Spatiotemporal characterization of droughts and vegetation response in Northwest Africa from 1981 to 2020

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A B S T R A C T

Drought has become one of the most devastating natural risks of agricultural production and the environment in almost all climate regions. Thus, understanding the spatiotemporal characteristics of drought and its associated impacts is crucial in drought early warning management and adaptation efforts. In this study, we used the 3-month Standardized Precipitation Index (SPI-3) obtained from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) to investigate the space–time characteristics of drought conditions. Also, this study examined the impact of the SPI-based drought on vegetation health conditions using the Advanced Very High Resolution Radiometer (AVHRR) Normalized Difference Vegetation Index (NDVI) time-series data from 1981 to 2020. The results revealed that the region experiences drought primarily between July and September, with the most prolonged drought events lasting up to five months. Morocco suffered from more frequent droughts than other countries in the region. The Mann-Kendall test showed that the trend of drought became drier over the last decade, whereas the period from 1981 to 2010 witnessed either wetting or no trends. This study also found that the response of crops and grasslands showed higher correlation with the SPI-3 and that the response of vegetation to droughts was higher during the dry season. The findings of this study provide useful information to support local and regional drought planning and adaptation programs and enhance the understanding of drought development in the region.

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1. Introduction

Drought is a natural phenomenon that has significant consequences for both the environment and the global economy (Dai, 2011; Ha et al., 2022; Hereher et al., 2022). It is a recurring climatic hazard that can occur in almost all climate zones, but it is more common and severe in arid and semi-arid environments. Drought can have a significant impact on agriculture, water supply, and energy production, and it can cause long-lasting environmental damage. In recent years, there has been growing concern about the increasing severity and frequency of droughts due to climate change. As a result, it is anticipated that droughts will become even more severe and widespread in the coming years, with some regions, such as Africa, expected to become one of the worst-hit regions (Xu et al., 2019).

In most African countries, the agricultural sector is particularly vulnerable to the negative impacts of drought hazards. In fact, nearly 80% of all direct consequences of drought fall on this sector, resulting in significant economic losses and food scarcity for local populations (Ha et al., 2022; Pourzand and Noy, 2022). These consequences can be particularly severe in regions where food and water insecurity are demanding, which increases the exacerbation of poverty and malnutrition. Moreover, droughts can have far-reaching environmental impacts, including significant threats to the region’s wildlife species. For instance, drought conditions can threaten the habitats of animals such as hippos, aquatic life, white rhinos, and buffaloes, thereby further endangering these already vulnerable species (Dube and Nhamo, 2020) in addition to natural ecosystems (Khosravi et al., 2017). As climate change continues to exacerbate drought frequency and severity, it is essential to
develop effective strategies to mitigate the impacts of droughts on both human and ecological systems.

Various drought indices have been developed and applied for drought monitoring at different scales, including the Standardized Precipitation Index (SPI), Standardized Precipitation Evapotranspiration Index (SPEI), and Soil Water Deficit Index (SWDI). Among these indices, the SPI has remained one of the most established indices. The SPI is versatile for different types of weather monitoring (e.g., meteorological and agricultural drought) due to its multi-timescale flexibility and its simple calculation method (Angelidis et al., 2012). In arid and semi-arid environments, several studies have successfully monitored drought conditions using the SPI, for example, in Iraq (Suliman et al., 2020) and Morocco (Hadri et al., 2012). In Northwestern Africa, it is crucial to characterize droughts and understand vegetation response to drought conditions to support water resources planning and mitigation strategies. Northwestern Africa's agriculture-based economy has suffered from lower crop production and water resource shortage over the past years (El Khatri and El Hairech, 2014), and this situation is expected to worsen due to global warming and precipitation deficit (Cook et al., 2014; Zhim et al., 2019). However, drought monitoring and assessment in the region have received little attention regarding studying the spatial and temporal characteristics of droughts and how vegetation responds to drought conditions. In this context, this study aims to harness long time-series satellite-based data to better understand the drought patterns and their impacts on local and regional vegetation. Specifically, this study examines various drought characteristics (e.g., duration, frequency, and severity) and the dynamics of vegetation response to drought based on the SPI-3 and NDVI. The results of this study can provide useful information to support drought planning and adaptation programs as well as enhance the understanding of drought development and its potential impacts in the region.

2. Study area and materials

2.1. Study area

The study area is located along the coast of northwestern Africa with varying elevations above sea level, covering Morocco, Algeria, and Tunisia (Fig. 1). The region is characterized with main types of land cover, agriculture and forest (e.g., bushes and shrubs) in addition to bare-land and urban settlements. Agriculture, shrubs, and grassland are accounted for the largest land use in the region. Fig. 1 indicated that cropland and grassland together accounted for about 60% of the vegetated areas (Sula-Menashe and Friedl, 2018). Nearly 40% of the area is cultivated with cereals, primarily in Morocco, whereas there is 16% of olive trees, especially in Tunisia (Le Michel Page and Zribi Mehrez, 2019). Given the increasing climate change and human-induced impact (Cline, 2007), the region is projected to suffer from more frequent and severe drought events with devastating impacts on crop production and local livelihoods. Masters William (2008) predicted that droughts among other natural hazards can reduce 30% of crop productivity in Algeria and Morocco in the coming decades.

2.2. Datasets

This study employed various publicly available remote sensing and reanalysis gridded datasets, including precipitation, vegetation time-series, and land cover products. We preprocessed and resampled all datasets to a common spatial resolution and geographic coordinate system across the entire study area.

2.2.1. CHIRPS precipitation data

The monthly precipitation is aggregated from Climate Hazards Group InfraRed Precipitation with Station (CHIRPS) product provided by the U.S Geological Survey Earth Resource Observation and Science Center (EROS) and Climate Hazards Center of the University of California (https://www.chc.ucsb.edu/data/chirps). The data is a quasi-global grid spanning from 50°S-50°N and 180°E-180°W with a spatial resolution (~5km). The CHIRPS product has over 40 years of history (from 1981 to the present) and was produced from a combination of satellite observations and in-situ measurements (Funk et al., 2015).

The product has been well-validated across the globe. In Africa the product demonstrated better performance in comparison with the African Rainfall Climatology version (ARC-2) and the Tropical Application of Meteorology using satellite data (TAMSAT) (Dinku et al., 2018). Another recent study evaluated the global performance of CHIRPS and revealed that CHIRPS observations are highly correlated with Global Precipitation Climatology Center (GPCC) measurements in Africa (Shen et al., 2020). In addition, the CHIRPS is considered the most suitable product for characterizing drought conditions among gridded precipitation products (Le et al., 2020). Given the high accuracy and spatiotemporal observations of the CHIRPS product, this dataset has been widely applied in regional and global drought studies over the past decades (Gao et al., 2018; Zambrano et al., 2017). In this study the CHIRPS product was used for calculating the SPI-3 to characterize drought conditions and assess the response dynamics of vegetation in the region from 1981 to 2020.

2.2.2. Land cover, soil moisture and NDVI data products

The Advanced Very High-Resolution Radiometer (AVHRR) product has become an essential source of data for routine drought monitoring and vegetation assessment. Here, the latest AVHRR Normalized Difference Vegetation Index (NDVI) time-series product (version 5) was acquired and utilized as a proxy indicator for vegetation health. This dataset is provided by the National Oceanic and Atmospheric Administration (NOAA) Center for Envi-
environmenal Information (https://www.ncei.noaa.gov/products) and accessed through Google Earth Engine (GEE) cloud computing platform. The NDVI product was produced daily from near infrared and red bands of the AVHRR surface reflectance measurements at a 5 km spatial resolution from 1981 to the present (Vermote et al., 2014). To match the CHIRPS precipitation observations, the NDVI AVHRR dataset was resampled into a monthly window using maximum value composite (MVC) whereas cloud-related pixels were removed from formal analysis.

The MODIS land cover product was derived from MODIS Terra and Aqua satellites and produced by the NASA Land Processes Distributed Active Archive Center (https://lpdaac.usgs.gov/products/mcd12q1v061/). This dataset is annually produced at a spatial resolution of 500 m and consists of 16 land cover classes (Sulla-Menashe and Friedl, 2018). For this study, we utilized the MODIS land cover product 2019 and reclassified its original classes into five main land cover types (as shown in Fig. 1) and resampled them to match the pixel size of the CHIRPS dataset using the nearest neighbor approach. Land cover classes include cropland, grassland, forest, shrublands, and others (e.g., urban, water, and bare-land) in the study region.

Monthly soil moisture observations were acquired from the Famine Early Warning Systems Network Land Data Assimilation System (FLDAS) at the Goddard Earth Sciences Data and Information Services Center (McNally, 2018) for three different depth layers (0–10 cm, 10–40 cm, and 40–100 cm). This soil moisture data dataset was available from 1982 to the present, and it was specifically produced to ensure food and water security in sub-Saharan Africa and other data-sparse countries (McNally et al., 2017). To ensure the consistency with the spatial resolution of the CHIRPS dataset, the FLDAS data was resampled from ~27 km spatial resolution to 5 km pixel size using bilinear approach.

### 3. Methods

#### 3.1. Standardized precipitation index (SPI)

The SPI is a frequently used measure for assessing and characterizing different aspects of drought conditions over different timescales. Shorter timescales (1–3 months) can represent soil moisture and agricultural droughts, whereas longer timescales can be related to hydrological droughts (e.g., groundwater and streamflow). Here, we are specifically interested in how drought affects agriculture and vegetation in Northern Africa, where are known to be highly vulnerable to water shortages. Therefore, we computed the SPI-3, which represents a timescale of 3 months, to examine the characteristics of drought and its impact on vegetation from 1981 to 2020. We have followed the methodology suggested by McKee et al. (1993) and Albarakat et al. (2022) to calculate the SPI using the equations (Eq. 1 – Eq. 4).

Computing cumulative precipitation at the timescale of interest:

$$ X_{i,m}^k = \sum_{i=0}^{k-1} X_{i,m-1} $$  \hspace{1cm} (1)

where $X_{i,m}$ is the precipitation, and $i$, $m$ is the specified year and month, respectively whereas $X_{i,m}^k$ is the cumulative precipitation at timescale $k$.

The cumulative probability function of gamma distribution for a given duration of time can be calculated as follow:

$$ G(x) = \int_0^x \frac{x^{z-1}\beta^\beta}{\Gamma(x)} \, dx $$  \hspace{1cm} (2)

where $\alpha$ and $\beta$ are the shape and scale parameters, respectively while $x$ represents the cumulative precipitation and $\Gamma(x)$ is gamma distribution function.

In case of the presence of zero values in time-series precipitation data, the cumulative probability function of gamma distribution can be expressed the following:

$$ H(x) = p + (1 - p)G(x) $$  \hspace{1cm} (3)

where $p$ is the probability of non-precipitation data.

The cumulative probability function is transformed to the normal distribution to produce the SPI:

$$ \text{SPI} = \begin{cases} \frac{-Z + \sqrt{Z^2 + 4Z}}{2} : 0 < H(x) \leq 0.5 \\ Z : 0.5 < H(x) \leq 1 \end{cases} $$  \hspace{1cm} (4)

where

![Study area map of coastal northwestern Africa with five main land cover types reclassified from MODIS land cover product 2019. The bar plot indicates the percentage of land cover pixels. The MODIS land cover product was obtained from the NASA Land Processes Distributed Active Archive Center.](image-url)
Based on the SPI-3, we explored various drought event characteristics, including drought duration, frequency, and severity. The drought event is a consecutive negative SPI value with a selected threshold of less than −1. As demonstrated by previous studies (Guo et al., 2018; Venturas et al., 2016), a location with prolonged and continuous low drought severity can significantly impact on agricultural production, vegetation health, and the local environment. Also, detecting early signs of droughts can provide critical information to monitor potential drought-prone areas, enabling timely interventions to minimize the impacts of droughts.

To characterize drought conditions, we employed various metrics: total drought duration (TDD), drought frequency (DF), and drought severity (DS). The TDD represents total number of consecutive drought months between the beginning of drought event and its termination while the DF accumulates drought months over the time period. The DS is the sum of time-series negative SPI values over the given period. The computation procedures of the TDD, DS and DF are given Eq. (5), Eq. (6) and Eq. (7) respectively:

\[ TDD = \sum_{i=1}^{m} D_i \quad (5) \]

where Di is the \( i^{th} \) drought duration, which the SPI value is below −1; m is the number of drought duration.

\[ DS = \sum_{i=1}^{m} SPI_i \leq -1 \quad (6) \]

where SPIi is the SPI value at \( i^{th} \) month.

\[ DF = \sum_{i=1}^{m} D_i \times 100\% \quad (7) \]

where Di is the \( i^{th} \) drought duration, which the SPI-3 value is below −1; m is the number of drought duration and N is the period of time in months.

3.2. Characteristics of drought conditions

3.3. Response of vegetation to drought conditions

Different vegetation types may show different sensitivity to drought conditions. Understanding the response of various vegetation to drought conditions can help assess the resistance and resilience of vegetation for better risk mitigation and planning. In this study we only focus on the response of vegetation and consider cropland, grassland, shrubs and forest whereas other land types are masked out such as urban, bare-land and water from the analysis. The monthly time-series AVHRR NDVI observations are used to examine the relationship between vegetation health and drought conditions. The NDVI represents variations of vegetation health and ranges from −1 to 1, where a positive value indicates more productive vegetation and a negative value is indicative of non-existent vegetation conditions.

The NDVI is computed using the following expression (Eq. 8) (Huete et al., 2002):

\[ NDVI = \frac{NIR - RED}{NIR + RED} \quad (8) \]

where \( NIR \) represents near infrared band whereas \( RED \) is red band of the electromagnetic spectrum.

For each grid cell, we examined the response of vegetation to drought conditions from 1982 to 2020 using Pearson’s correlation coefficient (R) for the SPI-3 during the drying and non-drying months. The coefficient was selected at a significance level of \( p \leq 0.05 \). The correlation coefficient ranges from −1 to 1, and the coefficient with a value greater than 0 indicates a positive correlation whereas a negative correlation has a value less than 0. The greater the absolute value of the coefficient indicates the higher correlation between the two variables.

3.4. Analysis of temporal drought conditions

The Mann-Kendall (MK) test is a rank-based non-parametric method of trend analysis developed by Mann (1945) and Kendall (1975). The MK test assumed that there is no significant monotonic trend in the time series (H0). This hypothesis is rejected if the p-value is greater than a given significance level. In this study the modified MK test and Sen’s slope together are applied to analyze the trends of drought condition (SPI-3) over the study region. The modified test is chosen due to its robustness to autocorrelated time-series data over the original MK test (Hamed and Rao, 1998). In addition, the MK and Sens’ slope are widely applied in hydrology, meteorology, and vegetation measurements (Abdel-Kader, 2019; Albarakat et al., 2022; Da Silva et al., 2015). The analysis of the trend test is undertaken at a significant level \( p \leq 0.05 \) whereas Sen’s slope was used to examine the magnitude of trends. A positive (negative) slope represents a significant increase (decrease) drought trend over the specified time period. The detailed computation procedures of both the modified MK test and Sen’s slope can be referred in the study of Hamed and Rao (1998).

3.5. Cross-verification of the SPI-3

While station-based soil moisture and/or climate measurements are sensitive to detect drought conditions, collecting such data over the study area can be challenging. As an alternative, we employed the FLDAS soil moisture to verify the SPI-3 condition over the study region at various depth layers. The FLDAS soil moisture measurements were transformed into soil water deficit index (SWDI) because this index is highly sensitive to drought and robustness to seasonal changes (Mishra et al., 2017).

The SWDI can be calculated at various levels of soil depth and accurately reflects the level of drought stress in plants. The specific approach is presented in the study of Mishra et al. (2017), but briefly the SWDI also takes clay, sand, and carbon organic matter contents into account. In this study the SPI-3 was cross-verified against three top soil moisture layers (0–10 cm, 10–40 cm, and 40–100 cm) respectively as crop vegetation and shrubs mainly depend on topsoil root zone (Raza et al., 2013). In some arid and semi-arid environments vegetation growth is also observed to rely on shallow soil moisture content such as in Central Asia (Egamberdieva and Öztürk, 2018). We calculated the Pearson correlation coefficients (R) between SWDI at different topsoil depths (10 cm, 40, 100 cm) and SPI-3. The correlation values run from −1 to 1 with higher positive (negative) values indicating a strong relationship between the two datasets.

4. Results and discussion

4.1. Cross-verification of drought severity

This study verified the SWDI and the SPI-3 in a monthly time-scale at each pixel over the period from 1982 to 2020. Overall, the R-values between the SPI-3 and SWDI had a strong correlation pattern at three different soil depth levels although there were
some variations observed in deeper soil levels. It is clear that the SPI-3-based drought severity is well correlated with the SWDI in the most cases of Algeria and Tunisia. Some areas in Morocco were observed with lower correlation values at deeper soil moisture, and this is likely due to variations in climate and human activities.

As can be seen from Fig. 2 that the highest R-value is observed between the SPI-3 and SWDI (0–10 cm soil depth layer) while deeper soil layers are less sensitive to drought detection. For example, the bar chart from Fig. 2 indicates that nearly 80% of pixels (R ≥ 0.8) had high correlation with the top 10 cm soil layer, but this figure for the 40–100 cm soil layer accounted for less than 10% of the pixels. This observation indicates that drought characteristics can be well extracted from the SPI-3 algorithm given the dependence of crops/shrubs on the rootzone soil moisture layer. In addition, higher R values were observed in the eastern parts of Algeria and the central coast of Morocco and Tunisia from deeper soil layers. By contrast, the lower R values were seen in the forested areas, indicating that agricultural land is more sensitive to drought conditions and that soil moisture is closely linked to precipitation deficit.

4.2. Spatiotemporal characteristics of drought

Due to atmospheric and local climate effects, drought conditions have varied in space and time over the study area over the past decades. These changes influence drought severity, so some years may experience more severe droughts than others. Fig. 3 illustrates the annual drought severity from 1981 to 2020 and the study region suffered from great variations. For example, more severe drought conditions were observed in 1981, 1983, 1993–1995, 2000–2001, 2005, 2015–2017, and 2019–2020. These years experienced more drought conditions partly because of El Nino effects (Nicholson and Kim, 1997). In addition, land use/land cover may also exacerbate the drought conditions (Biazin and Sterk, 2013), especially in arid and semi environments. For example, deforestation and urbanization can increase demand for water resources and higher land surface temperature, which in turn can alter local and regional climate pattern, exacerbating drought conditions.

In recent drought events, Algeria and Morocco have suffered from more severe drought conditions, especially in 2016–2017 and 2019–2020 whereas there was a little signal of drought severity in Tunisia during 2019. However, drought became more severe in Tunisia in 2017. A recent study performed drought analysis from 1983 to 2018 and revealed that the most recent drought events in Tunisia are observed in 2017–2018 (Ben Othman and Abida, 2022). In addition, an updated statistics of drought events from the International Disaster Databases reported that over the last 5 years Morocco suffered from multiple severe drought events in 2016, 2017 and 2018 whereas severe drought events were observed in Algeria in 2019 (EM-DAT, 2022). Notably, Tunisia has not recorded any extreme recent droughts in the database, although Fig. 3 shows a strong signal of drought in 2017. Overall the annual drought patterns identified in this study considerably reflected in the in-situ drought records, and most of the years suffered from drought conditions, except in 1996, 2010–2011, and 2018.

In addition, understanding the development of drought, especially the start and end, is essential for supporting drought preparedness and adaptation strategies. Here, this study identified the onset and the end of drought by calculating the frequency of drought start and end months over 40 years. The highest frequency (or majority votes) of start and end months is chosen to present the start and end months of drought events in the region, respectively. Fig. 4 shows the space–time variation of drought development. As can be seen from Fig. 4 (a), drought condition usually starts in July in western Morocco and Tunisia while most of the area in Algeria suffers from drought in August. It is noted that drought in the region lasts short, from one to three months and ends in September (Fig. 4 b). This information would be of great value to local policymakers and regional authorities to navigate water resources for agricultural development and planning.

From 1981 to 2020, the most prolonged accumulative drought duration was observed in Morocco and Algeria with a record of up to 125 months (Fig. 5-c). Consequently, the frequency and severity were also observed to be more intense in these areas where longer drought duration occurred (Fig. 5-a-b). Most of the drought events occurred from 4 to 5 months and tended more frequently in areas (Fig. 5-d). For instance, nearly 81% of drought lasted 4 months, whereas only 10% of events prolonged over 5 months.

Spatially the drought occurrence and severity have varied across the study area. Morocco likely experienced more prolonged

![Fig. 2. Pearson’s correlation coefficient (R) between SPI-3 and SWDI at top 10 cm (a), 10–40 cm (b), and 40–100 cm (c) soil moisture. The bar chart illustrates the percentage of pixels within pre-defined coefficient interval for each soil depths.](image-url)
Fig. 3. Annual variations of drought conditions from 1981 to 2020 in the coastal regions of Morocco, Algeria, and Tunisia.

Fig. 4. Spatial variations of drought started month (a) and ended month (b) in the study region calculating from the SPI-3 over the period of 40 years (1981–2020).

Fig. 5. Spatial distribution of drought frequency (a), absolute drought severity (b), total drought duration (c), and most prolonged drought events (d).
4.3. Variations of vegetation response to drought conditions

Precipitation is considered one of the most significant factors in regulating the temporal and spatial development of vegetation, especially in arid and semi-arid environments. A persistent lack of precipitation can cause widespread drought, which results in vegetation stress and land degradation.

Each vegetation type may have different responses to drought conditions and timeframe. Thus, we investigated the response of four major vegetation categories in the region, cropland, grassland, forest, and shrubs to the SPI-3 timescale. Overall, crop and grassland had the highest R-value compared to other land cover types given drying and non-drying months (Fig. 6).

During the drying months from June to September, the highest positive correlation of vegetation response to drought was observed with cropland. By contrast, the lowest correlations were mainly found in shrubland (Fig. 6). This indicates that farmland is likely more sensitive to drought conditions and becomes vulnerable to global warming, especially in arid and semi-arid environments (Ding et al., 2020). In addition, forest and grassland had similar R values although the correlation is moderately strong. Given the higher frequency and severity of drought conditions in the region, this ecosystem is likely to suffer from drought impacts such as loss of biodiversity (Cuttelod and García, 2009).

In addition, we considered the response of vegetation to non-drying months and its correlation is lower than that of drying months (Fig. 6). The lowest R values are found in forestland whereas this figure for shrubs remained stable. The stronger positive correlation between forest NDVI and drying-month SPI-3 indicated that the forest absorbs greater impacts whereas shrubs showed resistance and resilience during both drying and non-drying months.

4.4. Assessment of time-series drought trends

An increasing trend in drought conditions can have great impacts on crop productivity and vegetation growth. This study uses the MK trend test and Sen’s slope to detect the interannual significance and slope of drought patterns, respectively using the SPI-3 at a confidence level of $\alpha = 95\%$ from 1981 to 2020. The SPI-3 is more sensitive to detecting drought conditions and reflected agricultural drought. It is observed that drought conditions have become more intensified and severe over the recent decades, so we analyzed the trend in five different time windows, 1981–1990, 1991–2000, 2001–2010, 2011–2020, and 1981–2020. Overall, we observed an increase in drying trend over the last decade whereas wetter trends were observed in the 2000s.

From 1981 to 1990, it is observed that nearly 68% of the study area showed a decreasing drought trend but only 29.3% presented a statistical significance with a $p$-value $< 0.05$ (Fig. 7-a). Interestingly, Morocco witnessed the most wetting trend with positive Sen’s slope over this period whereas other countries exhibited no trend in drought/wetting conditions. By contrast, there were nearly no significant drying or wetting trends dominated in the region from 1991 to 2000 (Fig. 7-b). Several studies reported that the region has suffered from the most severe droughts in the early 1980s (Abdelmalek and Nouiri, 2020; Ouatiki et al., 2019) whereas a recent study found that the wettest years were observed in 1995 and 1996 using the station-based precipitation observations (Abdelmalek and Nouiri, 2020). These severe drought events in the early 1980s may be due to abnormal local and regional climate impacts, but the overall trend during these periods was more likely to be wetting or non-significant drying trend.

During the first decade of the 21st century, the wetting trend has remained primarily in Morocco, and in Algeria there was a sign of wetting trend observed (Fig. 7-c) and little drying. The largest percentage of wetting pixels was found in Morocco (~56%) whereas Algeria is ranked second with nearly 41%. The largest increase in Sen’s slope was observed ~0.4/year. Zerouali et al. (2021) reported that Algeria became wetter from 2002 to 2010. By contrast, the last decade witnessed a significant increase in drying trend over the region. Overall nearly 42% of the region suffered from drying trend whereas the rest exhibited no significant wet-

![Fig. 6. Correlation between SPI-3 and NDVI shows the response of various vegetation types during drying months (June – September) and non-drying months.](image-url)
The largest area of drying trend was observed in Morocco (nearly 48%), and Algeria ranked second with ~44% whereas Tunisia accounted for insignificant portion. Higher slope trends are found in Algeria and Morocco. This increasingly drying trend may explain the occurrence of multiple drought events in recent years. Habitou et al. (2020) reported that Morocco witnessed the driest condition in 2019 whereas the drought event in 2015–2016 in Tunisia greatly impacted its crop production (Bazza et al., 2018). Also, many studies have reported a decrease in precipitation in the region over the past decade and in the near future (Babaousmail et al., 2021; Zhim et al., 2019). Given climate change, the region is expected to suffer from substantial drought conditions which could threaten regional food security (Elkouk et al., 2021).

5. Conclusions

Understanding drought characteristics and their impacts on vegetation plays a key role in water resources, agricultural planning and ecosystem preservation. Based on the SPI-3 and NDVI time-series observations, this study provided a comprehensively spatiotemporal characteristics of droughts and their impacts on vegetation in the northeast coastal region of Africa. Our findings indicate that this region has experienced multiple drought events with varying duration, frequency, and severity over the past four decades. For example, severe drought years were observed in 1981, 1983, 1993–1995, 2000–2001, 2005, 2015–2017, and 2019–2020 in the region. The drought conditions in the study area usually starts in July and ends in September, while the spatial distribution of drought events tends to occur more frequently in Morocco and Algeria. This study identified that Morocco and Algeria suffered from severe drought conditions in 2016–2017 and 2019–2020.

Moreover, the Mann-Kendall test revealed that the region witnessed a wetter trend or non-significant drying pattern (p ≤ 0.05) or no data available.
Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

References


