BIO Web of Conferences **211**, 01006 (2026) https://doi.org/10.1051/bioconf/202621101006
ICWES 2025

Monitoring drought-induced degradation of olive and citrus tree crops in the Tadla plain (Morocco) with multi-sensor remote sensing

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Abstract. The Tadla plain, located in central Morocco, has experienced ongoing drought episodes in recent years, causing significant degradation of citrus orchards and olive groves. This study aims to evaluate the changes in these crops from 2018 to 2024 using multi-sensor satellite data (Sentinel-1 and Sentinel-2) and a supervised classification algorithm, the Support Vector Machine (SVM). To characterize the vegetation and water conditions of the crops, several biophysical indices were extracted, including the Normalized Difference Vegetation Index (NDVI), the Modified Soil-Adjusted Vegetation Index (MSAVI), the Normalized Difference Water Index (NDWI), and the Normalized Difference Moisture Index (NDMI). These indices help assess vegetation vigor, biomass, and water stress. Combining optical and radar data improved the detection of degraded areas, especially in sectors exposed to high water stress. Applying the SVM classifier to the combined Sentinel-1 and Sentinel-2 data achieved a high overall accuracy (OA) of 0.927, confirming the reliability of the mapping for monitoring the ongoing degradation of orchards. The diachronic analysis of cultivated areas shows a significant decline: citrus orchards lost about 38% of their area from 2019 to 2024, while olive groves decreased by 32%. At the same time, the reduction in vegetation and water indices indicates a decline in biomass, photosynthetic activity, and leaf water content, highlighting the combined effects of drought and groundwater overexploitation. These findings demonstrate the effectiveness of integrating remote sensing with machine learning techniques for environmental monitoring and agricultural planning. They offer a strategic tool to predict the impact of water stress on perennial crops and support the development of sustainable water management practices in vulnerable regions.

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1 Introduction

Climate change is one of the major factors destabilizing agricultural ecosystems in Mediterranean and semi-arid regions. The increasing frequency and intensity of droughts compromise crop resilience and exacerbate pressure on limited water resources [1]. In Morocco, particularly in the Tadla plain, recurrent droughts over the past decade have significantly impacted perennial crops, notably olive trees and citrus orchards, which constitute a key component of the regional agricultural economy [2].

Assessing the degradation of these agricultural systems requires reliable approaches capable of providing high-resolution spatio-temporal information. In this context, satellite remote sensing is a particularly suitable tool. Optical data from Sentinel-2 enable monitoring of vegetation dynamics through spectral indices such as NDVI and EVI, which are widely used to characterize crop health [3]. Meanwhile, Sentinel-1 radar data, which are insensitive to cloud cover, provide complementary information on vegetation structure and soil moisture, enhancing the detection of water stress and degraded areas [4].

Furthermore, the integration of machine learning techniques has significantly improved the classification of agricultural covers from multi-sensor imagery. Algorithms such as Random Forest (RF) and Support Vector Machine (SVM) have proven particularly effective in contexts of high spatial heterogeneity [5]. Several studies have shown that combining optical and radar data with these methods allows reliable crop discrimination and detailed assessment of climate change impacts on agriculture [6].

In this context, the present study aims to assess the degradation of citrus and olive orchards in the Tadla plain between 2018 and 2024 using Sentinel-1 and Sentinel-2 imagery combined with an SVM classifier. The objective is to quantify degraded areas, analyze the spatio-temporal dynamics of citrus and olive orchards, and provide insights into the effects of recurrent droughts on regional agriculture.

2 Materials and Methods

The present study was conducted in the Tadla plain (Figure 1), located in central Morocco, considered one of the country's main agricultural basins. This region is characterized by a semi-arid climate, marked by high interannual variability in precipitation (200–400 mm/year) and an increasing reliance on groundwater resources for irrigation [7]. The main tree crops in the area are olive and citrus orchards, whose productivity has significantly declined in recent years due to repeated rainfall deficits and overexploitation of the aquifer [8].

The data used was sourced from two complementary platforms. On one hand, optical Sentinel-2 images (spatial resolution of 10–20 m) covering the period 2018–2024 enabled the calculation of several vegetation indices, including the NDVI (Normalized Difference Vegetation Index), EVI (Enhanced Vegetation Index), SAVI (Soil Adjusted Vegetation Index), and GNDVI (Green Normalized Difference Vegetation Index), widely used to assess vegetation vigor and canopy density [3]. On the other hand, Sentinel-1 radar data in VV and VH polarization were utilized to extract textural parameters derived from the Gray-Level Co-occurrence Matrix (GLCM), such as variance, correlation, and entropy, allowing characterization of canopy structure and response to water stress [9].

Data preprocessing included generating a monthly NDVI to exclude areas with low vegetation activity (NDVI ≤ 0.2), followed by an intersection to retain only pixels with NDVI > 2, representing vegetation present throughout the year, mainly citrus and olive trees. A summer Sentinel-2 composite (July–August) was then produced to represent peak water stress conditions. Spectral bands, vegetation indices, and radar textures were combined into a multi-band image, integrated, and processed on the Google Earth Engine platform.

Supervised classification was performed using the SVM classifier, employing balanced samples representing the classes "citrus" and "olive" (Figure 1). The dataset was split into two subsets, with 70% used for training and 30% for validation. Classification quality was assessed using a confusion matrix and standard metrics such as overall accuracy (OA). Finally, areas classified as citrus and olive orchards were extracted, quantified, and vectorized to produce polygons suitable for spatial analysis.

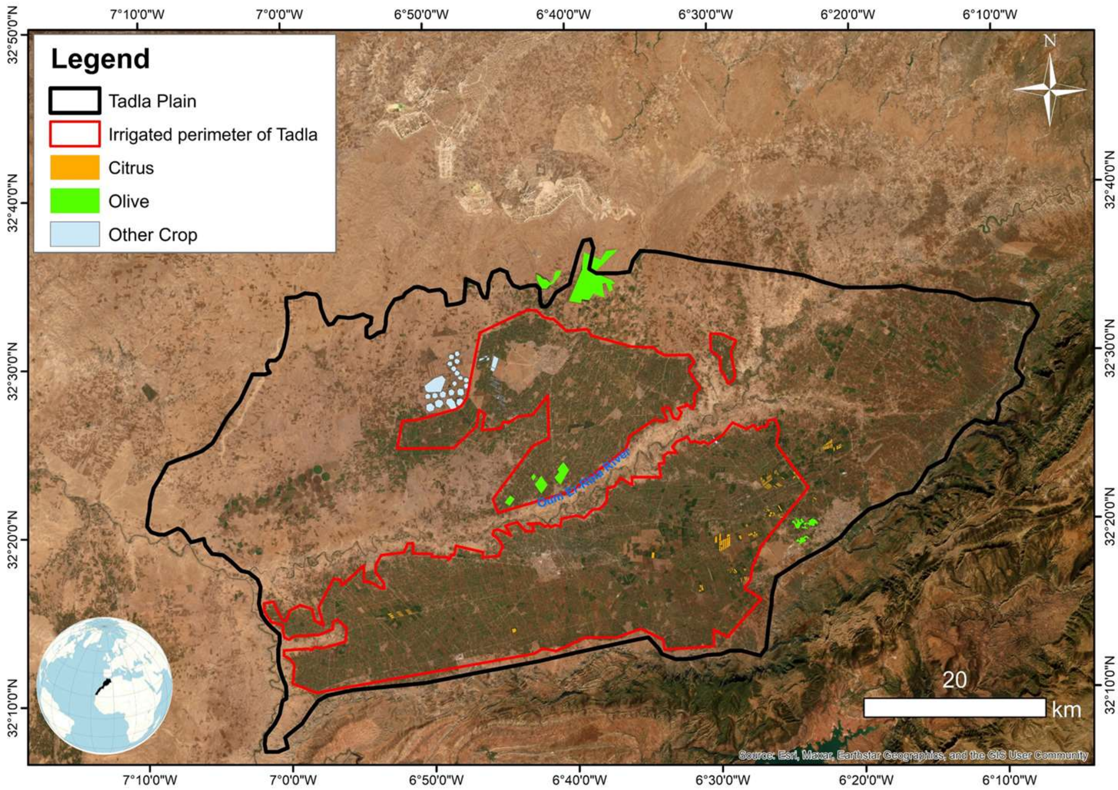

Fig. 1. Location of the Tadla plain showing the two irrigated perimeters as well as the training and validation zones used for citrus, olive, and other crop classes.

The physiological status of citrus orchards was monitored using several vegetation and moisture indices derived from Sentinel-2 imagery, allowing the assessment of canopy vigor, biomass, and water stress. The NDVI is a classical index that measures vegetation density and vigor (Equation 1) and is widely used to detect crop health and photosynthetic activity [10].

$$NDVI = \frac{NIR-RED}{NIR-RED} \qquad (1)$$

The Modified Soil-Adjusted Vegetation Index (MSAVI) (Equation 2) corrects for bare soil effects and improves biomass estimation, particularly useful in areas with sparse vegetation cover [11].

$$MSAVI = \frac{2NIR+\ \ \sqrt{(2NIR+\ \ )^2-8(NIR-R\ \ \ )}}{2} \qquad (2)$$

Water stress in citrus orchards was monitored using the Normalized Difference Water Index (NDWI) (Equation 3) [12] and the Normalized Difference Moisture Index (NDMI) (Equation 4) [13].

$$NDWI = \frac{GREEN-NIR}{GREEN+NIR} \qquad (3)$$

$$NDMI = \frac{NIR-SWIR}{NIR-SWIR} \qquad (4)$$

3 Results and Discussion

The supervised classification performed using the SVM classifier showed high performance, with an overall accuracy of 0.927, confirming the robustness of this approach for discriminating against citrus orchards, olive groves, and other crops from multi-source satellite data. These results are consistent with the findings of Mountrakis et al. (2011) and Khatami et al. (2016), which highlight the effectiveness of SVM in complex agricultural contexts [14, 15].

The diachronic analysis of cultivated areas reveals a concerning regression of the two studied crops (Figures 2 and 3). Citrus orchards decreased from 9,845 ha in 2019 to 6,115 ha in 2024, representing a loss of approximately 38%, with a particularly marked contraction from 2022 onwards. Olive groves, traditionally considered more resilient to climatic constraints, also experienced significant degradation, with a 32% decrease in area between 2019 and 2024. These observations indicate that even water-efficient crops, such as olive trees, are not immune to the combined impacts of climate change and anthropogenic pressures.

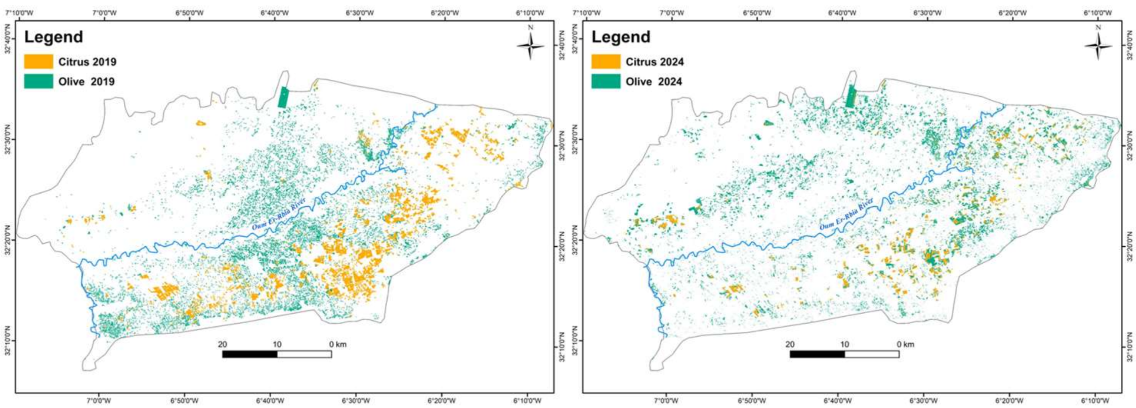

Fig. 2. Spatial distribution and evolution of citrus and olive orchards in the Tadla plain between 2019 and 2024.

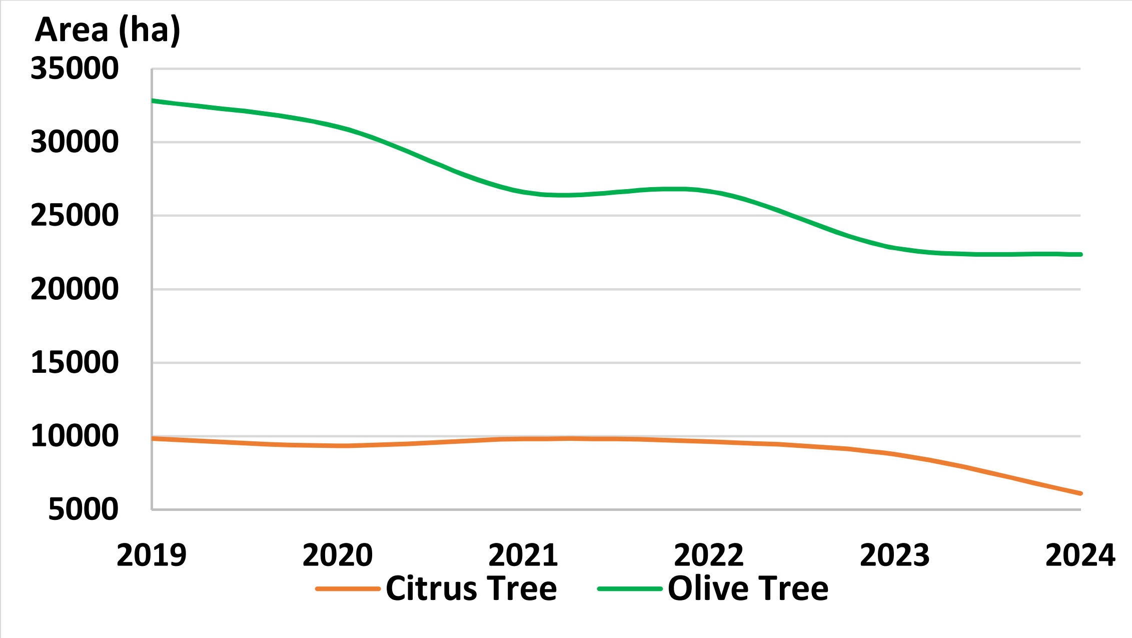

Fig. 3. Evolution of citrus and olive orchard areas in the Tadla plain between 2019 and 2024.

The analysis of vegetation and moisture indices (NDVI, MSAVI, NDMI, and NDWI) over the period 2019–2024 confirms this trend (Figure 4). For citrus orchards, NDVI and MSAVI decreased from 0.54 to 0.38, while for olive groves, they dropped from 0.51 to 0.34, indicating a reduction in canopy vigor and density as well as a decline in photosynthetic activity and biomass. Moisture indices (NDMI and NDWI) reveal a decrease in leaf water content, particularly pronounced for olive trees (from 0.12 to 0.07), highlighting their vulnerability to prolonged drought episodes.

Although citrus orchards generally show higher index values than olive groves due to initially denser biomass and higher water demand, their sensitivity to irrigation deficits makes them particularly susceptible to interannual fluctuations. Olive trees, known for their relative drought tolerance, nonetheless exhibit a continuous decline in their indices, confirming the impact of groundwater overexploitation on their sustainability in the studied area.

Fig. 4. Evolution of vegetation and water indices (NDVI, MSAVI, NDWI, and NDMI) in citrus orchards and olive groves over the period 2019–2024.

4 Conclusion

This study evaluated the evolution of citrus orchards and olive groves in the Tadla plain between 2018 and 2024 using multi-sensor satellite data and supervised classification with an SVM. The method demonstrated high performance (OA = 0.927), ensuring reliable mapping of degraded areas.

The results reveal a significant reduction in cultivated areas, with losses of approximately 38% for citrus orchards and 32% for olive groves. The analysis of biophysical indices (NDVI, MSAVI, NDWI, and NDMI) confirmed a decline in canopy vigor and density, as well as a reduction in leaf water content, indicating increased water stress due to drought episodes and groundwater overexploitation.

These observations highlight the vulnerability of tree crop systems to climatic variability and water constraints. They also underscore the value of remote sensing and machine learning as effective tools for environmental monitoring and agricultural planning. These findings provide a foundation for the development of sustainable water management strategies and adaptation measures aimed at enhancing the resilience of tree crop systems under prolonged water stress.

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