International Journal of Ecology and Environmental Sciences
www.ecologyjournal.in
Online ISSN: 2664-7133; Print ISSN: 2664-7125; Impact Factor: RJIF 5.28
Received: 19-08-2020; Accepted: 05-09-2020; Published: 20-09-2020
Volume 2; Issue 3; 2020; Page No. 349-356

Tree canopies extraction for tree outside forest areas using spectral, spatial, and vegetation indices attributes after applying the rule-based classification approach: a case study for Jodhpur, Rajasthan, India

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Abstract
This paper summarizes advances in rule based/object based extraction of tree crown in different stratum of TOFs area in Jodhpur Town using World view 2 data. The generation of image objects is offered through a convolution filter followed by an automatic image segmentation approach focused on spectral feature objects and range of Vegetation Indices (VIs). PCA analysis has also been performed to find variation among variables in the dataset and to represent the distribution of samples.
The overall accuracy detection rate and the Kappa coefficient were 98.25% and 91.86, respectively. Accuracy assessment carried out for the quality and quantity of crowns extracted. Qualitative analysis detected maximum accurate detection for planted areas 0.971 followed by scattered 0.886 and linear 0.73 TOFs.Quantitave accuracy assessments for tree delineation indicated highest Accuracy Index (AI) % index for Plantation (97.73%) while Crown detection error of 14% noted for single crowns and 49% for clustered crowns. Ultimately, the reliability of this process is seen by contrasting these graded crowns with those obtained using traditional manual methods.

Keywords: TOFs, segmentation, convolution filter, vegetation indices, accuracy index, kappa coefficient

Introduction

Tree Outside forests (TOFs) also known as called "trees that nourish" [1] are the trees on land which is not defined as forest and other wooded land. In urban environments they often exist as single discreet trees or isolated groups to systematically manage trees in agroforestry systems. They are important component of urban ecosystems and have many ecological benefits. At the end of the 1990s orbital remote sensing started providing very high resolution (VHR) satellite data with a spatial resolution of less than 1 m, which allowed the study of individual trees [2]. However, with high spatial resolution imagery the spectral response of the individual tree is influenced by changes in canopy illumination and topographical effects, which reduces accuracy for conventional pixel-based classifications [3]. In order to solve this problem, an object-based image analysis (OBIA) was introduced where the basic unit of classification is an object or segment against a pixel-based classification. OBIA removes the salt and pepper effects that are common in pixel based approach. Successful segmentation of the image is a basic condition for object-oriented image processing [4]. conducted studies to generate stand and individual tree-based data for understanding the combination of VHR satellite images and OBIA in forest areas using WorldView-2 (WV-2) MS imaging. This study clarifies that by means of OBIA and VHR satellite images, the number of trees per hectare and the width of the tree crown were obtained with adequate precision. Study also concluded that the set of rules drawn up for a particular object or class produces far better results than the set of rules prepared for the collection of many objects.OBIA can be examined in two phases: segmentation and classification. Segmentation breaks the images into smaller blocks based on discontinuity and heterogeneity in the spectral responses of satellite images. Small blocks generated called as objects/segments are groups of pixels that provide additional information. There are different algorithms available for urban tree canopy extraction. Segmentation is one of the methods used to extract urban vegetation [5]. In this analysis the multi-resolution segmentation algorithm (MRS) [6] accompanied by a rule based classification was used. MRS is a bottom-up region-merging method, beginning with 1 pixel and functions and is possibly the most common for the purpose of delineating fairly homogeneous and meaningful segments. MRS uses three parameters to divide an image into objects: shape, compactness, and scale. Where Scale plays a major role as it is correlated with the average size of resulting object, larger a scale value more will be the number of pixels per object and vice versa [6-8]. For the objects generated after segmentation multiple rules can be defined using rule based Classification approach to remove unwanted objects from so to only include desired objects [9]. Rule-based classification is feature extraction tools that partition the image data into feature classes based on user-defined rulesets. Accurate detection and delineation of each single tree crowns in high-resolution images is a crucial step since it produces the basic measuring unit on which other attributes are based [10]. The most commonly used method for expressing the accuracy of classification is error matrix, also known as confusion matrix and compare class by class relationship between reference and classified data [11]. Accuracy has different parameters, such as omission error, commission error, and quantitative, qualitative /visual analysis. Qualitative analysis can be validated by examining quality measures such as completeness, correctness and quality. Where completeness is the percentage of entities in the reference data that have been detected, the correctness indicates how well the detected entities match the reference data [12]. Quantitative assessment involves the detection and delineation of estimated tree locations and crown boundaries with reference data. Accuracy Index (AI) was suggested in literature to represent overall quantitative accuracy [13-14]. Principal component analysis (PCA) is one of the best known unsupervised multivariate methods. It decomposes data sets as a function of the variance in the data [15]. It involves three major steps to translate the data (i) generation of covariance or correlation matrix (ii) calculation of eigenvalues and eigenvectors (iii) calculation of principal components. PCA converts interrelated variables from a dataset to a new set of non-correlated variables called Principal Components (PCs). Most of the variations present in the dataset are retained by the first few of these PCs. These first few PCs are linear combinations of all the actual variables [16].

2. Materials and Methods

2.1 Study area

The study was conducted in and the surrounding areas of the city of Jodhpur Figure (1). Jodhpur spread over the north western part of Rajasthan, India between 26.2680 latitude and 73.0060 longitudes. It extends over an area of 214.5km2 and is located at 241 m above sea level. Climate in Jodhpur is one of the deserts characterized by an average rainfall of 362 mm with large fluctuations.

Noted as low as 24 mm and as high as 1,178mm in the past. In summer, high temperatures exceed 400C.With increase in humidity perception of heat rises in the city. April, May and October, with an average of 10 hours of sunshine, were recorded as the months with most sunshine.

Annual Potential evapotranspiration noted was 6.38mm / year. In general soils are sandy to sandy loam in texture for a few parts, while in other parts there is loamy fine sand to coarse. Sand with high percentage of soluble salt and high pH value and low in nitrogen. Soil fertility is low because of low water retention capacity.

Important tree species include *Acacia nilotica, Syzygium cumini, Tecomella undulata, Ziziphus mauritiana, Azadirachta indica, Millettia pinnata, Dalbergia sisoo, Broussonetia papyrifera, Phyllanthus emblica, Cassia angustifolia, Prosopis cineraria, Delonix regia, Albizia lebbek, Eucalyptus sps* etc.

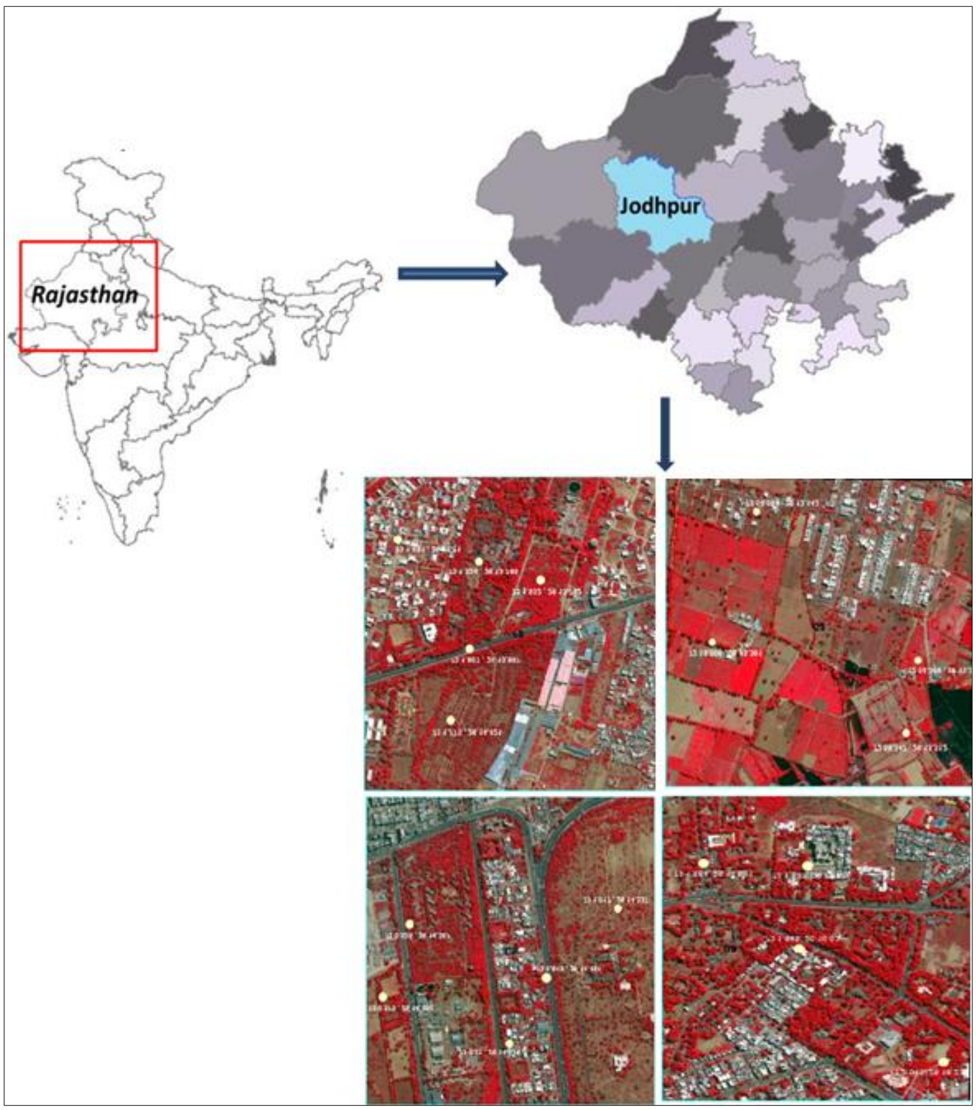


Fig 1: Study Area

2.2 Methodology

Dataset used: WorldView-2 (WV-2) imagery has been used for this study. (WV-2) VHR satellite imagery contains eight spectral bands with a spatial resolution of 0.5 m; four (4) standard colours (red, green, blue, and near-infrared 1) and four (4) new bands (coastal, yellow, red edge, and near-infrared 2).This study used a merged image of only standard colour bands. It has 11-bit radiometric resolution and the highest viewing angle, ±450 off-nadir, of any VHR imagery, which yields a 1651 km-wide swath [17].

The methodology followed to carrying out the current study shown in Figure 2. Figure (2 (a) showing broad methodology and (b) showing level wise steps followed and attributes used to remove extra objects other than crown)

Preprocessing: Filter of convolution applied to the image. Gauss Blur algorithm equation (1) sort with a kernel size of 3 applied to the image pixels. Gauss Blur is a convolution Operator used to remove noise. The formula is

$$G(x) = \frac{1}{\sqrt{2\pi\sigma}} e^{-\frac{x^2}{2\sigma x^2}} \quad (1)$$

Where σ is the standard deviation of the distribution [18].

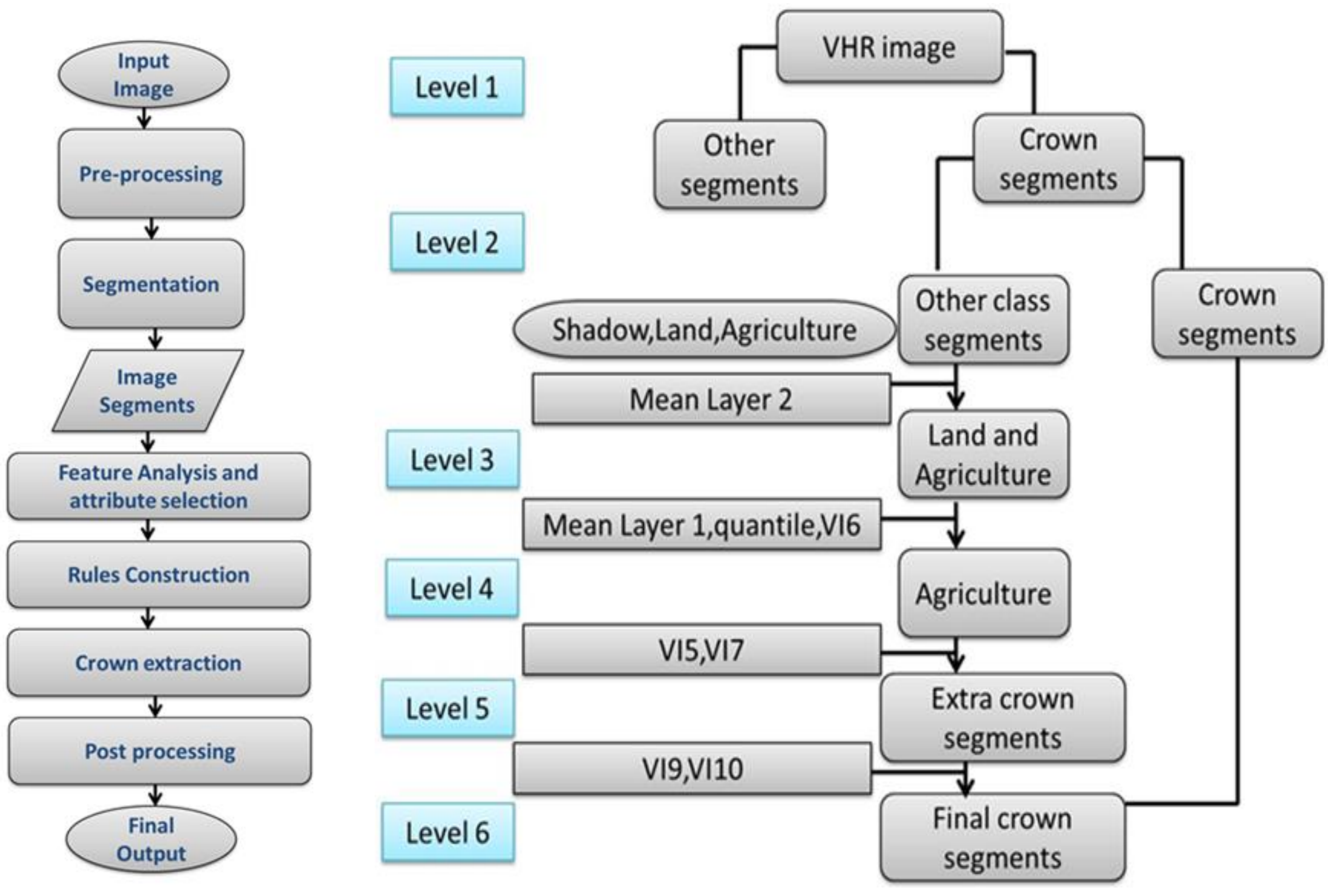


Fig 2: (a) Broad Methodology (b) Level wise feature selection

2.2.1 Segmentation

Multiresolution segmentation applied both at pixel level and at object level during the study. Begins with single-image artifacts of one pixel, merges them repeatedly into pairs of large units after going through multiple loops to the highest threshold homogeneity, where the seed searches for its best fitting neighbor for a possible merger. This measurement is determined by the scale parameter, which is directly proportional to the size of the segments / objects created. Five scale levels (40, 30, 25, 20 and 10) combined with 0.7 shape factor and 0.9 compactness were tested.

2.2.2 Feature Analysis and attribute Selection

To create a distinct and fully transferable rule base, attributes have been used to define object features Table (1).Under Object feature of feature view, 12 vegetation indices have been tested Table (2) along with Mean layer intensity value of few features and Geometry features, which are based on the image object shape derived from the pixels of their formation, have also been considered for image objects and their classification during rule formation.

Table 1: Selected attributes to define crown objects

Type	Feature
Customized	NDVI,SAVI, TVI, WDRVI, Atmospheric Resistance Vegetation Index,VI2-10,GSAVI,EVI2
Layer Value	Mean (L1, L2, Max diff), Pixel based(Min pixel frequency)
Geometry	Shape (Density, Asymmetry)

Table 2: Vegetation Indices used in the study

S. No	Vegetation Index	Description
1	Normalized Difference Vegetation Index (NDVI)	(NIR-Red)/ (NIR + Red)
2	Soil Adjusted Vegetation Index (SAVI)	((NIR-Red)*1.5)/ ((NIR + Red)+0.5)
3	Transformed Vegetation Index (TVI)	(NIR-Red)/ (NIR + Red)+0.5)
4	Wide Dynamic Range Vegetation Index (WDRVI)	(α*(NIR-Red))/(α *(NIR + Red))
5	Atmospheric Resistance Vegetation Index	((-0.18+1.17)*(NDVI))
6	Enhanced Vegetation Index 2 (EVI2)	(2.4*(NIR-Red))/ (NIR + Red)+1)
7	Vegetation Index 2 (VI2)	(NIR-Red)
8	Vegetation Index 3 (VI3)	(NIR-Green)
9	Vegetation Index 4 (VI4)	(NIR-Blue)
10	Vegetation Index 5 (VI5)	VI2/VI3
11	Vegetation Index 6 (VI6)	SAVI/TVI
12	Vegetation Index 7 (VI7)	(Green-Blue)/ (Green + Blue)
13	Vegetation Index 9 (VI9)	(Min Pixel value frequency/Min Pixel Value 4)
14	Vegetation Index 10 (VI10)	(Min Pixel value 3/Min Pixel Value 1)

2.2.3 Object Oriented Rule based Classification

Segments generated by segmentation must be categorized. Rule-based classification basically means integrating the best features of various data sources to more reliably extract land cover groups using certain rules to monitor attributes such as spectral, spatial, and texture details. Rules are built on the basis of spectral and spatial dataset information in the current study Table (1) and are applied to the image segments. The definition of rules may help to regulate the classification process and the number of misclassifications. Ended at 6 level Figure (2b) finally a set of rules is built to identify permissible crown features and to distinguish undesirable features from crown features. Final crown segments extracted here have been classified into three major linear, scattered and plantation stratums as (i) Linear comprised of Road, Railway and canal (ii) Scattered includes Settlement/Urban, Agriculture and Scrub (iii) Plantation. All stratums are divided into 6 subcategories based on their area as very small, small, medium, large, cluster small and cluster large. Cluster crowns are crowns in clusters that cannot delineate separate crowns.

2.2.4 PCA

In this study, PCA is used to evaluate the different sizes and stratum classes of crown segments and their anomaly and to find the degree of variance in the dataset in different dimensions after calculating their own vectors. A useful mathematical tool in the current Study PCA for generating different graphs representing the sample distribution and variation between data variables.

2.2.5 Accuracy assessment

Error matrix has been generated by the user, producer and overall accuracy, Kappa statistics [19].

Qualitative/Visual assessment: The consistency of the extracted crows has been validated by testing quality measures in two ways (i) Assessment of completeness, correctness and efficiency. Before applying these steps the extracted items have been labelled as True Positive (TP) is the number of pixels identified as being of interest, False Negative (FN) is the number of segments in the reference data that are not labelled as being interest in the automatic extracted image, and False Positive (FP) is the number of segments in the automatic extracted image [20]. (ii) The dissection, Aggregation and combination error were also evaluated. Dissection occurs when more than one image source of the recognition algorithm is associated with the same manual tree delineation. Aggregation is when more than one image object from manual tree delineation is associated with a single tree crown image object from a recognition algorithm. Combination error occurs when parts of the recognition algorithm are aggregated and parts dissected, as seen by assigning different image objects from each layer to the same image object in the other layer [21].

Quantitative assessment: In the case of crown detection evaluated using Accuracy Index (AI %), Commission errors occurred when a reference crown was detected as multiple tree crowns, or when tree crowns were incorrectly detected. Omission errors occurred when the reference crown was undetected. spearman (*rs*) Rho coefficient, Mean Absolute Error (MAE), Mean Relative Error (MRE), Mean Bias Error (MBE) was used for the Crown delineation quantitative evaluation.

3. Results and Discussion

3.1 Segmentation

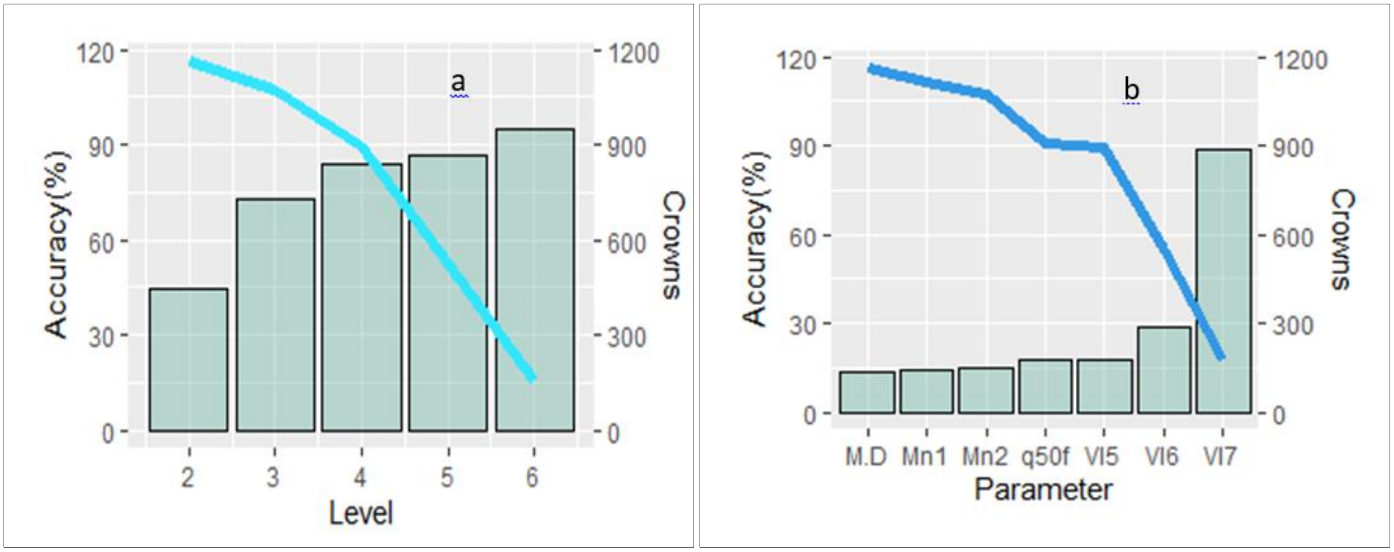
Five scale rates (40, 30, 25, 20 and 10) combined with shape factor 0.7 and compactness 0.9 were tested and one optimum scale parameter 20 for the segments of crowns was selected as it gave the best result for visualization based on color and homogeneity for optimal separation of crown segments compared to others. Image layers were assigned weights based on their importance for the results of segmentation. Highest weight was assigned to the pixel information of Layer 3 and Layer filtered.

3.2 Feature attribute selection

Separating tree crowns from other vegetation was challenging, as tree crowns are spectrally similar to other vegetation types, particularly bare ground and agricultural fields. Two objects with the same value for the selected spectral attribute, whose analysis is not sufficient to differentiate between them, caused a misclassification between two characteristics. In such examples, spectral attributes along with spectral indices and few spatial attributes have been used up to 6 stages. Our initial solution was to separate the maximum number of trees from other features. We used the spectral attribute 'maximum difference' to extract the segments of the crown.

It has been noted that agricultural fields, few patches of bare land and shadow have also been classified as tree crown segments. In such cases, we used other spectral attributes such as Mean layer 2 to mask shadows, VI6, quantile 50 and Mean layer 1 for bare ground VI7 and VI5 which showed very promising results for the removal of agricultural areas from the crown segment. While removing other features, it was noted that in a few places we lost information about the crown segments, so in those cases the spatial attributes such as VI9 and VI10 were useful to recover the crown segments back. Less crown segments were noted after level 6 after removing additional segments of the other groups

It was noted that the extra crown segments decreased with each increasing classification level, thus increasing the accuracy at each rising level Figure (3 (a) Crown segments and accuracy with each classification level (b) Different attributes and their corresponding crown segments and accuracy



*M.D=Max difference, Mn1=Mean layer 1, Mn2=Mean layer 2, q50f = quantile filtered (5), VI5 = Vegetation index 5, VI6 = Vegetation Index 6, VI7 = Vegetation Index 7

Fig 3: Accuracy between (a) Crown segments and each classification level (b) Attributes and their corresponding crown segments

A comparison was made for the number of crown segments in the reference data and in the OBIA segments, an increase in the number for each was noted for the segments extracted by OBIA. There were a few places where the overestimation of the crown was noted, although it was found for other groups that the crowns we were unable to extract manually were extracted by OBIA.

3.3 PCA analysis for number of Crowns and Size of crowns in different class

The PCA here was based on a matrix of correlation

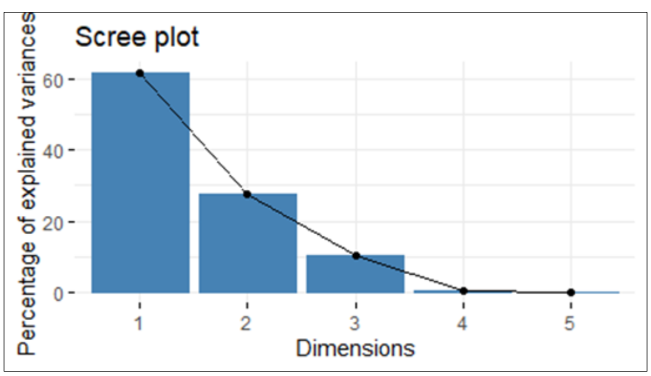


Fig 4: Scree plot showing Principal Components (PCs)

3.3.1 Number of crowns

Here a PCA analysis of the number of crowns in different classes Has been done. The dataset scree plot showing Figure (4) that the first two PCs have an eigen value greater than 1 and these two components themselves explain about 89.35 % of the variance in the data. It has been noted that after the third dimension of the PC line starts to be flattened, in this case we have taken into account only the first 2 PCs.

The coefficient between the coordinates of the entity on the dimension and the variable was determined, which automatically displays the variables where $p<0.05$ is used. It was noted that the "small" variable for 1st PCs showed the highest positive correlation followed by "medium", "large", "very small". Similarly, the "Cluster large" and "Cluster small" PCs have a strong correlation for PC2 while the p values for 2 dimensions are lower than the first one.

3.3.2 Biplots

Provide plots of n number of individuals along with plots of relative position of p variables in two dimensions. Superimposing two plots provides additional information on the relationship between variables and individuals [22].

Figure (5) shows the biplot for individuals and variables of the dataset indicating the relationship between individuals and variables.

High value for small, medium and very small segments of the crowns generated automatically in plantings and urban areas while For reference parts, high-value crowns for urban areas shown by large crown and low by small and wide clusters.

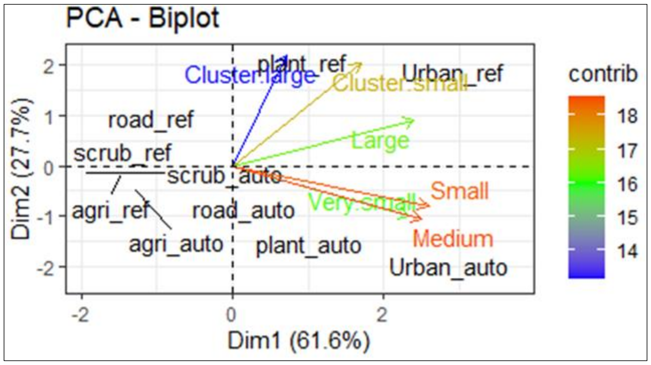


Fig 5: Biplot showing relation between individuals and variables

Crown area in different classes: PCA analysis for size / area of crowns in different classes has been done here.Figure (10) showing the scree plot for the dataset indicating that first three PCs have eigen value greater than 1 and these three components explains about 85.91% of variation in the data. Considering only the first two PCs for study, this explains about 66.34% of data variability.

It has been noted that the highest positive correlation has been shown for the 1st PC variable "Large" followed by "Very small", "Cluster small", "small". Similarly for 2nd PCs "Cluster high" showed good correlation.2-dimensional p values are less than 1

Biplots: Figure (6) shows the biplot for individuals and dataset variables suggesting relationships between individuals and variables. High value for the large, small and very small clusters noted for the 1 dimension segments of the reference crowns, While high value for small and low for very small and large segments for 2 dimensions of automated segments.

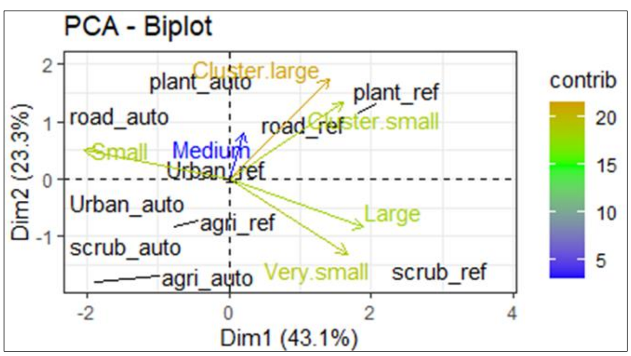


Fig 6: Biplot for variables and individuals

3.5 Accuracy assessment

Accuracy assessment was carried out following the selection of random points from the reference data and the overall accuracy and kappa coefficient for the extracted crown segments reported was 98.25% and 91.86, respectively. Accuracy assessment has been carried out at each increasing level.

Accuracy of users and producers has been checked. Where the accuracy of the producer indicates how well the situation / pixels or objects on the ground are mapped and relates to the error of omission as higher the omission less will be Producer accuracy. On the other hand, user accuracy conveys the reliability of the information on the map and higher the error of the commission, the less the accuracy of the user

Linear stratum (98.33), followed by scattered (93.65) and Plantation (92.12) have been noted to be the highest producer accuracy, whereas maximum value user accuracy noted for Scattered (96.65) and Linear (93.78) followed by plantation (92.67).

An increase in both the Producer and User accuracy table (10) noted for all classes of Post-modified crown segments Table (3).

Table 3: Producer and User accuracy in different classes for pre modified and post modified level

Levels	Class			
	Urban	**Agriculture**	**Plantation**	**Road**
Pre modified (1,2,3,4,5,6)				
Producer	76.765	54.46	83.70	87.53
User	96.89	97.89	99.03	94.02
Post modified				
Producer	95.39	90.17	96.66	91.85
User	98.05	100	99.77	98.41

3.6 Qualitative/Visual analysis

Once evaluated, the best qualitative results noted in the planted areas, followed by scattered stratum table (5) low values noted for linear Stratum due to high False Positive and False negatives

Table 4: Stratum wise Qualitative analysis

Stratum	Completeness	Correctness	Quality
Linear	0.78	0.804	0.657
Scattered	0.915	0.958	0.886
Plantation	0.994	0.976	0.971

Maximum True positive values noted for linear stratum Figure (7) due to low dissection, aggregation and combination error [21].

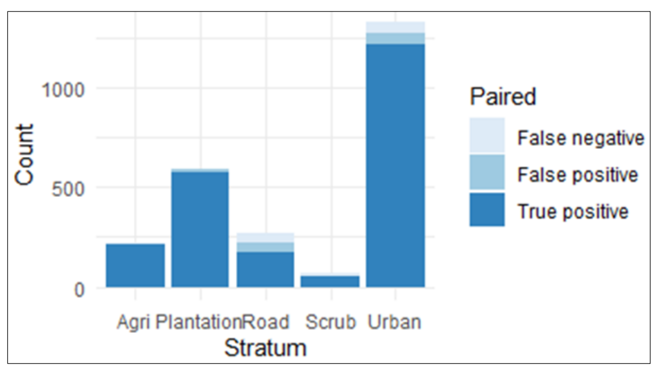


Fig 7: Showing values of True positive, False positive and False negative in different Classes

3.7 Quantitative Evaluation:

Tree detection accuracy: Tree detection evaluation was based on [13] accuracy index (AI), defined as:

$$AI\%=n-(o+c)/n*100$$

Where n represents the total number of reference trees and o and c represents error of omission and Commission Figure (6) respectively in the accuracy assessment dataset

Commission error refers to the number of reference crowns (manuals) detected as multiple tree crowns or where tree crowns are erroneously detected and omission errors are undetected as reference crowns.
The crown objects were reported against reference tree crowns to assess the accuracy of the tree detection table (6). Maximum accuracy index for urban areas (99.32 per cent) followed by agriculture (98.29 per cent) plantation (97.73 per cent) and road (95 per cent) clearly indicates proper extraction of crown objects in these areas, While the lowest scrub area value (81.49%) suggests a sparse distribution of irregular canopies in the field with a greater reflection on the ground item

Table 5: Accuracy Index for Crown classes

Class	Error of Commission	Error of omission	n	AI%
Urban	4.330	4.179	1268	99.328
Agriculture	0.938	2.764	217	98.293
Plantation	6.219	7.877	622	97.733
Road	7.329	1.666	180	95.001
Scrub	4.76	12.08	91	81.494

For all classes and for six sub-categories the accuracy of crown delineation focused on crown area (CA) was achieved.
Four steps were taken to evaluate the accuracy between reference CA and image CA (1) the correlation coefficient (Spearman's Rho; *rs*) (2) the mean absolute error (MAE) (3) the mean relative error (MRE),it is a measure of precision and the averaged ratio of the absolute error to field CA (4) The mean bias error (MBE) is defined as the difference between the mean delineated CA and the mean CA field and indicates the degree of over-or under-estimation. The statistical analysis was executed in R studio 3.1.6.

Table 6: Quantitative quality assessment for different crown size

Class	*rs*	MAE	MRE %	MBE
Very small	-0.6	1.09	10	1.03
Small	0.4	2.106	6	-1.6
Medium	-0.1	8.95	7	0.611
Large	0	73.25	14	73.25
Cluster small	0.89	80.361	38	-20.2
Cluster large	0.7	222.94	49	-222.9

In the process of assessing size-wise results table (6), the average MAE of single crowns was 73.25m2 and MRE=14 % for large trees, while the delineation error for small size trees was as low as 6 percent due to small crown size and the dispersed distribution of trees. Owing to high heterogeneity, poor accuracy can be observed either in the distribution of crowns or in the diversity of tree species or both. Overestimation noted for large crown areas (MBE=73.25) results overlapping of small tress by large trees so underestimation noted for small size trees(MBE=-1.6). Adjacent field vegetation dilutes the crown edges with bands' spectral response and their combination in the image causes overestimation. MAE=222.94m2 and MRE of 49 % were shown for clustered crowns in large clusters. Although Class wise table (7) highest delineation accuracy noted for agriculture expressed in rs=0.78, MAE=10.03m2 and MRE=14% followed by road with rs=0.41, MAE=81.71m2 and MRE=38%. Planting and scrubbing areas showed the lowest accuracy. Underestimation noted for almost all classes as arid zones for Tree Outside Forest areas result in high spectral crown variance and strong ground reflection influence on spectral response.

Table 7: Quantitative quality assessment for different TOFs classes

Class	*rs*	MAE	MRE%	MBE
Urban	-0.08	61.09	30	-37.67
Agriculture	0.78	10.03	14	8.97
Road	0.41	81.71	38	-81.71
Plantation	0.216	184.695	80	-90.25
Scrub	0.21	79.08	86	-28.74

4. Conclusion

The requirements for advanced knowledge on forest resources became a prime requisite. TOFs canopies extraction has great importance for environment management practices. Extraction of canopies in urban areas remains a complex problem for scientists. New generation of VHR satellite allows individual tree crowns to be visually identifiable. VHR had an intense effect in image processing techniques to extract information. Study aims to detect Tree Outside Forest crown canopies using satellite images via automatic analysis. The proposed methodology applied a set of organized rules on VHR image at different levels to improve extraction of the canopy class. The key issue faced in the canopy delineation is the overlap of the crown with certain groups of objects, such as shadows, crop fields and bare land. The detection of crop fields with full crop growth is an example of a major misclassification while extracting tree canopies. Such complications of misclassification have a negative effect on the accuracy of the classification process. Proposed methodology applied a set of organized rules using spectral attributes and indices at different levels to improve canopy class. Vegetation indices were generated to mitigate the adverse effects. These indices played an important role to discriminate between crown segments. For the current study Overall tree detection accuracy i.e. Accuracy index found to be high. Crown delineation accuracy shown that overestimation and underestimation.
Future work will include expanding the tree identification refining and segmentation results for the delineation of canopies; comparison and analysis of various filters across the same area; creation of new algorithms for the automated crown extraction in arid urban forest.

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