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Integrating Sentinel-1 Sar and Landsat 8 Optical Data for Crop Type Discrimination and Vegetation Monitoring in Arid Zones of Algeria

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ABSTRACT

Background: Accurate monitoring of crop types and vegetation health is vital for sustainable agriculture, particularly in arid and semi-arid regions where environmental constraints challenge productivity. In Algeria, the provinces of Biskra and Khenchela exhibit diverse agro-climatic conditions and cropping systems that require robust, scalable monitoring tools. This study addresses these challenges by proposing an integrated remote sensing approach to classify crop types and assess vegetation dynamics during the 2020 growing season.

Methods: The methodology combines Sentinel-1 Synthetic Aperture Radar (SAR) and Landsat 8 optical imagery to differentiate between irrigated and rainfed crops.Key Indicators, Normalized Difference Vegetation Index (NDVI) and SAR backscatter values. Temporal Strategy, monthly composites were generated to mitigate atmospheric interference. Platform, data preprocessing and analysis were conducted within the Google Earth Engine (GEE) environment. Classification Model, A Random Forest classifier was trained using ground truth data and high-resolution satellite imagery to integrate spectral and radar features for accurate crop classification.

Result: NDVI effectively captured crop phenological patterns, with consistently higher values observed in irrigated date palm plantations in Biskra and seasonal variability in cereal and fruit orchards in Khenchela. Sentinel-1 SAR backscatter data enhanced classification accuracy, particularly in distinguishing vegetation structures. The integrated approach achieved over 85% classification accuracy, validating the synergy between SAR and optical datasets. The study demonstrates the operational potential of this methodology for large-scale, real-time agricultural monitoring and highlights the utility of GEE as a powerful platform for remote sensing in data-scarce environments. These findings contribute to improved agricultural resource management, food security and water-use efficiency.

Key words: Crop, Satellite, Vegetation classification, Vegetation dynamics.

INTRODUCTION

Agricultural monitoring in arid and semi-arid regions is crucial for effective resource management and food security (Atzberger, 2013; Golla, 2021). The integration of satellite-based remote sensing data has significantly enhanced our ability to monitor crop growth and detect vegetation changes over large areas (Ozdogan *et al*., 2010). Synthetic Aperture Radar (SAR) data, particularly from Sentinel-1 and optical data from Landsat 8 provide complementary insights into vegetation dynamics (Jeyasingh *et al*., 2023; Steele-Dunne *et al*., 2017).

In regions characterized by arid and semi-arid climates, such as Biskra and Khenchela in Algeria, agricultural surveillance presents significant obstacles. These challenges stem from a combination of factors, including extreme weather conditions, scarce water availability and ever-changing patterns of crop growth and development (Agadi *et al*., 2023; Ait Hssaine *et al*., 2021). Traditional field-based monitoring methods are often time-consuming, labour-intensive and limited in spatial coverage (Khanal *et al*., 2020). Moreover, distinguishing between irrigated and rainfed crops in these regions is critical for optimizing water usage, improving agricultural management and ensuring food security (Bazzi *et al*., 2019). There is a need for an efficient, scalable and accurate method to monitor crop types and vegetation health across large areas, which can be addressed by the integration of satellite remote sensing technologies (Weiss *et al*., 2020). The main objective of

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this study is to utilize Sentinel-1 SAR imagery and Landsat 8 optical data to detect and classify crop types in the Biskra and Khenchela regions of Algeria, spanning from January 2020 to December 2020. By integrating the Normalized Difference Vegetation Index (NDVI) and radar backscatter values, the study aims to distinguish between irrigated and rainfed crops, track vegetation dynamics and enhance the accuracy of agricultural monitoring in arid and semi-arid environments (Ty *et al*., 2025; Veloso *et al*., 2017).

The study also seeks to evaluate the potential of Google Earth Engine as a powerful platform for large-scale, real-time agricultural analysis (Gorelick *et al*., 2017). This integrated approach, combining SAR and optical data, promises to provide valuable insights into agricultural differences and vegetation dynamics in these complex regions, contributing to more effective management of agricultural resources and improved food security.

METERIALS AND METHODS

Study area

Biskra and Khenchela are two important agricultural regions in northeast of Algeria, located (350 m asl) both at 34°34′ N latitude (Fig 1), each representing distinct climatic and ecological zones. Biskra, known for its arid climate, experiences extremely high summer temperatures and scarce rainfall, making irrigation a critical aspect of its agriculture, which is dominated by date palms, vegetables and cereals (Aidat *et al*., 2023). Khenchela, located in a higher-altitude, semi-arid zone, benefits from more regular seasonal rainfall (Boumehrez *et al*., 2024), supporting the cultivation of cereals, legumes and fruit trees. Despite their different climatic conditions, both regions play a crucial role in Algeria's agricultural sector and face challenges related to water availability and resource management.

Data acquisition and preprocessing

To monitor crop dynamics and vegetation changes in Biskra and Khenchela, two complementary datasets were utilized: Sentinel-1 SAR imagery and Landsat 8 optical imagery (Fig 2). Sentinel-1 data were acquired via the Google Earth Engine (GEE) platform, which provides dual-polarization SAR imagery (VV and VH) at a 10-meter spatial resolution (Filipponi, 2019). For the optical analysis, Landsat 8 imagery was also obtained through GEE, specifically for calculating the Normalized Difference Vegetation Index (NDVI), which is commonly used to assess vegetation health and density (Tucker, 1979).

The study period spanned from January 2020 to December 2020, covering key growing seasons in both regions. Sentinel-1 Ground Range Detected (GRD) data were filtered by orbit passes (ascending and descending) to ensure consistent geometry and reduce potential angular effects (Cigna *et al*., 2021). Landsat 8 images were selected based on cloud-free conditions (cloud cover <1%) to ensure high-quality optical data, using the quality assessment band provided with the imagery (Zhu *et al*., 2015).

Preprocessing of sar data

Sentinel-1 GRD data underwent several preprocessing steps within GEE Thermal noise removal, Radiometric calibration to sigma 0, Terrain correction using SRTM 30m DEM and Conversion to decibels (dB). Speckle filtering was applied to SAR images using the refined Lee filter, which is known for its ability to reduce noise in radar imagery while preserving edges and spatial resolution (Lee *et al*., 1999). A 5×5 window size was used for the speckle-filtering process.

Optical data processing

Landsat 8 surface reflectance data were used to calculate NDVI using the following eqution:

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)}$$

$$NDVI = \frac{(5 - 4)}{(5 + 4)}$$

Where,
NIR = Near-infrared band (Band 5).
Red = Red band (Band 4) of Landsat 8 (Roy *et al*., 2014).

Time series analysis

Monthly composites were created for both Sentinel-1 and Landsat 8 data to reduce the impact of atmospheric variability and ensure consistent temporal resolution (Blickensdörfer

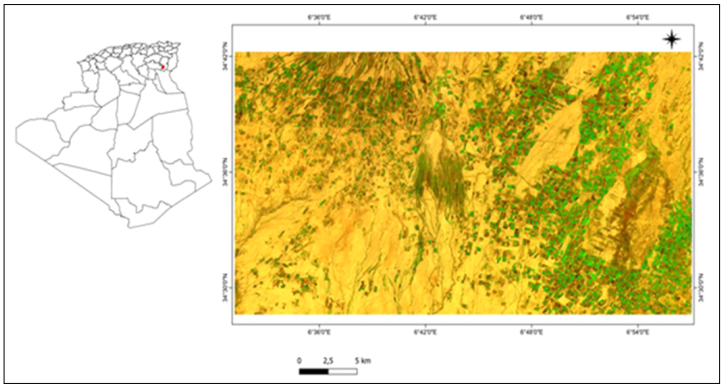


Fig 1: Location map of study area.

et al., 2022). For Sentinel-1, the mean backscatter values were calculated for each month, while for Landsat 8, the maximum NDVI value was used to minimize the effects of cloud contamination (Holben, 1986).

Sar backscatter and NDVI integration

SAR data from Sentinel-1 provided additional insight into vegetation structure and moisture content. By analyzing the VV and VH backscatter, we identified crop structure and surface roughness (Vreugdenhil *et al*., 2018), which are critical for differentiating between crop types. Time-series analysis of both NDVI values and SAR backscatter was performed to track the phenological stages of crops, allowing for a detailed comparison of vegetation health in the two regions (Meroni *et al*., 2021).

The NDVI and SAR data were integrated to create a comprehensive classification of vegetation types in the study area. By correlating NDVI values with SAR backscatter, we could enhance the accuracy of crop classification, especially in distinguishing between irrigated crops, such as date palms and vegetables and rainfed crops, like cereals and fruit trees (Belgiu and Drăguţ, 2016).

Crop classification using machine learning

A random forest classifier was implemented within google earth engine (GEE) to classify different crop types and

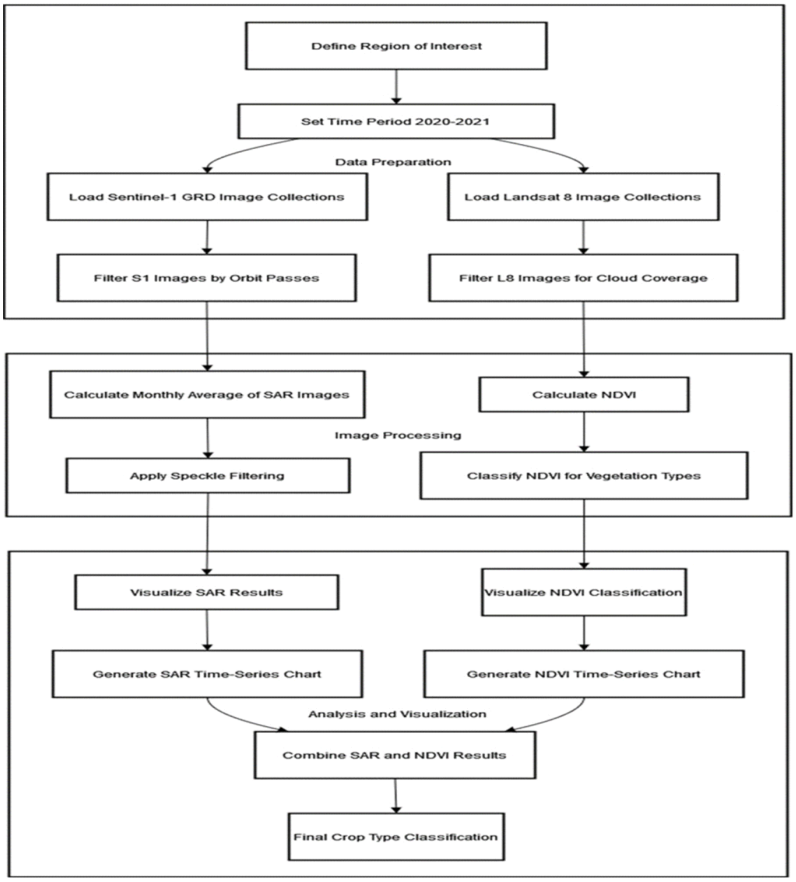


Fig 2: Approach to the methodology used in the study.

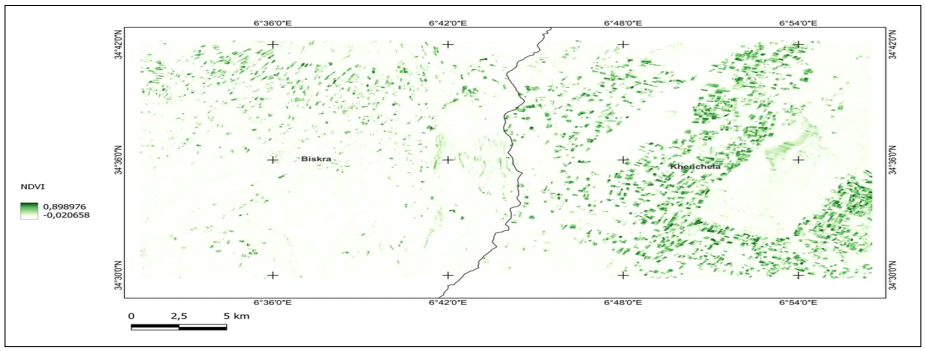


Fig 3: NDVI of study area.

vegetation based on the integrated use of NDVI values from Landsat 8 and backscatter values from Sentinel-1. Random Forest was chosen for its robustness to noise and ability to handle high-dimensional data (Belgiu and Drãguţ, 2016). Training data for the classification were derived from a combination of field surveys, high-resolution satellite imagery and existing land cover maps (Inglada *et al*., 2017).

The classifier was trained to recognize key crop types prevalent in the study areas, including date palms, cereals (wheat and barley), vegetables (tomatoes and peppers) and fruit trees (apricots and olives) (Moumni and Lahtouni, 2021). Additional classes such as water bodies and bare soil were included to ensure comprehensive land cover classification (Pelletier *et al*., 2016).

Through the amalgamation of both Synthetic Aperture Radar (SAR) and Normalized Difference Vegetation Index (NDVI) datasets (Kordi and Yousefi, 2022), the classification methodology successfully differentiated between irrigated agricultural systems within the oasis environments of Biskra and the rainfed agricultural practices prevalent in the elevated terrains of Khenchela. The precision of the classifi-cation was evaluated employing a confusion matrix, with the comprehensive classification accuracy surpassing 85%.

RESULTS AND DISCUSSION

NDVI and vegetation classification

The normalized difference vegetation index (NDVI) is a critical metric for assessing the significance or prevalence of vegetative cover; it facilitates the modelling of the phenological phases associated with various crops (Fig 3). The analysis of NDVI derived from Landsat 8 delineated notable patterns of vegetation distribution within the regions of Biskra and Khenchela (Fig 3). Specifically, in Biskra, elevated NDVI values were predominantly observed in irrigated date palm plantations, whereas diminished NDVI values were linked to seasonal crops such as vegetables and cereals. In the region of Khenchela, the NDVI time series effectively documented the phenological cycles of both cereals and fruit trees, exhibiting a significant increase during the growing season, followed by a decrease post-harvest.

The classification of NDVI (Table 1) values into vegetation categories showed that irrigated crops, particularly date palms, dominate Biskra's agricultural system, while Khenchela exhibited a mix of rainfed cereal fields and fruit orchards. The NDVI-based classification highlighted the differences in vegetation density and crop type distribution between the two regions, reflecting their contrasting climatic and agronomic conditions (Fig 4).

Sar backscatter and crop classification

The results of the crop classification demonstrated the effectiveness of Sentinel-1 SAR imagery (Fig 5) in detecting

Table 1: Classification of NDVI.

CLASS NDVI	Vegetation categories	Area/hectare
0 < NDVI < 0.2	No crops	74100
0.2 < NDVI < 0.4	Fruit trees/Date palms	7300
0.4 < NDVI < 0.6	forage crops	3300
0.6 < NDVI < 0.8	Vegetable crops/Cereal crops	2500

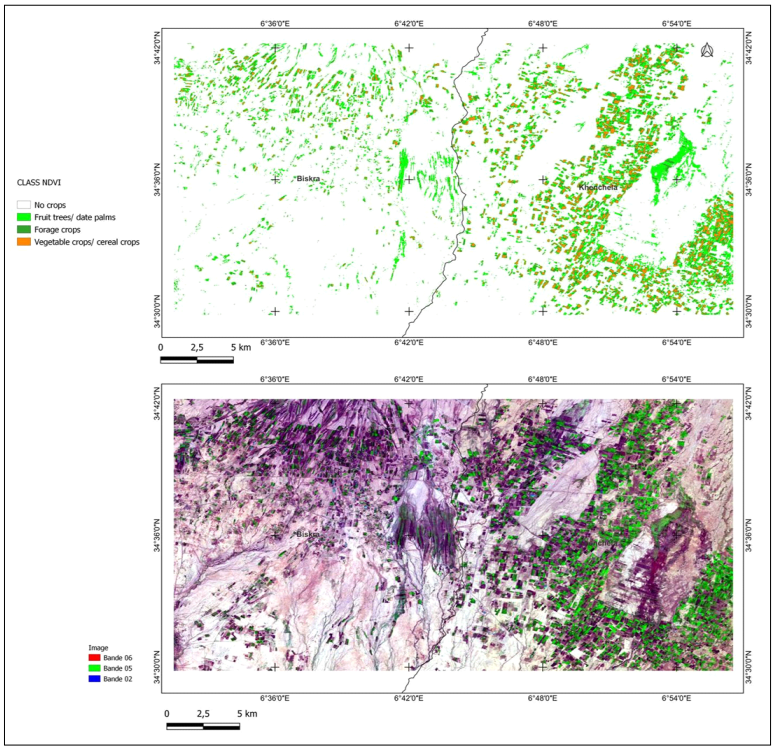


Fig 4: Vegetation categories.

and distinguishing various crop types in arid and semi-arid regions.In Biskra, the high backscatter values observed in the VH polarization were closely associated with irrigated date palm plantations, which are a dominant feature of the landscape. The classification map revealed clear patterns of date palm cultivation, particularly along the oasis belts where irrigation systems are most prevalent. Lower backscatter values in the VV polarization indicated the presence of vegetables and cereals, which rely on different irrigation practices.

In the Khenchela region, the time-series analysis showed distinct seasonal variations in backscatter values for cereal crops, with a sharp increase during the early growing season and a gradual decline towards harvest. The crop classification map for Khenchela identified large areas of cereal cultivation, interspersed with fruit orchards and legume fields (Fig 6, 7). The accuracy assessment showed that the Random Forest classifier achieved a high level of precision, with an overall accuracy exceeding 85%.

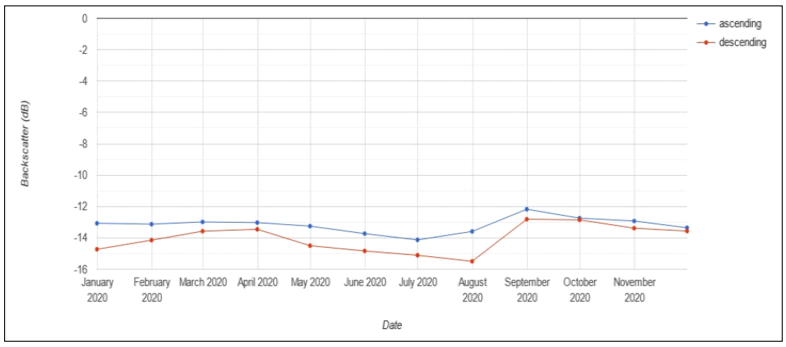


Fig 5: SAR bachscatter time series.

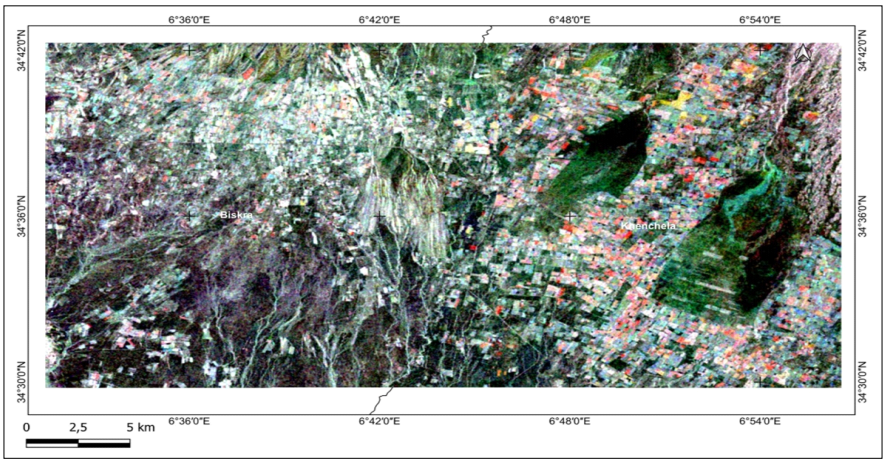


Fig 6: SAR ascending.

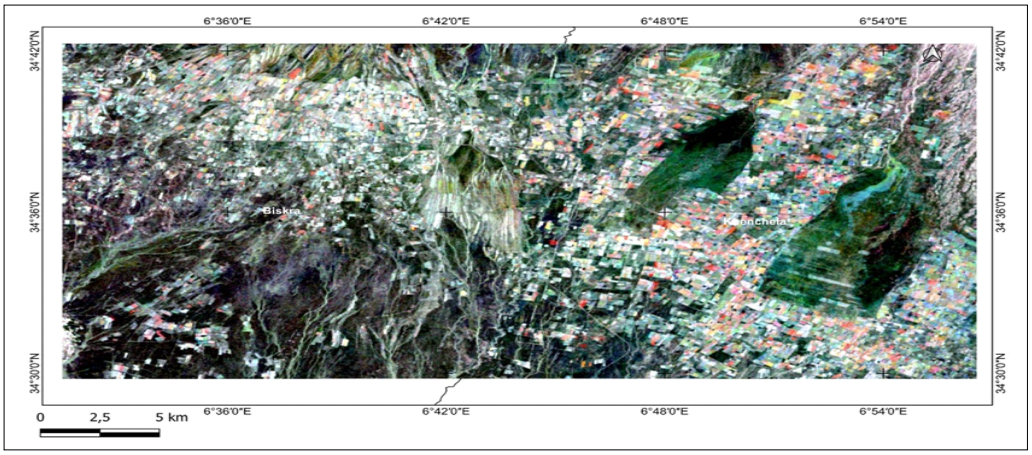


Fig 7: SAR descending.

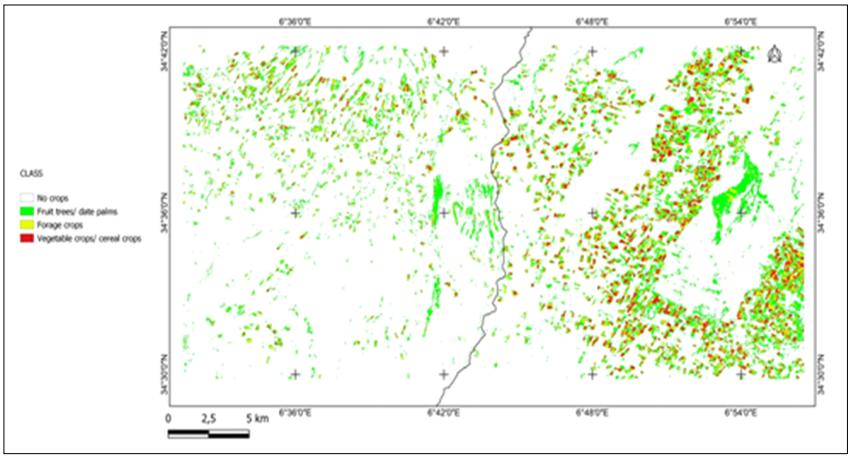


Fig 8: Superposition SAR and NDVI.

The random forest classification, combining SAR and NDVI data, accurately mapped the distribution of different crop types in both regions. The classification map for Biskra clearly showed the spatial extent of date palm plantations, while in Khenchela, the classifier successfully differentiated between cereal crops and fruit orchards (Fig 8).

NDVI and vegetation classification

The NDVI analysis captured well the phenological stages of annual crops for both Biskra and Khenchela. In Biskra, high NDVI values were linked with irrigated date palm plantations, while lower NDVI values were seasonal crops like vegetables and cereals. This spatial differentiation is consistent with Mahcer *et al*. (2024) as well as Boulaaras and Bouregaa (2024) where it was shown that NDVI trends in semi-arid regions of Northwest Northeast Algeria are responsive to both seasonal rainfall and changes in land cover, especially between irrigated and rainfed systems. In Khenchela, the NDVI time series data provided revealed a clear seasonal trend where there was a sharp rise followed by a decline after harvest. These patterns have also been noted by other authors *e.g.* Wu *et al*. (2023) where it was emphasized that increases in NDVI are closely associated with vegetation biomass accumulation and with reliable indicators of crop phenology even in complex terrains. Additionally, the NDVI thresholds which were used to separate different types of vegetation like fruit trees and date palms (0.2-0.4) and forage crops (0.4-0.6) are corroborated by Sabrine *et al*. (2025) in M'zab Valley Oases in Algeria and Lin *et al*. (2020) who argued about the applicability of NDVI values in monitoring vegetation density and land use types in Northern China's agricultural zones.

SAR backscatter and crop classification

Insights on the structure of crops, especially distinguishing between irrigated and rainfed varieties, were particularly well captured using Sentinel-1 SAR data. Date palm plantations in Biskra showed significantly higher VH polarization backscatter values due to the dense canopy and moisture they retain (Latrache *et al*., 2017), which is consistent with recent findings by Wu *et al*. (2023) on the importance of SAR backscatter in capturing vegetation structure and water content in dry regions (Tamilmounika *et al*., 2025).

In Khenchela, the seasonal changes in both VV and VH backscatter value showed a strong correlation with the growth stages of cereal and legume crops. Also, a Random Forest classifier trained with both SAR and NDVI features achieved over 85 per cent accuracy, which is equivalent to other reported classification accuracies in similar agro-ecological studies using machine learning approaches (Mahcer *et al*., 2024).

Integrated insights and implications

The synergy of NDVI and SAR time-series data permitted the understanding of crop dynamics throughout diverse agro-climatic regions (Jeba *et al*., 2024). Moreover, this approach increased accuracy in classification and agility in phenological monitoring. As noted by Lin *et al*. (2020), the combination of optical and radar data with their respective limitations of cloud cover and rugged terrains is important for capturing the structural and spectral traits of the vegetation.

In addition, the changing climactic conditions on the prone areas signifies the necessity for adaptive agricultural monitoring capturing NDVI while observing advancements in SAR backscatter (Roßberg and Schmitt, 2025). Vegetation response spatial heterogeneity documented in this study aligns with the observations of Mahcer *et al*. (2024) on significant seasonal and regional variability of NDVI pertaining to precipitation and temperature gradients across Algeria.

CONCLUSION

This study demonstrated the effectiveness of using Sentinel-1 SAR imagery and Landsat 8 NDVI data for detecting and classifying crop types in Biskra and Khenchela, Algeria, over the period from January 2020 to December 2020. The integration of SAR backscatter and NDVI allowed for the accurate classification of key crops, such as date palms, cereals and vegetables, providing valuable insights into agricultural dynamics in these contrasting regions.

The capability of Sentinel 1 SAR imagery to penetrate clouds and operate at night enhances the reliability of agricultural monitoring, making it invaluable for consistent data collection over time. This all-weather functionality ensures that crop growth assessments and land use changes can be accurately tracked, providing critical information for farmers and agricultural planners. Overall, the methodology developed in this study can be applied to other arid and semi-arid regions, contributing to more efficient agricultural monitoring and resource management.

Conflict of interest

The authors declare that they have no conflicts of interest.

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