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Mapping of Trees outside Forest (ToF) From Sentinel-2 MSI Satellite Data using Object-Based Image Analysis

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ABSTRACT

Trees outside Forests (ToF) have necessary socio-economic and environmental implications from local to global scales. In the current context of climate change, their importance is being increased dramatically for people's livelihoods and national economies, and also for various international processes that address global environmental and economic challenges like carbon sequestration, biodiversity loss, desertification, poverty alleviation etc. Assessment of Trees outside forests (TOF) is wide being recognized as an important theme, in sustainable natural resources management, because of their role in offering kind of goods, such as timber, fruits and fodder also as services like water, carbon, and biodiversity. Moderate resolution data (Sentinel-2A D) with different spatial resolution used, to get medium spectral and spatial resolution data (10m-60m range). Object-Based Image Analysis (OBIA) approach as implemented in commercial suite of e-Cognition (Version 9) consists of segmentation. The segmentation level of 10 proved to be very precise in the geometric delineation of individual trees and groups of trees, which were the target groups in this research.An area of about 178.63 sq.km. was delineated from the satellite image using the segmentation approach and overall accuracy was found to be at 93.57%.The object-based approach provided by eCognition software is a big step forward in interpretations of remote sensing images and is an efficient and practical approach for information extraction.

Keywords: Farmer Producer Companies, Kerala, SWOT Analysis

Trees outside forests (ToF) are considered a crucial land-use feature during a global context and have now been included as an attribute of interest within the United Nations' Global Forest Resource Assessment. By definition, ToFis "trees ashore not defined as forest and other wooded lands" (FAO, 2013); examples include trees that occur on agricultural and grazed lands, along with water bodies and roads, and in residential and concrete settings (Rawat *et al.*,2004). Technically, trees outside forest (TOF) are defined as the trees, which have attained 10 cm or more diameters at breast height, available on land, which are not notified as forests. In large portions of the central us where agriculture dominates the landscape, tree cover exists primarily as ToF. Although scarce in terms of overall coverage, ToF provides a spread of ecological benefits, including protecting soil and water resources, providing wildlife habitat, and improving farmstead energy efficiency and aesthetics and providing biomass for carbon sequestration (FSI, 2019).

Forests play a crucial role within the socio-economic and cultural lives of the people inhabiting these villages. They need to be been hooked into the forests for fuelwood, fodder, timber, and bamboo since ages but with the manifold increase within their population in the last 60 to 70 years, pressure on forests has additionally augmented within the likewise manner (Tapasi and Ashesh, 2014).The National Forest Policy of India (1988) has set a goal that 33 percent of the country's geographic area should be under forest and tree cover. All lands aside from the recorded forest area having a tree canopy density1 of 10 percent or more are often considered as TOF. In India, tree species like Peepal (*Ficus religiosa*) and Banyan (*Ficus bengalensis*) are traditionally worshipped as an abode of Gods and are commonly found on temple premises and roadsides. Also, the normal practice of maintaining homestead gardens of fruit-bearing trees and planting trees on farmlands, along roadsides and rivers have contributed significantly to this status of TOF. It includes woody vegetation like mango, neem, peepal, litchi orchards, etc. within the recent year's impetus has also been given to roadside, wasteland, and farm forestry plantations. This point bent the very fact that substantial tree wealth (TOF) exists

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within the country, which incorporates small wood lots (less than 1 ha in extent), block plantations, a linear plantation along roads, canals, etc., and scattered trees on homesteads, farmlands, and concrete areas. Considering its intrinsic and tangible contribution to the national bio-resource stock, it's essential to account for this valuable resource periodically.

The status of TOF would also indicate the success of afforestation projects like social forestry and wasteland development (Adekunle *et al.*, 2012). As the information on TOF is usually absent from official statistics, policy initiatives for its management also are hurdled with time-consuming methods of age-old inventorying. The significance of Trees outside the Forest (ToF) is often observed in countries with low forest cover TOF resources constitute the foremost source of wood and non-wood "forest" products. In urban areas, trees provide important aesthetic and environmental services additionally providing shade and greatly increasing the liveability of cities (Chhabra, 2004). Trees outside Forests (ToF) can play important roles in national economies, ecosystems, and international efforts for sustainability – and in many places they already done. At the local level, people have long relied on TOF in various land-use settings for food security, income, and biological diversity. Forest professionals in many countries support local use of trees for these purposes, outside forests also as in forest settings. More recently, international programs repose on trees' roles in providing essential environmental services to encourage sustainable land management, carbon sequestration to mitigate global climate change and native economic development (Chaudhary *et al.*, 2016).

In the recent past, the sector of remote sensing technology has made a quantum jump both in terms of technology development and in its management. Current remote sensing systems offer unique methods for detecting patterns at the surface of the world, and for acquiring data about the underlying processes at a spread of spatial scales, starting from centimetres to kilometres. Analysis and computing environments now allow data transformation from a various and multivariate form to a usable state. Parallel improvements within the understanding of how and why remotely sensed data and methods are important in forestry and forest science to have particularly aided information synthesis developments (Gupta and Bhadauria, 2014). During a complementary fashion, GIS provides opportunities to make multi-scale representations by incorporating and linking digital maps at different scales, and thru the event of statistical and mathematical functions to affect scale as a generic issue.Forestry applications vary alongside forest stands and canopy mapping, biomass measurements, clear cut mapping, burn detection, health assessment, species inventory then forth (Pujar *et al., 2014*).

Without remote sensing it might be difficult to perform these tasks, because traditional methods of forest assessment require longer, human and financial resources. In contrast, remote sensing provides digital data presenting tree crown characteristics in several spectral wavelengths which may be interpreted, analysed, evaluated and visualized (Kadu *et al.*, *2016*). Also, it can give near-real-time data about large areas, human access limited areas and is comparatively cost-effective.Recently, 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. Successful launch of very high resolution (VHR) commercial imaging satellites within the late 1990s are helpful for resource inventory and monitoring (Chaudhary *et al. 2016*). The VHR basic cognitive process is anticipated to be an alternate option to aerial images for characterization of forest structure and dynamics through automatic image classification technique (Pande-Chhetri *et al.,* 2017). In order to estimate more accurate results object-based feature extraction could also be a newly and widely used method recently utilized in many study areas. Within the traditional pixel-based approaches for information extraction only the pixels spectral information is used to extract surface features (Pandey, 2008).

Object-based image analysis is implemented so to extract relevant surface information, combining spectral and spatial information. Thereby, with the thing-based approach not only the spectral information within the image is getting to be used as classification information, the texture and context information within the image are going to be combined into classification also (Singh and Chand, 2012). The concept of object-based information extraction is that 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). To extract certain features only from high-resolution images, we'd wish to utilize the spatial and contextual information of an object and its surroundings. The object-oriented approach takes into consideration the shape, textures and spectral information. The thing bound classification part starts with the crucial initial step of grouping neighbouring pixels into meaningful areas to extract homogeneous image objects, which can be handled within the later step of classification. Consistent with the resolution and thus the size parameter of the expected objects segmentation and topology generation must be set. The objective of the study is to demarcate boundary of ToF and estimate the contribution of TOF in tree cover with the help of image segmentation in eCognition software on different parameters.

Study Area

Bandipora District Administrative head quarter is in Bandipora. It's 14th Largest District within the State by population. It's Located at Latitude-34.4°N, Longitude-74.6°E. Bandipora District is sharing a border with Kargil District to the East (Fig.1). Bandipora District occupies an area of roughly 3200 sqkm (3152.74 sq km shape file area). It's within the 1581 meters to 1578 meters elevation range. This District belongs to Northern India. Bandipore is situated on the banks of the Wular, the foremost important fresh-water lake in Asia which is home to plenty of migratory birds. The climate of the district has its peculiarities. The seasons are marked with sudden change and thus the climate is often divided into six seasons of two months each. These include, spring (16 March to fifteen May), summer (16 May to fifteen July), season (16 July to fifteen September), autumn (16 September to fifteen November), winter (16 November to fifteen January) and Ice Cold (16 January 15 March), of these seasons, are locally mentioned as 'Sont', 'Retkol', 'Waharat', 'Harud', 'Wandh' and 'Shishur' respectively. Winters are usually harsh thanks to heavy snowfall and low temperatures. The area under forest within the district (Bandipora) is about 1993.96sqkm excluding snow/barren) (2661.51 sq km shape file area) of land. The analysis was carried out only for the non-forest area i.e. 491 sq km.

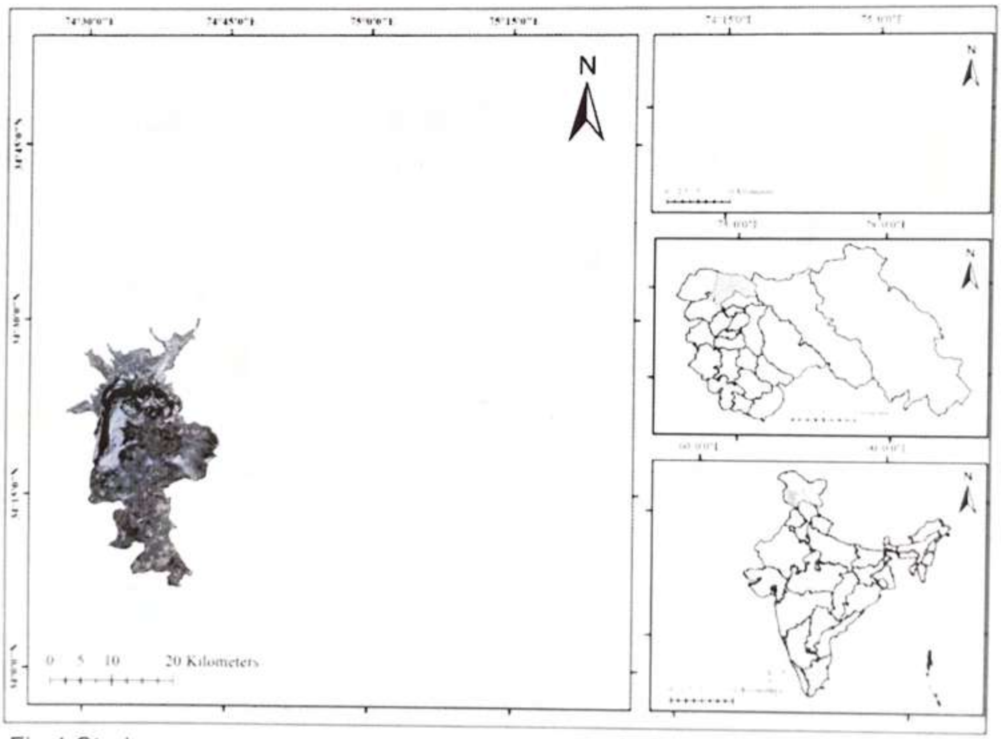

Fig 1 Study area

MATERIAL AND METHODS

The study has been conducted using both remote sensing data and field measurement data to infer the results. The assessment of TOF was carried out using typical assessment technique rather than conventional forest inventory because of specific characteristics of the trees such as density, diameter distribution on the forest and non forest land classes.

The accuracy assessment was carried out using correlation points from High Resolution Google Earth images.

We used the Sentinel-2A bands with spatial resolutions of 10m and 20m during this study. Two cloud-free Sentinel-2A MSI granules freely downloaded from https://eos.com/landviewer. Subsequently, image subset operation was done to retrieve the area of interest for the study area. The Forest cover mask was derived from existing land use/landcover map. Then image segmentation using eCognition was performed using selected algorithms among the different segmentation approaches available. This was followed by Tree delineation; random plots were allocated to overcome the 'H-resolution problem'. Roundness, crown area, and length/width ratio of the trees were calculated from the satellite imageries and used for the OBIA to generate CPA. Image analysis was administered using Object-based image processing (OBIA), wherein the concept of the pixel is relegated at the early stage of processing and group of pixels constituting a homogeneity is taken into account as the segment. Because the present study envisages the study of the effect of spatial resolution on TOF classification, availability, selection, and procurement of knowledge sets of varying spatial resolutions was the primary and crucial step initiated

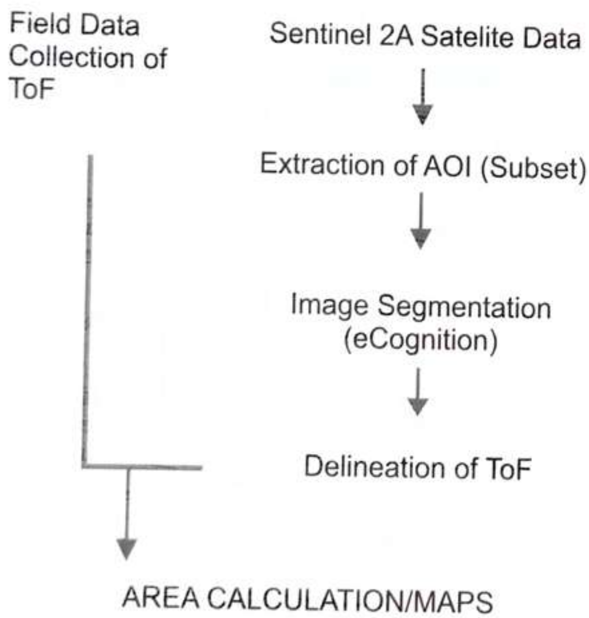

Fig 2 Flowchart methodology

within the entire exercise.

The accuracies of the pixel- and object-based classifications obtained were evaluated in terms of overall accuracy, producer's accuracy, user's accuracy metrics (Congalton, 1991), and kappa coefficient (Cohen, 1960) using the formula given below:

$$\text{Kappa Coefficient} = \frac{\text{TS} \times \text{TCS} - \sum \text{COL. TOTAL} \times \text{ROW TOTAL}}{\text{TS2} - \sum \text{COL. TOTAL} \times \text{ROW TOTAL}} \times 100$$

RESULTS AND DISCUSSION

Accurate segmentation is a crucial issue within the context of object-oriented classification. During the segmentation process, meaningful image objects are created on the thought of several adjustable factors of homogeneity and heterogeneity in color and shape (Seidel et al., 2015). Thereby the classes are organized within a category hierarchy. Multi-resolution segmentation may be a bottom-up region-merging approach, starts with the one-pixel object, and smaller image objects are merged into larger ones within the subsequent segmentation steps thus constructing a semantic hierarchy, so on finding desired single objects of interest. The influence of color vs. shape homogeneity on the thing generation is often adjusted with the help of these parameters. The upper the shape criterion the less spectral homogeneity influences the thing generation. When the shape criterion is larger than 0 the user can determine whether the objects shall become more compact (fringed) or smoother (Meneguzzo et al., 2013).

The segmentation phase is followed by the accurate classification of images by fixing of classification rules called rule bases, eCognition software offers two different classifiers: the nearest neighbour (NN) classifier and fuzzy membership functions. Both classifiers act as class descriptors. Within the proposed method nearest neighbour (NN) classifier is used for classification which assigns classes to image objects supported minimum distance measurements. NN classifier is suitable for describing variation in fine resolution images. Thereby each feature offered by eCognition is often wont to determine the feature space for the closest neighbour classifier. Multi-resolution segmentation forms the base of object-oriented classification. The image is segmented to supply meaningful polygonal image objects by setting certain parameters of homogeneity and heterogeneity in color and shape (Kumar *et al.*, 2008).

Different segmentation approaches are available of which selected algorithms were used. Within the current study, multi-resolution segmentation was adopted, to deal with the segregation of treesin target landscapes. Datasets were subjected to segmentation in the e-Cognition 9.0 environment first at scale value of 30followed by a scale value of 10. Segmentations used parameters of shape and compactness at 0.1 and 0.5. Parameters of shape and compactness help to manage the nature of the segments derived and act synergistically to regulate the nature of resultant objects, hence are provided as user-controlled units.

Higher shape index produces very narrow and linear looking formations while lesser compactness leads to very roundish shapes.Finally, the resultant image objects classified supported the principle of the nearest neighbour. The result of segmentation achievedgood effect. Afterimage segmentation, the polygonal image objects of interest are generated. The layer object hierarchy is based on 4 classes: tree cover, settlement, other land (Agriculture, wasteland and wetlands) and open Waterbody (Table 1). Each class was assigned a different color to determine which class an object belongs.After defining the parameters, eCognition produced a replacement image with a new grouping of pixels (Fig.3). Four classes were defined using ground truth and high resolution google earth sample points. The membership function of every class is provided by eCognition software. The overall accuracy reaches 91.14 % (Table 2).

The multi-resolution segmentation method applied has proven to be very efficient in extracting the segments required for the classification of forest, non-forest, and TOF on 10m ground resolution sentinel image. The segmentation level of scale value 10 proved to be very precise in the geometric delineation of individual trees and groups of trees, which were the target groups in this research. Because non-forest areas surround TOF objects, these objects were segmented using a finer segmentation resolution, while larger objects represented the non-forest areas. Area under water body was 36.807 sqkm, whereas agri/wasteland/wetland combined occupied and area of 239.38 sqkm. The settlements also covered a significant area of 36.40 sqkm. Since the main thrust of the study was trees outside forest, the area under this category was found to be 178.63, mostly composed of trees like willow, poplar, apple, walnut, etc. Therefore, it was found that Bandipora district is rich in trees outside forest and can support, bat, wicker willow and horticulture industry, besides providing an excellent sink for CO_2.

Thus, it was possible to define relations between objects of different sizes and use the contextual information in the classification algorithm (Fig.3). The use of very even moderate-resolution images for TOF information extraction, produced important differences in comparison to other images of desirable spatial resolutions.

Table 1 Land use/land cover area (sqkm)

S. No	Class	Area (sq. Km)
1	Water body	36.807
2	Agri/wasteland/wetland	239.389
3	Tree cover	178.630
4	Settlement	36.404
	Total Area (Masked)	491.230

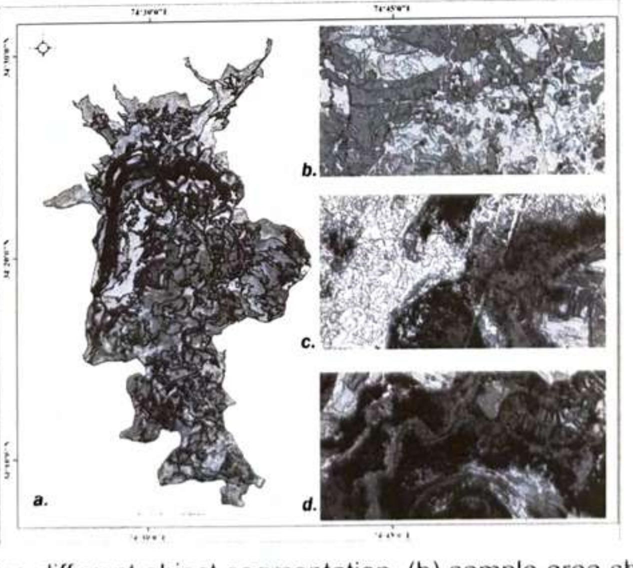

Fig 3 (a) Masked area showing different object segmentation. (b) sample area showing horticultural crop. (c) sample area showing willow plantations. (d) sample area showing water bodies/wetlands/agriculture area. Parcels are extracted in the final segmentation (blue lines). The images are shown in false color composite.

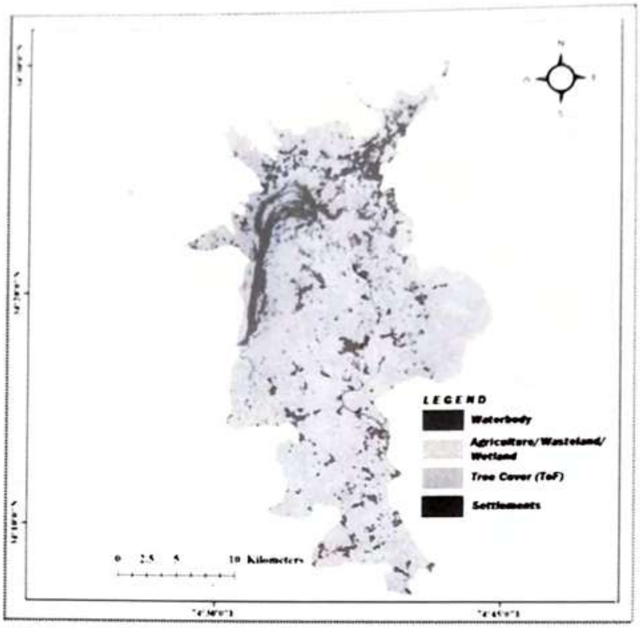

Fig 4 Land use/Land cover map

A total of 140 points (water body 24, Agri/Waste/Wetland 40, Tree Cover 36 and settlements 40) were verified from high-resolution google earth images and field data of the study area. We achieved good classification results in all three four classes, the overall accuracy of the process is is 93.57% with the kappa coefficient of 0.91 (Table 3).

Table 2 Overall accuracy assessment

S. No	Class	Waterbody	Agri/Wasteland /Wetland	Tree Cover	Settlement
1	Water Body	22	1	0	0
2	Agri/Wasteland/Wetland	2	38	0	2
3	Tree Cover	0	0	36	3
4	Settlement	0	1	0	35

Table 3 Calculation of kappa coefficient.

CLASS	USER'S ACCURACY	PRODUCER'S ACCURACY
Water Body	95.65	88.00
Agri/Wasteland/Wetland	86.36	92.68
Tree Cover	87.80	100.00
Settlement	97.22	83.33
Overall Accuracy	93.57%	
Kappa Coefficient	0.91	

CONCLUSION

In this study, Sentinel-2 was used as data input for mapping of trees outside forest using OBIA method. The analysis was applied on pixels and objects, in the test areas with different landuse/landcover and geometry of parcels. OBIA outperformed all test areas in terms of the quality of the classification outputs, as measured by the overall accuracy metric and in terms of computational time as well. It also performed better where the within-field heterogeneity was very high. OBIA proved to be more robust than normal supervised and unsupervised classification techniques. Automated segmentation of using eCognition based algorithm generated a satisfactory delineation of the trees outside forests and other landuse categories. Given the high classification accuracy obtained without human intervention and the reduced computational time, the OBIA method applied to objects could be integrated into operational programs dedicated to mapping of trees outside forest and their monitoring based on satellite image time series. It was found that this technique can rapidly support the decision makers for setting up local industries for bat, wicker willow and horticulture, besides providing an excellent sink for CO_2.The object-based approach provided by eCognition software is a big step forward in interpretations of remote sensing images and is an efficient and practical approach for information extraction.

Conflict of Interest: Authors declares that he/she has no conflict of interest.

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