Detection of urban tree canopy from very high resolution imagery using an object based classification

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ABSTRACT

Tree that grows within a town, city and suburban areas, collection of these trees makes the urban forest. These urban forest and urban trees have impact on urban water, pollution and heat. Nowadays we are experiencing drastic climatic changes because of cutting of trees for our growth and increasing population which leads to expansion of roads, towers, and airports. Individual tree crown detection is necessary to map the forest along with feasible planning for urban areas. In this study, using WorldView-2imagery, trees in specific area are detected with object-based image analysis (OBAI) approach. Therefore with improvement in spatial and spectral resolution of an image, extracted from WorldView-2 carried out urban features with better accuracy. The aim of this research is to illustrate how object-based method can be applied to the available data to accurately find out vegetation, which can be further sub-classified to obtain area under tree canopy. The result thus obtained gives area under tree canopy with an accuracy of 92.43 % and a Kappa coefficient of 0.80.

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1. INTRODUCTION

Individual tree detection performs an analytical aspect in adequate, decisive, organized and systematic mapping of the forest [1]. Data collected through remote sensing satellites which provide high resolution images just like the WorldView-2 which can provide data changes with time and can be used for environmental monitoring. In remote sensing imagery, many vegetation indexes have been widely used for extraction of vegetation information from such imagery [2]. Traditional methods for urban trees mapping are visual interpretation and field investigation. Both the methods are time consuming and labor consuming hence it has been replaced with this new methodology.

Trees play an important role in the urban ecosystem such as maintaining water level, temperature, air quality and flood risk. Different remote sensing techniques are used to detect trees or species of trees with the help of high spatial resolution imageries which are acquired by IKONOS, QuickBird, and WorldView-2, and WorldView-3 satellites. Urban areas are surrounded by non-tree objects whereas forest areas trees crown are densely distributed, so it is tedious to detect tree canopy in urban area [3]–[7]. There have been tremendous improvements in optics and sensor technologies, high resolution data through satellites such as WorldView-2, and Quickbird, maps the forest quite exceptionally well. This includes classification of vegetation and structure extraction of trees.

Various techniques and models for studying the biophysical parameter of vegetation have been developed. There have been several mathematical combinations of multiple spectral bands and spectral indices proposed. The normalized difference vegetation indices, which are based on the principle of a relationship between visible light absorption and persistent near-infrared light reflectance, have been shown to be an effective and accurate tool for canopy mapping. The main goal of this study was to create an object-based classification framework for detecting two different types of urban vegetation [8]–[10]. This study has three objectives: the first is to figure out how to choose an original source for segmentation, the second is to figure out how to extract thematic information at various scales and how to determine scales, and the third is to figure out how to choose a feature space to classify objects.

In our evaluation researcher consider pictorial representation of urban area of Mumbai acquired by using the WorldView-2 satellite [11]. WorldView-2 was one of the first satellites that could capture high resolution imagery. Since supplementary data is essential for this research to meet its purpose, we utilize very high upscale resolution of WorldView-2 (WV-2) along with increased spectral reliability for the study. The resultant image obtained through WV-2 imagery comprises of 9 spectral bands and has radiometric resolution. From the 9 bands, 8 bands are multispectral with resolution 2 meters each whereas the last band is panchromatic with a spatial resolution of 0.5 meters. Pan sharpening is a resolution merging process. It creates a single finalized very high resolution color image. This image is a product of color information in high resolution grey scale band, spatial information and multispectral band information. This paper is structured in few sections, here section 2 discusses about proposed methodology while section 3 highlights result and discussion, and conclusion of this study is brought in section 4.

2. PROPOSED METHOD

To import an image into eCognition, a new project is created with options for a project title, number of bands with in image, and subset selection. eCognition can work with a wide range of typical imaging formats used in the remote sensing field. When adding new image layers into eCognition, information on the radiometric resolution of various layers are displayed along with geographic coordinates. Urban area of Mumbai acquired by using the WorldView-2 satellite is shown in Figure 1. Figure 1(a) original image. In addition, Figure 1(b) shows false color composite of original image for extraction of vegetation [12].

(a) (b)

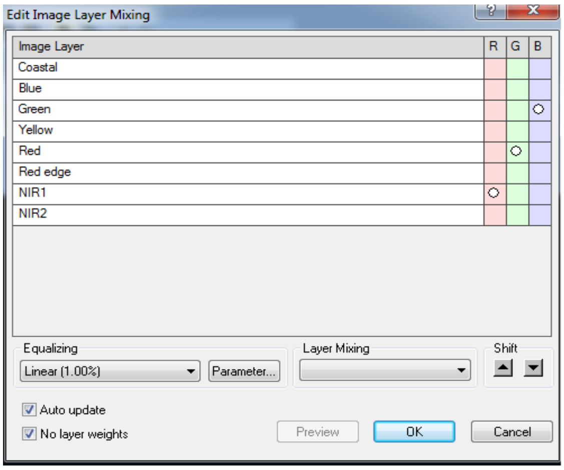
Figure 1. World-view-2 satellite imagery of Powai area (a) original image and (b) false color composite of original image for extraction of vegetation

For vegetation analysis false color composite image (FCC) is more useful as vegetation has strong reflectance in near infrared (NIR) band. Edit image layer mixing window is used to select required bands of Multispectral image. The normalized difference vegetation index (NDVI) is generated as a separate band to improve the spectral power of imagery for vegetation extraction.

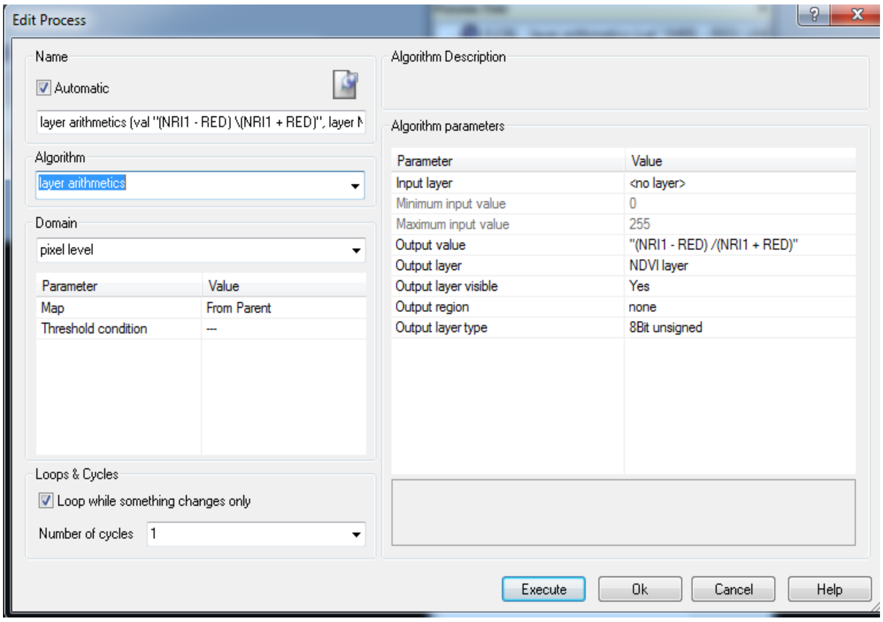
NDVI is defined as (1):

$$\text{NDVI} = \frac{\text{NIR}-\text{RED}}{\text{NIR}+\text{RED}} \tag{1}$$

NDVI layer is created using (1) as shown in Figures 2 and 3. Figure 2(a) three layer mixing. In addition, Figure 2(b) shows creating NDVI layer.



(a)



(b)

Figure 2. Layer arithmetic algorithm is used to compute NDVI band (a) three layer mixing and (b) creating NDVI layer

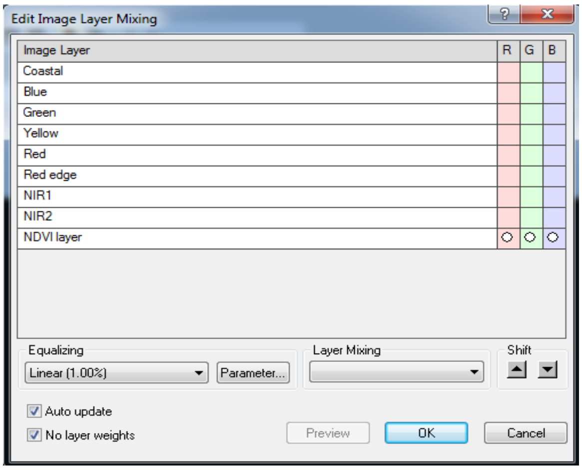


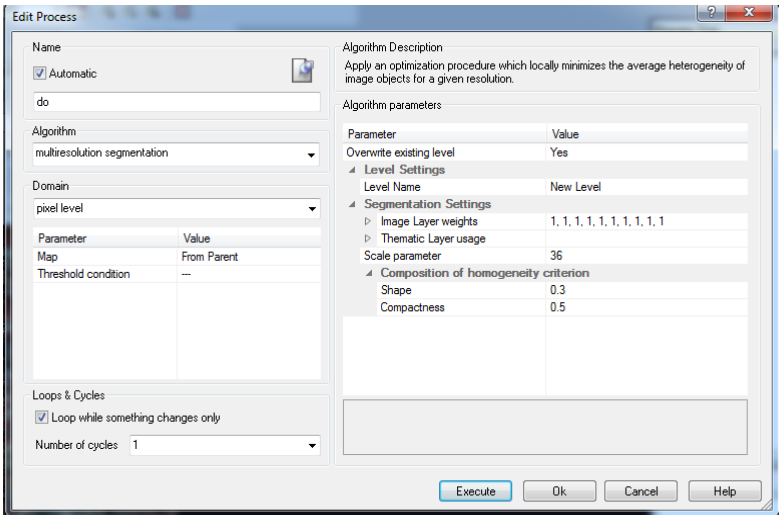
Figure 3. NDVI layer creation by eCognition for vegetation detection

2.1. Image segmentation

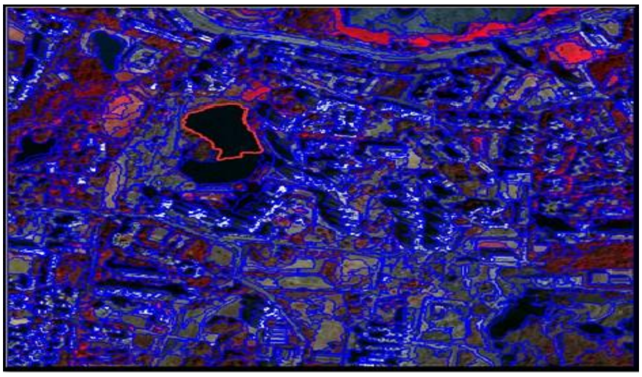
Image segmentation is one of important step before classification. In object based image analysis, small pixels are grouped together to form vector objects. Objects of images are building blocks for further segmentation and classification. Scale and size are two parameters determine the maximum heterogeneity within object [12]. By changing the scale parameter the size of an image object can be varied. Segmentation is the part and parcel of object based image analysis [13]. There are two basic segmentation principals used in eCognition are top-down segmentation and bottom-up segmentation as follows: i) top-down segmentation incorporate contrast split segmentation, quadtree-based segmentation, and chessboard segmentation and ii) bottom-up segmentation incorporate multiresolution segmentation and spectral difference segmentation.

Segmentation breaks image into objects. Classification classifies all these objects based on spectral and spatial properties. In this research, multiresolution segmentation was used, where both shape and color features of objects are considered [14]. This segmentation used iterative methods to create objects. Scale, shape and compactness are the parameters needed to be set in multi resolution segmentation. Spectral variations in objects are controlled by scale parameters. Shape-color parameter is used for weighing object's shape and color. If weighing between objects, shape and color, which if zero then color is considered, and if it is greater than zero then both parameters are considered [15].

Compactness is one of the parameters used during the segmentation. Vegetation detection is a first level of segmentation completed by putting values in all parameters. Contra-split segmentation algorithm is used on NDVI layer to differentiate vegetation and non-vegetation area. Further, the image is segmented with the help of multiresolution analysis algorithm of eCognition software [16]–[20] as shown in Figure 4. Figure 4(a) composition of homogeneity criterion. In addition Figure 4(b) shows multiresolution segmentation output by eCognition.



(a)



(b)

Figure 4. Applying an optimization procedure (a) composition of homogeneity criterion and (b) multiresolution segmentation output by eCognition

2.2. Image classification

After segmentation the next step is classification, here image is first classified into vegetation and non-vegetation. Vegetation is further classified into trees and grass. Object based image analysis method combines textural, contextual, and spectral and class related features of objects to assign class with threshold. Each parent class is divided into subclasses called child classes to give more detailed land cover [21].

Objects are fundamental units of object-based image analysis (OBIA) method, in which objects are basically segments of homogeneous areas in the image. Instead of objects one can argue for per-pixel classification but it is not suitable for processing of very high resolution image [22]. Information content of the image is directly proportional to spatial resolution. Spatial auto correlation removes prominent boundaries and delivers uniform shapes and textures.

Vegetation: NDVI, this index can be used for the extraction of vegetation from multispectral imagery using the NIR and red bands [23]. After segmentation different features for the objects can be obtained like texture, and spectral. Once objects are formed then, they can be classified with the help of advanced classifiers. These features are used to model the occurrences of trees in different areas [24].

Grass and Trees: vegetation is further classified into trees and grass based on their homogeneity values [25]–[27]. Here grey level co-occurrence matrix (GLCM) is used with texture measure. The GLCM is a value that describes how frequently various combinations of pixel brightness values appear in an image. The texture classification approach is used in a GLCM [15], [28]. The homogeneity value is used in texture classification. For each pixel within the image, the homogeneity value is determined. A matrix of values is formed after the homogeneity values have been calculated. If the homogeneity value of a pixel changes, the GLCM [29], [30] value is calculated. Vegetation is larger in NIR band so this band is used for GLCM texture calculation. Classification of grass and trees is second level of segmentation. Figure 5 shows the flow diagram of proposed methodology for tree extraction.

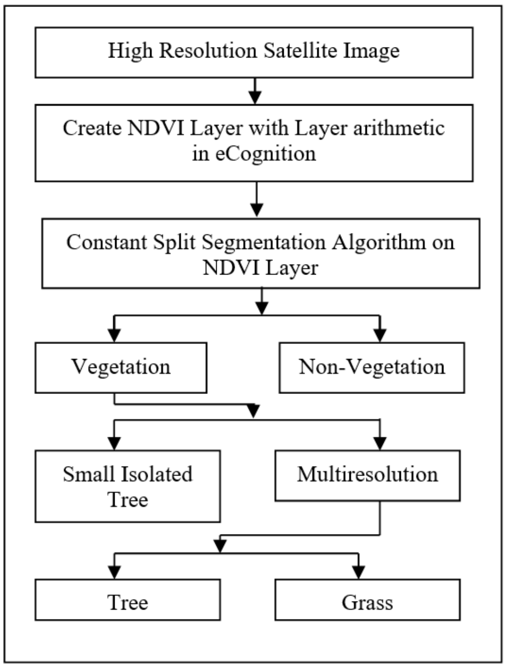
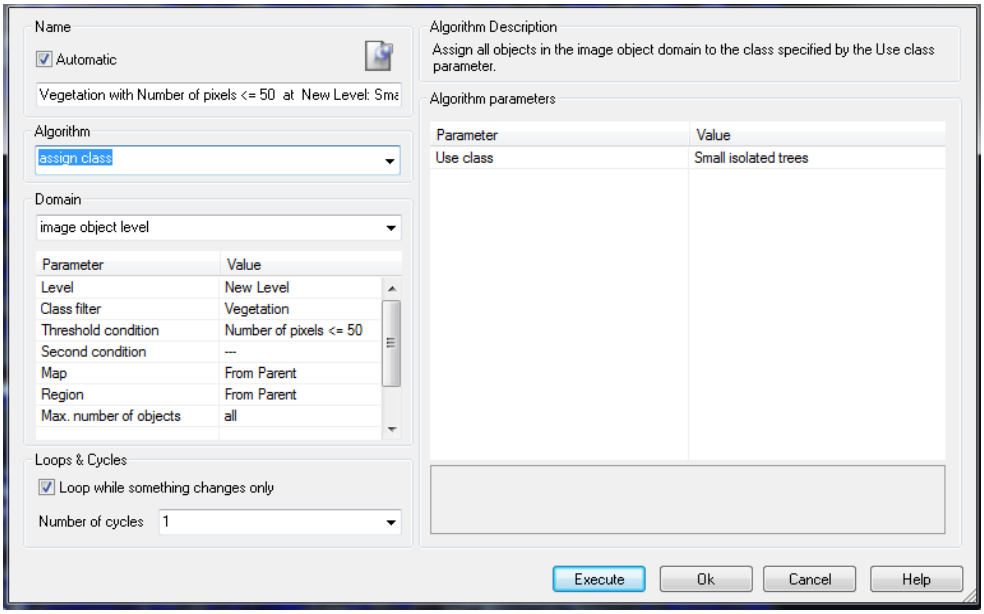


Figure 5. Flowchart for proposed methodology used for tree extraction for object based classification

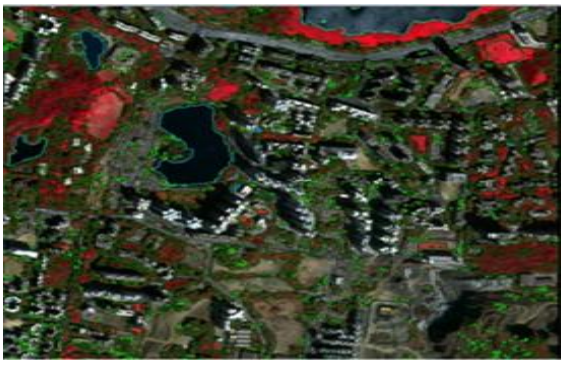
3. RESULTS AND DISCUSSION

Contrast split segmentation is top down segmentation which divides objects into smaller parts. It is most convenient segmentation algorithm for separation of vegetation and non-vegetation area as it segments the images into dark and bright images as shown in Figure 6. NDVI layer is selected for contrast split segmentation algorithm. As a result, individual trees with contrasting backgrounds can be quickly distinguished as shown in Figure 7. Figure 7(a) apply threshold condition. In addition Figure 7(b) shows classification of original image into small isolated trees. Lastly, image was classified into trees, Grass and Small isolated trees and area covered under tree canopy as shown in Figure 8(a) classes as grass, small isolated tree and 8(b) extraction of area covered by tree canopy.

Figure 6. Classification of original image into vegetation and non-vegetation



(a)



(b)

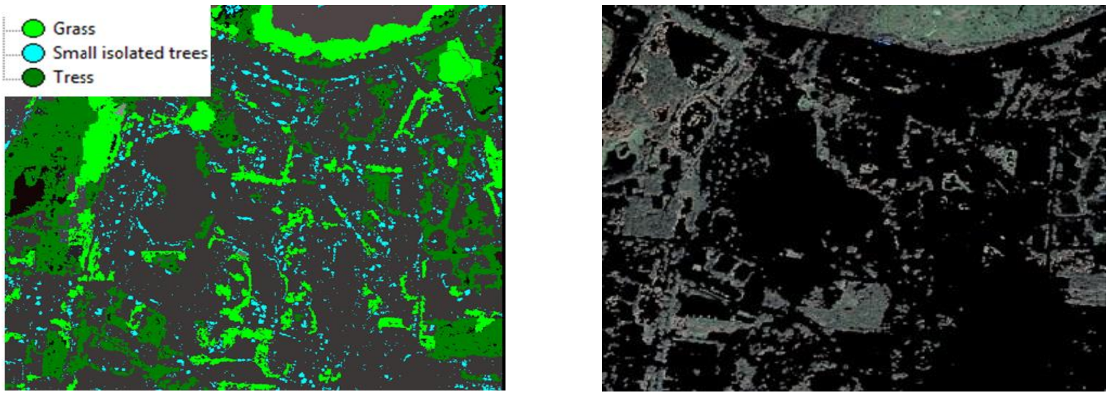
Figure 7. Assign class for extraction of small isolated trees (a) apply threshold condition and (b) classification of original image into small isolated trees

Terms used for analysis are condition positive (P), condition negative (N), true positive (TP), true negative (TN), false positive (FP), false negative (FN).

$$\text{Accuracy} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{2}$$

Area Covered By Tree Canopy = 1572072 Pixels of 4000000 Pixels = 39%.
Overall Accuracy: 92.43 %, Kappa Coefficient: 0.8013

The suggested method performs relatively well in detecting canopy and non-canopy areas. Table 1 shows the values of performance factors related to classification. The Kappa coefficient produced a result of 0.8013 with an accuracy of 92.43%. For an 8-band WorldView-2 image, the area covered by tree canopy was found to be 39%.



(a) (b)

Figure 8. Final output with (a) classes as grass, small isolated tree and trees and (b) extraction of area covered by tree canopy

Table 1. Classification results for WordView-2 image

Class Name	Non-Canopy	Canopy
Non-Canopy	[2834565]	[9880]
Canopy	[292982]	[862573]

4. CONCLUSION

Analysis of high resolution images becomes simple, flexible, time efficient through object based image analysis method. To monitor and manage urban area very high resolution satellite images help to get detailed information on tree distribution. Heterogeneous and complex urban areas can be classified accurately with object based image analysis method. This method uses full image information which increases the classification accuracy. The accuracy can be improved further with light detection and ranging (LiDAR) data which gives height and intensity features. The classification of multispectral data can be improved further by incorporating thematic layer or ancillary data. Change detection can be carried out with multi-temporal data set. Subsequently within the area of detected vegetation, area of tree canopy was detected and segmented. Thereby the overall accuracy achieved through OBIA is 92.43%.

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