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Mapping coconut plantation in Western Agro-Climatic zone using object-based classification and machine learning technique

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Abstract

Coconut (*Cocos nucifera*), a key crop for over 10 million farming families in India, is vital in the agricultural economies of southern states like Tamil Nadu. However, traditional methods of monitoring coconut plantations are challenging due to the crop's geographical dispersion and seasonal variations. This study focuses on mapping coconut plantations in the Western Agro-Climatic Zone of Tamil Nadu using Object-Based Classification (OBC) and machine learning techniques. A ten-year time series of Landsat 7 optical satellite data (2012-2013 and 2022-2023) was employed, combined with ground truth surveys across the region. The study utilized Support Vector Machine (SVM) and Random Forest (RF) classifiers, with RF demonstrating superior accuracy. The RF classifier achieved an accuracy of 91.7% in 2012-2013 and 90.3% in 2022-2023, outperforming SVM, which hovered around 70%. The research also conducted a change detection analysis, revealing a net increase of 3,270 hectares of coconut plantations over the decade, with the Coimbatore district contributing the most significant growth of 2,560 hectares. This study underscores the effectiveness of integrating OBC and machine learning, mainly RF, for accurate and efficient mapping of coconut plantations using Landsat satellite data.

Keywords

area mapping; change detection; coconut; Landsat 7; machine learning; object-based classification

Introduction

Coconut (*Cocos nucifera*), a perennial crop, is extensively cultivated in the tropics and subtropics of India, the Philippines, Malaysia, Sri Lanka, the Indian Ocean and the South Pacific islands. This versatile palm, known as "Kalpavriksha" or "Heaven's Tree" in Sanskrit, is vital to the livelihoods of 10 million farming communities in India. It is a crucial crop in South Indian states such as Tamil Nadu, Kerala, Karnataka and Andhra Pradesh, playing a significant role in their agricultural economies(1).

The coconut palm thrives in regions with abundant and well-distributed rainfall (over 200 cm annually). Good irrigation is essential during the summer months when rainfall is scarce. A lack of irrigation is one of the primary reasons for low productivity levels. Coconuts are grown in over 80 countries worldwide and their economic importance in India is immense. The coconut tree profoundly impacts the rural economy, providing livelihoods to over 10 million people. Coconut oil contributes 6% to the national edible oil pool and adds approximately Rs. 7000 crores annually to the Gross Domestic Product (GDP)(2, 3). Hence, the cultivation of Coconut is spreading to non-traditional areas

Traditional data collection methods for decision-making and managing the coconut ecosystem are challenging due to the complexity and delays caused by hierarchical aggregation from farm to national levels. Satellite-based remote sensing has proven to be an effective and unbiased information system, providing regular and timely data. This technique is widely used in various countries to gather essential information on crops, soils, water resources, droughts and floods' impact on agriculture (4, 5). Coconut cultivation in Western Tamil Nadu faces climate variability and yield optimization challenges. Studies have shown that weather variables, particularly temperature and relative humidity, significantly influence coconut yield across different agro-climatic zones in India (6, 7).

This study used Object-Based Classification (OBC) and machine learning techniques for coconut mapping. Based on the discussions above, this study was taken up with the following objectives: To classify the coconut cultivation areas in the western agro-climatic zone of Tamil Nadu by integrating object-based classification techniques with machine learning methods. Additionally, the study aims to perform a change detection analysis to assess shifts in coconut plantation areas from 2012-2013 to 2022-2023. This approach will provide insights into the region's spatial and temporal changes in coconut cultivation, offering valuable data for future planning and development.

Materials and Methods

Study area:

Kerala borders the Western Agro-Climatic Zone on the west, the Central Zone on the east, the Northern Zone on the north, and the Southern Zone on the south. Its geographical positioning along the Western Ghats influences its climate and agricultural practices. The total geographical area of the Western Agro-Climatic Zone is approximately 0.25 million hectares. The zone faces water scarcity, soil erosion and market price fluctuations. Efforts are underway to promote sustainable agricultural practices and improve water management. The western agro-climatic zone of Tamil Nadu is presented below in Fig.1.

Satellite data:

Optical remote sensing has proven highly effective for crop area estimation and identification, especially for long-duration crops and plantations(8). One significant advantage of this method is that cloud cover during the cropping season does not impede satellite data analysis. Optical remote sensing utilizes visible, near-infrared and shortwave infrared sensors to capture detailed information about the Earth's surface by detecting solar radiation reflected from ground targets (9). The database used for this study consists of a ten-year time series of optical data from Landsat 7. Table 1 shows the band designation for the Landsat satellite and the data acquisition information is provided in Table 2

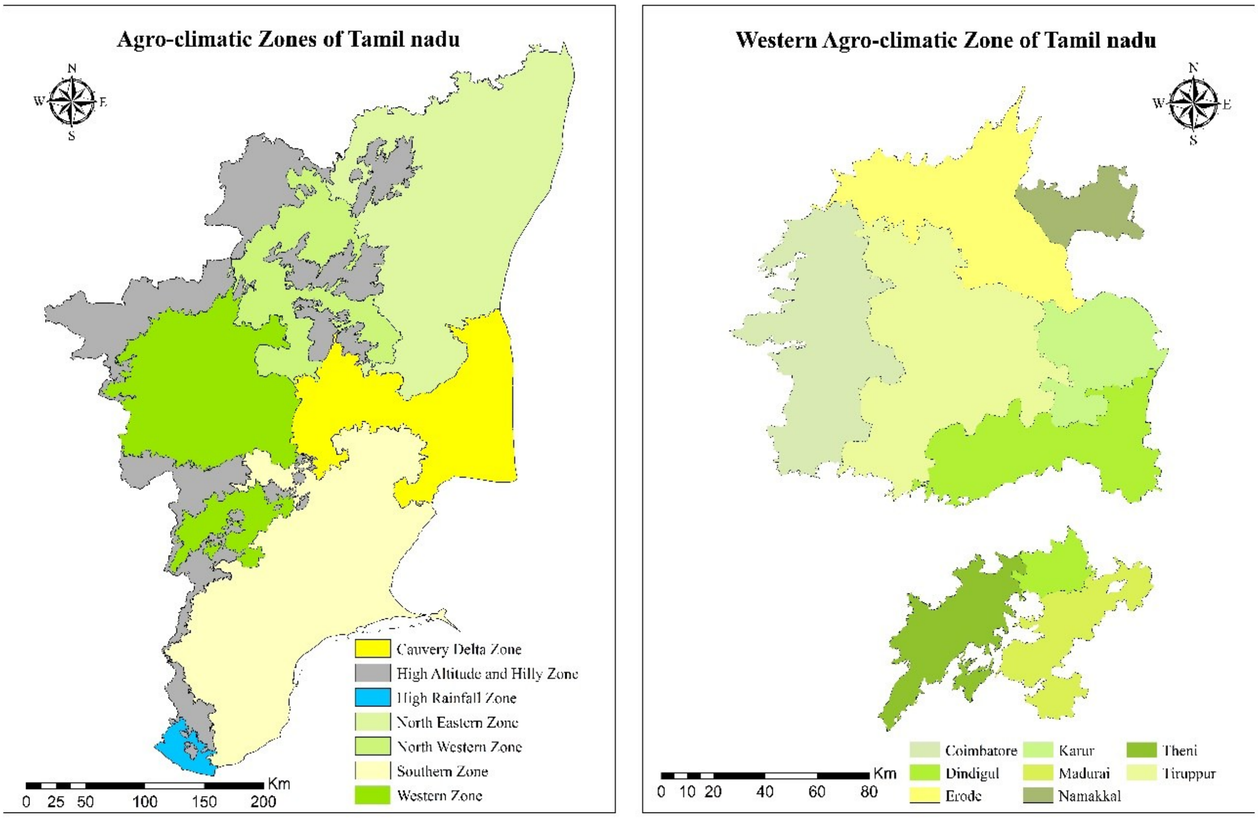


Fig.1. Study area map of western Agro-climatic zone of Tamil Nadu

Table 1: Landsat7 Bands and their corresponding wavelength:

Band	Resolution (Meters)	Wavelength (micrometres)	Description
Band 2	30	0.45-0.51	Blue
Band 3	30	0.53-0.59	Green
Band 4	30	0.64-0.67	Red
Band 5	30	0.85-0.88	Near Infrared (NIR)

Table 2: Data acquisition schedule of Landsat 7 for the Study Area

S.No	Scene	Districts covered	Sensing date	
			2012 - 2013	2022 - 2023
1.	LE07_L1TP_144052	Coimbatore, Erode, Tiruppur	2013/12/17	2023/05/20
2.	LE07_L1TP_144053	Coimbatore, Tiruppur, Theni	2013/12/17	2023/05/20
3.	LE07_L1TP_143052	Erode, Karur, Namakkal	2013/11/08	2023/06/28
4.	LE07_L1TP_143053	Dindigul, Madurai, Theni	2013/10/07	2023/06/28

Ground Truth collection:

Ground truth surveys were conducted across the study area, focusing on coconut-growing regions in Coimbatore, Tiruppur, Theni, Madurai, Dindigul, Namakkal, Erode and Karur districts. The aim was to gather information on land cover and validate the coconut plantation areas identified from satellite data (10). Observations were made using the Google Earth platform (11), and data points were collected for each class throughout the districts in the western agro-climatic zone of Tamil Nadu. Three hundred sixty points were collected during the ground truth survey, with 60% used for training and 40% for Validation. Of the 360 points, 300 were coconut points, and 60 were non-coconut points. The ground truth points collected are presented as a map in Fig. 3 and the ground truth points for Coconut in the Western agro-climatic zone of Tamil Nadu used are shown in Table 3.

Table 3 Ground truth points for Coconut in the Western agro-climatic zone of Tamil Nadu.

	No. of. Points used for training	No. of. Points used for Validation
Coconut	170	130
Non-coconut	46	14

Coconut area estimation:

The pre-processed Landsat 7 optical satellite data were classified using object-based classification to identify and extract areas of coconut plantations (12). Ground truth points collected during the area survey were utilized to train the classification models, enabling accurate area estimates of the coconut plantations. Fig. 3 outlines a methodology for tracking coconut plantation changes using Landsat 7 satellite data. Specifically, data from 2012-2013 and 2022-2023 is processed to identify and segment areas of interest. Extracted features from these segments train a classification model, categorizing land cover, including coconut plantations. The model's accuracy is assessed before quantifying coconut plantation areas in both periods. By comparing these areas, changes in coconut plantation extent over the decade can be determined.

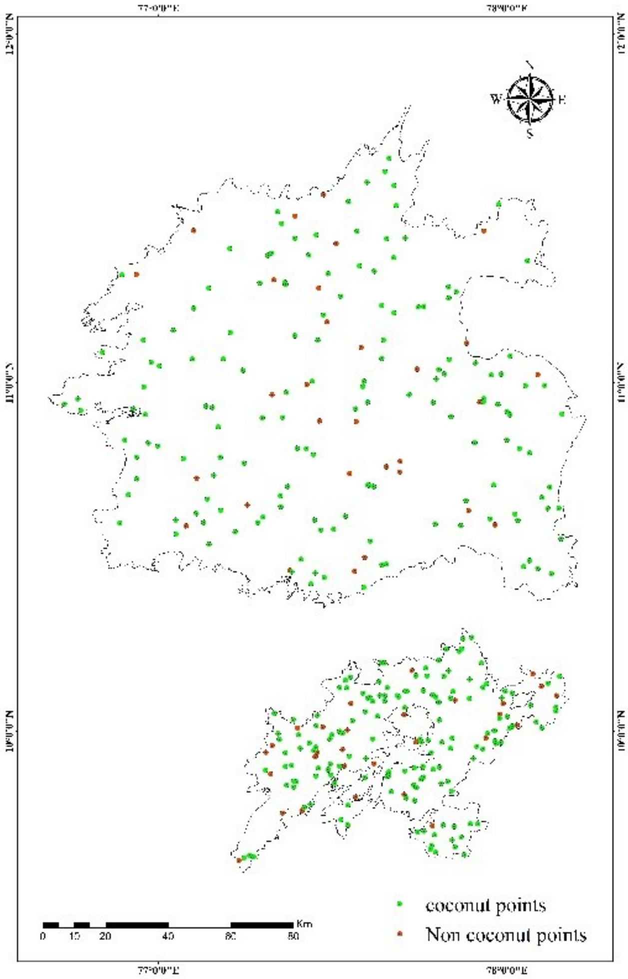


Fig. 2. Ground truth points collected in the Western agro-climatic zone of Tamil Nadu

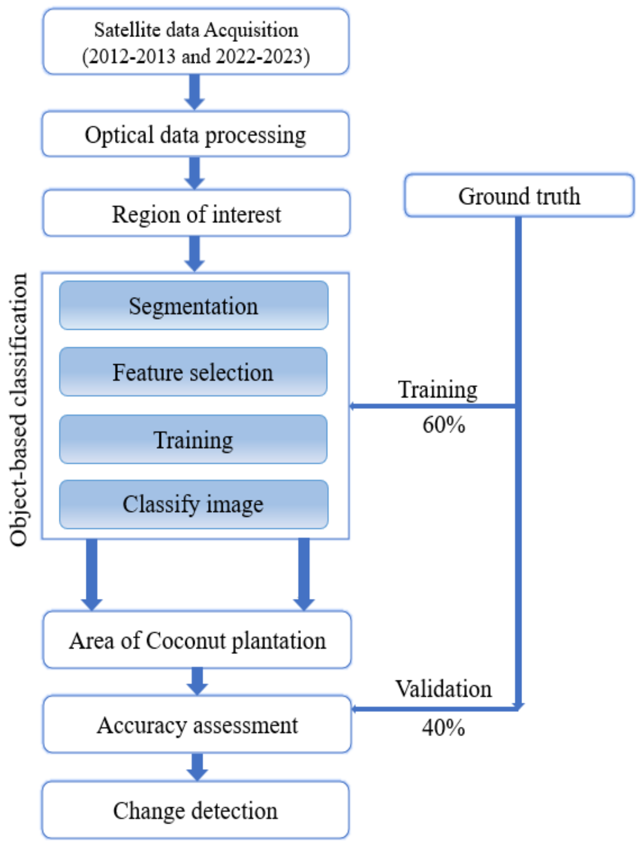


Fig. 3. Methodology for mapping coconut plantation

Object-based classification:

The "hybrid classification" approach described in (13, 14) combines pixel-based and object-based classification methods for LULC mapping. It uses multi-resolution image segmentation to delineate urban objects based on spectral and shape properties. Per-pixel classification is less preferred for high-resolution images due to their significant information content, which increases variability and reduces classification accuracy. Unlike maximum-likelihood classification, object-based classification does not rely on a single pixel for statistical analysis (15). Among various segmentation techniques, the multi-resolution technique is widely used to delineate clusters of homogeneous segments, known as objects, in an image. These objects are formed through spatial segmentation based on geometrical properties such as shape, texture, geographic context and spectral properties. Homogeneous objects are then used as training areas with ground truth points for more accurate classification (16).

Machine Learning techniques

A Support Vector Machine (SVM) is a supervised machine learning method that performs classification based on statistical learning theory. It works by finding the optimal hyperplane separating different feature space classes. On the other hand, the K-nearest neighbour algorithm (K-NN) classifies objects based on their proximity to the closest training examples in the feature space (17). The decision tree methodology is widely employed to make predictions. Researchers commonly opt for this technique due to its simplicity and clarity in identifying patterns within both extensive and limited datasets and its ability to forecast values(18).

The Random Forest machine-learning algorithm enhances regression analysis accuracy, addresses decision tree limitations, and requires fewer classification parameter configurations (19, 20). In this process, pre-processed Landsat 7 images are classified using the object-based classifier in eCognition Developer software to identify and delineate coconut plantations.

Accuracy Assessment:

The Error matrix (21) and Kappa statistics were employed to assess the accuracy of the estimated Coconut area (22). The classification accuracy was determined by comparing pixel allocations in the classified image to corresponding reference data. An error matrix was constructed to compile pixels of agreement and disagreement, with rows and columns denoting all classes and matrix elements indicating pixel counts in the testing dataset (23). The accuracy metrics, including overall accuracy and producer's and user's accuracy, were derived from the error matrix.

The overall accuracy, reflecting correctly classified instances along the diagonal (24), was calculated accordingly:

$$\text{Overall Accuracy} = \frac{\Sigma\ (\text{Correctly classified classes along diagonal})}{\Sigma\ (\text{Row Total or Column Total})}$$

Producer's accuracy, which reflects errors of omission, was calculated by dividing the number of correctly classified samples by the total number of reference samples for each class(25). Similarly, the user's accuracy, indicating errors of commission, was determined by dividing the number of correctly classified samples in a class by the total number of samples (26) verified to belong to that class as follows.

$$\text{Producer's Accuracy} = \frac{\text{Number of correctly classified class in a column}}{\text{Total number of items verified in that column}}$$

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified item in a row}}{\text{Total number of items verified in that row}}$$

The kappa coefficient is calculated using a formula that applies to an error matrix with an equal number of rows and columns, typically represented by $\hat{K}$ (26, 27).

$$\hat{K} \quad \frac{NA - B}{N^2 - B}$$

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)

N = the number of pixels in the error matrix (the sum of all r individual cell values)

Results and Discussion

Landsat :

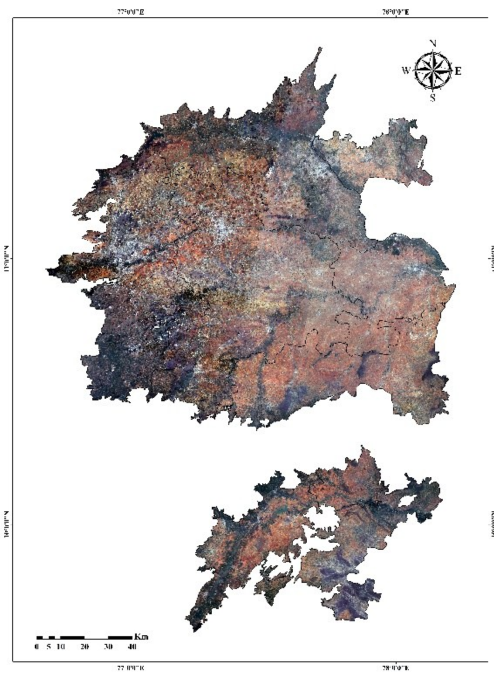
Fig. 4 presents the Landsat 7 satellite image of resolution 30m for the years 2012-2013 and 2022-2023 is downloaded, processed and classified under object-based classification and machine learning technique by which the area of coconut plantation is calculated for the western Agro-climatic zone of Tamil Nadu.

Accuracy metrics :

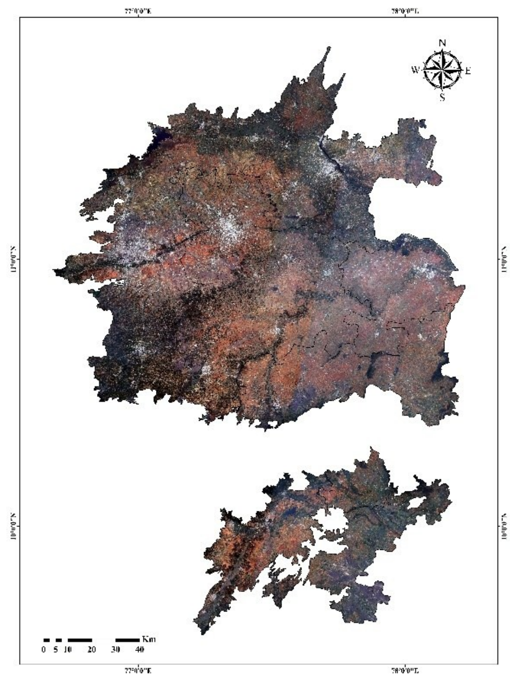
The area estimated for Coconut from Landsat 7 data using SVM and Random Forest was assessed for accuracy using a confusion matrix. Forty per cent of the ground truth points (130 Coconut points) collected during the area survey were used for the accuracy assessment (28).

Machine learning - Support vector machine vs Random forest

Table 4 shows that the model can identify Coconut areas, but the high number of misclassifications and low reliability for the Non-Coconut class indicate significant challenges. Both Coconut and Non-Coconut classifications have roughly similar accuracies (around 70-71%). The Coconut class has high reliability (95.8%), indicating that it is usually correct when the model predicts Coconut. On the other hand, the non-coconut class has very low reliability (20.8%), suggesting that many instances predicted that Non-coconuts are coconuts. The Kappa index 0.42 indicates a moderate agreement between the predicted classifications and the actual classes. The overall accuracy is 70.8%, which is relatively low for classification.



2012-2013



2022-2023

Fig. 4. LANDSAT 7 satellite image

Table 4: Confusion matrix for Coconut area estimate using SVM of the year 2012-2013

	Predicted class from the map			
	Class	**Coconut**	**Non-Coconut**	**Accuracy**
Actual class from the survey	**Coconut**	92	38	70.8%
	Non-Coconut	4	10	71.4%
	Reliability	95.8%	20.8%	70.8%
Average accuracy		71.1%		
Average reliability		58.3%		
Overall accuracy		**70.8%(Low accuracy)**		
Kappa index		0.42		

Table 5 shows that the accuracy for classifying coconut areas is 73.1%, slightly higher than that for non-coconut regions (64.3%). The Coconut class has high reliability (95.0%), indicating that it is usually correct when the model predicts Coconut. However, the non-coconut class has very low reliability (20.5%), suggesting that many instances predicted that Non-coconuts are coconuts. The overall accuracy is 72.2%, which, although slightly improved, is still considered low for classification tasks.

Table 5 Confusion matrix for Coconut area estimate using SVM of the year 2022-2023

	Predicted class from the map			
	Class	**Coconut**	**Non-Coconut**	**Accuracy**
Actual class from the survey	**Coconut**	95	35	73.1%
	Non-Coconut	5	9	64.3%
	Reliability	95.0%	20.5%	72.2%
Average accuracy		68.7%		
Average reliability		57.7%		
Overall accuracy		**72.2% (Low accuracy)**		
Kappa index		0.44		

Table 6: Confusion matrix for Coconut area estimate using RF of the year 2012-2013

	Predicted class from the map			
	Class	**Coconut**	**Non-Coconut**	**Accuracy**
Actual class from the survey	**Coconut**	120	10	92.3%
	Non-Coconut	2	12	85.7%
	Reliability	98.4%	54.5%	91.7%
Average accuracy		89.0%		
Average reliability		76.5%		
Overall accuracy		**91.7% (Good accuracy)**		
Kappa index		0.83		

Table 6 provides the confusion matrix that represents the accuracy and reliability of a Random Forest (RF) model for estimating coconut areas for 2012-2013. The model shows good overall accuracy at 91.7%, with a Kappa index of 0.83, indicating substantial agreement. Coconut area accuracy is 92.3% and non-coconut area accuracy is 85.7%, with respective reliabilities of 98.4% and 54.5%. Average accuracy and reliability are 89.0% and 76.5%, respectively.

The confusion matrix for coconut area estimation using Random Forest (RF) for 2012-2013, shown in Table 7, indicates a good overall accuracy of 90.3% and a Kappa index of 0.81, suggesting substantial agreement. Coconut classification accuracy is 90.0% and non-coconut classification accuracy is 92.9%, with reliabilities of 99.2% and 50.0%, respectively. The average accuracy is 91.4% and the average reliability is 74.6%.

Table 4 and 5 show the Confusion matrix for the Coconut area estimate using SVM for 2012-2013 and 2022-2023. Tables 6 and 7 show the confusion matrix for coconut area estimation using RF of 2012-2013 and 2022-2023. From this, it is demonstrated that SVM has lower accuracy than Random forest, which has 91.7% and 90.3% for 2012-2013 and 2022-2023, respectively. Therefore, Higher accuracy is achieved in Random forest.

Table 7: Confusion matrix for Coconut area estimate using RF of the year 2022-2023

	Predicted class from the map			
	Class	**Coconut**	**Non-Coconut**	**Accuracy**
Actual class from the survey	**Coconut**	117	13	90.0%
	Non-Coconut	1	13	92.9%
	Reliability	99.2%	50.0%	90.3%
Average accuracy		91.4%		
Average reliability		74.6%		
Overall accuracy		**90.3%(Good accuracy)**		
Kappa index		0.81		

Change detection in the coconut area from the base year 2012-13

Table 8 Change detection in the coconut area

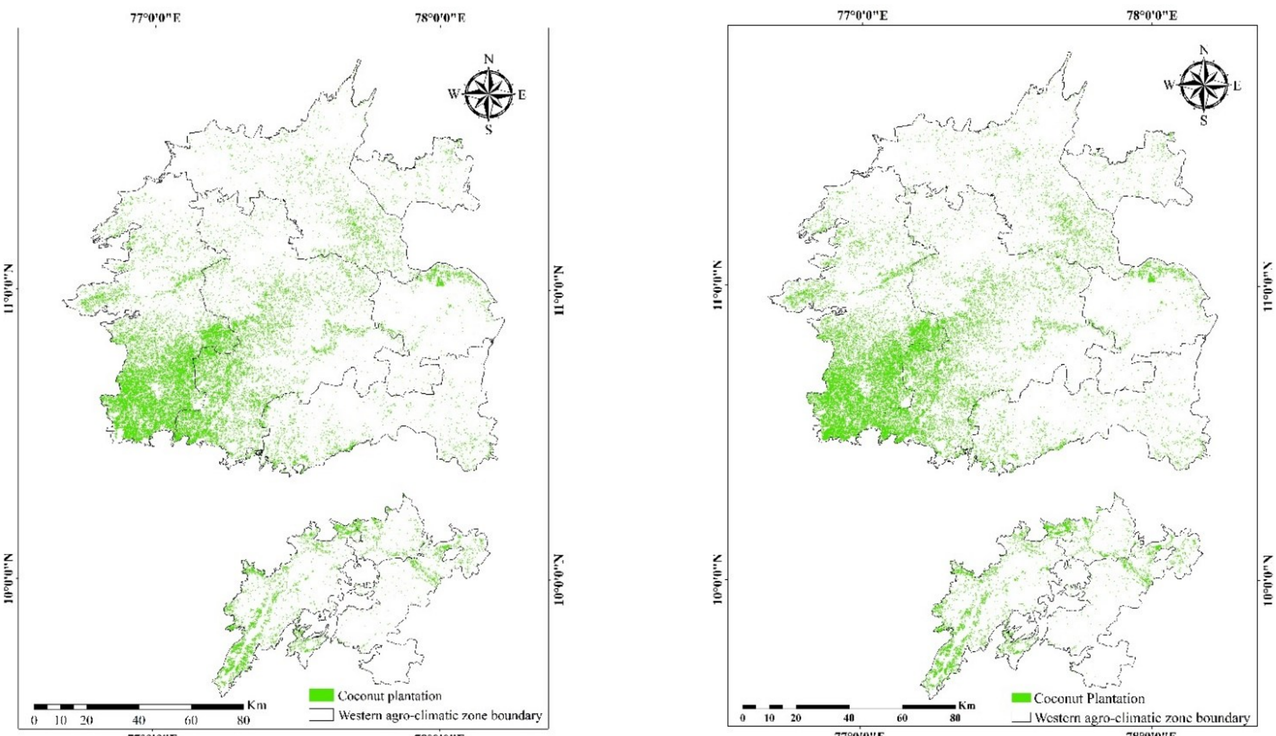
Districts	2012-2013 ('000 ha)	2022-2023 ('000 ha)	Difference ('000 ha)
Coimbatore	83.65	86.21	2.56
Dindigul	14.69	14.76	0.07
Erode	13.95	14.04	0.09
Karur	6.07	6.18	0.11
Madurai	5.12	5.12	-0.01
Namakkal	2.38	2.39	0.01
Theni	19.95	20.28	0.33
Tiruppur	59.50	59.60	0.10
TOTAL	205.31	208.58	3.27

The data on mapping of coconut area in the year 2012-13 has been utilized to understand the change detection concerning the current study over the year, and the results were presented in Table 8

The result compares agricultural land area in the western agro-climatic zone of Tamil Nadu, India, between 2012-2013 and 2022-2023. Except for Madurai, the areas are measured in thousands of hectares ('000 ha). All districts experienced an increase in agricultural land over the ten years. The agricultural land in Madurai remained almost constant, with a negligible decrease of 0.01 thousand hectares. Coimbatore district saw an increase of 2.56 thousand hectares in agricultural land over the decade. Dindigul experienced a slight increase of 0.07 thousand hectares. Erode increased marginally by 0.09 thousand hectares. Karur saw a minor increase of 0.11 thousand hectares in agricultural land. Namakkal had a slight increase in agricultural land by 0.01 thousand hectares. Theni experienced an increase of 0.33 thousand hectares, and Tiruppur saw a slight increase in agricultural land by 0.10 thousand hectares. Overall, there was a total increase of 3.27 thousand hectares in agricultural land across the districts surveyed from 2012-2013 to 2022-2023. The change detection of coconut-grown areas over the years in the western agro-climatic zone of Tamilnadu is shown in Fig. 5.

Summary and Conclusion

Coconut is a crucial crop for over 10 million farming families in India, especially in the southern states, where it plays a key role in the rural economy. Coconut oil makes up 6% of the country's edible oil supply. Despite its importance, traditional methods of gathering data to manage coconut ecosystems are often difficult, leading to satellite-based remote sensing



2012-2013 **2022-2023**

Fig. 5. Coconut-grown areas of the western agro-climatic zone

for better crop monitoring. This study uses object-based classification (OBC) and machine learning techniques to map coconut plantations in Tamil Nadu's Western agro-climatic zone, which grapples with challenges such as water shortages and soil erosion.

To conduct the research, Landsat 7 optical satellite data from the periods 2012-2013 and 2022-2023 was used, along with ground truth surveys to validate the identified coconut plantation areas. Several machine learning models, including Support Vector Machine (SVM) and Random Forest (RF), were tested. Random Forest (RF) is preferred in this study because it requires fewer decision-making parameters than other classification tools, making it more efficient. Additionally, RF is considered a "black box" classifier due to its ability to handle missing values effectively, as noted by (29). Similar success with RF was observed by (30), who achieved high accuracy and a strong kappa score of 0.95 when using object-based classification to map wetlands. Given these advantages, this classification task selects Random Forest over other machine-learning models. In 2012-2013, RF achieved a 91.7% accuracy rate; in 2022-2023, it reached 90.3%, while SVM showed lower accuracy, hovering around 70%. The study also carried out change detection analysis, uncovering an increase of 3,270 hectares in coconut cultivation over the decade, with Coimbatore experiencing the most significant growth, adding 2,560 hectares.

This study highlights the effectiveness of integrating object-based classification with machine learning, particularly Random Forest, to map coconut plantations accurately using Landsat satellite data. The results show a steady rise in coconut cultivation in Tamil Nadu's Western Agro-Climatic Zone, with a moderate expansion in plantation areas over the last decade. While the Support Vector Machine (SVM) faced some difficulties in classification, Random Forest emerged as a dependable tool. These advancements in remote sensing and machine learning offer valuable insights for agricultural decision-making and can improve coconut cultivation management, overcoming traditional methods' limitations.

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Authors' contributions

KPR carried out the Data collection and drafted the manuscript. PS carried out processing satellite data. RK participated in the Manuscript alignment. PL participated in the the performed the statistical analysis. All authors read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest: Authors do not have any conflict of interest to declare.

Ethical issues: None

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