Wolter, P. T., Krylov, A., Vladimirova, N., & Radeloff, V. C. (2014). Landsat remote sensing of forest windfall disturbance. *Remote Sensing of Environment, 143*, 171-179. https://doi.org/10.1016/j.rse.2013.12.020

Belote, R. T., Prisley, S., Jones, R. H., Fitzpatrick, M., & De Beurs, K. (2011). Forest productivity and tree diversity relationships depend on ecological context within mid-Atlantic and Appalachian forests (USA). *Forest Ecology and Management, 261*(7), 1315-1324. https://doi.org/10.1016/j.foreco.2011.01.010

Bendixsen, D. P., Hallgren, W. S., & Frazier, A. E. (2015). Stress factors associated with forest decline in xeric oak forests of south-central United States. *Forest Ecology and Management, 347*(3), 40-48. https://doi.org/10.1016/j.foreco.2015.03.015

Benoumeldj, M., Rached-Kanouni, M., Chouiter, N., Bouchareb, A., & Ababsa, L. (2023). Exploring the association between vegetation cover and land surface temperature in Constantine: A comparative analysis. *Revue des BioRessources, 13*(2), 50-65. https://dspace.univ-ouargla.dz/jspui/handle/123456789/35369

Bento, V. A., Gouveia, C. M., DaCamara, C. C., & Trigo, I. F. (2018). A climatological assessment of drought impact on vegetation health index. *Agricultural and Forest Meteorology, 259*, 286-295. https://doi.org/10.1016/j.agrformet.2018.05.014

Blanca, M. J., Alarcón, R., Arnau, J., Bono, R., & Bendayan, R. (2017). Non-normal data: Is ANOVA still a valid option? *Psicothema, 29*(4), 552-557. https://doi.org/10.7334/psicothema2016.383

Blanca, M. J., Alarcón, R., Arnau, J., Bono, R., & Bendayan, R. (2018). Effect of variance ratio on ANOVA robustness: Might 1.5 be the limit? *Behavior Research Methods, 50*(3), 937-962. https://doi.org/10.3758/s13428-017-0918-2

Boucif, O. E. W., Rached-Kanouni, M. & Chouiter, N. (2024). Phytochemical characterization and valorization of *Quercus ilex* (west of Algeria). *Global NEST Journal, 26*(10).06636. https://doi.org/10.30955/gnj.06636

Bouget, C., Cours, J., & Sallé, A. (2023). Forêts en crise et biodiversité : menaces et opportunités. Effets des dépérissements et de leur gestion sur la biodiversité forestière. *Revue forestière française, 74*(2), 193-199. https://doi.org/10.20870/revforfr.2023.7594

Cao, L., Liu, H., Fu, X., Zhang, Z., Shen, X., & Ruan, H. (2019). Comparison of UAV LiDAR and digital aerial photogrammetry point clouds for estimating forest structural attributes in subtropical planted forests. *Forests, 10*(2), 145. https://doi.org/10.3390/f10020145

Castro, A. A., Lacerda, M. C., Zanuncio, T. V., de S, Ramalho, F., Polanczyk, R. A., Serrão, J. E., & Zanuncio, J. C. (2012). Effect of the insect growth regulator diflubenzuron on the predator Podisus nigrispinus (*Heteroptera: Pentatomidae*). *Ecotoxicology, 21*, 96-103. https://doi.org/10.1007/s10646-011-0769-z

Catry, F. X., Branco, M., Sousa, E., Caetano, J., Naves, P., & Nóbrega, F. (2017). Presence and dynamics of ambrosia beetles and other xylophagous insects in Mediterranean cork oak forest following fire. *Forest Ecology and Management, 404*, 45-54. https://doi.org/10.1016/j.foreco.2017.08.029

Catry, F. X., Moreira, F., & Cardillo, E. (2012b). Post-fire management of cork oak forests. *Managing Forest Ecosystems, 24*, 195-222. https://doi.org/10.1007/978-94-007-2208-8_9

Catry, F. X., Moreira, F., Pausas, J. G., Fernandes, P. M., Rego, F., & Cardillo, E. K. (2012a). Cork oak vulnerability to fire: The role of bark harvesting, tree characteristics and abiotic factors. *PLoS ONE, 7*(6), 1-18. https://doi.org/10.1371/journal.pone.0039810

Chouiter, N., Rached-Kanouni, M., Laala, A., & Redjaimia, L. (2022). Floristic composition and structure of the Zouagha forest (Eastern Algeria). IN *PROCEEDINGS OF IV. International Agricultural, Biological & Life Science Conference Agbiol 2022* (P. 45).

Chouiter, N., Rached-Kanouni, M., Redjaimia, L., Benaicha, K., Ababsa, L., & Rahab, R. (2023). Évaluation de l'état de vitalité du *Quercus suber* L dans la forêt de Zouagha. *Revue des BioRessources, 13*(1), 20-27. https://dspace.univvouargla.dz/jspui/handle/123456789/33176

Chouiter, N., Rached-Kanouni, M., Benoumeldjad, M., & Ababsa, L. (2024 a). Structure et régénération du chêne afares (*Quercus afares*, Pomel) dans la forêt de Zouagha. *Revue des BioRessources, 14*(2), 23-30. https://dspace.univ-ouargla.dz/jspui/handle/123456789/37863

Chouiter, N., Rached-Kanouni, M., & El Wahida Boucif, O. (2024 b). Assessment of the health status of oak trees in the Zouagha forest (north-east of Algeria). *Ekológia (Bratislava), 43*(2), 158-166. https://doi.org/10.2478/eko-2024-0016

Coulter, L., Stow, D., Tsai, Y. H., Chavis, C., Lippit, C., Fraley, G., & McCreight, R. (2012). Automated detection of people and vehicles in natural environments using high temporal resolution airborne remote sensing. In Proceedings of the *ASPRS Annual Conference*, Sacramento, California, USA, March 19-23

De la Cruz, A. C., Gil, P. M., Fernández-Cancio, Á., Minaya, M., Navarro-Cerrillo, R. M., Sánchez Salguero, R., & Grau, J. M. (2014). Defoliation triggered by climate-induced effects in Spanish ICP Forests monitoring plots. *Forest Ecology and Management, 331*(9), 245–255. https://doi.org/10.1016/j.foreco.2014.08.010

De Vivo, F., Battipede, M., & Johnson, E. (2021). Infra-red line camera data-driven edge detector in UAV forest fire monitoring. *Aerospace Science and Technology, 111*, 106574. https://doi.org/10.1016/j.ast.2021.106574

Direction Générale des Forêts (DGF). (2010). Fiche signalétique de la forêt domaniale de Santé des forêts : Maladies, insectes, accidents climatiques. Diagnostic et prévention. Forêt Zouagha.

Direction Générale des Forêts (DGF). (2020). Fiche signalétique de la forêt domaniale de Santé des forêts : Maladies, insectes, accidents climatiques. Diagnostic et prévention. Forêt Zouagha.

Direction Générale des Forêts (DGF). (2022). Fiche signalétique de la forêt domaniale de Santé des forêts : Maladies, insectes, accidents climatiques. Diagnostic et prévention. Forêt Zouagha

Encinas-Valero, M., Esteban, R., Heres, A. M., Vivas, M., Fakhet, D., Aranjuelo, I., Solla, A., Moreno, G., & Curiel Yuste, J. (2022). Holm oak decline is determined by shifts in fine root phenotypic plasticity in response to belowground stress. *New Phytologist, 235*(6), 2237-2251. https://doi.org/10.1111/nph.18182

Fayech, D., & Tarhouni, J. (2021). Climate variability and its effect on normalized difference vegetation index (NDVI) using remote sensing in semi-arid area. *Modeling Earth Systems and Environment, 7*(3), 1667–1682. https://doi.org/10.1007/s40808-020-00896-6

Frolking, S., Palace, M. W., Clark, D. B., Chambers, J. Q., Hugart, H. H., & Hurtt, G. C.

(2009). Forest disturbance and recovery: A general review in the context of spaceborne remote sensing of impacts on aboveground biomass and canopy structure. *Journal of Geophysical Research: Biogeosciences, 114*(G2), 1–27. https://doi.org/10.1029/2008JG000911

Gentilesca, T., Camarero, J. J., Colangelo, M., Nolè, A., & Ripullone, F. (2017). Drought-induced oak decline in the western Mediterranean region: An overview on current evidences, mechanisms and management options to improve forest resilience. *iForest, 10*(5), 796-806. https://doi.org/10.3832/ifor2317-010

Getzin, S., Wiegand, K., & Schoning, I. (2012). Assessing biodiversity in forests using very high-resolution images and unmanned aerial vehicles. *Methods in Ecology and Evolution, 3*(2), 397–404. https://doi.org/10.1111/j.2041-210X.2011.00158.x

Giannetti, F., Chirici, G., Gobakken, T., Næsset, E., Travaglini, D., & Puliti, S. (2018). A new approach with DTM-independent metrics for forest growing stock prediction using UAV photogrammetric data. *Remote Sensing of Environment, 213*, 195–205. https://doi.org/10.1016/j.rse.2018.05.016

Gidey, E., Dikinya, O., Sebego, R., Segosebe, E., & Zenebe, A. (2018). Analysis of the long-term agricultural drought onset, cessation, duration, frequency, severity and spatial extent using vegetation health index (VHI) in Raya and its environs, Northern Ethiopia. *Environmental Systems Research, 7*, 13. https://doi.org/10.1186/s40068-018-0115-z

Hrůza, P., Mikita, T., & Janata, P. (2016). Monitoring of forest hauling roads wearing course damage using unmanned aerial systems. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis, 64*(5), 1537–1546. https://doi.org/10.11118/actaun201664051537

Huete, A. R. (1988). A soil-adjusted vegetation index (SAVI). *Remote sensing of environment*, *25*(3), 295-309. https://doi.org/10.1016/0034-4257(88)90106-X

Hyyppä, E., Hyyppä, J., Hakala, T., Kukko, A., Wulder, M. A., White, J. C., Pyörälä, J., Yu, X., Wang, Y., Virtanen, J. P., & Pohjavirta, O. (2020). Under-canopy UAV laser scanning for accurate forest field measurements. *ISPRS Journal of Photogrammetry and Remote Sensing, 164*, 41–60. https://doi.org/10.1016/j.isprsjprs.2020.03.021

Ji, L., & Peters, A. J. (2003). Assessing vegetation response to drought in the northern Great Plains using vegetation and drought indices. *Remote Sensing of Environment, 87*(1), 85-98. https://doi.org/10.1016/S0034-4257(03)00174-3

Jurjević, L., Gašparović, M., Liang, X., & Balenović, I. (2021). Assessment of close-range remote sensing methods for DTM estimation in a lowland deciduous forest. *Remote Sensing, 13*(11), 2063. https://doi.org/10.3390/rs13112063

Kim, H. Y. (2015). Statistical notes for clinical researchers: Post-hoc multiple comparisons. *Restorative Dentistry & Endodontics, 40*(2), 172–176. https://doi.org/10.5395/rde.2015.40.2.172

Meera, G. G., Parthiban, S., Nagaraj, T., & Christy, A. (2015). NDVI: Vegetation change detection using remote sensing and GIS – A case study of Vellore district. In *3rd International Conference on Recent Trends in Computing 2015 (ICRTC-2015), Procedia Computer Science, 57*, 1199–1210. https://doi.org/10.1016/j.procs.2015.07.415

Mersha, E., Degefa, S., Argaw, M., & Mengist, W. (2024). Impact of land use land cover changes on ecosystem service values: Implication for landscape management, 18(1), 115-126. https://doi.org/10.2478/jlecol-2025-0004

Moreira, F., Catry, F., Duarte, I., Acácio, V., & Silva, J. (2009). A conceptual model of sprouting responses in relation to fire damage: An example with cork oak (*Quercus suber* L.) trees in Southern Portugal. *Plant Ecology, 201*(1), 77-85. https://doi.org/10.1007/s11258-008-9476-0

Mushtaq, A. G., & Asima, N. (2016). Determining the vegetation indices (NDVI) from Landsat 8 satellite data. *International Journal of Advance Research (IJAR), 4*(8), 1459-1463. https://doi.org/10.21474/IJAR01/1348

Nadezhdina, N., Ferreira, M. I., Silva, R., & Pacheco, C. A. (2008). Seasonal variation of water uptake of a *Quercus suber* tree in Central Portugal. *Plant and Soil, 305*, 105–119. https://doi.org/10.1007/s11104-007-9398-y

Quezel, P., & Barbero, M. (1990). Les forêts méditerranéennes problèmes posés par leur signification historique, écologique et leur conservation. *Acta Botánica Malacitana, 15*, 145–178. https://doi.org/10.24310/abm.v15i.9300

Rahimi, E., Dong, P., & Ahmadzadeh, F. (2025 a). Iran’s dam waterbodies: A 10-Year Trend Analysis (2013–2023). *Journal of Landscape Ecology*, 18(1),102-113. https://doi.org/10.2478/jlecol-2025-0006

Rahimi, E., & Dong, P. (2025 b). The influence of spatial extent shape on Lst-Ndvi patterns: A Multi-scale perspective, *Journal of Landscape Ecology*, 18(1), 115-126. https://doi.org/10.2478/jlecol-2025-0007

Roula, S. E., Bouhraoua, R. T., & Catry, F. X. (2020). Factors affecting post-fire regeneration after coppicing of cork oak (*Quercus suber*) trees in northeastern Algeria. *Canadian Journal of Forest Research, 50*(4), 371-379. https://doi.org/10.1139/cjfr-2019-0181

Rondeaux, G., Steven, M., & Baret, F. (1996). Optimization of soil-adjusted vegetation indices. *Remote sensing of environment*, *55*(2), 95-107. https://doi.org/10.1016/0034-4257(95)00186-7

Ruxton, G. D., & Beauchamp, G. (2008). Time for some a priori thinking about post hoc testing. *Behavioral Ecology, 19*(3), 690–693. https://doi.org/10.1093/beheco/arn020

Sanchez-González, M., Stiti, B., Chaar, H., & Cañellas, I. (2010). Dynamic dominant height growth model for Spanish and Tunisian cork oak (*Quercus suber* L.) forests. *Forest Systems, 19*(3), 285-298. https://doi.org/10.5424/fs/2010193-8495

Tiberi, R., Branco, M., Bracalini, M., Croci, F., & Panzavolta, T. (2016). Cork oak pests: A review of insect damage and management. *Annals of Forest Science, 73*, 219-232. https://doi.org/10.1007/s13595-015-0534-1

Xue, J., & Su, B. (2017). Significant remote sensing vegetation indices: A review of developments and applications. *Journal of sensors*, *2017*(1), 1353691. https://doi.org/10.1155/2017/1353691

Zou, X., Zhu, S., & Mõttus, M. (2022). Estimation of canopy structure of field crops using Sentinel-2 bands with vegetation indices and machine learning algorithms. *Remote Sensing, 14*, 2849. https://doi.org/10.3390/rs14122849