

Multidimensional analysis of NDVI dynamics in response to climate and land use/land cover change in Northwest Algeria

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Abstract: Climate change has emerged as a major concern at both regional and global scales in recent decades. North-western Algeria is particularly vulnerable as a semi-arid zone, where changes in climate and land cover (LC) will have a significant impact on vegetation in the long term. This study analyses, through a multidimensional approach, the influence of climate change and LC on vegetation dynamics. Hierarchical partitioning (HP) analysis was conducted to determine the most influential climatic variables (precipitation, temperature) on the dynamics of NDVI. The results show that the annual NDVI shows a fluctuating spatial trend between decrease and increase in different regions. Trends in seasonal NDVI are spatially varied and less uniform. Variations in precipitation are stable, while temperatures show clear and consistent significant increases across the region, with a general tendency to increase ($p < 0.01$) in spring and summer. In mountainous areas, NDVI shows an increasing trend both annually and seasonally. The correlation (r^2) between NDVI, temperature and precipitation (0.75–1.0) over the different seasons reveals significant seasonal and regional variability. LC transition patterns also influence spatio-temporal trends in vegetation cover. They reveal that the rate of change of NDVI varies between LC types and regions, with resilience in forests and grasslands. These variations have significant implications for vegetation dynamics, as observed by NDVI.

Keywords: Climate change; NDVI; Climatic factors; Trend; LC; Northwest Algeria.

INTRODUCTION

One of the most complex threats of the 21st century is climate change. The latest IPCC report (IPCC, 2022) highlights how the rise in extreme weather events is causing irreversible damage to both natural and human systems. Global climate models indicate that ecosystems will experience more frequent and longer-lasting droughts due to substantial warming (Huang and Kong, 2016).

Vegetation is a key monitoring parameter in response to climate change (Ayantobo and Wei, 2019; Jin et al., 2021; Li et al., 2020). Multiple authors have shown that anthropogenic factors are the primary drivers of climate change (Huang et al., 2018; Shang et al., 2022; Zhao et al., 2017; Zhou et al., 2011). Consequently, there is a growing interest in analysing spatio-temporal change in vegetation indices (Babüroğlu et al., 2021; Cai et al., 2021; Liu et al., 2020; Xu et al., 2022). Vegetation changes may be due to both direct anthropogenic land use land cover (LULC) changes and physiological adaptation to climate change (Buyantuyev and Wu, 2009; Hu et al., 2021).

Remote sensing-based indices such NDVI (Normalized Difference Vegetation Index) have emerged as one of the common vegetation indices used among several. They enable the quantitative assessment of vegetation dynamics and ecological response to climate change (Milics, 2021; Zaidi et al., 2017). Significant inter-annual variability and trends in the NDVI time series were observed for the past decades. NDVI increased or decreased depending on location, suggesting that multiple mechanisms may outweigh each other (Fensholt et al., 2012).

Many authors have studied how changes in temperature and rainfall on vegetation development, using NDVI to determine the impact of climate change on vegetation (Lin et al., 2022; Sun and Qin, 2016). Previous research has established the two climatic

variables that have the most significant impact on the development of vegetation are rainfall and temperature (Fu and Burgher, 2015; Wen et al., 2012; Zhang et al., 2013). Due to the complex interactions between vegetation characteristics and climate, results can vary considerably from one location to another. At the global scale, Yang et al. (2019) found that precipitation primarily drives vegetation development and changes, with temperature also playing a significant role. In the semi-arid continental monsoon climate of Asia, Li et al. (2021) reported that there is a positive correlation between NDVI and rainfall, and a robust positive relationship with air temperature. In arid and semi-arid areas, studies often focus primarily on precipitation, as water is a critical limiting factor for vegetation activity (Barbosa et al., 2006; Birtwistle et al., 2016; Formica et al., 2017; Gaughan et al., 2012; Hawinkel et al., 2016; Liu et al., 2021; Sohoulane et al., 2015). Air temperature also influences vegetation development, particularly in the Horn of Africa where both temperature and rainfall have an impact on NDVI variations (Ghebregabher et al., 2020). In the African Sahel, Gaughan et al. (2012) observe significant spatial variations in the relationship between NDVI and precipitation. In West Africa, climatic and topographical conditions favour natural vegetation collapse (Zoungrana et al., 2018).

Compared to many other countries and regions of the world, the Mediterranean region has shown a more marked decreasing trend in the NDVI (Julien et al., 2006; Liu et al., 2015), highlighting its vulnerability to ongoing climate change (Giorgi and Lionello, 2008). A strong relationship has been found between the NDVI slope and precipitation from findings of some studies related to North Africa, suggesting that drought is a major contributor to this reduced vegetation (Rhif et al., 2022).

There have been many investigations that have employed various methods to study the relationship between climate change

and changes in NDVI. RDA and Variance Decomposition are used to evaluate the effects of factors on NDVI (Li et al., 2021). The application of LSTM-based forecasting introduced by Cavalli et al. (2021) integrates NDVI data with information on precipitation and temperature to forecast levels of NDVI, while also machine learning techniques for shifts detection replicating values of NDVI and identifying spatial changes in influencers level contributions (Jin et al., 2021). On the other hand, the geographical detector approach looks into reasons behind changes at different locations with the help of NDVI composite value and studies interrelationships among various elements (Han et al., 2023), contributing substantially to our understanding of trends in NDVI, and revealing how climatic factors impact vegetation coverage.

The vegetation dynamics in Algeria's forest ecosystems are influenced largely by climate and anthropogenic factors (Benaissa and Benabdeli, 2019). Northwest Algeria is recognized as a significant agricultural area that has experienced notable changes in LULC as well as climatic transitions over recent decades (Chraïr et al., 2020). Climate change has led to increased temperatures and altered precipitation patterns, potentially impacting vegetation productivity (Beddal et al., 2020). The climate variability depicted in this area shows a distinct decreasing trend in precipitation with a strong opposing increase in temperature based on reports from various studies (Amer et al., 2021; Baahmed et al., 2015; Gherissi et al., 2021; Meddi et al., 2010). Algeria surpassed its national heat record of 51.3 °C on July 5, 2018, as reported by the World Meteorological Organization (WMO). Few studies have investigated vegetation cover changes in north-western Algeria (Bentekhici et al., 2020; Chraïr et al., 2020; Tayeb and Kheloufi, 2019). These studies reported significant changes in LULC in the region, but none explored the role of climate change in explaining these significant changes. Even with great advancements in GIS and remote sensing, current methods for studying NDVI changes in response to climatic conditions have major limitations. One significant shortcoming is the inability to distinguish sub-regional differences in NDVI trends. Wei et al. (2022) showed that the NDVI dynamics between sub-regions varied significantly, but their studies used low spatial resolution that precluded capturing local differences. Anyamba et al. (2014) found large temporal anomalies in NDVI trends in the Sahel area; however, their analysis was limited by poor temporal resolution. Our study fills this gap by developing an analytical framework to assess temporal changes in NDVI dynamics in the region and to explore the relationship between

these changes and climate factors. Specifically, this study aimed to achieve the following objectives:

1. Analyzing the spatio-temporal evolution of annual and seasonal changes in NDVI trends across north-western Algeria.
2. Identifying trends and changes in annual and seasonal time series of climate variability through trend tests.
3. Identifying the regional correlation between NDVI and climatic factors, employing Hierarchical Partitioning.
4. Examining of the impact of LULC change status on vegetation growth under different types of LULC classes.

MATERIALS AND METHODS

Study area

The studied domain is the north-western part of Algeria, between the time zones 1°51'0.846" and 0°37'20.9" west-east longitude and between the meridians 33°19'55.23" and 36°14'27.9" north latitude (Fig. 1). The climate varies from hot and arid in the southern part of the region to semi-arid and humid in the north. Four categories of land use dominate the land use pattern: woodland, cropland/agricultural land, forest, and shrub land. The main water and weather features of the studied area are listed in Table 1.

Data sources and pre-processing

Normalized Difference Vegetation Index dataset (NDVI)

In this study, the PKU GIMMS NDVI (Li et al., 2023) dataset is used. It is based on AVHRR data (1982–2015) and consolidated with MODIS NDVI (1982–2022). It provides a spatiotemporally consistent bi-monthly dataset at a 1/12° resolution. Developed using biome specific BPNN models, the PKU GIMMS NDVI incorporates the GIMMS NDVI3g product and 3.6 million high-quality global Landsat NDVI samples. It has been further enhanced with MODIS NDVI (MOD13C1) to extend the temporal coverage to 2022 using a pixel-level random forest fusion method. A key strength of the PKU GIMMS NDVI product lies in its effective mitigation of the impacts of NOAA's orbital drift and AVHRR sensor degradation. The consolidation of PKU GIMMS NDVI data with MODIS NDVI data results in a globally consistent and reliable NDVI dataset. This product was developed to address major uncertainties in existing long-term global NDVI datasets. The acquisition steps are explained in (Fig. 2). The lack of spatial coherence between NDVI datasets

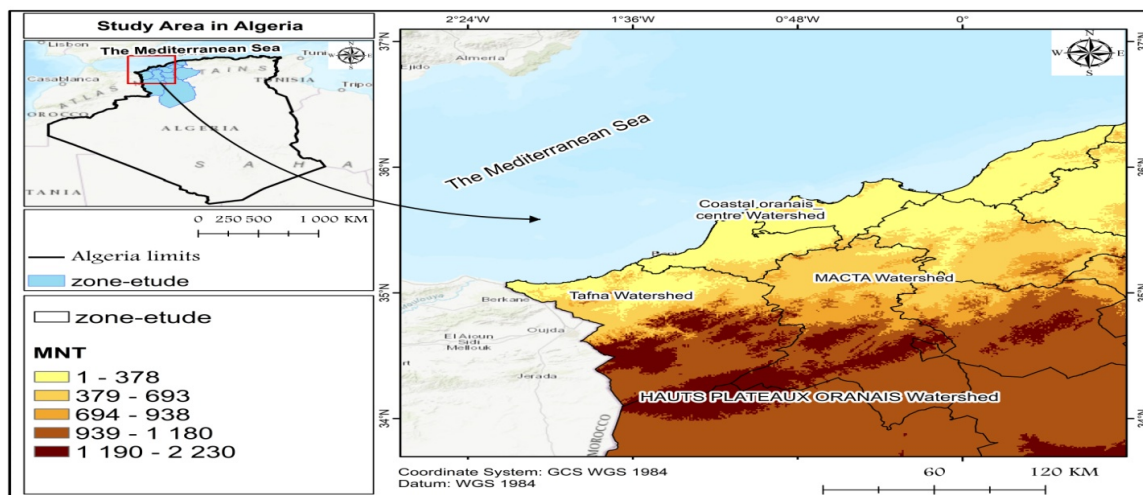
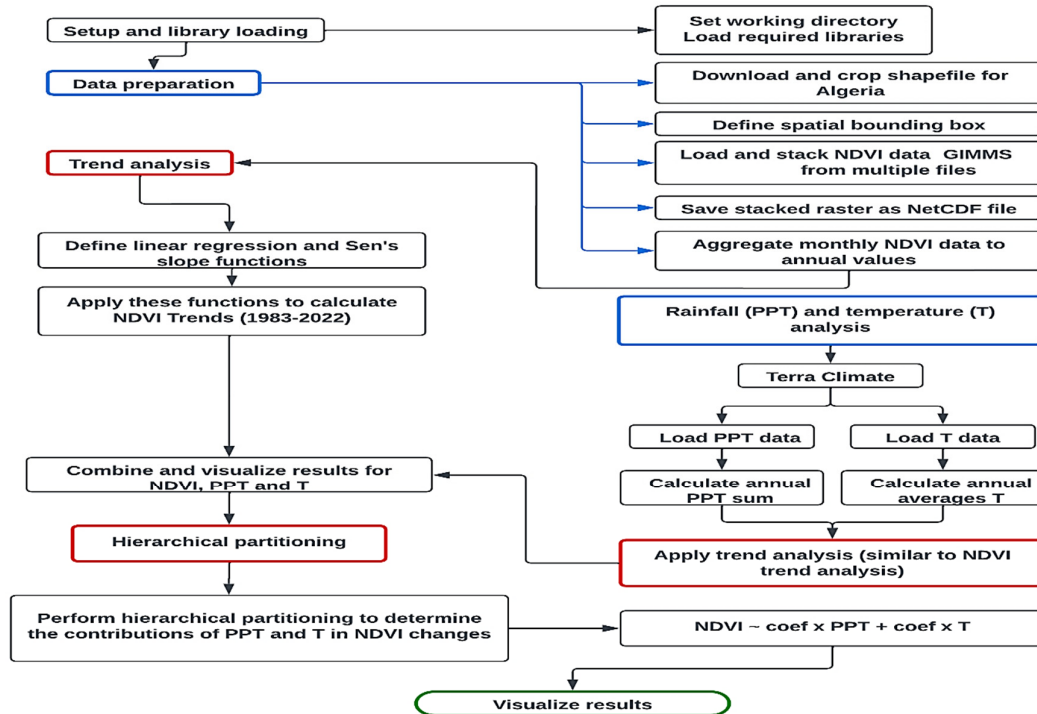


Fig. 1. Showing the studied area's location, elevation, and the distribution of the official weather stations.

Table 1. Hydroclimatic characteristics of the north-western Algerian watersheds.

Catchments	Tafna	Macta	Côtier Oranais
Code	16	11	04
Area (Km ²)	7245	14750	4591
Mean annual precipitation (mm/year)	300–600	230–550	249–389
Mean annual temperature (°C)	16–17	17–19	12–26.6
Number of studied meteorological station	10	10	27
Elevation max (m)	1810	1600	1021–1061
Elevation min (m)	100	–10	15

**Fig. 2.** Methodological diagram used to calculate.

can lead to reliability and accuracy issues in data interpretation and trend analysis. Known discrepancies between GIMMS and MODIS NDVI datasets must be accounted for. Atzberger et al. (2014) found only moderately good agreement between GIMMS and MODIS NDVI datasets. Similarly, Wenxia et al. (2014) discuss the importance of normalizing and integrating NDVI data from multiple sensor systems, such as GIMMS and MODIS, to create a coherent long-term dataset. The PKU GIMMS NDVI product is, therefore, a valuable resource that provides a robust and consistent dataset for assessing vegetation dynamics and their implications for climate change, from local to global scales.

Climatic factors dataset

The precipitation and air temperature dataset used in this study are derived from TerraClimate (Abatzoglou et al., 2018) data spanning from 1983 to 2022. TerraClimate provides high-spatial resolution (1/24°, ~4-km) monthly climate variables. TerraClimate uses climatically aided interpolation, combining high-spatial resolution climatological normal from the WorldClim dataset, with coarser resolution time varying (i.e., monthly) data from Climate Research Unit time series data (Harris et al., 2014) and the Japanese 55-year Reanalysis (Kobayashi et al., 2015). Although other climatic factors are important for exploring their

contributions to NDVI dynamics, the selection of precipitation and temperature is based on several considerations. Firstly, the availability and reliability of long-term, high-resolution datasets for precipitation and temperature within our study area were key determinants. The interaction between temperature and precipitation is particularly significant in our study area, where hot and dry conditions often exacerbate water resource scarcity. Previous studies have demonstrated that these two parameters are critical factors influencing vegetation growth and NDVI dynamics (Dagnachew et al., 2020; Luo et al., 2021).

Gridded climate monthly time series were reprojected on the coarser NDVI grid. Annual and seasonal temporal aggregations were made on both climate and NDVI time series. Fig. 2 depicts the workflow of the study, including data processing and methods that are described in the next sections.

Methods used for data analyses

Linear regression and Sen's slope test

In this study, the temporal of NDVI, precipitation, and temperature are analysed using two parameters: the slope and the p-value. The slopes for each pixel are determined by a unit linear regression between time as the independent variable and NDVI, precipitation and air temperature as the dependent variables (Hou et al., 2015).

The non-parametric Sen's Slope test is used to analyse trends in time-series data, such as NDVI, to understand the long-term dynamics of vegetation health and productivity. This method evaluates the slope between two pairs of data in a time series by calculating the median of the slopes between all point-pair combinations, to establish trends representative of overall changes in a time series (Zhang et al., 2023). The use of Sen's Slope regression has many advantages over traditional linear regression methods, such as its robustness to outliers, computational efficiency, high breakpoint, non-parametric nature, simple computation, wide applicability, interpretability, competitive performance and historical significance (Shah et al., 2016), making it a reliable choice for analysing trends in NDVI, precipitation and temperature.

Hierarchical partitioning

A hierarchical partitioning (HP) analysis was conducted to determine the most influential climatic variables (precipitation, temperature) on the dynamics of NDVI. Hierarchical partitioning (HP) of variance involves calculating the (r^2) for all possible orders of variables, then averaging the joint variance of these variables. The independent variance explained by each variable is the sum of the marginal variance and the average joint variance for each variable. This approach reduces multicollinearity by defining the independent contribution of each explanatory variable to the response variable, allowing for the ranking of the importance of covariates when interpreting response variables (Wang et al., 2022). More information on HP can be found in the literature (Chevan and Sutherland, 1991). Hierarchical partitioning was performed using the "hier.part" package in R. The results from "hier.part" provided the independent and joint contributions of precipitation and temperature variables to the explained variance of the NDVI variable.

Analysis of the relationship between NDVI distribution and land cover (LC)

The land cover (LC) matrix dataset for the year 2000, available on the website (<https://forobs.jrc.ec.europa.eu/glc2000>) in ADF format, was selected to analyse NDVI trends under different land

cover types. The images were processed in two different ways: filtering the S-10 time series of NDVI and calculating monthly images over critical periods. After cross-verifying the models with local maps and Google Earth Pro satellite images for other years and the year 2000, the focus was on this year due to the accuracy in representing the distribution of each LC class and their slight changes. The LC data were loaded, cropped according to the study area, and reprojected to match the NDVI raster data. Four terrain categories were distinguished: forest, shrubs, grasslands, and croplands (Fig. 3). Other types of classes were not included in the NDVI analysis as they were not relevant. Subsequently, binary masks were created for each LC type to separate the pixels corresponding to each type of land cover in the NDVI data. This isolation allows for the precise determination of the average NDVI for each LU category, which is crucial for studying the impact of different LC classes on NDVI values. Finally, the calculation of the average NDVI and monthly NDVI averages by class was performed to create anomalies. The anomalies better detect exceptional events and changes affecting vegetation.

RESULTS AND DISCUSSION

NDVI trend variation analysis

Annual NDVI

Fig. 4 shows annual NDVI variations in north-western Algeria during the 1983–2022 period. This period is marked by a decrease in vegetation cover in the south-west and center moving northwards (–2.5 to –5%), probably due to intensive agricultural practices or climate change. The eastern region shows fluctuations with phases of increase (Slope-lin 0–5%) and a more marked decrease in the south-east (Slope-Sen –2.5%). The prevalence of NDVI increase in this area appears to be higher, suggesting a general improvement in vegetation health or density in these areas during the study period. These trends suggest the significant influence of human activities and environmental conditions on the region's vegetation.

Seasonal NDVI

Fig. 5 provides a detailed analysis of NDVI change trends for each season over the period 1983–2022. This figure offers a clear

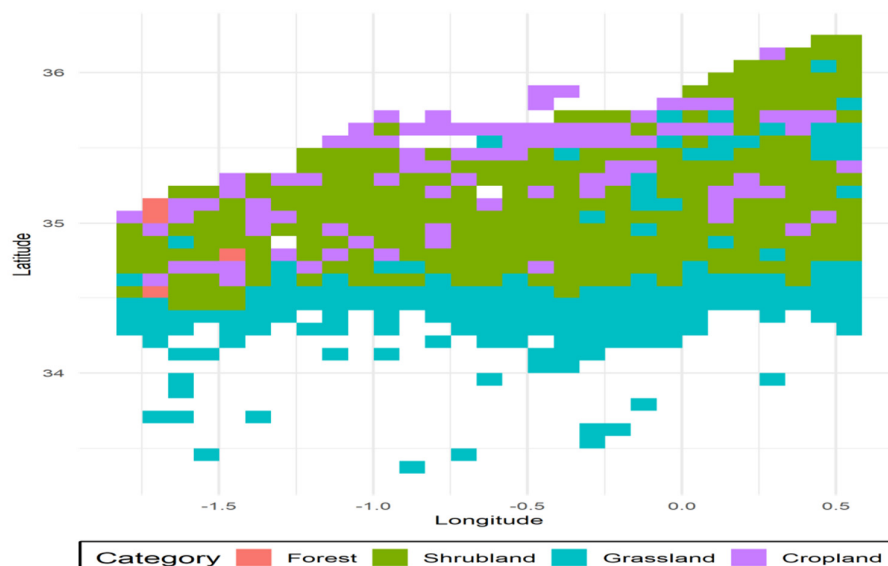


Fig. 3. Spatial distribution of LULC for the three catchments in Northwest Algeria for 2000.

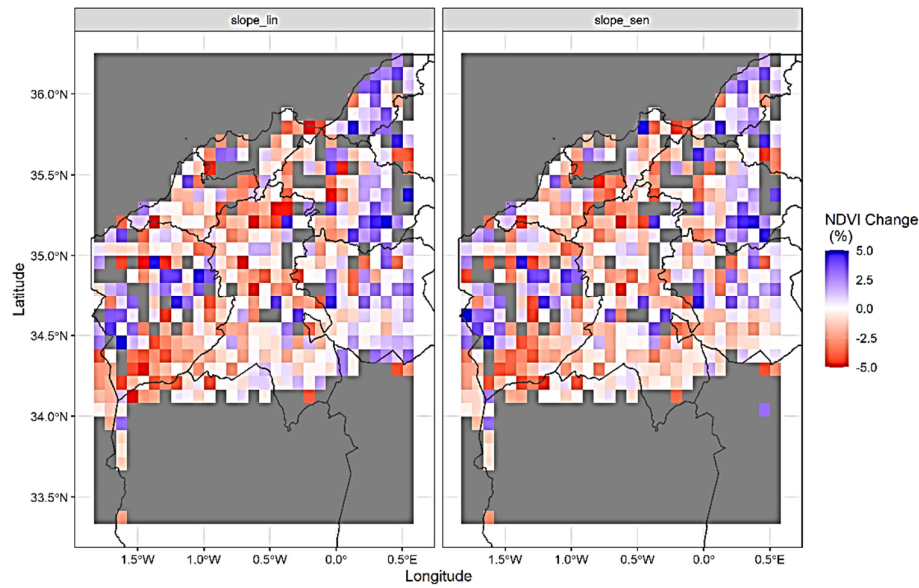


Fig. 4. Annual NDVI trend for the period 1983–2022.

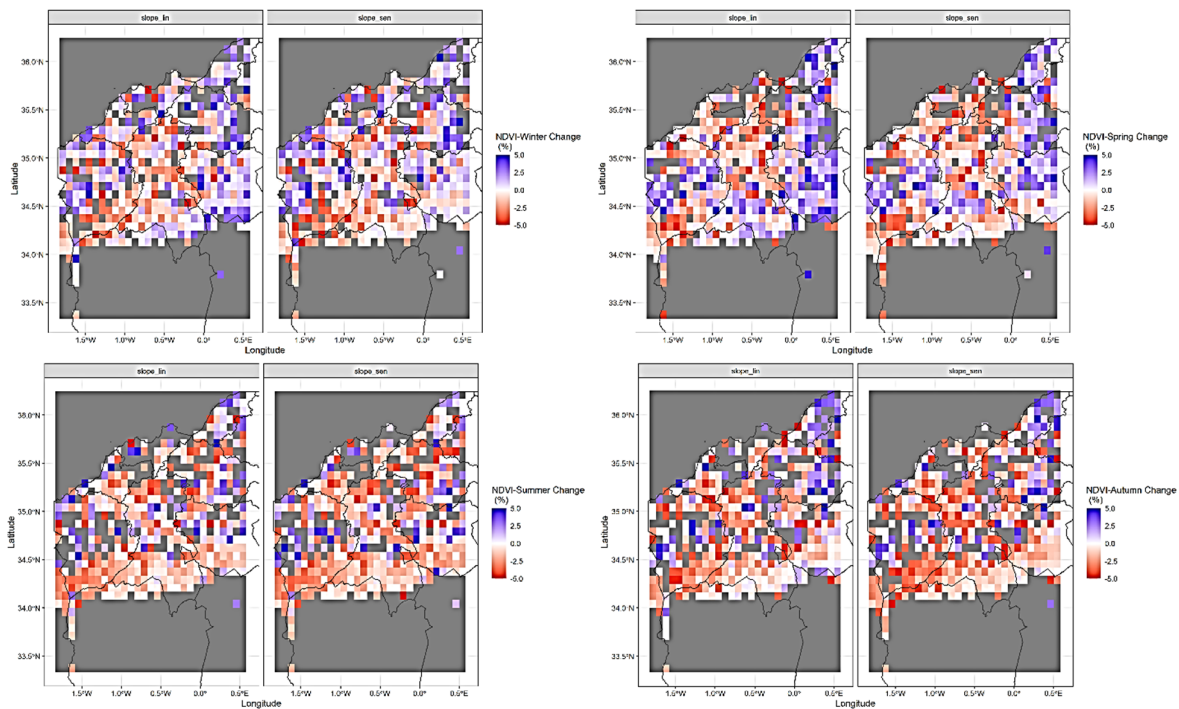


Fig. 5. Seasonal NDVI trend for 1983–2022.

Table 2. Detailed statistical measures of seasonal NDVI trends.

Season	Linear slope - main trend	Sen's slope - main trend
Winter (DJF)	Widespread decrease with some localised increase	Similar to a linear slope with a significant decline
Spring (MAM)	General decrease with dispersed increase	Similar to linear slope with a generalised decrease
Summer (JJA)	Significant decrease with some localized increase	Similar to linear slope with significant decrease
Autumn (SON)	Mix of decrease and increase	Similar to linear slope with a mix of trends

geographical representation comparing two different slope calculations: linear slope and Sen's slope, highlighting areas with significant percentage changes. Table 2 summarizes the generalized results, indicating that the region is experiencing

more decline than improvement in vegetation health, with seasonal fluctuations. The variations are similar between the two slope calculations, confirming the observed trends.

Trend analysis of climatic factors Combined with NDVI

Annual trend

The annual precipitation from 1983 to 2022 shows no significant change, as illustrated in Fig. 6. Suggesting that annual precipitation levels have remained stable in the region. However, there has been a widespread increase in temperature across the region. Notably, the areas exhibiting an increase in NDVI coincide with the areas experiencing a temperature rise. This could imply that certain types of vegetation have adapted positively to higher temperatures, potentially due to reasons such as longer growing seasons or other factors. The lack of significant changes in precipitation makes it challenging to interpret the direct relationship between changes in NDVI.

Seasonal trend

The results of the analysis of seasonal trends in climatic factors and NDVI from 1983 to 2022 are presented in (Fig. 7). Table 3 summarizes the main interpretations of the results concerning the trends in precipitation and temperature combined with NDVI. Precipitation variations appear to be minimal or non-existent across all seasons, suggesting no apparent trend. The increase in temperature trends is very clear and consistent in the region, especially in the southern areas during winter and autumn, with a generalized increase in spring and summer. Meanwhile, changes in NDVI are more spatially varied and less uniform.

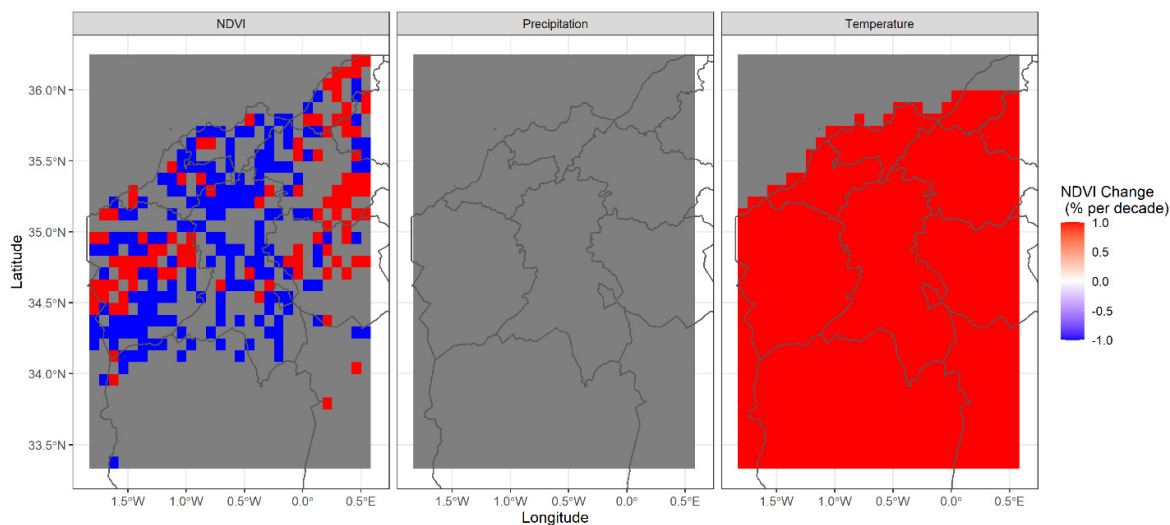


Fig. 6. Spatial analysis of annual changes in precipitation, temperature and combined with NDVI (1983–2022).

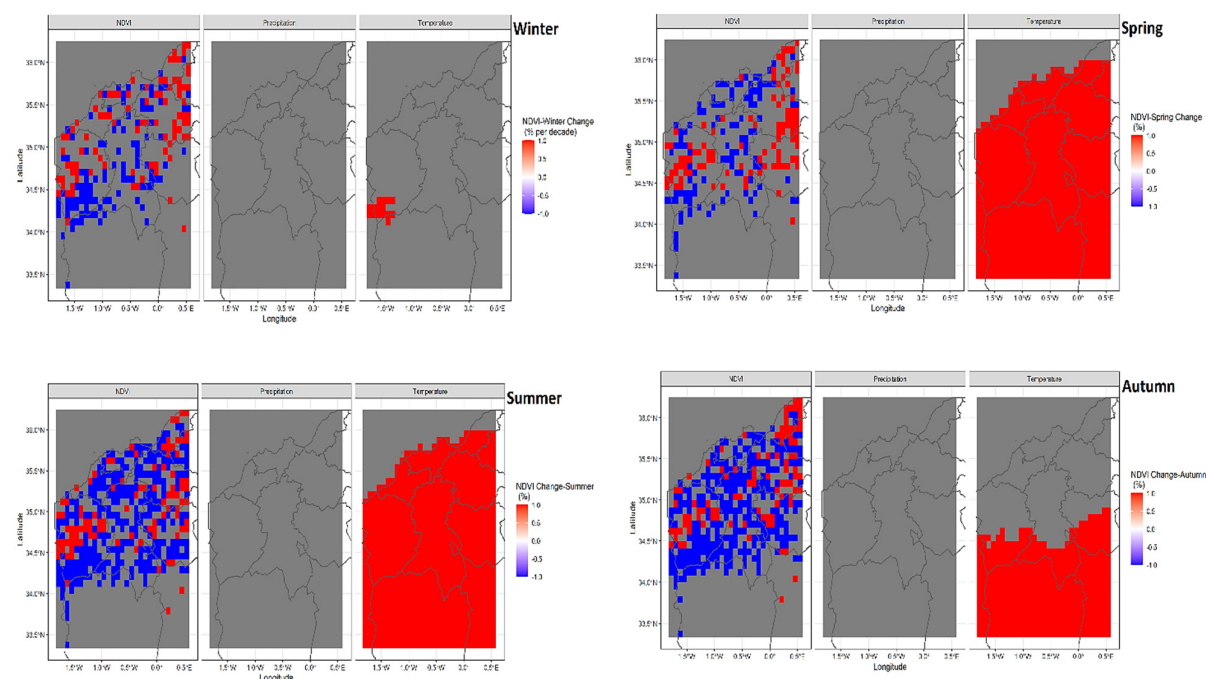
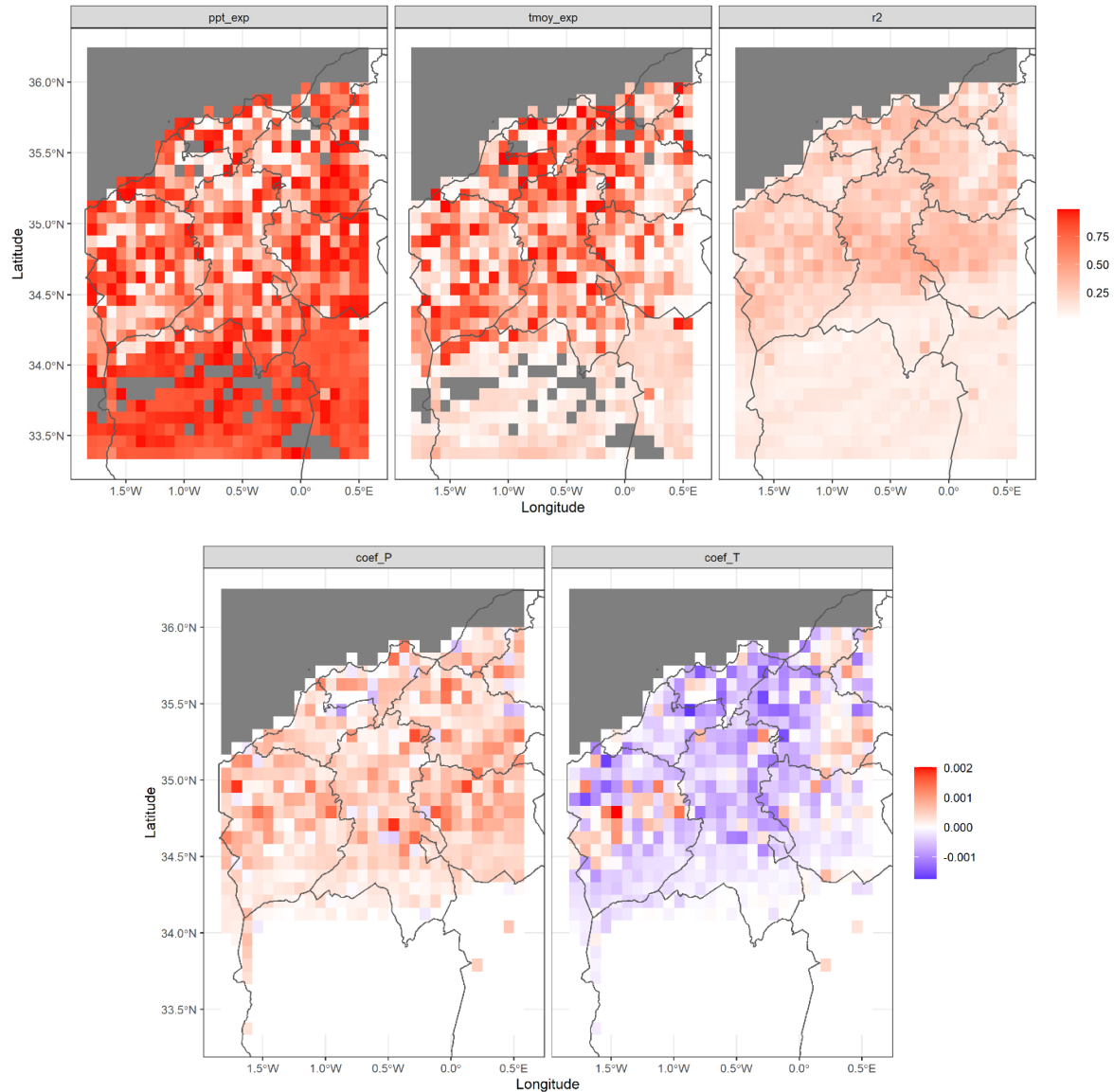


Fig. 7. Spatial analysis of seasonal changes in precipitation, temperature and combined with NDVI (1983–2022).

Table 3. Detailed result of analysis of trends in climatic factors combined with NDVI.

Season	NDVI changes	Precipitation changes	Temperature changes
Winter (DJF)	Increase in northern/central regions, decrease in southern regions	No significant changes	increase located in a small region of the south
Spring (MAM)	Scattered increases and decreases, increase in central/northern regions	No significant changes	Significant and widespread increase
Summer (JJA)	Increase in northern regions, varied in central/southern areas	No significant changes	Significant and widespread increase
Autumn (SON)	Increase in northern regions, varied in central/southern areas	No significant changes	significant increase in southern regions

**Fig. 8.** Annual spatial distribution of NDVI correlation with precipitation, temperature (1983–2022).

Analysis of the relationship between NDVI distribution and climatic factors

Annual relationship

Fig. 8 presents the results annual of the relationship between NDVI and climatic factors in the northwest region of Algeria from 1983–2022, analysed through hierarchical partitioning. The results illustrate the independent contribution of precipitation's

impact on NDVI, highlighting higher r^2 values in the southern and northern regions. However, the influence of temperature on NDVI is more pronounced in the central regions ($r^2 = 0.25–0.75$). The regression coefficient (Coef_P) shows a positive relationship with NDVI in the northern, south-eastern, and central regions, although some areas exhibit negative relationships, indicating that an increase in precipitation may not lead to an increase in NDVI. The entire region displays negative

Coef_T values. The southern, central, and some peripheral northern regions show negative coefficients, suggesting an inverse relationship with NDVI, potentially due to thermal stress or reduced water availability. The north-eastern and central-western regions indicate positive coefficients, meaning that temperature increases are associated with increases in NDVI. The coefficient of determination (r^2) indicates the overall fit of the model to the data. Lower values suggest the possible influence of other factors, while moderate r^2 values in some central and northern regions imply that climatic factors are driving the variability in NDVI in these areas.

Seasonal relationship

The study of the relationship between NDVI and precipitation (ppt) and mean temperature (Tmoy) during different seasons (DJF, MAM, JJA, SON) highlights a significant seasonal and regional variability in the vegetation's response to these climatic factors (Fig. 9). In winter (DJF), precipitation reveals high R^2 values (0.75–1.0) in most central and southern parts of the region. However, northern areas exhibit slightly lower values. The regression coefficient (Coef_P) shows a positive relationship with NDVI, suggesting that increased winter

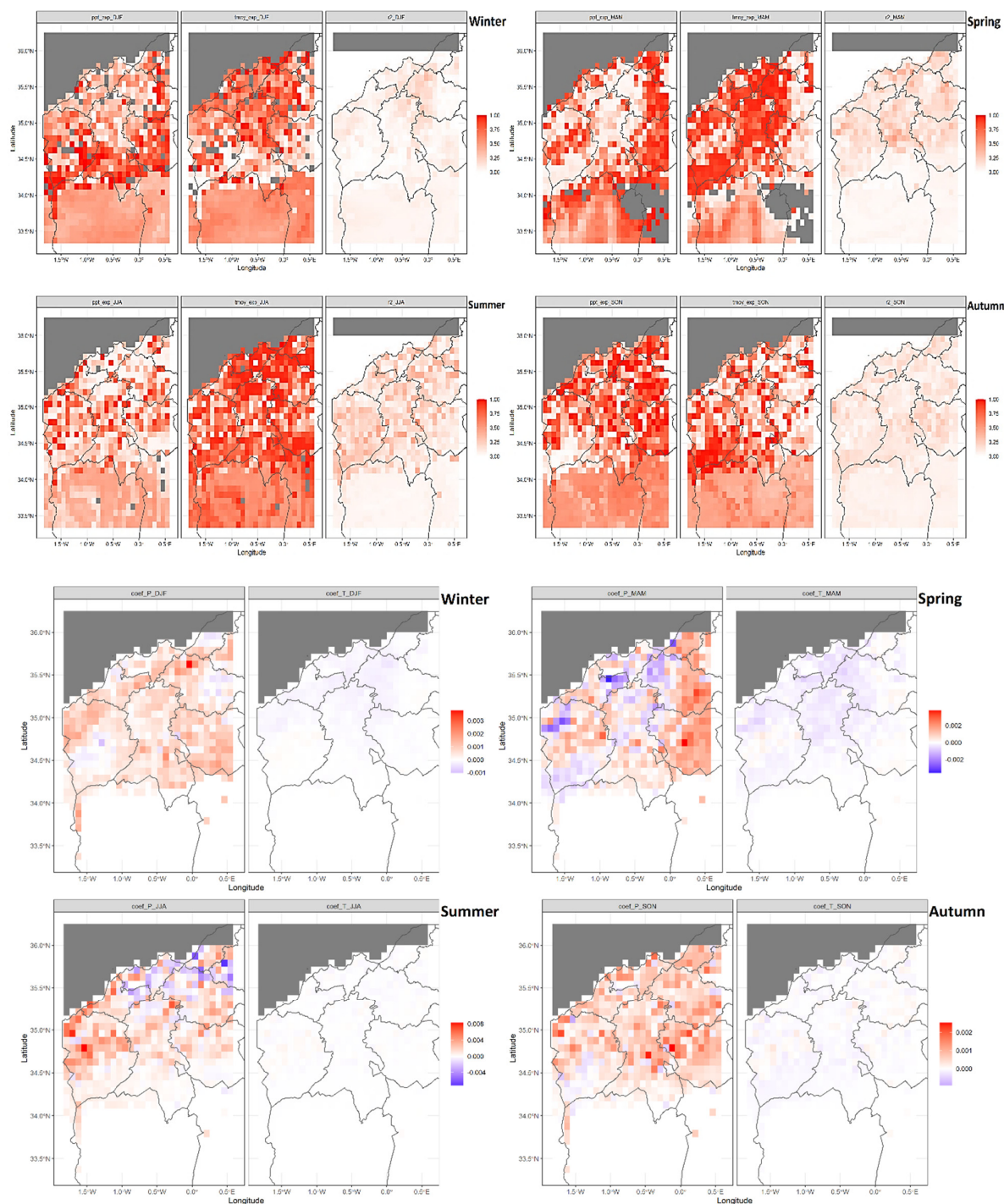


Fig. 9. Seasonal spatial distribution of NDVI correlation with precipitation, temperature (1983–2022).

precipitation positively impacts NDVI in most regions. Some areas in the northwest display a negative coefficient, indicating a less direct or negative impact in these regions. Temperatures show high R^2 values throughout the region, particularly in the central and northern parts. The Coef_T presents very slight negative effects, indicating that in winter, temperature has a minimal direct impact on NDVI compared to precipitation. The overall model fit to the data displays a moderate R^2 in most areas. In spring (MAM), both factors play a crucial role, but their influence varies spatially. The R^2 values demonstrate significant influence (0.75–1.0) but with greater variability compared to winter. The Coef_P shows a strong positive relationship in some areas, while others show a slight negative impact. The Coef_T presents low values with slight positive or negative effects, indicating the variable impacts of spring precipitation and the mixed impact of spring temperatures on NDVI. Summer vegetation (JJA) is primarily affected by temperature. High R^2 values (0.75–1.0) are observed, mainly in the northern and central regions, indicating that temperature is the dominant factor affecting vegetation during the summer season, compared to precipitation, which has less influence. The combined R^2 variation remains high in many regions, suggesting that even though the impact of precipitation is less significant, the temperature combined with other factors explains a large part of the NDVI variation. In autumn (SON), the R^2 values show that precipitation exerts a significant but variable influence. This is the period of dormancy or preparation for winter when precipitation can restore soil moisture. Temperatures show a high correlation in the northern and central regions. In autumn, temperature has a limited direct impact on vegetation health compared to precipitation.

Analysing NDVI variability in response to LULC from 1983 to 2022

NDVI anomalies over time are illustrated in (Fig. 10), divided into annual and seasonal trends (DJF, MAM, JJA, SON) across

four different land cover types: forest, shrubland, grassland, and cropland. The annual anomalies for forests and grasslands show more pronounced positive peaks after 2000, suggesting periods of above-average vegetation density throughout the study period. The annual density of shrublands and croplands exhibits stable trends, with minor variations and low variability, indicating consistent density.

Table 4 interprets seasonal trends based on the variations in each season. Forests exhibit the greatest variability among all land cover types, reflecting their sensitivity to environmental changes and seasonal variations. Croplands exhibit low to moderate variability, indicating effective land management practices that uphold stable growing conditions. Shrubbylands display low vegetation variability and resilience to environmental changes. In contrast, grasslands show moderate to high variability, reflecting the dynamic nature of grassland ecosystems and their response to seasonal changes.

Fig. 11 presents a boxplot diagram illustrating the distribution of NDVI values across different land use types. The key observations are as follows: Forests exhibit higher NDVI values, indicative of dense vegetation. Cultivated lands (> 50%) show lower NDVI values compared to forests, reflecting the variability in vegetation cover associated with agricultural practices. Open deciduous shrubs have slightly lower NDVI values than cultivated lands, indicating less dense vegetation, while grasslands display the lowest NDVI, suggesting sparser vegetation. NA represents non-vegetated areas, showing NDVI values close to zero.

DISCUSSION

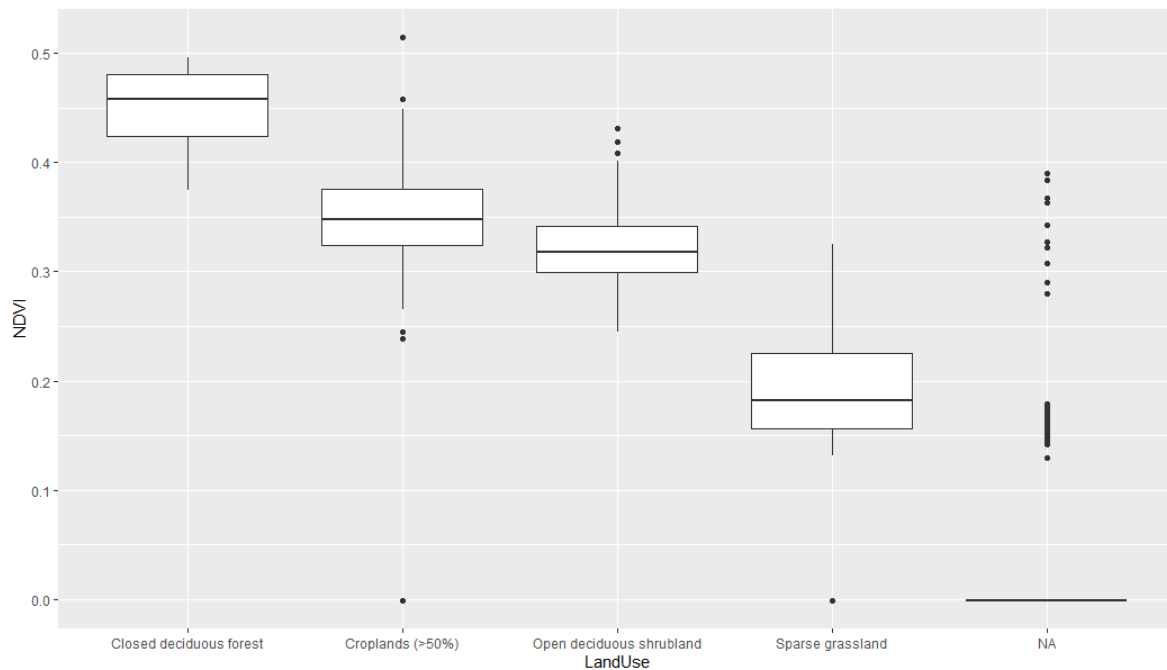
The evolution of NDVI has exhibited a general downward tendency to the dynamics of vegetation across the region. Both positive and negative changes in the Northwest and Southwest NDVI point to local factors that may differently influence vegetation through changes in land use, management practices, or micro-climatic conditions. Lack of moisture due to aridity



Fig. 10. Analysis of annual and seasonal vegetation anomalies for four different land cover types: forest, shrubland, grassland and cropland.

Table 4. Interpretation of seasonal vegetation anomalies for four different land cover types: forest, shrubland, grassland and cropland.

Season	Land cover type	Trend (1980-2000)	Trend (after-2000)	Overall variability
Winter	Forest	Stable with minor fluctuations	Slight upward trend with more frequent positive anomalies	Moderate variability
Winter	Shrubland	Stable with anomalies close to zero	Stable	Low variability
Winter	Grassland	Slight fluctuations with anomalies close to zero	Minor positive anomalies	Low to moderate variability
Winter	Crop land	Stable	Slight positive anomalies	Low variability
Spring	Forest	Stable with minor fluctuations	Increased variability with significant positive anomalies	High variability
Spring	Shrubland	Generally stable	Stable with minor positive anomalies	Low variability
Spring	Grassland	Stable with minor fluctuations	Increased variability with significant positive anomalies	Moderate to high variability
Spring	Crop land	Stable	Slight positive anomalies	Low variability
Summer	Forest	Relatively stable with minor positive anomalies	Significant increase in positive anomalies	High variability
Summer	Shrubland	Stable	Minor positive anomalies	Low variability
Summer	Grassland	Stable with minor positive anomalies	Significant increase in positive anomalies	Moderate to high variability
Summer	Crop land	Stable	Slight positive anomalies	Low variability
Autumn	Forest	Stable with minor positive anomalies	Notable increase in positive anomalies	High variability
Autumn	Shrubland	Stable	Minor positive anomalies	Low variability
Autumn	Grassland	Stable with minor positive anomalies	Increased variability with significant positive anomalies	Moderate to high variability
Autumn	Crop land	Stable	Slight positive anomalies	Low variability

**Fig. 11.** Boxplot of NDVI values by land cover type.

coupled with desertification is seen as a major cause for reduced vegetation leading to a drop in NDVI; however, the central part shows widespread increments in NDVI. A study by (Li et al., 2021; Xie et al., 2015) found that these elevations were driven by increased efficiency of photosynthesis and water use: they report that this was brought about by high air temperatures, thus promoting the growth of vegetation within the region despite other limiting factors. In all seasons, changes in NDVI reveal strong variability, suggesting that plant response to climate variability is not uniform. Amidst the period of growth, an

observable decline in NDVI is noted which implies negative impacts on vegetation health due to seasonal factors likely driven by increasing temperatures, as shown in other studies (Wang et al., 2022). Spatial analyses of NDVI trends unveil a direct correlation between distribution and climatic factors: hierarchical analysis shows precipitation has a direct relationship with NDVI while temperature has an inverse one, depending on spatial location. In regions with low precipitation and high temperatures such as arid or semi-arid areas the stress imposed by water scarcity plus thermal conditions leads to lower values

of NDVI (Bai et al., 2023). This is because environmental suitability restricts vegetation growth potential; hence, it can be inferred that these contexts determine how different climatic elements act in unison (as varying combinations) upon vegetative cover.

The work also underscores the sensitivity of variations in temperature and precipitation based on future research outcomes for NDVI (Lin et al., 2022). Climatic variables have a significant impact on NDVI, which is an indication of vegetation growth and health since statistically significant (Ghebregabher et al., 2020) trends (particularly at $p < 0.01$) in climatic variables were observed to affect NDVI substantially. The lack of significant changes in precipitation was noted from this study, thus suggesting that local variations of NDVI may be more closely related to temperature changes as opposed to other climatic factors. According to (Ghebregabher et al., 2020; Wang et al., 2001) this result is the contrary. They found that temperature variations had no significant effect on NDVI dynamics, and that precipitation is a good predictor of the regional spatial pattern of NDVI. A negative influence was observed during spring and autumn on NDVI due to air temperature fluctuations: an implication that temperature has a critical effect on vegetation growth. When temperatures go beyond the optimal range for plant development photosynthesis decreases while respiration increases leading to adverse effects on plant growth (Luo et al., 2021). This discovery aligns with the findings of (Mao et al., 2012), who found that the link between temperature and NDVI was greater than that between NDVI and precipitation. Liu et al. (2016) found that vegetation dynamics in "hotspot" locations might be adversely affected by climatic variability, which is in line with observations made in semi-arid regions.

The influence of LULC on vegetation may have a variety of consequences. These effects may cause changes in the type, structure, and distribution of vegetation. Besides climate change impacts, anthropogenic effects as changes in land use due to urbanization or other human activities, can result in the destruction and loss of vegetation cover (Jiang et al., 2021). Our results indicate that the amplitude of the NDVI trends and the various LULC classes (cropland and shrubland) has stable, while forest and grassland NDVI variations are transitioning from stable to positive. These results corroborate the idea of (Ghebregabher et al., 2020), who also found that the NDVI of forests is less vulnerable than the NDVI of savannahs, and shrub lands which are more sensitive to climate change. Several environmental, climatic, and anthropogenic factors, such as agricultural expansion, urbanization, and grazing, can have a significant impact on both land cover and NDVI. From 1983 to 2022, the analysis of the Fig. 10 and Table 4 exposes the evolution of several class types. The conversion of natural vegetation to cropland or urban areas contributed to the reduction of NDVI; which is due to the loss of vegetation cover and the increase in surface temperatures. Furthermore, climate variability affects the relationship between NDVI and LC in north-western Algeria (Berhail et al., 2022). This is in part a response to changes that occur every year due to the seasons and which may not always bring about such notable variation in NDVI. There could be seasonal changes in rainfall and temperature where during drought or high temperature periods, vegetation cover might decrease which would lead to a reduction of NDVI and vice versa with periods of heavy rainfall enhancing vegetation cover leading to an increase of NDVI. The mid-altitude belt has a high sensitivity on to the change rate of NDVI with respect to climate change according to Gang et al. (2016) so are the improved parts located mainly in the high-altitude southern part of the study area. These results are in agreement

with the findings of Yang et al. (2019) who showed that vegetation cover increases with elevation and that the mean area of vegetation cover varies weakly with mean elevation, indicating that vegetation growth is affected by elevation to some extent.

CONCLUSION

This study analysed the variation of NDVI on a spatiotemporal scale and its response to climatic factors in north-western Algeria over the last 40 years. The results reveal that NDVI trends are highly variable across space and time in response to regional climatic conditions, particularly precipitation and temperature. Precipitation generally promotes vegetation growth, while rising temperatures have a negative impact on the NDVI, potentially leading to a decrease in vegetation cover in semi-arid regions. This variation in geographical trends across the region as a whole underscores the importance of considering localized changes at the sub-regional scale.

The study has demonstrated that NDVI is an important tool for evaluating the impact of climate change on the study area. However, the majority of these studies have not focused on the larger-scale climate factors that contribute to changes in regional climate parameters. By understanding the interaction between NDVI and climate parameters, it is possible to forecast future changes. There are limitations to this study, such as the limited number of climatic factors studied that influence vegetation growth.

This study provides a comprehensive understanding of the patterns of spatial and temporal variation in vegetation and its response to climatic factors, despite the aforementioned drawbacks. Their impact on vegetation growth can also be used to plan and manage natural resources in Northwest Algeria in the context of climate change. Future studies can take into account different vegetation types and many more climatic (evapotranspiration, in semi-arid regions soil moisture) and non-climatic (geographical, anthropogenic) factors that will need to be undertaken for the prediction of vegetation change trends and take as case studies regions where the NDVI is positive, and which adapt to high temperatures; this is most important for the development and restoration of vegetation and its response to climate change.

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