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Research article

Agroforestry area mapping using medium resolution satellite data and object-based image analysis

M. Varshitha*, T. Chaitanya, T. L. Neelima and G. Jayasree

Professor Jayashankar Telangana State Agricultural University, Hyderabad-500030, India
*Corresponding author email: varshitha.bscag@gmail.com

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Abstract

Agroforestry is gaining increased attention within global policy processes and has been promoted as a strategy for working towards better food security, climate change adaptation and mitigation and livelihood resilience. With this gaining importance of agroforestry, site-specific studies are required to delineate different agroforestry systems and estimate the exact area under agroforestry. In this study remote sensing and GIS techniques were used for the estimation of area under agroforestry using medium-resolution satellite (sentinel 2A and 2B) data. Agroforestry area classification and estimation were done in e-Cognition developer software (10.0 version) through multiresolution segmentation and object-based image analysis (OBIA). The agroforestry area estimated in the erstwhile Warangal district was 3753 ha with an overall accuracy of 86% and a kappa coefficient of 0.84. The major agroforestry systems observed in the erstwhile Warangal district were eucalyptus, subabul, malabar neem, teak, sandalwood and red sanders.

Keywords: Agroforestry, e-Cognition software, Multiresolution, OBIA, Remote sensing

Introduction

Agroforestry, being a dynamic, ecologically based, natural resource management system, through the integration of trees on farms and in the agricultural landscape, diversifies and sustains production for increased social, economic and environmental benefits for land users at all levels (FAO, 2015). Woody species have been widely demonstrated to accumulate soil organic carbon through time and agroforestry holds a great potential for creating C sinks and mitigating GHG emissions from agriculture (Duguma *et al*., 2017).

In order to harness the potentiality of agroforestry, it is important and necessary to know the extent of the area under it and create a digital spectral library for agroforestry systems. Without remote sensing, agroforestry area mapping might be difficult, because traditional methods of area assessment require longer, human and financial resources. Also, it can give near real-time data about large areas, and human access to limited areas and is comparatively cost-effective. A major problem in estimating the area under agroforestry is the lack of procedures for delineating the area influenced by trees in a mixed stand of trees and crops. The problem is more difficult in the case of practices such as windbreaks and boundary planting where although trees are planted at wide distances between rows (windbreak) or around agricultural fields (boundary planting) because the influence of trees extends over a larger than easily perceivable extent of areas (Nair *et al*., 2009).

ICAR-Central Agroforestry Research Institute, Jhansi, started working on mapping of agroforestry in 2007, using medium-resolution data with a methodology in which areas under agroforestry, forest and plantation were separately identified. This got momentum when ICRAF's South Asia Regional Programme (SARP) joined this aspect in 2014 to develop new approaches for mapping complex agroforestry systems (Rizvi *et al*., 2020). The object-based image analysis (OBIA) approach has been widely utilized for remote sensing studies as an alternate and also comparatively better classification approach to the traditional pixel-based image classification techniques. In order to estimate more accurate results, object-based feature extraction could be a widely used method in many study areas (Hassanin *et al*., 2020). The concept of object-based information extraction is to interpret an image, the relevant semantic information is represented by meaningful image objects and their mutual relationship rather than individual pixels (Schnell *et al*., 2015).

The overall area under agroforestry for all 15 agroclimatic zones (ACZs) of India was 28.427 M ha, which is about 8.65% of the total geographical area of the country (328.747 M ha). Among the 15 ACZs, seven (1, 3, 5, 7, 11, 12 and 13) had more than 10% area under agroforestry. ACZs 1, 5, 7, 10, 11 and 13 had more than 2 M ha area under agroforestry. For area estimation, sub-pixel classification and object-based image analysis methods were used for medium-resolution (LISS III- 23.5 m) and high-resolution (LISS IV/Sentinel 2- 5.8/10 m) remote sensing data, respectively. The accuracy of the estimation was > 75% and > 90% for sub-pixel classification and object-based image analysis methods, respectively (Arunachalam *et al*., 2022). Rizvi *et al*. (2019) concluded that OBIA approach could be an appropriate method for mapping all types of agroforestry (scattered trees, boundary and block plantations) existing on farmlands.

Though there are many preliminary studies and works on the delineation of agroforestry areas in India through sub-pixel and OBIA methods, so far, estimation of the area under agroforestry in Telangana state has not yet been done. With this perspective, an attempt was made to delineate and estimate agroforestry areas in the erstwhile Warangal district of Telangana state with the help of multiresolution segmentation and object-based image analysis in e-Cognition software.

Materials and Methods

Study area: Erstwhile Warangal district in Telangana state is spread across an area of 12,846 km^2. It is located between 78°50′ to 80°40′ East Longitudes and 17°20′ and 18°32′ North Latitudes in the southern part of India, with an average elevation of 302 meters (990 ft). The district is in the eastern part of the Deccan Plateau (Fig 1). It comes under agro-eco-sub-region (AESR) 7.2 and its climate is characterized as hot, semi-arid moist, with dry summers and mild winters. The annual average temperature stands at 26°C and annual rainfall stands at 666.36 mm in the region. The monsoon usually lasts from June to September.

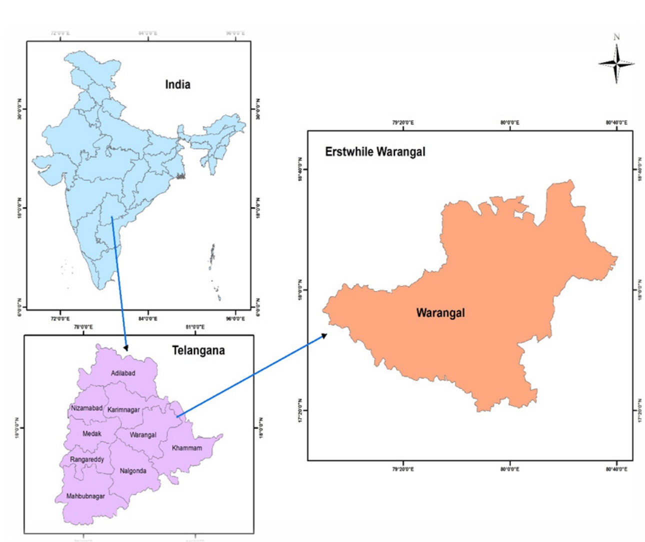

Fig 1. Location of study district

Methodology adopted for mapping: Quantum GIS (version 3.8.0), ERDAS imagine (version 16.5.0) and e-Cognition developer (10.0 version) software were used for the present study and the standard methodology was adopted for the generation of agroforestry maps. Toposheets of the study area (erstwhile Warangal district of Telangana state) were procured from the Survey of India website (https://soinakshe.uk.gov.in) and were georeferenced, subsetted and mosaicked for delineation of the study area. District shape files are also available with Survey of India, Dehradun. Ground truth data (GPS locations) were also collected during the survey across the district covering 17 mandals and 31 villages (Fig 2).

Remote sensing data was also obtained from sentinel 2A and sentinel 2B satellites. These satellites systematically acquire Optical data at high resolutions (10, 20 and 60 m). Satellite data of sentinel 2A and 2B (Optical) with 10 m spatial and temporal resolution was downloaded from the Copernicus Open Access hub of the European Space Agency (ESA) website for the months of October, November, and December 2021 (Copernicus, 2022). Care was taken to choose the cloud free data to the possible extent. Satellite data was then processed, which included layerstacking, mosaicking and subsetting. The whole satellite data processing was done in ERDAS imagine software (version 16.5.0).

Again forest area was masked out from the study area with help of 2015 LULC forest layer procured from NRSC, Hyderabad and digitized portions by overlaying on the FCC image (Figs 2-3) using the QGIS software (version 3.8.0) and ERDAS imagine software (version 16.5.0). In the e-Cognition developer software, FCC image with masked forest area was subjected to classification through its special features, multiresolution segmentation and OBIA. Index layer calculation was intended to calculate the

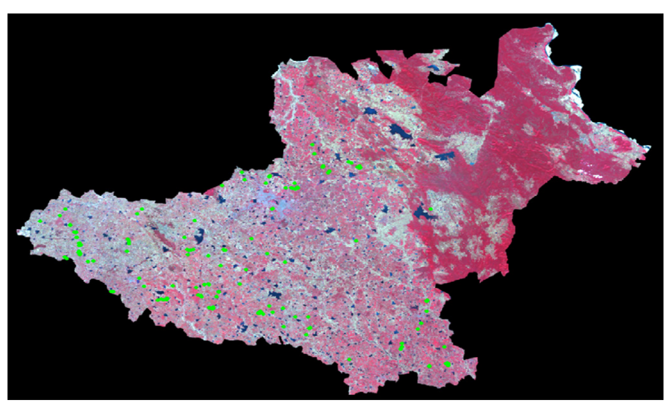

Fig 2. False color composite image of erstwhile Warangal district with ground truth locations of agroforestry parcels (green color dots)

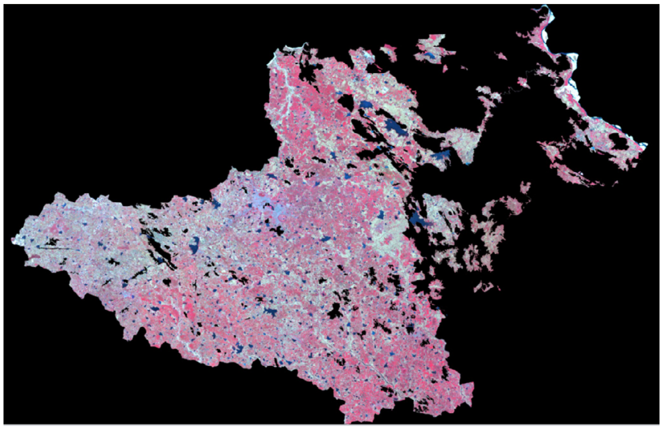

Fig 3. FCC image after masking of forest area

normalized difference vegetation index (NDVI) value utilizing spectral bands of red and near-infrared and normalized difference water index (NDWI) using green and near-infrared bands of remote sensing images. NDVI is an index useful for the detection of vegetation cover on the imagery. Indeed NDWI is preferred to identify and separate water body areas during classification.

While multiresolution segmentation is an algorithm for segmentation procedures run under artificial intelligence (AI) direction that facilitates OBIA, includes image segmentation and grouping pixels into homogeneous objects or segments that could be analyzed based on the objects instead of analyzing individual pixels (Holloway and Mengersen, 2018). Segmentation was done through spectral differences among objects where pixels with similar spectral signatures (according to the color/tone, texture, etc. of the image) were segmented into several image objects; thus image object level was higher than the pixel level. Thus, multiresolution segmentation formed the base of object-oriented classification. Segmentation was performed with a scale parameter = 20 (polygon size), Shape = 0.1, Compact = 0.5, for spectral difference calculation maximum 10 or more no. of pixels as the grouped feature was chosen. The image was segmented to supply meaningful polygonal image objects by setting certain parameters of homogeneity and heterogeneity in color and shape (Kumar *et al*., 2008).

Allocating training samples: Classification was done on the basis of representative training samples for each land cover class. The image object hierarchy was based on eight classes: agroforestry, harvested, settlements, orchards, scrub, river beds, water bodies and unclassified. Each class was assigned a different color to determine which class an object belonged. Agroforestry objects were defined using ground truth and high-resolution Google Earth sample points. Samples for training areas, *i.e.*, for agroforestry (1134), crop (1955), harvested (3685), orchards (1039), scrub (591), settlements (368), water bodies (3914), river beds (3778) were given. Of the total ground truth data collected, 80% was utilized in training the agroforestry samples and the remaining samples were used for accuracy assessment.

Supervised classification: An algorithm-supervised classification was chosen to run a random forest type of classification process. Random forest classifier is a feature space optimization technique in the mapping of tree species. It is an ensemble classifier that produces multiple decision trees using a randomly selected subset of training samples and variables. This classifier has become popular within the remote sensing community due to the accuracy of its classifications. It has its sensitivity when training samples are class-balanced, representative of the target classes, and large enough to accommodate the increasing number of data dimensions (Mariana and Lucian, 2016). Removal of mixed pixels was then done through an algorithm 'Remove Objects' with the help of fill and merge filter options based on pixel shape and color.

Accuracy assessment; Accuracy in the classification of agroforestry areas was done with the remaining GPS points by overlaying them on the classified map and crosschecking it with classified agroforestry parcels. Technically, classification accuracy was determined by using an error matrix or confusion matrix to evaluate the accuracy. The confusion/error matrix indicates the accuracy of classification (Foody, 2002). The relationship between the reference field data (ground truth) with the corresponding results of a classification was compared in the matrix. The producer's accuracy describes the number of errors of omission, which is a measure of how well real-world land cover types can be classified. The user's accuracy describes the number of errors of omission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location (Jensen, 2005). The accuracy assessment was indicated through the following: user's accuracy, producer's accuracy, overall accuracy and Kappa coefficient.

$$\text{KHAT statistics was computed as } K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} * x_{+i})}$$

Where K = Kappa co-efficient (KHAT statistics), N = total number of observations included in the error matrix, r = no. of rows in error matrix, x_{i+} = total of observations in row i (shown as marginal total to right of matrix), x_{+i} = total of observations in column i (shown as marginal total at the bottom of the matrix), x_{ii} = number of observations in row i and column i (on the major diagonal).

Results and Discussion

Land use land cover mapping using e-Cognition: Different segmentation approaches are available, of which selected algorithms were used for classification in e-Cognition software. In the current study, an algorithm, 'Index layer calculation' NDVI and NDWI calculation, were used for the detection and identification of vegetation cover and water body areas, respectively, on the imagery and separated during classification. By the algorithm 'Multiresolution segmentation,' all the pixels were segmented into objects, facilitating OBIA. Segmentation was performed with a scale value = 20 (polygon size), shape = 0.1, compact = 0.5, for spectral difference calculation maximum of 10 or more no. of pixels as the grouped feature was chosen. A random forest classifier was used for classification, which assigned classes to image objects that supported minimum distance measurements, while a supervised classification algorithm was chosen to run a random forest type of classification process. A random forest (RF) classifier is an ensemble classifier that produces multiple decision trees using a randomly selected subset of training samples and variables. This classifier has become popular within the remote sensing community due to the accuracy of its classifications (Mariana and Lucian, 2016). Agroforestry objects were defined using ground truth sample points.

OBIA method: Each class was assigned a different color to determine an object to which a class belongs. After defining the parameters, e-Cognition produced a replacement image with a new grouping of pixels. Eight classes, *i.e.*, agroforestry, crop, scrub, waterbody, harvested fields, settlements, orchards, and riverbeds were defined through ground truth and high-resolution Google Earth sample points (Table 1). The membership function of every class was provided by e-Cognition software. In this study, OBIA outperformed all test areas in terms of the quality of the classification outputs, as measured by the overall accuracy and in terms of computational time as well. The object-based approach provided by e-Cognition software is a big step forward in interpretations of remote sensing images and is an efficient and practical approach for information extraction. OBIA proved to be more robust than normal supervised and unsupervised classification techniques (Hassanin *et al*., 2020). Automated segmentation in an e-Cognition-based algorithm generated a satisfactory delineation of the agroforestry area in the erstwhile Warangal district.

Different classification methods were used for land use and land cover (LULC) analysis, *viz*., Parasai-Sindh watershed land use and land cover analysis was done using LISS–III data in ERDAS Imagine software by supervised method of classification by Kumar *et al*. (2021) and the acreage estimation of rabi fodders was done using ISODATA clustering method using normalized difference vegetation index in seven districts of Madhya Pradesh by Karwariya *et al*. (2022).

Accuracy assessment: The results of the accuracy assessment portrayed that the producer's accuracy in the classification of agroforestry was 63%, whereas the user's accuracy was found to be 79% with an overall accuracy of 86%. The kappa coefficient was 0.84, which was on par with overall accuracy (Table 2). Similarly, the accuracy assessment was done by Rizvi *et al*. (2017) to estimate areas under agroforestry in the Rudraprayag and Uttarkashi districts of Uttarakhand state.

Assessment of agroforestry area in erstwhile Warangal district: The estimated area under agroforestry in the erstwhile Warangal district was found to be 3753 ha, covering 0.29% of the total geographical area of the district. The estimated agroforestry area included tree species of eucalyptus, malabar neem, subabul, teak, sandalwood, and red sanders. Through the classification, besides agroforestry, area under other land use features was also found, *i.e*., area under crop was 115851.4 ha (9.02%), orchards were 84599.84 ha (6.58%), scrub occupied 22541.22 ha (1.75%), river beds were 7948.35 ha (0.62%), settlements covered 23267.55 ha (1.811%) and harvested fields occupied significant area of 507352.9 ha (Fig 4). The object-based approach provided by e-Cognition software

Table 1. Confusion matrix for land use and land cover map of erstwhile Warangal district

User class/Sample	AF	Crop	WB	HF	S	O	Scrub	River beds
Agroforestry	1134	54	0	0	0	129	96	0
Crop	93	1955	0	0	0	33	17	0
Water body	0	0	3914	0	0	0	0	0
HF	0	0	0	3685	4	0	0	30
Settlements	0	0	7	14	368	0	0	40
Orchards	186	95	0	0	1	1039	76	0
Scrub	201	16	0	0	0	44	591	0
River beds	0	0	0	0	3	0	0	3778

AF: Agroforestry; WB: Water body; HF: Harvested fields; S: Settlements; O: Orchards

Table 2. Accuracy assessment of land use features through error matrix

Accuracy	AF	Crop	WB	HF	S	O	Scrub	River beds
Producer	0.63	0.76	0.99	0.86	0.92	0.77	0.72	0.97
User	0.79	0.89	1	0.98	0.78	0.74	0.69	1
KIA per class	0.6	0.73	0.99	0.84	0.92	0.75	0.71	0.97

AF: Agroforestry; WB: Water body; HF: Harvested fields; S: Settlements; O: Orchards

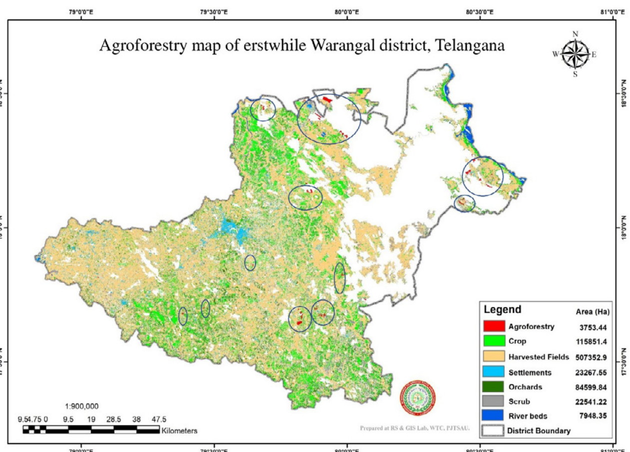

Fig 4. Map showing agroforestry area in erstwhile Warangal district

was thus a big step forward in the interpretation of remote sensing images and is an efficient and practical approach for information extraction (Hassanin *et al*., 2020).

Rizvi *et al*. (2021) reported an accuracy of 91.6 to 93.9% in agroforestry area classification and estimation using multispectral, high-resolution LISS-IV data using by OBIA method. Hassanin *et al*. (2020) also reported an overall accuracy of 91.14% along with kappa coefficiency of 0.91 in the assessment of trees outside forests (ToF) through sentinel 2A moderate resolution data with different spatial resolutions (10 and 20 m) using OBIA and multiresolution segmentation method in e-Cognition software (ver.9).

Conclusion

The delineated area under agroforestry was 3753 ha, covering 0.29% of the total area (12,84,600 ha) of the erstwhile Warangal district. The study throws light on the chance of further improvement of agroforestry areas in the district for sustainable development. The classification, mapping and estimation of agroforestry areas through OBIA in e-Cognition was efficient and reliable. This would help in future planning and identifying the agroforestry hotspots for suitable interventions in the district.

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