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RESEARCH ARTICLE

Advanced mapping of mango orchards in Chittoor district through object-based image analysis approach using Sentinel-2 imagery

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Abstract

Mango is crucial in India's agricultural economy, particularly in the Chittoor District of Andhra Pradesh. As mango cultivation transitions from subsistence farming to large-scale commercial operations, accurate mapping and monitoring of mango plantations are essential for sustainable agricultural management. This study explored the application of Object-Based Image Analysis (OBIA) using high-resolution Sentinel-2 satellite imagery for mapping mango plantations in Chittoor District. OBIA, a more advanced approach than traditional pixel-based methods, integrates spectral, spatial and contextual data, enabling the identification of mango orchards with higher accuracy. Sentinel-2 multispectral bands were utilized to distinguish mango plantations based on canopy density, inter-row spacing and orchard layout. Ground-truth data collected from 531 points across the district validated the classification process. The results show that OBIA achieved an overall accuracy of 87.0 % with a Kappa index of 0.74, signifying strong agreement with the ground truth data and the total mango area mapped in Chittoor District is 97,006 hectares. This study highlights the effectiveness of OBIA for accurate mango area estimation and suggests potential improvements, including the integration of hyperspectral data and advanced algorithms. This study offers valuable insights for agricultural management, resource optimization and policy planning, with implications for broader crop mapping and precision agriculture applications.

Keywords: crop area estimation; mango; object-based image analysis; Sentinel 2

Introduction

Mango (*Mangifera indica* L.), renowned as the "king of fruits," is deeply rooted in Indian culture for its rich flavour, cultural significance and economic value. Mango cultivation plays a significant role in India's agricultural sector, particularly in states like Andhra Pradesh. India ranks first in global mango production, making it a crucial crop for its economy and rural livelihood (1). In India, the total mango cultivation area in 2022-23 is 2.346 million hectares, with Andhra Pradesh contributing 0.3988 million hectares (2). In the Chittoor District, mango orchards have transitioned from small-scale subsistence farming to large-scale commercial cultivation, significantly contributing to both regional and national economies. The economic importance of mangoes underscores the need for precise and efficient monitoring of their cultivation and distribution. Accurate crop mapping is fundamental for agricultural planning, sustainable resource management and food security (3, 4). Conventional ground survey methods, while effective, are often constrained by their labour-intensive nature, high cost and limited scalability. These limitations highlight the need for innovative approaches to crop identification and mapping (4). With its ability to provide large-scale, detailed and timely data, remote sensing has emerged as a transformative agricultural tool. Within this domain, Object-Based Image Analysis (OBIA) has proven to be an advanced and efficient technique for addressing the challenges of crop classification, particularly mango area mapping (5). OBIA's ability to group pixels into coherent objects based on spatial and spectral characteristics could improve classification accuracy by reducing misclassifications due to mixed pixels. Additionally, OBIA's multi-scale and multi-feature analysis enables detailed and precise mapping of orchards, allowing for better delineation of orchard boundaries. This approach, combined with the high resolution of Sentinel-2 imagery, enhances the efficiency of monitoring large-scale commercial mango farming operations.

Despite significant advancements in remote sensing and high-resolution satellite imagery for crop mapping, several gaps remain in current methodologies (3). Traditional pixel-based classification techniques often struggle to accurately distinguish between crop types and land-cover classes, particularly in heterogeneous and fragmented agricultural landscapes (6). These methods rely on analysing individual pixels without considering spatial relationships, which can lead to misclassifications, especially in areas with complex patterns, such as mango plantations. In addition, pixel-based approaches tend to have lower accuracy in identifying subtle features, such as orchard layouts and canopy structures characteristic of specific crops. Object-Based Image Analysis (OBIA) has emerged as a promising solution to address these limitations. OBIA overcomes the constraints of pixel-based methods by segmenting images into meaningful objects based on their spectral, spatial and contextual properties. This approach enhances classification accuracy and allows for the inclusion of structural and spatial characteristics unique to mango plantations, such as row spacing and canopy density. By integrating these elements, OBIA offers a robust and reliable method for crop mapping, making it a valuable tool for agricultural monitoring and management (7, 8).

Unlike traditional pixel-based classification methods that analyze individual pixels independently, OBIA clusters pixels into meaningful image objects based on their spectral, spatial and contextual properties. This approach enables extracting features, such as shape, texture, size and neighbourhood relationships, which are particularly beneficial for identifying agricultural patterns in heterogeneous and fragmented landscapes (9, 10). For instance, mango plantations often display distinct spatial characteristics, including orchard layouts, canopy structures and inter-row spacing, which can be effectively analyzed and classified.

High-resolution imagery from sensors such as Sentinel-2 provides critical inputs for OBIA, capturing detailed spectral information across the visible, near-infrared (NIR) and shortwave-infrared (SWIR) bands. These bands are sensitive to vegetation biophysical properties such as chlorophyll content and canopy density, making them particularly useful for identifying mango plantations. OBIA leverages these spectral features with spatial parameters, enabling a comprehensive analysis beyond simple pixel-based approaches. Object-Based Image Analysis (OBIA) groups pixels into objects based on spatial, spectral and textural characteristics, which reduces noise and improves classification accuracy, especially in high-resolution, heterogeneous data. It offers better interpretability since the classification is based on discernible objects and considers contextual relationships.

In contrast, machine learning classifiers like Random Forest and CNNs classify pixels independently and may struggle with high-resolution data unless tailored to account for context. While CNNs are powerful for large datasets, they are computationally expensive and require large amounts of labelled data. OBIA is more efficient after segmentation and is particularly suited for remote sensing applications with multi-source data. OBIA excels in high-resolution, complex datasets, while machine learning classifiers perform better in large-scale applications. Studies have demonstrated that OBIA outperforms pixel-based methods in terms of accuracy, mainly when applied to complex agricultural environments with mixed land-cover types (11).

In addition to enhanced accuracy, OBIA offers flexibility in incorporating hierarchical classifications and rule-based algorithms, allowing crop types and varieties to be differentiated. This capability is critical for mango plantations, as varieties may differ in their canopy structure, growth patterns and spectral signatures. This level of detail is essential for precise mapping and agricultural decision-making, such as monitoring plantation health, optimizing resource allocation and supporting market planning.

The objective of this study was to leverage OBIA to map the spatial distribution of mango plantations using high-resolution satellite imagery. This approach integrates spectral and spatial data to create a detailed and accurate classification validated through ground truth data collection. This study aims to demonstrate the potential of OBIA in advancing agricultural mapping, offering a scalable and cost-effective solution for managing mango cultivation in the Chittoor District.

Materials and Methods

Study area

Chittoor District, situated in the southeastern region of Andhra Pradesh, covers a geographic area of approximately 15,150 sq. km, with elevations ranging from 100 m to 1,200 m above the mean sea level (MSL). The district is bordered by Tamil Nadu to the South, Karnataka to the West, Annamayya District to the North and Tirupati District to the east. The district's central coordinates were approximately 13° 13' 1.5456″ N and 79° 6' 2.4372″ E. Chittoor district holds a significant position in mango production and is the largest hub for mango processing in Andhra Pradesh. The mango processing industry in Chittoor minimises post-harvest losses and generates substantial income and employment opportunities for the local population. The district's agro-climatic suitability and well-established processing infrastructure make it an ideal location for this study. The study was conducted between March and May 2024. The location map of the study area is shown in Fig. 1.

Satellite data collection

The primary dataset for this study was Sentinel-2 optical imagery, chosen for its ability to capture high-resolution spectral and spatial details that are essential for mapping mango plantations. Sentinel-2A and Sentinel-2B, operated by the European Space Agency (ESA), provide complementary multispectral data across 13 bands, including the visible, near-infrared (NIR) and shortwave-infrared (SWIR) regions (12) (Table 1). These bands are particularly effective in detecting vegetation characteristics such as canopy cover and chlorophyll content (13). The twin satellites, with a combined revisit interval of five days, ensured consistent temporal coverage, allowing the observation of seasonal and phenological patterns critical to identifying mango plantations. All Sentinel-2 data were accessed from the Copernicus Open Access Hub to ensure consistent and reliable data availability.

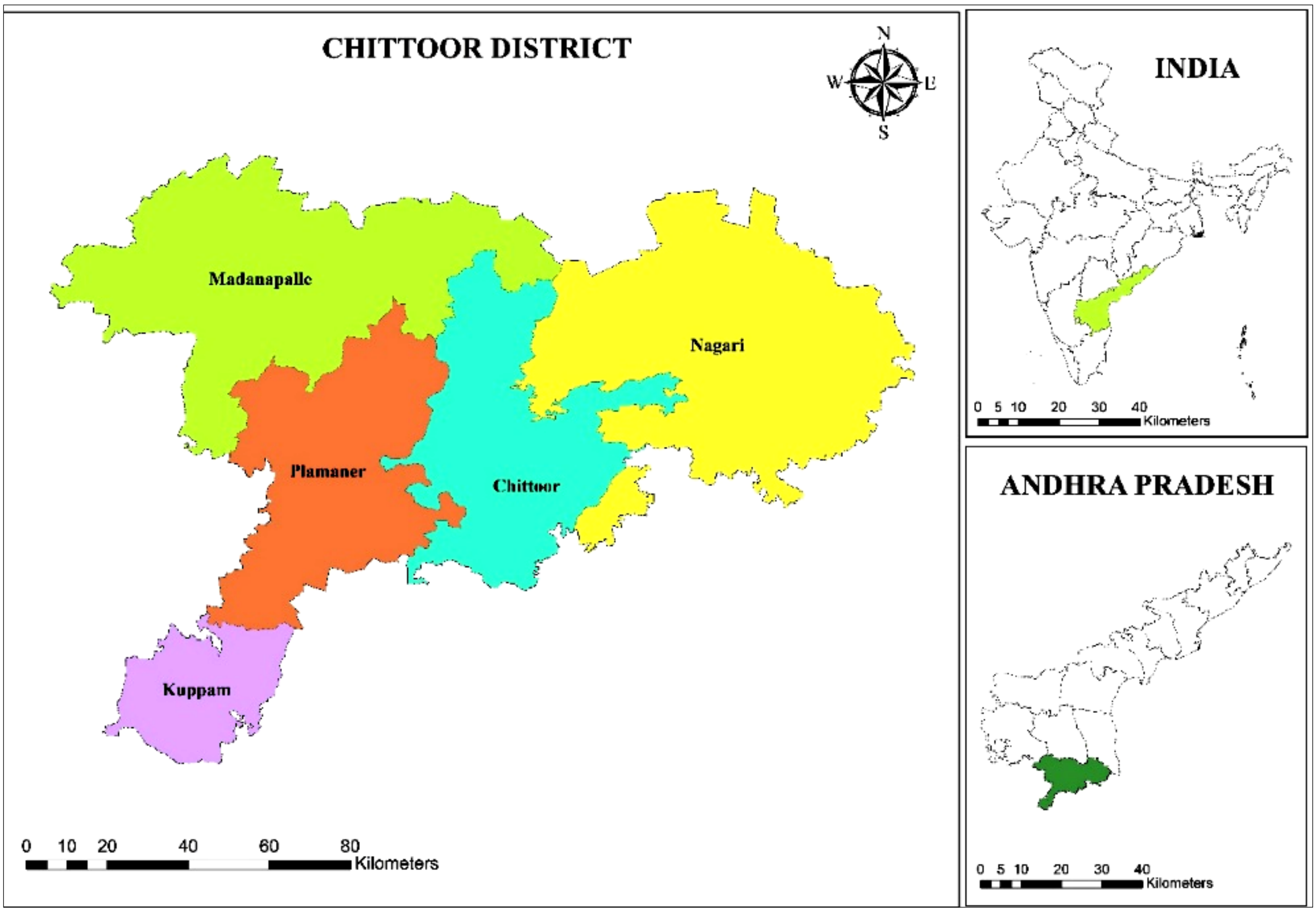

Fig. 1. Study area map.

Table 1. Features for Sentinel-2 satellites

Feature	Details
Sensor	Multispectral Instrument (MSI)
Spectral bands	13 bands across visible (VIS), near-infrared (NIR) and shortwave infrared (SWIR)
Spectral range	443 nm (Coastal Aerosol) to 2190 nm (SWIR)
Spatial resolution	10 m for bands: B2 (Blue), B3 (Green), B4 (Red), B8 (NIR) 20 m for bands: B5, B6, B7, B8A, B11, B12 60 m for bands: B1 (Coastal Aerosol), B9 (Water Vapor), B10 (Cirrus)
Swath width	290 km
Revisit time	10 days per satellite; 5 days with Sentinel-2A and Sentinel-2B combined
Orbit altitude	786 km
Orbit type	Sun-synchronous, polar orbit
Field of View	20.6°
Temporal coverage	Global land coverage between 56° South and 84° North, including coastal zones and islands
Radiometric resolution	12-bit per pixel, allowing for detailed intensity measurements
Key bands	B4 (Red, 665 nm) B3 (Green, 560 nm) B2 (Blue, 490 nm) B8 (NIR, 842 nm)
Data products	Level-1C (Top-of-atmosphere reflectance) Level-2A (Bottom-of-atmosphere reflectance with atmospheric correction)

Ground truth collection

Extensive ground truth data were collected throughout the study area in Chittoor District to support and validate the classification process. Five hundred thirty-one ground truth points were gathered, comprising 349 points for mango plantations and 182 points for non-mango land cover (Fig. 2). These points were selected to provide a representative sample of various land-cover types within the study area. Detailed observations were made at each location to document the characteristics of mango plantations, including tree health, age, density and management practices. This information plays a vital role in training the classification models and ensuring the accuracy of the final outputs. The ground truth data also served as a baseline for assessing the reliability of object-based classification results.

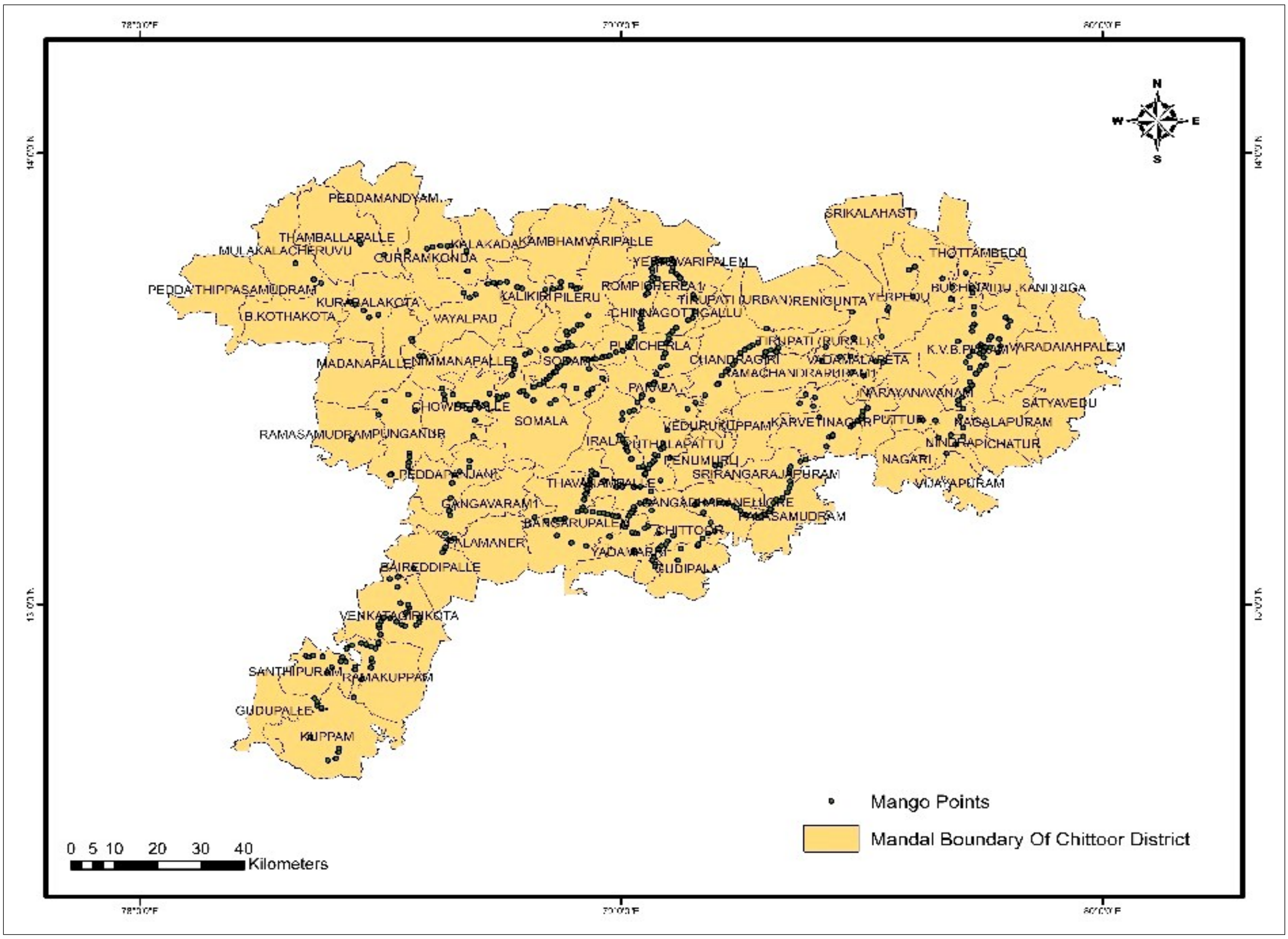

Fig. 2. Mango ground truth points in Chittoor district.

Software used for analysis

The analysis of Sentinel-2 imagery requires specialized software to manage, process and analyze spatial data effectively. The eCognition Developer was the primary tool for object-based image analysis (OBIA). Its advanced capabilities allow for the segmentation of images into meaningful objects and subsequent classification based on both spectral and spatial features. ArcGIS and QGIS were used for geospatial data management, map preparation and the integration of results. Microsoft Excel complemented these tools by enabling statistical analysis and visualization of data trends. These software packages facilitated a streamlined workflow for data preprocessing, classification and mapping. These software tools support essential preprocessing tasks, such as atmospheric correction, cloud masking and data resampling, ensuring high-quality inputs for classification.

Data preprocessing

Preprocessing was a critical step in ensuring the quality and reliability of the Sentinel-2 imagery for subsequent analyses. Atmospheric correction was performed using the Sen2Cor processor, which converts top-of-atmosphere (TOA) reflectance to bottom-of-atmosphere (BOA) reflectance, providing accurate surface reflectance values (14). Cloud masking was performed using the scene classification layer provided by Sen2Cor with additional manual checks to eliminate residual cloud shadows and other artifacts (15). All datasets were resampled to a uniform spatial resolution of 10 m to ensure compatibility and alignment and were co-registered. These steps are vital for maintaining the data integrity and ensuring the spatial accuracy of the classified outputs.

Mango area estimation

The identification and estimation of mango plantation areas in Chittoor District were performed using Object-Based Image Analysis (OBIA), as depicted in Fig. 3. Unlike pixel-based methods that analyze individual pixels independently, OBIA segments satellite imagery into homogenous image objects based on their spectral, spatial and contextual properties (16). This approach allows the consideration of larger spatial patterns, such as orchard layouts, canopy structures and inter-row spacing, characteristic of mango plantations.

The segmentation process was conducted using multi-resolution segmentation in the eCognition Developer software, with the following parameter settings: scale = 10, shape = 0.1 and compactness = 0.5. These parameters were carefully chosen to ensure meaningful object delineation that aligns with the physical structure of mango orchards.

After segmentation, features such as spectral indices, including the Normalized Difference Vegetation Index (NDVI) and spatial attributes, including shape and texture, were extracted for each object. These features provided a comprehensive dataset for classification. The classification process was carried out in the eCognition Developer, where

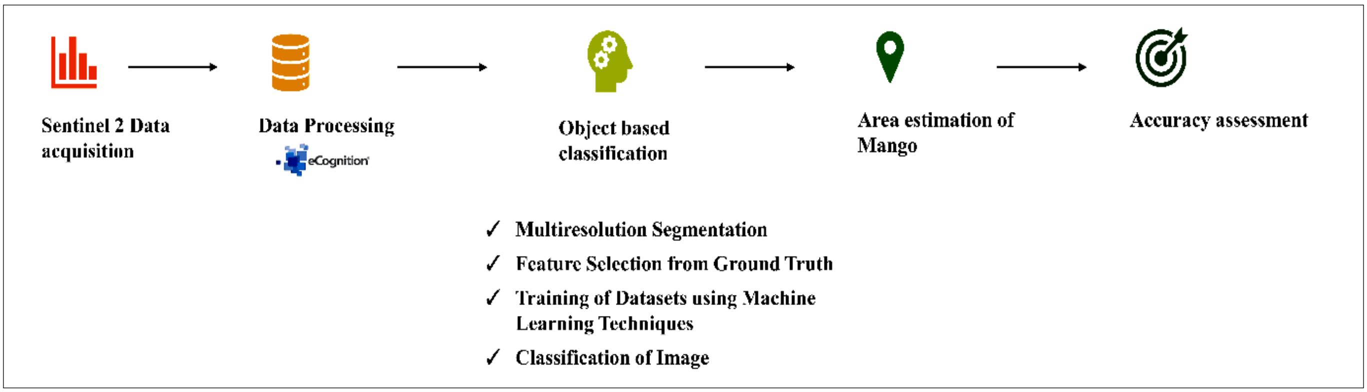

Fig. 3. Methodology for mango area estimation.

machine learning algorithms, such as Random Forest and Support Vector Machines, were used to assign land cover classes to segmented objects. Ground-truth data collected during field surveys were used to train these algorithms, ensuring that the models captured the variability within the study area. Object-based classification significantly enhanced the ability to accurately delineate mango plantations from other land cover types (17,18).

Validation and accuracy assessment

The classification results were validated using an independent set of 250 ground-truth points distributed across the study area. A stratified random sampling approach was adopted to ensure a balanced representation of different land cover classes. Accuracy assessment metrics were calculated using a confusion matrix. Cohen's kappa coefficient was used to measure the agreement between the classified outputs and ground truth data. The results demonstrated that OBIA, with its ability to incorporate spatial and contextual features, provided a significant improvement in the accuracy of mango plantation mapping compared with traditional pixel-based approaches. The overall accuracy and kappa coefficient is estimated as follows,

$$\text{Overall accuracy} = \frac{\Sigma(\text{Correctly classified classes along diagonal})}{\Sigma(\text{Row Total or Column Total})} \qquad \text{(Eqn. 1)}$$

The formula for an error matrix with r rows and therefore an equal number of columns allows one to determine the kappa coefficient.

$$\widehat{K} = \frac{\mathrm{NA} - \mathrm{B}}{N^2 - B} \qquad \text{......(Eqn. 2)}$$

Where, A = the sum of r diagonal elements, which is the numerator in the computation of overall accuracy, B = sum of the r products (row total x column total) and N = the number of pixels in the error matrix (the sum of all r individual cell values)

KAPPA SCORE	AGREEMENT
< 0.20	Poor
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Good
0.81 – 1.00	Excellent

Results and Discussion

This study emphasizes the effectiveness of object-based classification using high-resolution Sentinel-2A imagery to delineate mango plantations in Chittoor District accurately. By leveraging advanced segmentation techniques and the nearest neighbor algorithm, the object-based approach demonstrated exceptional accuracy in identifying mango plantations, demonstrating its robustness in agricultural mapping.

Object-based classification, conducted using the eCognition Developer software, segmented the study area into homogenous image objects based on spectral, spatial and textural characteristics. Using ground truth data from 531 stratified random sampling points, this method classified a total mango plantation area of 97,006 ha (Fig. 4), while 1,06,332 ha of mango area was reported by Chittoor horticultural department. The block-wise mango area is provided in Table 2. The classification achieved an overall accuracy of 87.0 %, average reliability of 87.3 % and average accuracy of 80.6 %; the Kappa index was calculated to be 0.74, indicating substantial agreement (Table 3).

The accuracy assessment demonstrated a marked improvement over traditional pixel-based classification methods. While traditional approaches typically struggle with the fine spatial distinctions required for accurately identifying mango plantations, OBIA demonstrated its robustness by correctly identifying 96.3 % of mango points, classifying 360 of 374 points accurately. In contrast, the accuracy for non-mango points was lower (65.0 %), correctly identifying 102 of 157 points. This disparity aligns with findings from similar studies, where object-based classification methods excel at identifying target classes (e.g., mango plantations) but face challenges with non-crop areas due to overlapping spectral signatures (19, 20). Studies such as (21) and (14) similarly reported accuracy improvements of up to 96 % using object-based classification, emphasizing its suitability for structured agricultural systems.

Sentinel-2 bands, including red, green, blue and NIR, were crucial in differentiating mango plantations based on canopy density and chlorophyll content. The NIR band, which is sensitive to vegetation could have highlighted the dense canopy and healthy vegetation, providing clear differentiation between mango trees and surrounding areas. The red band, known for its sensitivity to chlorophyll absorption, may have been useful in identifying areas with higher chlorophyll content, suggesting healthy mango trees.

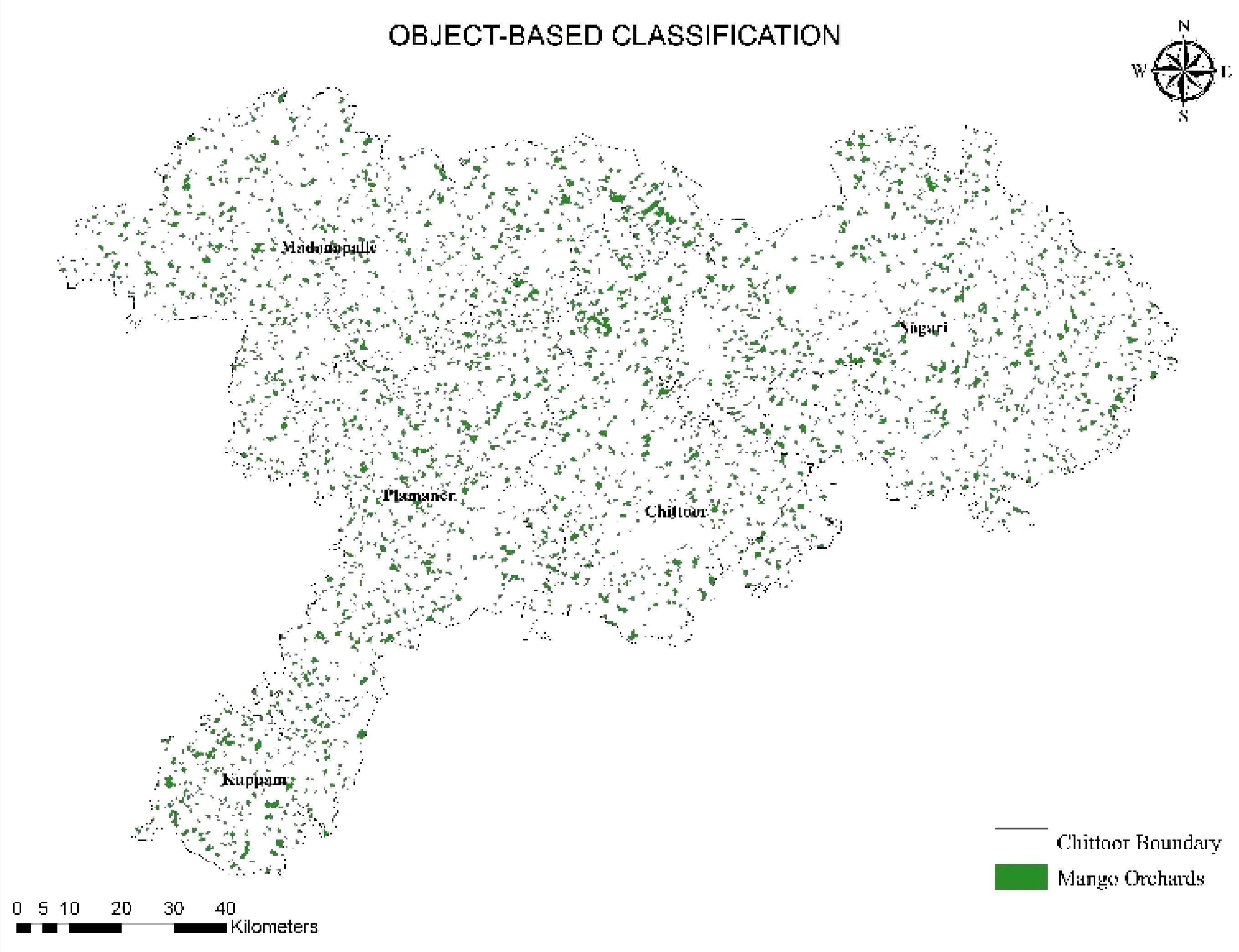

Fig. 4. Object-based classification for mango area estimation in Chittoor district.

Table 2. Block wise mango area of Chittoor district based on object-based classification

Block	Mango area (ha)
Chittoor	23,456
Nagari	15,789
Kuppam	19,874
Palamner	21,543
Madanapalle	16,344
Total	97,006

Table 3. Validation of mango area estimate using Confusion Matrix of Object-based classification

Confusion matrix computations for Object-based classification				
		Predicted class from the map		
		Mango	**Non-Mango**	**Accuracy**
Actual class from survey	Mango	360	14	96.3 %
	Non-Mango	55	102	65.0 %
	Reliability	86.7 %	87.9 %	87.0 %
Average accuracy		80.6 %		
Average reliability		87.3 %		
Overall accuracy		87.0 %	Good Accuracy	
Kappa index		0.74	Good Accuracy	

The green and blue bands might have further refined the distinction, possibly enhanced spatial resolution and helping to outline plantation boundaries or canopy structures. These spectral characteristics, when combined, likely supported the identification and mapping of mango plantations based on key vegetation features.

Implications for agricultural management

The results of this study have significant implications for various stakeholders in the agricultural sector. For plantation managers and farmers, accurate mapping supports resource optimization, yield management and informed decision-making for effective crop management.

The accurate delineation of mango plantations allows farmers to precisely identify areas with higher canopy density or better vegetation health, enabling targeted interventions such as irrigation, fertilization and pest management. This ensures that resources are utilized effectively, reducing waste and enhancing overall productivity. Additionally, the high accuracy in mapping can assist farmers in managing their plantations more efficiently by identifying areas that require additional inputs or attention, ultimately leading to better yield forecasting and management.

For policymakers and planners, the spatial insights derived from this study provide a foundation for evidence-based planning and resource allocation. Accurate plantation maps allow policymakers to prioritize infrastructure investments, such as irrigation systems and subsidies for mango farmers, ensuring that resources are allocated to areas with the highest growth potential. Furthermore, these insights assist in land-use planning, as policymakers can identify regions where mango cultivation is most productive and sustainable, guiding decisions on zoning, land conservation and crop diversification. By fostering sustainable agricultural development through these informed decisions, the study's methodologies pave the way for the integration of advanced data sources like hyperspectral imagery, UAV-based data and temporal SAR datasets, which could further improve accuracy and efficiency in future research.

Limitations and future scope

Despite its success, this study has identified areas for improvement. The relatively lower accuracy for non-mango points suggests refining classification methodologies, potentially by incorporating hyperspectral data or drone imagery. Improving the accuracy of non-crop areas could provide more detailed land-use insights, assisting policymakers in identifying and managing areas unsuitable for mango cultivation or those requiring intervention for land rehabilitation. Moreover, integrating temporal datasets and exploring advanced algorithms may enhance classification reliability and computational efficiency. These advancements could provide even finer detail, further supporting resource allocation and land-use planning, especially in dynamic agricultural environments where seasonal variations and long-term land-use changes must be closely monitored.

Conclusion

This study demonstrates a significant advancement in remote sensing applications for mango plantation management by leveraging Sentinel-2A optical imagery, SAR data and object-based classification techniques. The high accuracy achieved in mapping mango plantations underscores the potential of this approach for practical application in agricultural monitoring and planning. The findings of this study highlight the importance of high-resolution, cloud-free satellite imagery in achieving consistent results and the effectiveness of modern classification tools in bridging precision gaps. While varietal discrimination achieved moderate accuracy owing to limitations in multispectral data, this can be addressed in future studies with hyperspectral or drone-based high-resolution imagery. These implications extend beyond mango plantations, offering a scalable framework for monitoring other perennial crops. As remote sensing technologies evolve, this study is a foundation for further developments in precision agriculture, benefiting stakeholders across the agricultural value chain. Future research can build upon these methodologies to enhance their accuracy and efficiency, thereby advancing sustainable agricultural practices and resource management.

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Authors' contributions

SP carried out the experiment observation, drafted the manuscript, guided the research by formulating the research concept and approved the final manuscript. ST experimented, observed and drafted the manuscript, conceived of the study and participated in its design and coordination. KR guided the research by formulating the research concept and helped secure funds. NS performed the statistical analysis. SS[1] conceived the study and participated in its design and coordination. SS[2] participated in the data analysis and revised manuscript. All authors reviewed the results and approved the final version of the manuscript. [SS[1] stands for S. Satheesh and SS[2] stands for S. Sakthivel].

Compliance with ethical standards

Conflict of interest: The authors declare no conflict of interest.

Ethical issues: None

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