

Article

Spatio-Temporal Assessment of Drought Impacts on Olive Groves Using Sentinel-2 and CHIRPS Data in Central Morocco: A Case Study of the Beni-Amir Perimeter, Central Morocco

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Abstract

Climate variability represents a major threat to agricultural systems, particularly in arid and semi-arid regions such as the Beni-Amir irrigated perimeter, located in the Tadla plain in central Morocco. In this perimeter, olive trees are exposed to multiple environmental and management-related factors that are associated with variations in phenology and vegetation vigor, such as successive drought episodes. This study represents a spatio-temporal assessment of drought impact on olive using satellite-derived vegetation indices from Sentinel-2 imagery and precipitation satellite data from CHIRPS over the period 2015–2024. The Standardized Precipitation Index (SPI-12) was used to identify wet and dry phases over this period. The results indicate an alternation of dry and wet periods between 2015 and 2021, followed by a predominance of dry conditions from September 2021. Over the same period, the time series of the Normalized Difference Vegetation Index (NDVI) and the other vegetation indices reveals marked interannual variability and a progressive degradation of olive tree phenological cycles. A land cover map derived from a supervised support vector machine (SVM) under three classification scenarios achieved high overall accuracies exceeding 94%. Post-classification change detection highlights a substantial reduction in mapped olive-growing areas between 2016 and 2024, with an estimated 72% loss of the initial area. The findings reported in this study indicate that the succession of drought episodes may have contributed to olive grove degradation, including disruptions in phenological cycles and a decline in maximum NDVI values. Even the most resilient olive groves appeared affected following the severe drought period after 2021. The study underscores the usefulness of satellite-derived vegetation indices and drought indicators for the effective monitoring of drought-related stress and supporting improved management practices under climate change.



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1. Introduction

The succession of drought episodes in recent years is a real challenge that threatens the survival of species and the integrity of ecosystems around the world, especially in arid and semi-arid regions such as Morocco [1]. In Morocco, agriculture is a fundamental pillar of the national economy, thanks to its important role in the economic and social livelihoods of the population [2]. Cultivated land accounts for 15% of the national territory (approximately 1.5 million hectares) and contributes nearly 45% of the agricultural gross

domestic product and nearly 75% of agricultural exports per season [3]. However, irrigation in the agricultural sector is a major consumer of water, which generates significant pressure on water resources and requires sustainable and more efficient management [4].

The Beni-Amir irrigated perimeter, located in central Morocco, is characterized by intensive agricultural systems, and large quantities of water have been lost through evapotranspiration (ET). Decision support systems must therefore be developed to enable farmers to manage water resources in a sustainable, rational, and efficient manner [4]. At the same time, olive trees, the dominant crop in this area, have become increasingly vulnerable to climate variability and successive droughts. For this reason, drought assessment has become essential for ecosystem monitoring, water resource management, and the adaptation of agricultural systems to climate variability.

Drought is considered the most limiting factor for agricultural productivity worldwide [5]. Rising global temperatures, shifts in precipitation regimes, and the increasing frequency of extreme climate events such as droughts, floods, and heat waves are already affecting agricultural productivity worldwide. Climate projections for Mediterranean regions indicate the continuation of these trends, characterized by a marked decline in precipitation, increasing temperatures, and intensified evapotranspiration, with direct implications for agricultural systems and perennial crops. These changes will affect agricultural production, including olive cultivation, by influencing plant growth rates, transpiration, photosynthesis, and the reduction in crop productivity, and will impact the quality of olive fruits and olive oil [6–8]. The effects of drought impact in agriculture can be felt at different levels; temperature and water resource availability, among other factors, affect plants' development and productivity, the possibility of executing agricultural operations, and the geographical distribution of crops [9].

In this context, new space technologies, such as remote sensing, provide a powerful and reliable tool for collecting and managing spatial data. Satellite-derived products at the field scale can deliver information on crop growth and health, as well as on water requirements under conditions of water stress. Such data offer valuable real-time guidance for implementing strategies that ensure crop sustainability and natural resource conservation through large-scale operational mapping with higher spatial and temporal resolutions [10]. To this end, the use of satellite products has shown strong potential for change detection and for the extensive and continuous monitoring of agricultural areas [11,12].

A wide range of Earth observation satellites is currently available; however, Sentinel-2 is the most powerful due to its advanced spatial and spectral characteristics. Sentinel-2A and Sentinel-2B satellites, launched by the European Space Agency (ESA), have significantly improved the potential for precision agriculture by providing high-resolution multispectral data. These features make Sentinel-2 a powerful resource for the research community and agricultural development applications [13,14]. Among the most widely used remote sensing products is the Normalized Difference Vegetation Index (NDVI), which was developed by Rouse et al. [15] to simplify spectral information related to vegetation. NDVI has become one of the most commonly applied indices for real-time monitoring and surveillance of vegetation growth [16,17]. Nevertheless, under conditions of dense vegetation cover or heterogeneous soil backgrounds, NDVI may exhibit certain limitations. This has led to the development of other vegetation indices such as the Normalized Difference Water Index (NDWI), the Soil-Adjusted Vegetation Index (SAVI), and the Modified Soil-Adjusted Vegetation Index (MSAVI), which better account for water stress and the structural characteristics of vegetation.

Several studies have confirmed the reliability of vegetation indices for extracting phenological parameters, especially when derived from time-series data, which provide more accurate results compared to studies based on a single date imagery [11]. Time

series data analysis enables continuous monitoring of crop growth using NDVI, which generally increases during vegetation development, reaches a maximum corresponding to peak growth, then gradually decreases as senescence begins [18]. Based on these temporal dynamics, phenological parameters can be extracted, providing valuable information on plant phenology [19,20].

In the Beni-Amir irrigated perimeter, most existing studies have primarily focused on crop mapping and evaluating the potential of satellite data to discriminate between different crop types, identifying favorable dates, and extracting phenological metrics, as reported by EL Hachimi et al. [4] and Saad El Imanni et al. [21]. However, few studies have focused on mapping agricultural systems and assessing the impact of drought using drought indices such as the Standardized Precipitation Index (SPI) with spectral indices, as in the case of Ben Abdelmalek and Nouri [22], Lebrini et al. [23], Oussaoui et al. [24], Zambrano-Bigiarini and Baez-Villaneuva [25].

At the national scale, previous studies have demonstrated a strong correlation between drought episodes and vegetation degradation. In this regard, Bijaber et al. [26] developed an integrated remote-sensing-based drought monitoring framework combining SPI, NDVI, land surface temperature, and evapotranspiration anomalies, demonstrating strong links between drought severity and agricultural productivity. Serbouti et al. [27] indicates that the expansion of irrigated land is significantly correlated with an increase in the severity of droughts. Oussaoui et al. [28] reported a significant impact of drought on olive groves, covering 12,127 ha in the Tadla plain, including the two irrigated perimeters of Beni Amir and Beni Moussa, as well as the Tassaout region. Their analysis also identified 1154 km² of vulnerable areas, highlighting the increased sensitivity of olive groves to prolonged drought conditions. Ouelkabir et al. [29] showed that the drought indices revealed a marked increase in drought frequency and severity starting in the early 1990s, with the most critical period occurring between 2020 and 2023. In parallel, the NDVI exhibited moderate interannual variability, with lower values observed during drought years. Despite all this, a significant gap remains in understanding the long-term and cumulative impacts of recurrent drought events on olive grove ecosystems in semi-arid regions. In addition, the interactions between climatic variability, phenological responses derived from time-series satellite data, and land-cover changes are still rarely analyzed within a fully integrated framework. This limits the ability to assess whether observed vegetation responses reflect temporary stress or longer-term ecosystem degradation. Addressing this gap is essential for improving the understanding of olive grove resilience and vulnerability under increasing climate variability.

The main objective of this study is to assess the impact of climate variability on olive trees by integrating CHIRPS climate data and Sentinel-2 satellite imagery in order to map and identify the spatio-temporal change induced by periods of drought. More specifically, this study is structured around the following scientific questions: (i) how drought conditions evolve based on the SPI derived from CHIRPS data, (ii) how olive trees respond phenologically to drought variability using time series of vegetation indices, and (iii) quantify land use/land cover changes between 2016 and 2024 through post-classification comparison to identify the spatio-temporal dynamics of olive groves under recurrent drought conditions.

To achieve these objectives, the innovative cloud-based geospatial platforms, such as Google Earth Engine (GEE), have optimized spatial data analysis by enabling efficient processing of satellite imagery, large-scale extraction of spectral indices, and time series generation [30].

2. Materials and Methods

2.1. The Study Area

The study focuses on the irrigated perimeter of Beni-Amir, located in the Tadla plain in the center of Morocco between the latitudes $32^{\circ}20'$ and $32^{\circ}34'$ North and longitudes $6^{\circ}30'$ and $6^{\circ}48'$ West (Figure 1). It covers about 34,000 ha and is bordered by phosphate plateaus in the north and by the Oum Errbia river in the south, with an average altitude of 400 m. The perimeter is irrigated by the regularized waters of the El Hansali dam (670 million m³ of capacity) [24]. The climate of the study area is arid to semi-arid, with a maximum temperature of 46 °C and an average annual rainfall of 305 mm between 1983 and 2024. The interannual contrast observed in temperature and precipitation patterns indicates an increased exposure of the perimeter to climate change effects. The size of the parcels is typically very small, and 86% of parcels are less than 5 ha; only 5% of parcels exceed 10 ha in area [31]. The perimeter is chosen due to several considerations, namely the strategic role in the national food and similar climatological and environmental conditions.

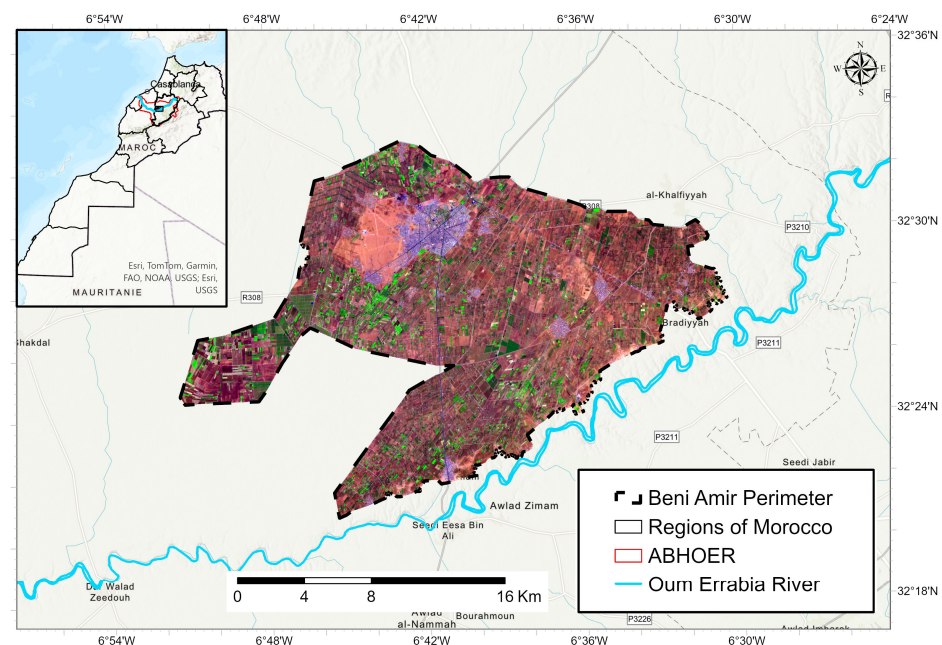


Figure 1. Location of the study area in Morocco.

2.2. Ground Truth (GT) Data

The sampling was carried out in two complementary stages, combining satellite image analysis with field verification. First, sampling points were selected based on Sentinel-2 imagery and high-resolution Google Earth basemaps, ArcGIS Pro (version 3.0, Esri, Singapore) ensuring homogeneous coverage and representativeness of all classes of interest, including olive groves, other crops, urban areas, water bodies, and no crops. This step allowed the identification of homogeneous areas and the planning of the field mission. Subsequently, a field campaign was carried out in July 2024 to validate the preliminary classification, collect ground-truth data, and record parcel characteristics such as vegetation type, condition, and phenological stage, employing stratified random sampling to collect 360 georeferenced observation points (Table 1). Each sampling point was georeferenced, and its attributes were integrated into a GIS, ensuring adequate spatial distribution and sufficient representativeness for SVM classification and the analysis of spatiotemporal crop dynamics.

Table 1. Description of land cover classes with the number of reference samples and representative field observations.

Land Cover Class	Total Samples	Training	Validation	Observations
Olive	120	96	24	Unimpacted; Non-impacted; New olive plantations
Other crops	100	80	20	Alfalfa (Green; cultivated) and Niora
No crops	70	56	14	Bare soil; Harvested field
Water bodies	40	32	8	Irrigation ponds
Urban area	30	24	6	cities and villages

2.3. Satellite Data

Sentinel-2 consists of two satellites: Sentinel-2A, launched on 23 June 2015, and Sentinel-2B, launched on 7 March 2017. Both satellites are equipped with the same multispectral sensor (MSI) with 13 bands (Table 2) ranging from visible to infrared with a spatial resolution of 10 m (visible and near-infrared bands), 20 m (red-edge and thermal infrared bands), and 60 m (aerosol, water vapor, and cirrus bands). After the second launch, Sentinel-2 provided higher temporal resolution with a revisit frequency of 5 days instead of 10 days previously [13]. The MSI sensor is characterized by spectral richness, particularly in the infrared bands with Red-Edge bands that are sensitive to vegetation structure and health.

Table 2. Characteristics of the Sentinel-2 MSI.

Band	Purpose	Wavelength Range (nm)	Spatial Resolution (m)
Band 1	Coastal aerosol	433–453	60
Band 2	Blue	458–523	10
Band 3	Green	543–578	10
Band 4	Red	650–680	10
Band 5	Red-Edge1	698–713	20
Band 6	Red-Edge 2	733–748	20
Band 7	Red-Edge3	773–793	20
Band 8	NIR	785–900	10
Band 8A	NIR narrow	855–875	20
Band 9	Water Vapor	935–955	60
Band 10	Shortwave infrared/Cirrus	1360–1390	60
Band 11	SWIR 1	1565–1655	20
Band 12	SWIR 2	2100–2280	20

2.4. CHIRPS Data

Climate Hazards Group InfraRed Precipitation with Station Data (CHIRPS) is a rainfall dataset developed by the Climate Hazards Group at the University of California. CHIRPS is a near-global precipitation dataset covering the period from 1981 to the present, extending from 50° S to 50° N. It combines satellite-based infrared imagery at a spatial resolution of $0.05^\circ \times 0.05^\circ$ with in situ stations to produce precipitation time series for the purpose of analyzing drought trends [32,33]. INTEGRATED CHIRPS combines adjusted infrared observations with calibrations from the Tropical Precipitation Measurement Version 7 (TMPA 3B42 v7), together with cold cloud duration (CCD) estimates. CCD values serve as satellite-derived proxies for cloud shielding and provide a reliable indicator of storm intensity. The system uses weather-station data in two sequential steps to generate two products. The first is a preliminary dataset, available with a 2-day lead time, created by adjusting CCD estimates and incorporating GTS rain-gauge data. After three weeks, a fully consistent final product is generated by merging monthly station observations with CCD estimates to produce coherent precipitation fields resembling those of the GPCC [34].

2.5. Methods

To assess the impact of drought periods on olive trees in the Beni-Amir irrigation area, the methodology in the workflow presented in Figure 2 was adopted to achieve the objective of this study.

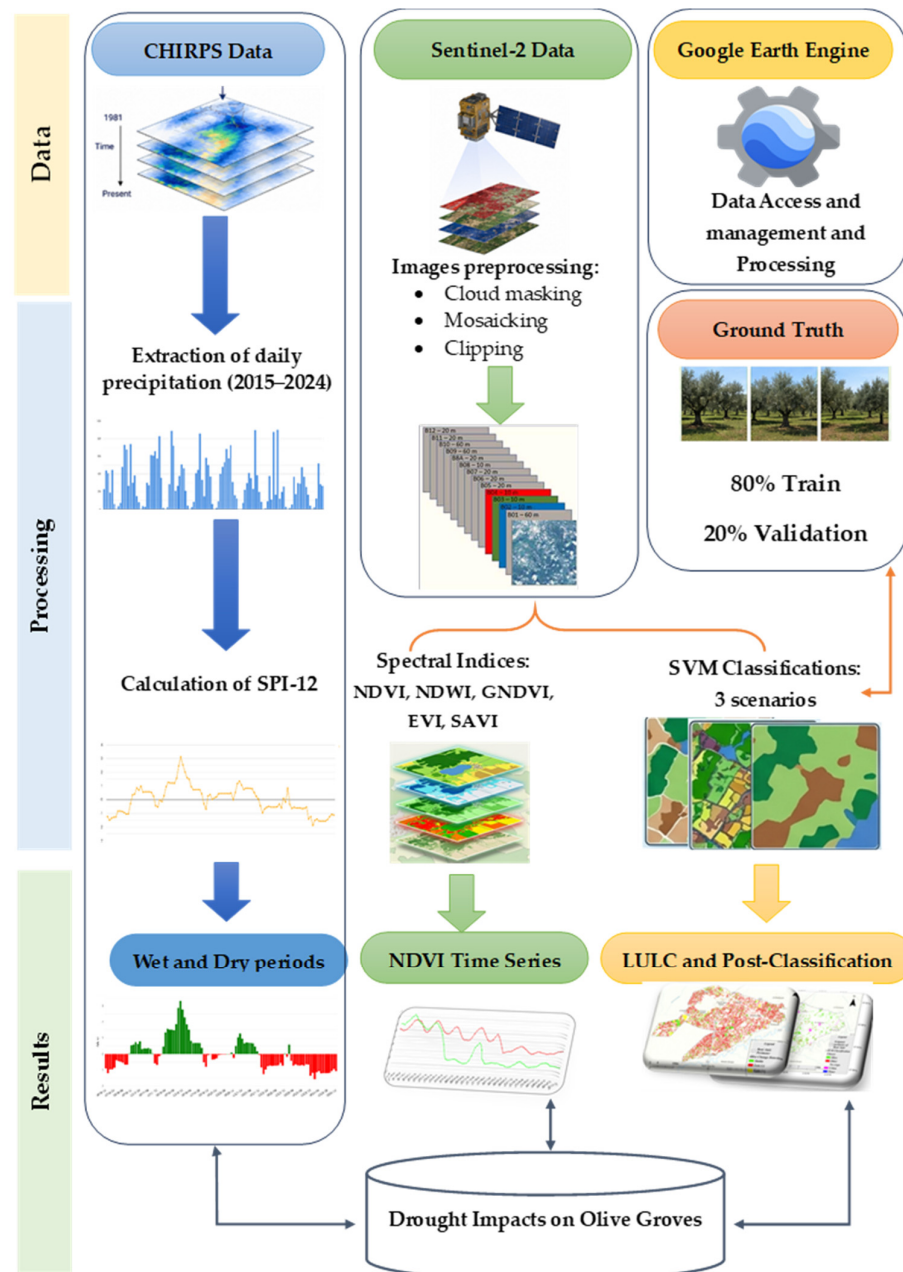


Figure 2. Flowchart of the methodology used.

Precipitation data obtained from the CHIRPS dataset were initially analyzed to derive the 12-month Standardized Precipitation Index (SPI-12), which enables the characterization of wet and dry conditions at an interannual timescale. This analysis establishes a long-term climatic baseline by capturing the occurrence, persistence, and severity of drought events that can exert sustained impacts on perennial agricultural systems, including olive groves.

In parallel, Sentinel-2 imagery was used to derive a set of spectral vegetation indices, enabling a more comprehensive monitoring of vegetation dynamics. In addition to NDVI, indices such as EVI, NDWI, SAVI, and GNDVI were integrated to capture vegetation vigor, canopy structure, and water content. The analysis of these time series provides

a phenological interpretation of vegetation responses to water availability, highlighting variations in growth patterns, anomalies in vegetation vigor, and potential disruptions in phenological cycles.

Supervised classifications were performed using the Support Vector Machine (SVM) algorithm across three experimental scenarios, based on 80% of the regions of interest (ROIs) used as a training dataset. The first scenario relied exclusively on spectral bands to map crops and tree cover. The second combined spectral bands with the Normalized Difference Vegetation Index (NDVI) to enhance vegetation discrimination. The third integrated spectral bands with multiple spectral indices to further improve class separability. The resulting classifications were evaluated and compared using the remaining 20% of field data as an independent validation set. This step provides an essential basis for restricting the climatic and phenological analysis to olive orchard areas only, thereby ensuring a more targeted and relevant interpretation of the results.

Post-classification change detection was then applied by comparing the classified maps of 2016 and 2024. This approach enabled the identification of land-cover transitions at the pixel level without requiring direct pixel-based temporal modeling. A change matrix was generated to quantify transitions between classes, enabling the assessment of spatial land use dynamics patterns over the study period. This procedure provided a robust and interpretable framework for detecting gains, losses, and conversions among land cover types, particularly within agricultural and olive-dominated areas. It is important to note that the post-classification change detection approach is inherently affected by uncertainties associated with the classification results obtained for both reference years (2016 and 2024). Indeed, despite the high overall accuracies achieved in the SVM classifications, residual errors of omission and commission may persist at the pixel level. These uncertainties can propagate during the comparison process between the two classified maps and may consequently influence the estimated magnitude of land cover transitions. For this reason, the reported changes in olive grove extent should be interpreted as reliable indicators of general trends rather than exact quantitative measurements. Nevertheless, the consistency of the observed spatial patterns provides a robust basis for interpreting the overall dynamics of land use change within the study area.

Finally, the integration of the three components establishes a coherent analytical framework to assess the spatio-temporal impacts of drought on olive orchards. The climatic component (SPI-12) characterizes drought conditions over time, the land use/land cover classification delineates the spatial distribution of olive orchards, and the phenological time series capture vegetation responses to environmental variability. By restricting vegetation and phenological analyses to validated olive orchard areas, the study ensures consistency between climatic forcing, land cover structure, and vegetation dynamics. This integrated approach enables a robust assessment of drought impacts on olive orchards by explicitly linking climatic variability with spatially explicit land cover information and vegetation temporal behavior.

This data is processed via the Google Earth Engine platform as a geospatial data processing and analysis environment, following its ability to manage and directly access satellite data. In addition, it effectively fills gaps in time series based on seasonal patterns and historical data.

2.5.1. Image Composites

The choice of the right color composition and spectral bands was made with the aim of optimizing the discrimination of olive groves and analyzing their biophysical condition. The SWIR, NIR, and Red spectral bands are used to create a false-color composite shown in Figure 3. The Red band is characterized by its high chlorophyll absorption. The NIR

band highlights high reflectance, while the SWIR band is sensitive to the water content of vegetation and soil. This combination allows for good distinction between cultivated areas and bare soils, as well as between stressed and unstressed vegetation (Figure 4).

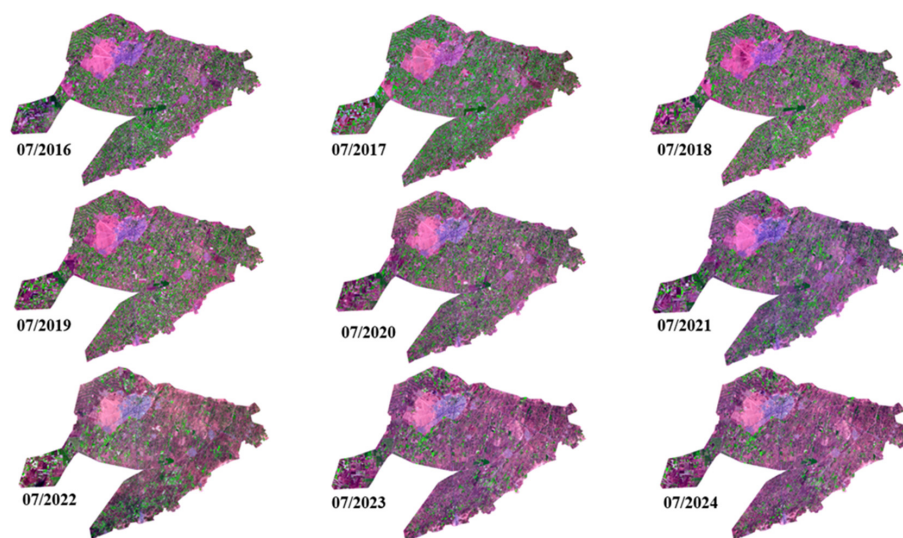


Figure 3. Sentinel-2 RGB yearly images (False color Combination: SWIR-NIR-R), where healthy vegetation appears in green and bare soil in shades of brown to pink.



Figure 4. Olive trees observed during the field survey.

The scenes used in this study were acquired in July, as this period corresponds to the stage when olive trees are the dominant crop within the parcels. During this time, the presence of other crops is minimal, which reduces spectral mixing and limits confusion with secondary vegetation as shown in Figure 5. In July, olive orchards exhibit stronger and more consistent spectral responses compared with other months, when multiple crops often coexist within the same parcels, such as olive trees intercropped with alfalfa or cereals. This seasonal context enhances the spectral separability of olive orchards and supports the choice of July imagery for the analysis.

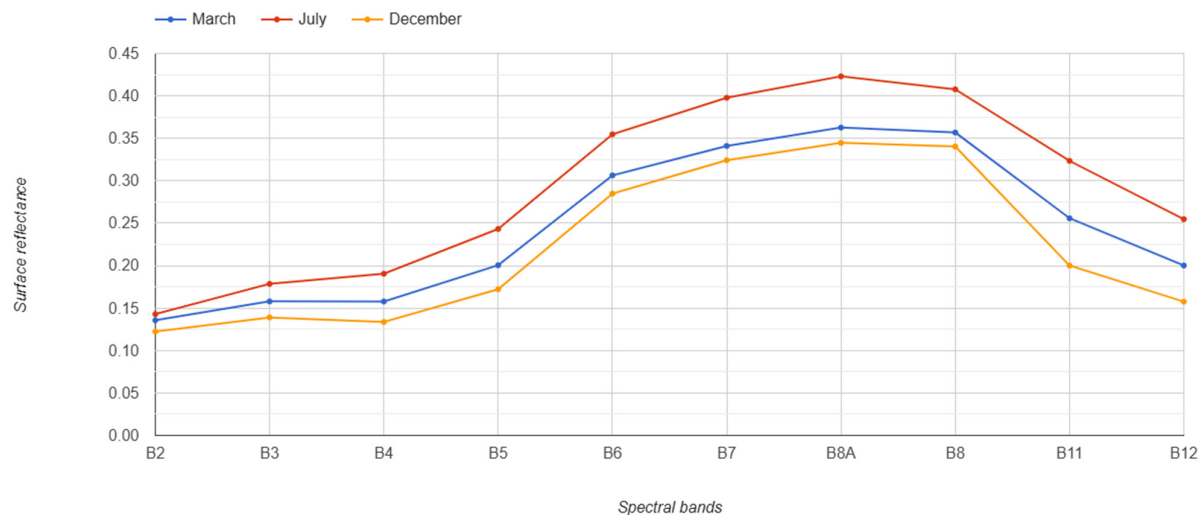


Figure 5. Spectral reflectance signatures of olive orchards across different months.

2.5.2. Spectral Indices

Spectral indices are key indicators of olive tree health. In this study, five spectral indices were calculated from the available image, as shown in Table 3. NDVI is the most commonly used vegetation index for monitoring vegetation density, health, and growth [35], as it reflects the vigor and strength of vegetation on the Earth's surface [36]. It is obtained from the reflectance in the red (R) and near-infrared (NIR) parts of the spectrum [37]. The SAVI developed by Huete et al. [38] is an intermediate index between ratio-based indices and perpendicular indices. It incorporates a soil adjustment factor (L) to reduce the impact of soil brightness. This factor varies between 0 and 1. The most commonly used conventional value for medium-density vegetation is 0.5. The EVI has been used in areas with high biomass to improve the sensitivity of vegetation signals by minimizing the influence of canopy background and atmospheric effects [39]. EVI is computed using reflectance values from the Red (R), Blue (B), and Near-Infrared (NIR) bands [37]. The NDWI developed by McFEETERS et al. [40] is a spectral index used to estimate the liquid water content of vegetation, using the same principle adopted for the derivation of the NDVI. The NDWI is calculated using reflectance in the Green (G) and Near Infrared (NIR) bands. In contrast, the GNDVI developed by Gitelson et al. [36] has proven to be more reliable than the NDVI for estimating chlorophyll concentration levels. Gitelson improved that the Green (G) spectral band should be more reliable than the Red (R) band for assessing chlorophyll variability in vegetation [36].

Table 3. Vegetation indices extracted from Sentinel-2 images.

Indices	Formulas	Authors
NDVI: Normalized Difference Vegetation Index	$\frac{B8 - B4}{B8 + B4}$	[15]
GNDVI: Green Normalized Difference Vegetation Index	$\frac{B8 - B3}{B8 + B3}$	[36]
NDWI: Normalized Difference Water Index	$\frac{B3 - B8}{B3 + B8}$	[40]
SAVI: Soil-Adjusted Vegetation Index	$\frac{(B8 - B4)(1 + L)}{B8 + B4 + L}$	[38]
EVI: Enhanced Vegetation Index	$B3 \times \frac{B8 - B4}{B8 + C1 \times B4 - C2 \times B2 + L}$	[41]

2.5.3. Standardized Precipitation Index (SPI)

The SPI index developed by McKee et al. [42] was calculated using precipitation data to represent meteorological drought in the Beni-Amir Perimeter. This index is widely used to assess meteorological drought by evaluating the variability of precipitation on different time scales. It is based on the probability of precipitation for a given location and can be used to identify periods of drought or surplus (Equation (1)). SPI analysis helps determine the intensity (Table 4), duration, and spatial extent of drought episodes, providing valuable information for policymakers to develop effective drought adaptation and mitigation policies [24]. The SPI index was designed to quantify the rainfall deficit at multiple time scales. These time scales reflect the impact of drought on the availability of different types of water resources [34].

Table 4. Classification of drought and wetness categories based on SPI values.

SPI Value Range	Classification
$SPI > 2.0$	Extremely wet conditions
$1.5 < SPI < 1.99$	Very wet conditions
$1.0 < SPI < 1.49$	Moderately wet conditions
$-0.99 < SPI < 0.99$	Near normal conditions
$-1.49 < SPI < -1.0$	Moderate drought
$-1.99 < SPI < -1.5$	Severe drought
$SPI < -2.0$	Extreme drought

In this study, the Standardized Precipitation Index (SPI) was computed over a 12-month accumulation to characterize long-term drought conditions. This timescale is particularly effective in perennial agroecosystems, particularly olive groves, whose physiological functioning and productivity are driven by cumulative, long-term water deficits rather than short-term precipitation fluctuations. Compared to shorter accumulation periods, SPI-12 is more suitable for capturing sustained drought conditions, interannual moisture anomalies, and hydrological stress, which are key drivers of vegetation dynamics in woody species. This temporal scale is therefore well aligned with Mediterranean climatic conditions, where drought impacts often manifest through prolonged soil moisture depletion. Consequently, the use of SPI-12 is consistent with the study objective of assessing the long-term effects of drought on vegetation behavior and phenological dynamics.

Generally, CHIRPS data have become an indispensable resource for studying climate change phenomena due to their high spatial resolution, long temporal coverage, and frequent validations. CHIRPS data provide essential information on precipitation patterns and their implications [43].

The formula of SPI:

$$SPI = \frac{P_i - \mu}{\sigma} \quad (1)$$

where

P_i : is the precipitation for the i th time period (1, 3, 6, 9, 12, or 24 months)

μ : is the mean precipitation for the selected timescale.

σ : is the standard deviation of the precipitation for the selected timescale

2.5.4. Support Vector Machine Classifier (SVM)

Support vector machine (SVM) is a nonparametric supervised classification algorithm. This mathematical technique has a great capacity for solving classification problems, offering strong potential for generalization even when the training sample is small or the scale of the study is local [44,45]. The fundamental principle of this technique, whose theoretical basis was developed in the late 1970s, is based on projecting data into a multidimensional

space using kernel functions, then searching for the optimal hyperplane that ensures the best separation between different classes [46]. This algorithm has been widely applied in vegetation mapping studies due to its high accuracy and robustness in discriminating between crop types, as illustrated by the works of El Hachimi et al. [4], Lebrini et al. [23], Oussaoui et al. [24], and Saini et al. [47]. The use of the Support Vector Machine (SVM) classifier is justified by its robustness in high-dimensional feature spaces and its strong generalization capability with limited training samples, which are common constraints in remote sensing studies. SVM efficiently models non-linear class boundaries through kernel functions, enabling accurate discrimination of olive orchards from other land-cover types based on spectral information.

To ensure the performance of SVM classification for the three scenarios, several metrics from the confusion matrix were used, including overall accuracy (OA) (Equation (2)), kappa coefficient (Equation (3)), user accuracy (UA) (Equation (4)), producer accuracy (Equation (5)), and F1 score (Equation (6)). For classification training, 80% of the regions of interest in each class were chosen at random, while the remaining 20% were used to evaluate the models.

Overall accuracy is calculated by dividing the number of correctly classified pixels by the total number of reference pixels. The Kappa coefficient measures the degree of compatibility between predicted and observed data, considering random agreement. Producer accuracy (PA) corresponds to the probability that a reference pixel belonging to a given class will be correctly classified. User accuracy (UA) indicates the probability that a pixel classified in a given class actually corresponds to the same class in the field. The F1 score is defined as the harmonic mean of user accuracy (UA) and producer accuracy (PA), thus balancing these two metrics [48].

The formulas used to calculate these indices are presented below:

$$OA (\%) = \frac{\sum_{i=1}^n P_{ii}}{N} \times 100 \quad (2)$$

$$K = \frac{N \sum_{i=1}^n P_{ii} - \sum_{i=1}^n (P_{i+} \times P_{+i})}{N^2 - \sum_{i=1}^n (P_{i+} \times P_{+i})} \quad (3)$$

$$UA_i (\%) = \frac{P_{ii}}{P_{i+}} \times 100 \quad (4)$$

$$PA_i (\%) = \frac{P_{ii}}{P_{+i}} \times 100 \quad (5)$$

$$F\text{-score} = 2 \times \frac{UA_i \times PA_i}{UA_i + PA_i} \quad (6)$$

where:

p_{ii} : number of correctly classified pixels for class i

p_{i+} : total number of pixels classified into class i

p_{+i} : total number of reference pixels belonging to class i

N : total number of validation pixels

n : total number of classes

2.5.5. Statistical Tests and Correlation Analysis

Pearson Correlation Analysis

The Pearson correlation coefficient method quantifies the linear correlation between drought indicators and vegetation indices, thereby revealing the relationship between drought and vegetation growth. The correlation coefficients indicate the degree to which the SPI reflects the relationship between water changes and vegetation; a positive correlation indicates that the drought index is strongly correlated with the vegetation condition. The

larger the correlation coefficient, the closer the relationship between precipitation and vegetation [49]. The Pearson correlation coefficient can not only analyze the correlation between drought and vegetation but also reveal the lagged phenomenon between drought and vegetation [50,51]. Currently, the Pearson correlation coefficient is widely used in drought research. It helps to comprehensively assess the relationship between drought and vegetation growth and provides a scientific basis for ecosystem protection and management. The formula for the correlation coefficient is as follows:

$$R = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_i^n (X_i - \bar{X})^2 + \sum_i^n (Y_i - \bar{Y})^2}}$$

where:

X_i : SPI values

$\bar{X}$: mean of SPI-12 values

Y_i : NDVI values

$\bar{Y}$: mean of NDVI

n : number of observations

Mann–Kendall Test

Mann et al. [52] and Kendall et al. [53] introduced the Mann–Kendall (M–K) test to evaluate the significance of trends in time-series data. As a non-parametric statistical test, it does not require any assumption about data distribution and is not affected by outliers. Consequently, the M–K test has been widely applied to assess the significance of trends in hydrometeorological time-series data [54]. The M–K test statistic is defined as:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i)$$

$$\text{sgn}(x_j - x_i) = \begin{cases} +1, & \text{if } x_j - x_i > 0 \\ 0, & \text{if } x_j - x_i = 0 \\ -1, & \text{if } x_j - x_i < 0 \end{cases}$$

where n refers to the time series data length, and x_i and x_j are the data values in the time series data at times i and j , respectively. When $n > 10$, the statistic S approximately equals the standard normal test statistic (Z) value, which can be used to test the trend as follows:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}(S)}}, & \text{if } S < 0 \end{cases}$$

$$\text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18}$$

where n refers to the time series data length, m is the number of repeated data sets in the time series data, and t_i denotes the repeated data values in the i th group. When $|Z| > Z_{1-\alpha/2}$, the null hypothesis can be rejected, meaning the existence of a significant trend in this data. When $|Z| < Z_{1-\alpha/2}$, the null hypothesis of trend will be accepted. In this study, $\alpha = 0.01$ and $\alpha = 0.05$ are defined as the given significance levels; $Z_{1-\alpha/2}$ is equal to 2.576 and 1.96, respectively.

Sen's Slope

Sen et al. [55] proposed an estimator to analyze the slope trend of time series data. Sen's slope is a non-parametric method requiring the test data to be independent and insensitive to missing and abnormal data. The Sen's slope is computed as follows:

$$\text{Slope} = \text{Median} \left[\frac{x_j - x_i}{j - i} \right], \forall 1 \leq i < j \leq n,$$

where x_i and x_j are the values at times i and j , respectively, and $1 \leq i < j \leq n$. n refers to the time series data length (i.e., 10 years from 2015 to 2024) in the current study. The slope sign reflects the data trend, indicating the rate of variation in the time series data. Slope > 0 means the upward trend, and Slope < 0 indicates a downward trend. Since this method lacks statistical significance testing for the trend, we assessed it using the Mann–Kendall test method, which is also a non-parametric statistical test.

3. Results

3.1. Drought Severity Indices

Analysis of the variation in the Standardized Precipitation Index (SPI) between 2015 and 2024 highlights alternating dry (negative values shown in red) and wet periods (positive values shown in green), as shown in Figure 6. The years from 2015 to early 2018 show near-normal drought conditions with values ranging between -1 and 1 . In contrast, 2018 and 2019 experienced moderate to extreme wetness, reaching a maximum value exceeding $+3$, indicating very significant water recharge. The period between 2019 and 2021 was a transition phase in which drought was close to normal, with values close to 0 reflecting generally stable conditions. From 2022 onwards, there was a remarkable drop in SPI values, which exceeded -1.5 in 2024. This period saw a water deficit and severe drought, which is heading towards extreme levels.



Figure 6. Standardized precipitation index (SPI-12) over the study area between 2015 and 2024.

3.2. NDVI Time Series

The analysis of NDVI time series (Figure 7) derived from Sentinel-2 images for the two regions of interest over the period 2017–2024 highlights remarkable seasonal and interannual variations, reflecting the disruption of olive tree phenological cycles.

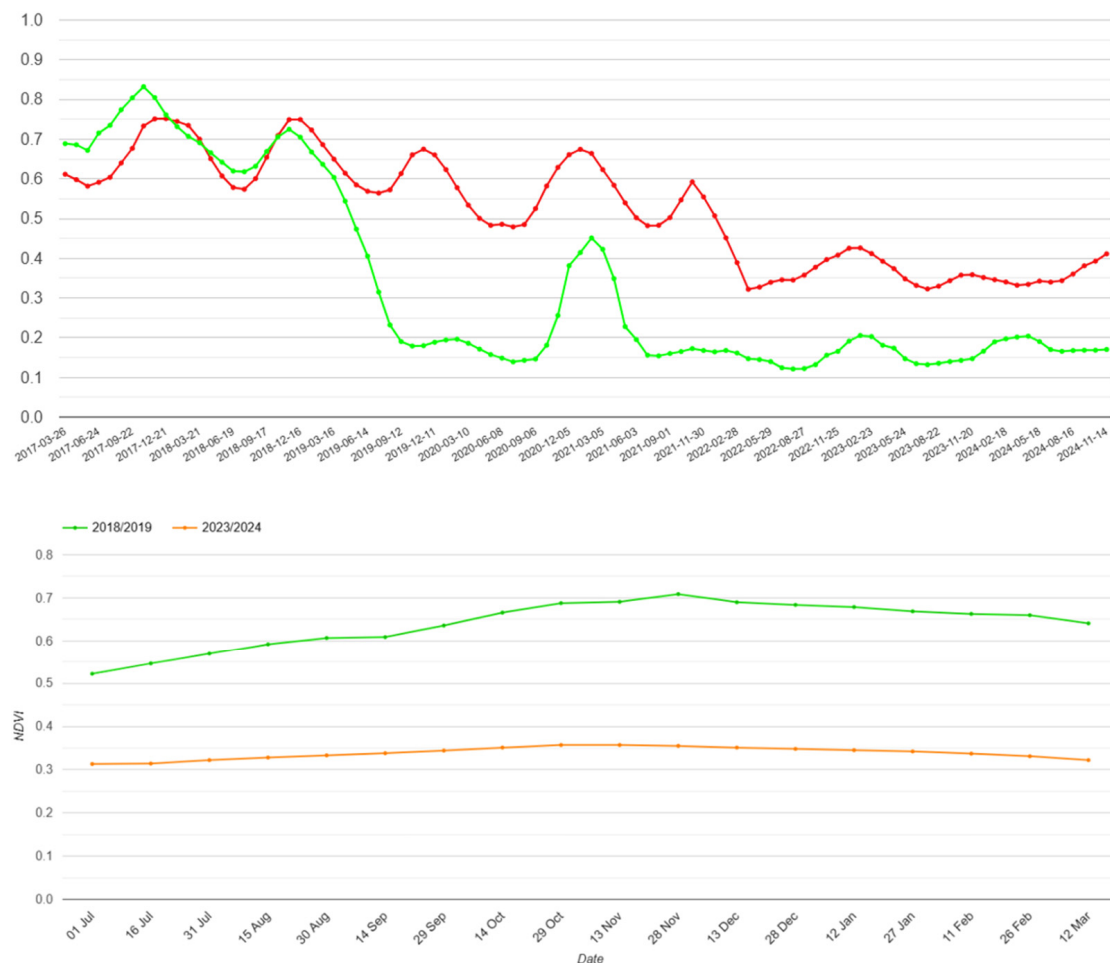


Figure 7. Time Series Analysis (2017–2024) with a comparison of NDVI phenological profiles between the 2018/2019 (Green line) and 2023/2024 (Orange line) seasons.

The NDVI time series for the two regions from 2017 to 2024 shows pronounced interannual variability and a clear long-term degradation of vegetation dynamics, with particular emphasis on the early-period peak conditions. During the 2017–2018 seasons, both regions reached high levels of vegetative vigor, with peak NDVI values exceeding 0.7, indicating dense and well-developed canopy conditions and a fully expressed growing season. These early years are characterized by an early and well-defined Start of Season (SOS), a rapid green-up phase, and a sustained peak period before a clearly identifiable End of Season (EOS), reflecting optimal phenological functioning. From the 2019–2020 period onwards, a marked change has occurred. In the first region, although seasonal cycles remain discernible, maximum NDVI values gradually decline below the 2017–2018 peak; the start of the growing season (SOS) is delayed and the end of the growing season (EOS) is brought forward, resulting in a shorter growing season. In contrast, the second region shows a much more abrupt response, with maximum NDVI values well below 0.2, an ill-defined SOS and a premature EOS, resulting in a significant compression of the phenological window, accompanied by a marked flattening of the seasonal NDVI curve. While the second maintained its normal pace throughout 2019, it then experienced a rapid decline in 2020. A partial recovery was observed in 2021, reaching a peak of 0.45, but this occurred late in February, indicating a shift in the phenological cycle. This recovery is temporary, as 2022, 2023, and 2024 saw a further decline in NDVI, with less pronounced cycles and lower maximum values than the first region.

After describing the dynamics of phenological profiles over the period 2017–2024, the next step highlights a comparison of two different seasons corresponding to the periods before and after the disturbances shown in the previous section. In order to ensure a consistent and relevant comparison, the satellite images used to extract the NDVI for the 2018/2019 and 2023/2024 seasons were acquired on the same date. During the 2018/2019 season, the NDVI increases gradually from July onwards, reaching a maximum at the end of November, reflecting high vegetative production and optimal olive tree activity. Subsequently, a slight decrease is observed during the winter period, while values remain relatively high. In contrast, the 2023/2024 season is characterized by lower NDVI values, with a moderate increase between summer and autumn, followed by stagnation and then a slight decrease during the winter period.

3.3. Correlation and Trend Analysis Between SPI and NDVI

The correlation matrix (Figure 8) reveals a positive relationship between the drought index (SPI-12) and both NDVI time series, although with different magnitudes. The correlation coefficient between SPI-12 and NDVI 1 is 0.61, indicating a moderate to relatively strong positive correlation. This suggests that improvements in hydrological conditions (higher SPI values) are generally associated with increased vegetation vigor in area 1, while drier conditions correspond to reduced NDVI values. In the case of NDVI 2, the correlation with SPI-12 is 0.55, which also reflects a moderate positive correlation, but slightly weaker than that observed for NDVI 1. This implies that vegetation in area 2 shows a similar statistical relationship with drought variability, although with a lower magnitude, and the sensitivity appears somewhat lower, potentially due to local factors such as soil properties, management practices, or additional stressors.

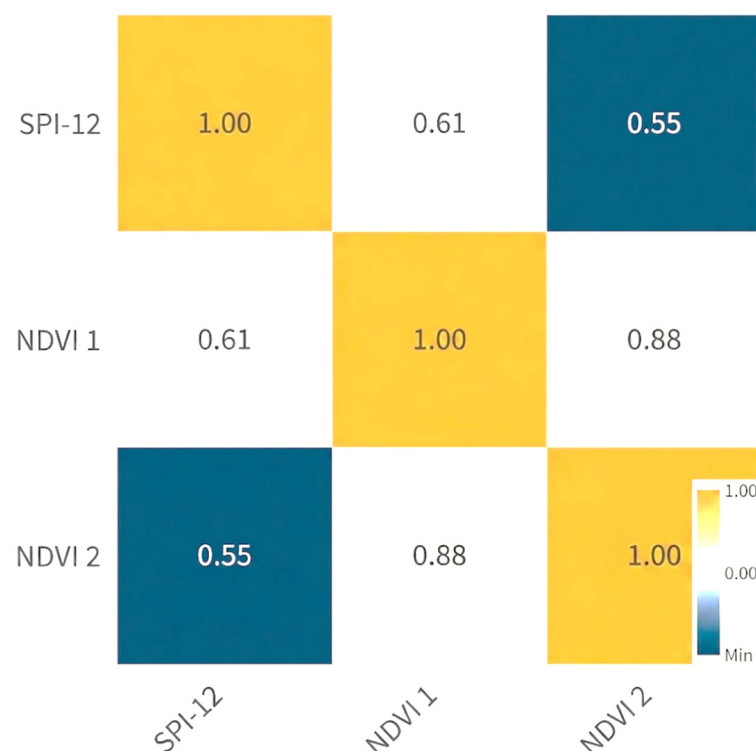


Figure 8. Correlation matrix between SPI-12 and NDVI time series.

Overall, these results indicate statistically significant associations between vegetation dynamics and drought conditions, with a stronger response observed in the NDVI 1 area compared to NDVI 2. Finally, the strong correlation between NDVI 1 and NDVI 2 ($R = 0.88$)

indicates that both areas exhibit broadly similar temporal vegetation dynamics, despite differences in their sensitivity to climatic variability.

The results derived from the Mann–Kendall trend test combined with Sen’s slope estimator reveal statistically significant decreasing trends in both vegetation indices and the SPI-12 series over the study period (Table 5).

Table 5. Mann–Kendall trend test and Sen’s slope results for SPI-12 and NDVI time series.

Variables	S (Tendence)	Z-Statistic	<i>p</i> -Value	Sen’s Slope (β)
NDVI 1	−510	−2.18	0.029	−0.0018
NDVI 2	−650	−2.78	0.005	−0.0026
SPI-12	−981	−3.15	0.0016	−0.0148

For NDVI 1, the negative Z-value ($Z = -2.18$) and associated *p*-value ($p = 0.029$) indicate a significant downward trend, while Sen’s slope ($\beta = -0.0018$) suggests a gradual decline in vegetation greenness. Similarly, NDVI 2 exhibits a stronger and more statistically robust decreasing trend ($Z = -2.78$, $p = 0.005$), accompanied by a larger negative Sen’s slope ($\beta = -0.0026$), reflecting a more pronounced reduction in vegetation vigor. Consistent with the vegetation trends, the SPI-12 series shows the most substantial negative trend ($Z = -3.15$, $p = 0.0016$), with a Sen’s slope of -0.0148 , indicating a significant intensification of long-term drought conditions.

Overall, the concurrent negative trends observed in both SPI-12 and NDVI time series highlight a coherent temporal association between declining hydroclimatic conditions and vegetation condition at the interannual scale.

3.4. Crop Type Mapping Using SVM Classifier

A supervised classification using SVM was performed for the five selected land cover classes (olive trees, no crops, other crops, water, and urban) according to three scenarios: The first scenario is based solely on the spectral bands of the Sentinel-2 MSI sensor. The second scenario combines spectral bands and the NDVI vegetation index. The third scenario encompasses spectral bands and spectral indices.

In this section, we discuss the accuracy metrics of SVM classifications for the three scenarios. The maps of crop types obtained were validated by calculating the Overall Accuracy (OA), Kappa coefficient (K), Producer’s accuracy (PA), User’s accuracy (UA), and the F-score for each classification. The accuracy metrics are presented in Figure 9, while the results of the confusion matrices are shown in Table 6.

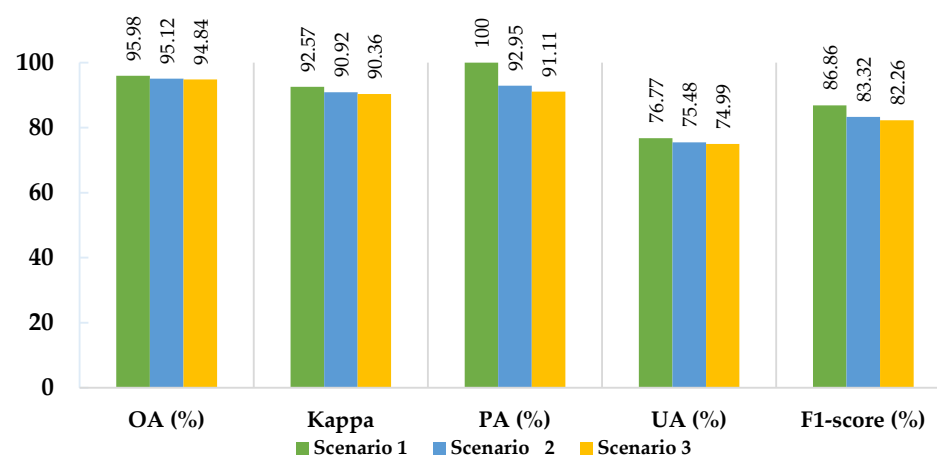
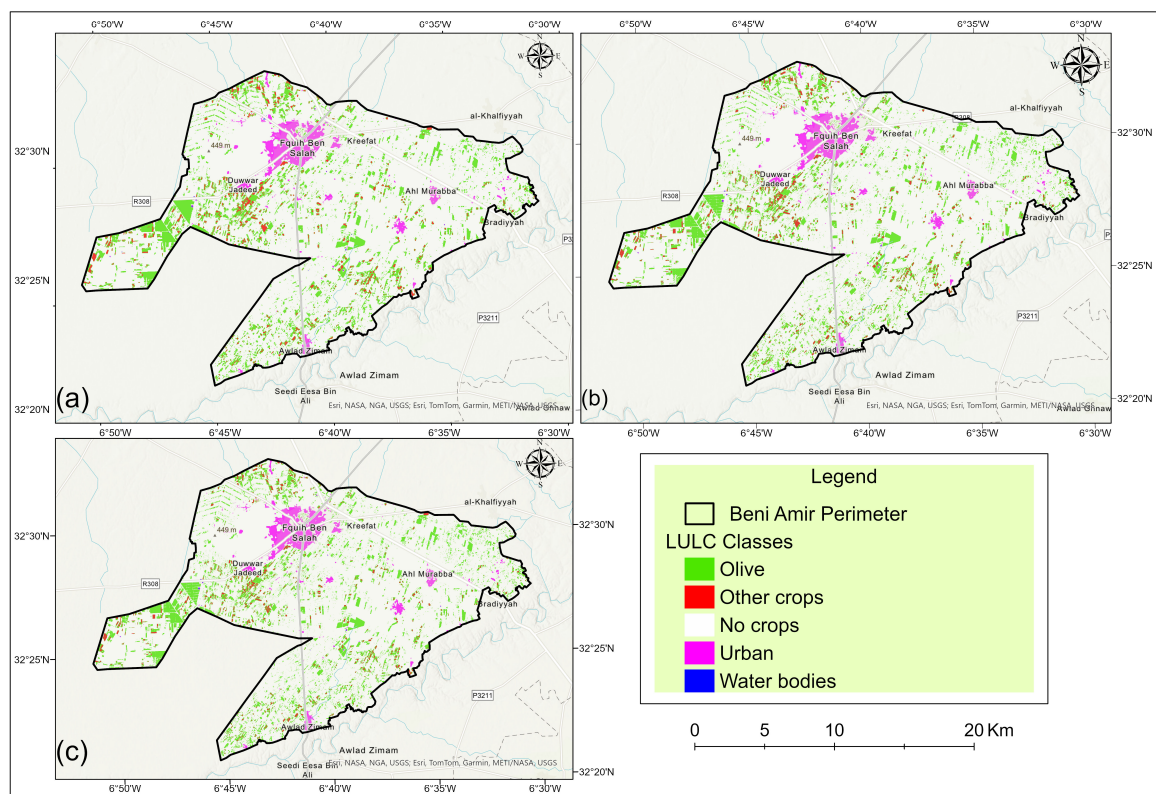


Figure 9. Accuracy coefficient of the SVM classifications.

Table 6. PA and UA (%) derived from the confusion matrices for each land-use/land-cover class and classification scenario.

	Producer's Accuracy (%)			User's Accuracy (%)		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
Olive	100.00	92.95	91.11	76.77	75.48	74.99
Other Crops	18.08	19.06	16.91	100.00	100.00	100.00
No crops	99.97	99.99	99.99	99.27	97.93	97.54
Water	50.00	0.00	0.00	100.00	0.00	0.00
Urban	97.80	97.78	97.78	100.00	100.00	100.00

The performance analysis of the maps derived from the SVM classifier under the three scenarios, presented in Figure 10, reveals consistently high results. Overall accuracy (OA) remains high for all scenarios, with values of 95.98% for the first scenario based on spectral bands, 95.12% for the second scenario incorporating NDVI, and 94.83% for the third scenario integrating multiple spectral indices. The Kappa coefficient shows a similar trend, with values of 0.92, 0.91 and 0.90, respectively, indicating a strong correlation between the classification and the field data. At the class level, the Producer Accuracy (PA) reaches 100% for the first scenario and exceeds 91% for the other two scenarios, indicating a very low rate of omission errors and a good ability to correctly identify classes. In contrast, the User Accuracy (UA) ranges between 74% and 77%, indicating the presence of commission errors related to the spectral similarity between the degraded olive orchard and other crop classes. The F1 score, which combines PA and UA, shows values between 82% and 87%.

**Figure 10.** Land cover map derived from three classification scenarios: (a) spectral bands; (b) spectral bands and NDVI; (c) spectral bands and vegetation indices.

The SVM classification according to the first scenario, which is based solely on spectral bands, showed a producer accuracy (PA) of 100%. This means that all olive tree sampling

pixels were classified correctly without any omission errors. However, the user accuracy (UA) shows an accuracy of 76.77%. This value indicates that there are commission errors, i.e., some pixels that were classified as olive trees actually belong to other classes. These errors are due to the spectral similarity between degraded olive groves and other types of vegetation, as well as the heterogeneity of agricultural plots containing several types of vegetation.

No crops class exhibited excellent classification performance in all scenarios, with PA values close to 100% and UA values above 97%, indicating minimal omission and commission errors and strong spectral separability from vegetated classes. Similarly, the urban class showed stable and high accuracies, with PA values around 97.8% and UA consistently reaching 100%, highlighting the clear distinction between built-up areas and surrounding land covers. In contrast, the other crops class was characterized by low PA values (16.91–19.06%), indicating that a large proportion of reference pixels were misclassified, while its UA reached 100% in all scenarios, suggesting a conservative classification in which only pixels with highly distinctive spectral signatures were assigned to this class. The water class displayed variable and generally low performance, with PA decreasing from 50% in Scenario 1 to 0% in Scenarios 2 and 3, a result likely related to the small size of water bodies and their spatial localization within olive orchard parcels, which makes their spectral separation more difficult.

Overall, the similarity of accuracy patterns across the three scenarios indicates that increasing the complexity of input features did not lead to substantial improvements in classification accuracy for the different land-cover classes.

In terms of spatial representation, the second and third scenarios offer a significant advantage. The integration of spectral indices has made it possible to better highlight the boundaries of plots and uncultivated areas, resulting in a clear demarcation of the edges. This spatial improvement can be explained by the ability of spectral indices to minimize the effect of bare soil and enhance cultivated plots, particularly in transition areas between olive trees or at the edges of plots (Figure 11).

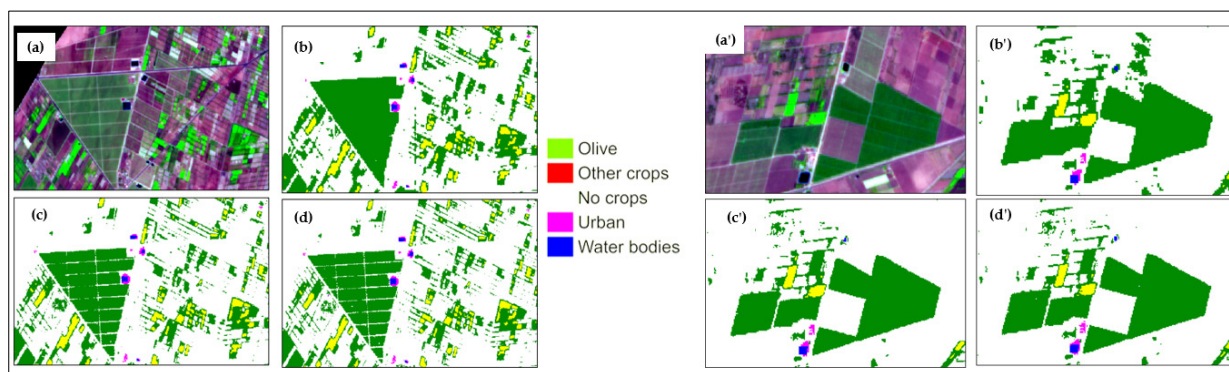


Figure 11. Zoomed-in view of agricultural parcels showing RGB imagery (a,a') and crop classification results (b,b') scenario 1, (c,c') scenario 2 and (d,d') scenario 3.

3.5. Post Classification

To quantify spatial changes in olive trees and monitor their spatiotemporal dynamics between 2016 and 2024, a thematic change analysis was conducted. This method is based on post-classification comparison, which involves cross-referencing two land-cover maps derived from supervised classifications of images acquired during the corresponding periods. By comparing the classified maps directly, it becomes possible to identify gains, losses, and stable areas, providing a precise assessment of land-use transitions within the study area. This approach is particularly valuable for evaluating the effects of climate variability

on olive groves and for supporting adaptive management strategies aimed at maintaining the sustainability of irrigated agriculture in semi-arid regions. The principle behind this method is to compare each pixel between the two dates in order to identify transitions between classes. This enabled us to generate a change map showing the dynamics: loss or gain of olive trees, or no change.

The post-classification change detection analysis provides a detailed assessment of olive tree dynamics within the Beni Amir perimeter between 2016 and 2024. By comparing each pixel in land-cover maps derived from supervised classifications of images acquired at both dates, the method identifies three main types of change: stable areas, where olive trees persisted throughout the study period; loss areas, where olive groves were converted to other land-cover types; and gain areas, corresponding to newly established olive plantations on previously non-olive land. The transition matrix analysis of land cover within the Beni Amir perimeter demonstrates substantial spatial and temporal changes in olive cultivation between 2016 and 2024. In 2016, olive groves occupied approximately 12,824 ha, but by 2024 this area had contracted dramatically to 3630 ha, representing a loss of about 72% over the eight years. The largest portion of this decline corresponds to areas converted into non-cultivated land; approximately 10,091 ha of olive groves were abandoned and converted into non-cultivated land, representing the largest single type of land cover change for olives during this period, reflecting a widespread abandonment of olive orchards likely caused by recurring droughts, water scarcity, and environmental stress. A much smaller portion of olive groves, approximately 295 ha, was converted to other crops, whereas the stable olive areas, totaling around 2431 ha, remained limited and were primarily concentrated in well-irrigated plots managed sustainably. Meanwhile, new olive plantations appeared on lands that were previously left fallow as well as on areas formerly occupied by other crops, reflecting targeted replanting initiatives and the adoption of drought-tolerant varieties. During the same period, non-cultivated land expanded markedly, growing from 18,703 ha in 2016 to 28,177 ha in 2024, and became the dominant land cover type across the study area. Urban and water-covered areas increased only slightly, indicating that the main driver of land cover change is the abandonment of agricultural land rather than urban expansion. These dynamics are clearly illustrated in Figure 12, which provides a visual comparison of land cover areas and transitions between 2016 and 2024, highlighting gains, losses, and stable zones for each class.

The results reveal pronounced dynamics in olive orchard distribution between 2016 and 2024, with a clear dominance of olive loss (72%), while stable olive areas account for 19% and gains remain limited to 9%. This imbalance highlights a marked contraction of olive cultivation within the study area over the analyzed period. The prevalence of loss suggests that olive orchards have been particularly vulnerable to recent environmental and land-use pressures, despite the irrigated context of the perimeter. The relatively low proportion of stable olive areas indicates that long-term persistence of orchards is spatially constrained and linked to local factors, including the availability of irrigation infrastructure, soil properties, farm management practices, and olive tree varieties. In contrast, the relatively small proportion of olive gains reflects a cautious expansion process, suggesting that new plantations have been established primarily to offset widespread losses and to introduce varieties better adapted to increasing water scarcity. This pattern points to a restructuring rather than a simple redistribution of olive cultivation across the landscape.

Summarily, the results underline that recent olive orchard dynamics are dominated by contraction processes, with important implications for the sustainability of olive cultivation in the region. The strong contrast between loss, stability, and gain categories provides a clear spatial framework for identifying priority areas where adaptive management strategies may be required to mitigate further decline.

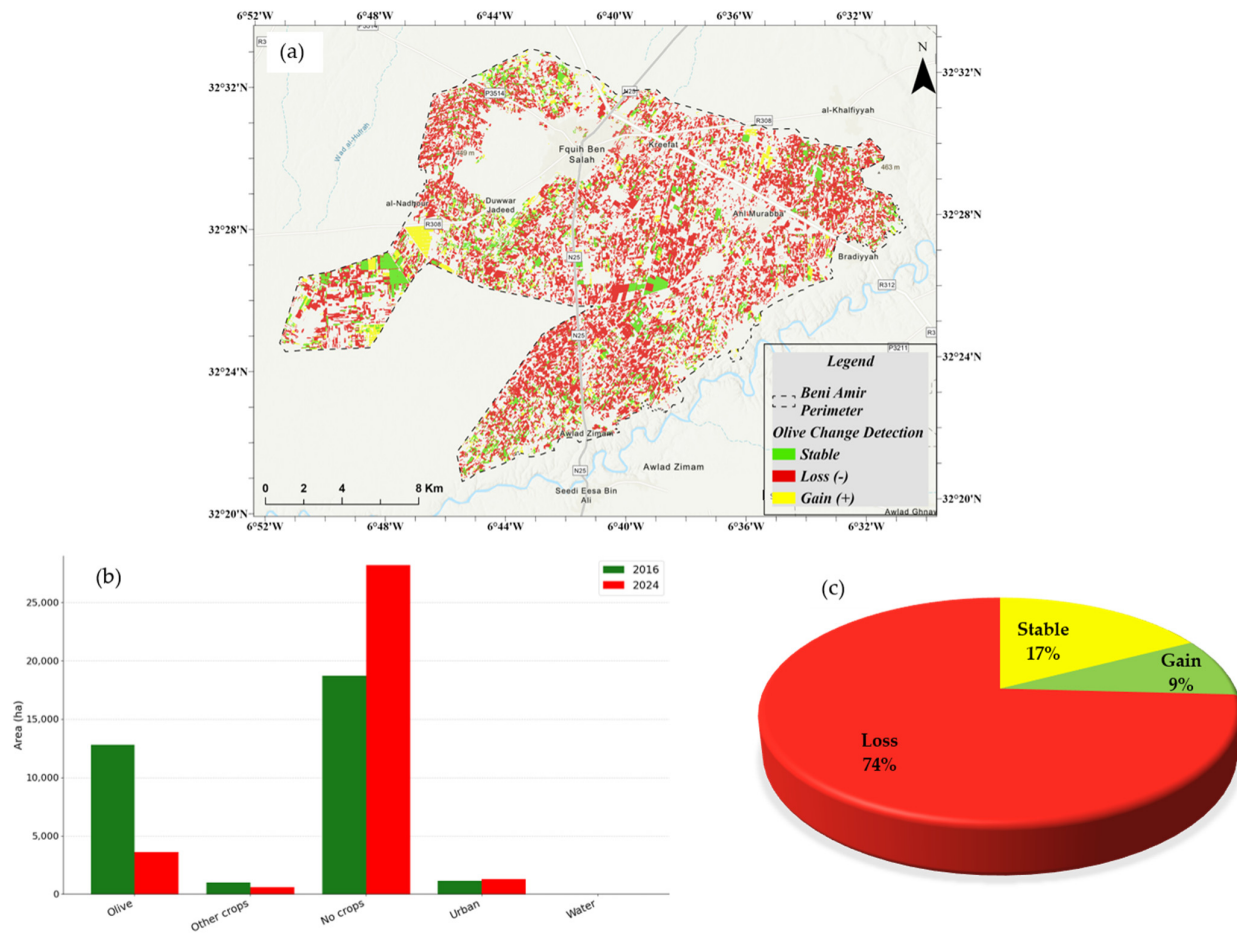


Figure 12. (a) Post-classification change map (2016–2024) illustrating the spatial dynamics of olive groves; (b) Comparison of land cover change areas across different classes; (c) Distribution of olive orchard dynamics between 2016 and 2024.

4. Discussion

4.1. Drought Dynamics and Vegetation Response

The study highlights a strong association between drought conditions and olive groves dynamics based on satellite observations from Sentinel-2 and CHIRPS data. The analysis of precipitation data and calculation of the SPI-12 were conducted to identify dry and wet periods between 2015 and 2021. The results reveal an alternation between dry and wet conditions from 2015 to 2021; however, since September 2021, dry conditions have become dominant. This finding is consistent with the results reported by Oussaoui et al. [28], who identified September 2021 as the beginning of a major drought episode in the region. This period marked the start of a severe rainfall deficit compared to long-term average conditions in the region. The start of this episode coincides with a notable deterioration in vegetation cover, clearly visible in the annual color composites (Figure 3). To capture this deterioration, an analysis of NDVI time series in two distinct areas revealed that, from the end of 2021, seasonal dynamics became increasingly altered. This was reflected in a marked decline in NDVI values and shifts in the timing of the growing season, with, in some cases, a disruption of typical seasonal patterns. In addition, the NDVI time series and the SPI-12 exhibited a positive relationship, with strong correlations ranging between 0.55 and 0.61. Furthermore, trend analysis revealed statistically significant decreasing trends in both NDVI and SPI-12, indicating a concurrent decline over the study period (Table 5).

4.2. Land-Cover Classification and Olive Grove Decline

The post-classification analysis further revealed substantial changes in olive grove extent. Although the classification results achieved high overall accuracies (OA > 94%) and Kappa coefficients exceeding 0.90, some uncertainty remains associated with the detected land-cover transitions. This slight uncertainty is mainly related to potential classification errors, particularly in areas where degraded olive groves exhibit spectral responses similar to those of other crops or sparsely vegetated surfaces. Moreover, the post classification between 2016 and 2024 showed a sharp decline in olive groves, from approximately 12,824 ha in 2016 to 3630 ha in 2024, corresponding to a loss of about 72% of the initial olive-growing area. Consequently, the estimated transition areas should be interpreted as approximations of change rather than exact values. Nevertheless, the high classification performance supports the reliability of the overall spatial patterns and trends identified in this study.

4.3. Ecological Implications and Study Limitations

The observed vegetation dynamics indicate a progressive decline in olive grove condition under prolonged drought stress. The response of vegetation to this climatic variability is characterized by a progressive decline in NDVI values, reflecting reduced canopy vigor and photosynthetic activity, accompanied by disruptions in seasonal growth patterns and increased sensitivity of olive groves to prolonged drought conditions, particularly at the interannual scale. Overall, this dynamic suggests limited vegetative growth and a more pronounced state of stress in the vegetation. Some limitations should be considered when interpreting the results of this study. The observed vegetation responses cannot be attributed solely to climatic variability, as olive grove dynamics are also likely associated with other interacting factors, including irrigation practices, soil properties, temperature extremes, and management conditions, which may modulate the magnitude and spatial expression of the observed NDVI changes.

4.4. Future Research Perspectives

Building on these findings, future studies could integrate additional environmental indicators and extend the analysis to other regions in order to further validate and improve the proposed approach. Furthermore, future research should also aim to disentangle the combined effects of climatic, agronomic, and socio-economic drivers by incorporating high-resolution irrigation data, farm management records, and pest/disease monitoring, thereby enabling a more robust attribution of observed land-cover changes.

5. Conclusions

This study provides an integrated spatio-temporal assessment of drought conditions and vegetation dynamics in the Beni-Amir irrigated perimeter by combining CHIRPS precipitation data, the Standardized Precipitation Index (SPI-12), Sentinel-2 satellite imagery, and a Support Vector Machine (SVM) classification framework. The analysis highlights noticeable temporal variability in precipitation patterns over the study period, together with corresponding variations in vegetation indices and phenological behavior of olive orchards. The results indicate a coherent relationship between hydro-climatic variability and vegetation dynamics, where periods characterized by lower precipitation levels are generally associated with reduced vegetation vigor and altered seasonal patterns. However, these findings should be interpreted in terms of association rather than direct causation, as additional environmental, agronomic, and management-related factors may also contribute to the observed variability. The post-classification change detection analysis reveals a substantial reduction in olive orchard extent between 2016 and 2024, with a 72% reduction rate.

The proposed methodological framework demonstrates the effectiveness of integrating remote sensing data, drought indices, and machine learning techniques for monitoring agricultural systems under semi-arid conditions. However, its transferability to other regions should be considered with caution, as performance may depend on local climatic conditions, crop structure, data availability, and management practices. Overall, this study provides useful insights into the spatio-temporal dynamics of olive orchards under climate variability and offers a scalable approach for vegetation monitoring, while highlighting the importance of considering methodological limitations and contextual factors in the interpretation of results.

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