MANGO AREA MAPPING USING VERY HIGH-RESOLUTION SATELLITE DATA REFERENCE TO MAJOR BLOCKS OF KRISHNAGIRI DISTRICT, TAMIL NADU, INDIA

Abstract

A research study was carried out for mapping mango plantation from LISS IV data in the major blocks of Krishnagiri district, Tamil Nadu where there is substantial production of Mango. A very high-resolution satellite data namely LISS IV was acquired and processed with GIS tools. Ground truth data gathered during the survey were utilized to identify significant dB values for mango plantations, which were then used to classify the mango pixels in the study region using supervised classification technique. The Mango area in major blocks of Krishnagiri district was found to be 9077.9 ha during the year 2023. Accuracy assessment and cross validation was done using confusion matrix with the ground truth points collected. The classification resulted with an overall accuracy of 91.2 *per cent* with a kappa score of 0.62.

Keywords: LISS IV, Mango, Area mapping, Supervised classification

1. Introduction:

Mangoes are high value crops grown as plantations and as individual trees. Mango (*Mangifera indica*) is the most important commercially grown crops of India Pasha *et al.* (2023). India produces 12.5 million tonnes of Mangoes annually (40 per cent of the world production) (Kulshreshtha *et al.*, 2023). Tamil Nadu ranks fifth in the production of Mangoes with an area of 1,25,100 ha and productivity of 4.30 t/ha which accounts for 5 lakh tonne yearly. The Major varieties are Banglora, Banganapalli, Neelum, Rumani, Mulgoa, Alphonso. The crop is majorly grown in Salem, Krishnagiri, Dharmapuri districts of Tamil Nadu.

For several reasons, crop identification and mapping are essential. Planning and management of sustainable resource use involve crop and area estimation monitoring. Regional agricultural boards, insurance companies, and national and international agricultural organisations all produce crop type maps to compile an inventory of the crops that were cultivated where and when (Gokool *et al.*, 2023). This helps with grain supply forecasting (yield prediction), crop production statistics collection, crop rotation records facilitation, soil productivity mapping, identification of factors influencing crop stress, evaluation of crop damage caused by storms and drought, and activity monitoring in agriculture. The traditional method of estimating crop acreage through survey is typically a time-consuming, inaccurate, and expensive operation(Guan *et al.*, 2023).

Singh *et al.* (2016) states that in his study, shows classification accuracy increased from 55% while using LISS III to 77% when using LISS IV. Also, according to classified outputs and NDVI values obtained, April and May months were identified as optimum bio-window for crop identification. Pixel based classification often fails to capture the spectral variability in high resolution images while delineating of horticulture crops, especially orchards. It tends to classify individual pixels on the assumption that individual classes contain uniform spectral behaviour but does not include contextual information like texture, shape etc. High resolution imagery of IRS-Resourcesat 2 - LISS IV have been used (Roy *et al.*, 2018).

2. Review of Literature:

(i) Need for crop area estimation: Kelly *et al.* (1995) conducted research on the demand for quick, accurate, high-quality data on production and productivity. In order to track data trends and evaluate deterministic elements in crop production, commercial and public sector businesses and policy-making organisations must always have access to such data. The tiny size of inaccuracies, however, leads to skewed production and inaccurate estimates of agricultural productivity.

(ii) Importance of Mango: A mango's kernels make about 17% to 22% of the fruit. Unsaturated and saturated fatty acids are present in equal amounts. During *E. coli* outbreak in Japan, phenolic components, tannins, and flavonoids from Mangoes were employed as anti-microbial agents. According to Soong and Barlow (2004), mango seed kernels are great source of phenolic chemicals.

(iii) Remote sensing for area estimation: For the major agricultural monitoring systems, crop discrimination is not persuasive. Due to socio-economic factors, crop destruction techniques, and geographical similarities, estimating crop acreage is challenging. Crop evaluation using remote sensing has replaced conventional survey techniques. (Shewalkar *et al.*, 2014).

(iv) High-resolution satellite data for area estimation: Roy *et al.* (2018) employed high-resolution IRS-Resourcesat-2-LISS IV satellite data from April, May, and November to map mango orchards in Uttar Pradesh using pixel-based classification and object-based classification. After evaluating using ground truth points, the accuracy for pixel-based and object-based categorization was found to be 65% and 92% respectively.

3. Materials and Methods:

3.1 Study area:

Among the Mango producing districts of Tamil Nadu, Krishnagiri ranks first in Mango production accounting for more than 60 *per cent* of the total production. Major Mango growing blocks in Krishnagiri district were selected for this study. This district is entirely bounded by Karnataka state in the West and in the North, Andhra Pradesh state and Tiruppatur district in the East and Dharmapuri district in the South. The district extends from 11º 12' N to 12º 49' N latitude and 77º 27' E to 78º 38' E longitude. The total geographic area of Krishnagiri district is 5143 sq. km with an elevation from 300 m to 1400 m above MSL. The study area is clearly shown in Fig.1.

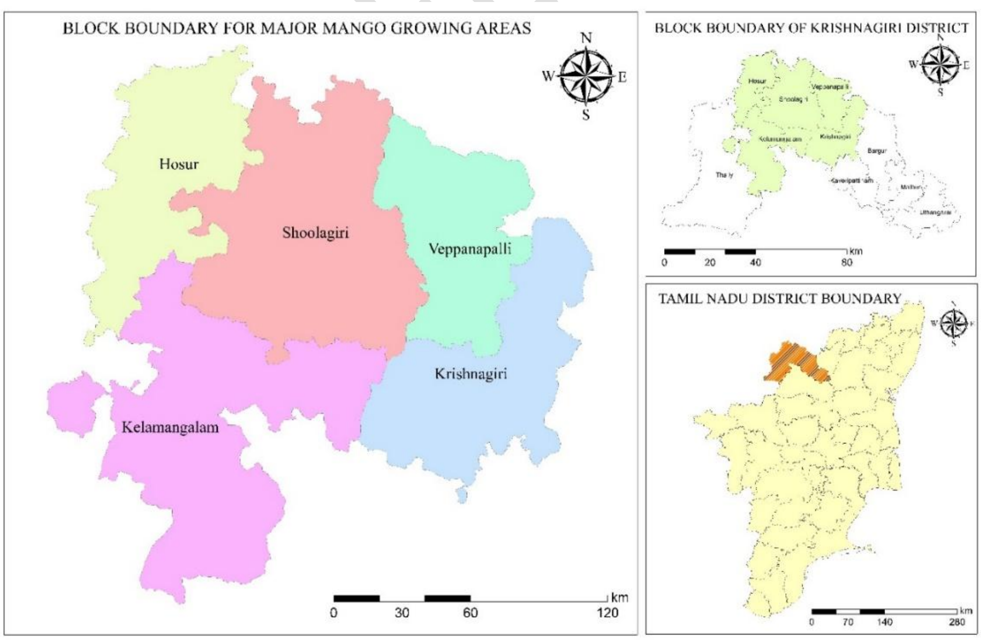


Fig.1. Study area map of major Mango producing areas in Krishnagiri district

3.2 Satellite Data:

LISS-IV is a high resolution multi-spectral sensor operating in three spectral bands (B2 0.52 - 0.59, B3 0.62 - 0.68, B4 0.77 - 0.86) (Table .1.). LISS-IV provides a ground resolution of 5.8 m (at nadir). The source of LISS IV data used for Mango area estimation is NRSC, Hyderabad (National Remote Sensing Centre). The data was then optimized for classification methodology through a series of processing techniques (Fig..2.)

(i) *Composite Bands* - to obtain an RGB image of the high-resolution satellite data

(ii) *Mosaic to new raster* - to obtain a single image of different scenes

(iii) *Extract with Mask* – to get a LISS IV image of major mango producing blocks of Krishnagiri district.

Table 1. LISS IV Bands and their corresponding wavelengths

LISS IV Bands	Wavelength(µm)	Resolution (m)
Band 2 – VIS	0.52 to 0.59	5.8
Band 3 – VIS	0.62 to 0.68	5.8
Band 4 – NIR	0.77 to 0.86	5.8
	Source: nrsc.gov.in	

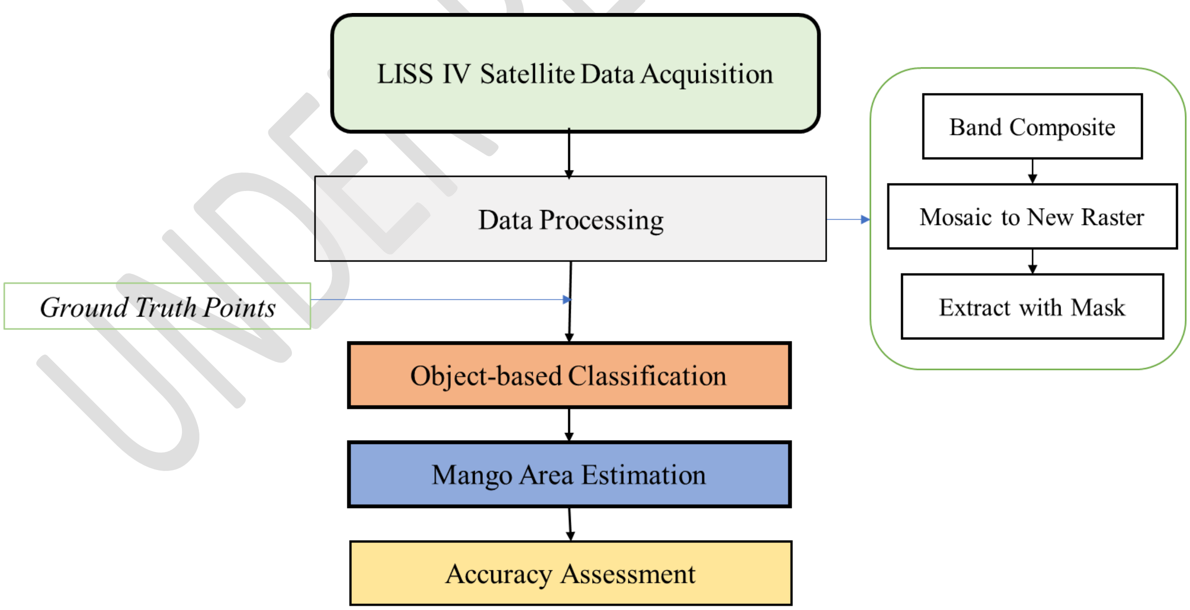


Fig.2. Methodology for Mapping Mango Area from LISS IV data

3.3 Software used for analysis:

LISS IV optical data provides information in all 3 bands at a higher resolution. Based on the application and user requirements, these bands were utilized individually or compositing which requires specialized image processing software. Processing of satellite data, analysis and mapping require advanced GIS tools. Hence different image processing and GIS software were used for accomplishing the objectives of the present investigation. Following are the software packages used for specific purposes.

- ArcGIS and QGIS: Handling spatial datasets and GIS operations
- eCognition Developer: Object-based image classification
- MS-Excel: Generation of graphs and deriving statistics.

System requirements: The systematically working procedure for such complex datasets and algorithm to perform smoothly normally requires high-end configurations and takes longer time to process. The fact that the study area is limited to major blocks favors the end user to perform the classification process without any hardships. The data processing at major block level takes a lesser duration than processing data for district level.

3.4 Ground truth data collection:

Ground truth points of Mango plantations were collected covering the entire study area. A total of 250 points (60 per cent mango points and 40 per cent non-mango points) were collected during ground truth survey which were then used for training and validation purposes.

3.5 Supervised Classification:

The two methods of image classification techniques, frequently employed for diversification related studies are supervised and unsupervised classification. When compared to unsupervised classification, supervised classification achieves a higher level of accuracy (Jiang *et al.*, 2023).

Object-based Classification: Due to the high information richness, per-pixel categorization is less desirable for high-resolution imageries. In contrast to maximum-likelihood classification, object-based classification does not perform statistical analysis on a single pixel. The objects are created by spatially segmenting pictures based on their geometrical characteristics, such as form, texture, location, and spectral characteristics.

3.6 Accuracy assessment:

Error matrix and Kappa statistics were used to determine the accuracy of classification. According to (Lillesand *et al.*, 1994), an error matrix is created using the pixels of agreement and disagreement. This error matrix can be used to calculate the Kappa Coefficient, producer's accuracy, user's accuracy, and overall accuracy (Congalton, 1991).

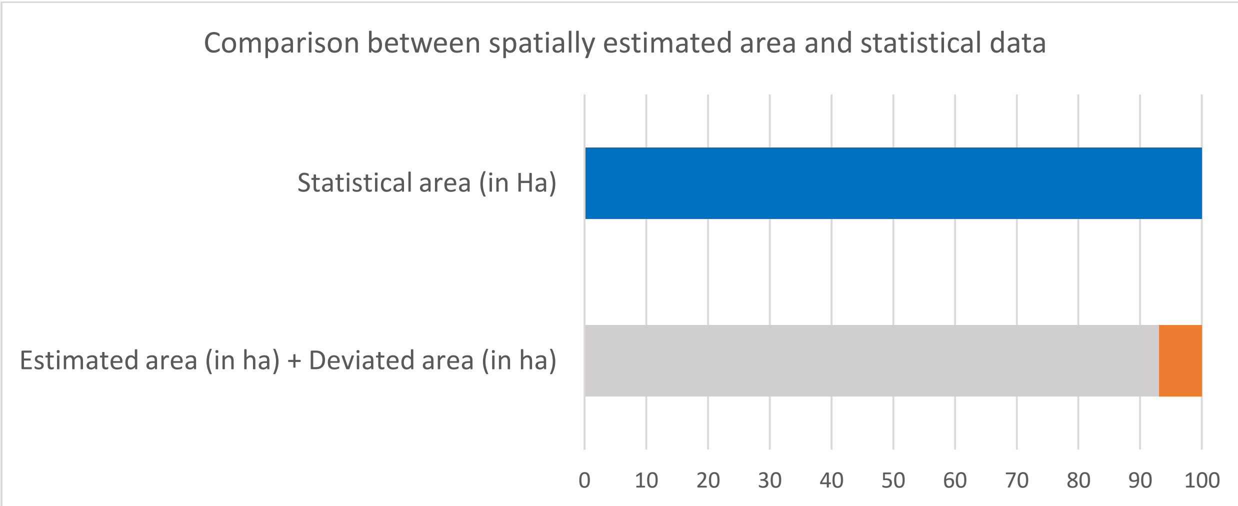
4. Mango area estimation:

Sixty per cent of the ground truth points collected during the area survey was utilized for the training the process tree module of eCognition software to perform Object-based classification. The representative objects for the Mango crop were carefully delineated to train the module, and the process was iterated to attain higher classification accuracy. Refinement of training objects was done for every iteration, and classification was performed to derive the Mango area map in the study districts. The output of the Object-based classification was statistically analyzed to derive the Mango area for the study districts.

5. Results and Discussion:

The estimated Mango area in major blocks of Krishnagiri district was **9077.9 hectares** (Fig.3.), while the statistical area from **Department of Economics and Statistics** were found to be 9746.2 hectares. The estimated area was 6.85 percent deviated from the Statistical data (Table 2). The area of mango plantation was distributed within the blocks were uneven. The Krishnagiri and Shoolagiri blocks were distributed with high mango plantation area of 2726.3 and 2893.0 hectares, respectively. Mango plantation area in Kelamangalam and Veppanapalli blocks of Krishnagiri district were 1086.0 and 1686.2 hectares, respectively. Mango area in Hosur block was 686.4 hectares, which indicates the chances of growth of other major crops like cut flowers, vegetables, etc., (Table .3.).

Table 2. Comparison of output with standard data from DES



District	**Estimated area** (in Ha)	**Statistical area** (in Ha)	**Deviation** (in *per cent*)
Major blocks of Krishnagiri	9077.9	9746.2	6.85

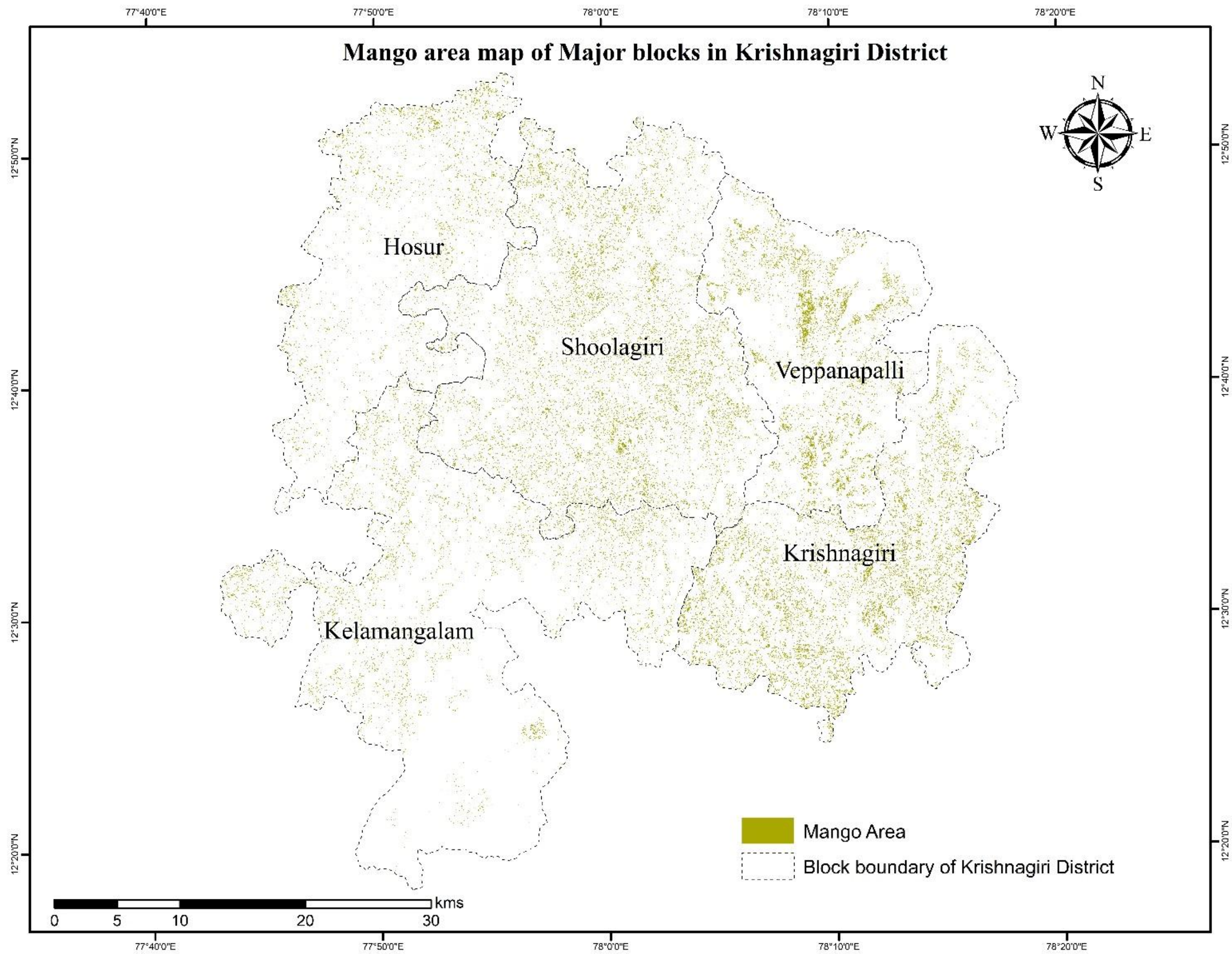


Fig.3. Mango area Map for major blocks of Krishnagiri District

Name	Block area (In ha)
Shoolagiri	2893.0
Krishnagiri	2726.3
Veppanapalli	1686.2
Kelamangalam	1086.0
Hosur	686.4
Total	**9077.9**

Table 3. Mango area of major blocks in Krishnagiri district

5.1 Discussion

(Sabthapathy *et al.*) used Sentinel-2A data for estimation of Mango and Cashew area for few districts of Tamil Nadu and estimated that 39313.01ha for entire Krishnagiri district. Similar to this, (Kannan *et al.*, 2021) calculated 82231.93 hectares utilizing optical data in the Cauvery delta zone of Tamil Nadu using Sentinel-2 data and Sentinel-1A SAR data.

Sentinel-1A VH polarized SAR data based acreage estimation of maize and cotton produced higher accuracy using maximum-likelihood classification (Kumaraperumal *et al.*, 2017). Mansaray *et al.* (2017) mapped rice fields in Shanghai, China, from Sentinel-1A and Landsat 8 data using maximum-likelihood classification, producing overall accuracy of 85 *per cent* with a kappa score of 0.81

5.2 Accuracy Assessment:

40 *per cent* of the Mango points were used for Accuracy assessment purpose. These points were validated with classified outputs. A total accuracy of 91.2% was obtained, with producer and user accuracy for mango being 79.5 percent and 96.6 percent, respectively. For non-mango, producer and user accuracy were 92.6 percent and 62.5 percent, respectively was obtained. The Kappa index of 0.62 was achieved, which shows a good qualification accuracy (Table 4.).

The results mirrored those of (Kaplan and Avdan, 2017) mapping of wetlands using Sentinel-2 satellite imagery, which had a kappa score of 0.95 and an overall accuracy of 99%. While (Belgiu and Csillik, 2018) showed that utilizing high-resolution data, cropland mapping under three different climatic circumstances generated accuracy ranging from 78.08% to 96.19%.

Table 4. Confusion Matrix for accuracy assessment

Actual class from survey	**Predicted class from the map**			
		Mango	Non-Mango	Accuracy
	Mango	58	15	79.5%
	Non-Mango	2	25	92.6%
	Reliability	96.6%	62.5%	91.2%
Average accuracy				86.1%
Average reliability				79.6%
Overall accuracy				91.2%
Kappa index				**0.62**

6.Conclusion:

With the development of new instruments and technologies over the years, estimations of crop area based on remote sensing studies have gotten better. Even if the crop mapping forecasts made using different technologies offer a compelling result with improved accuracy, there is still an opportunity to improve the accuracy. High-resolution data and sophisticated technologies can close the gap in estimating accuracy. The current study has shown to achieve greater accuracy in crop area estimation than the traditional methods when utilizing high-resolution satellite data in conjunction with sophisticated categorization algorithms.

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