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Geospatial Analysis Of Tree-Based And Shrub-Dominated Land Cover In Ayodhya District, Uttar Pradesh, India

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ABSTRACT:
Woody vegetation systems – encompassing tree-based and shrub-dominated land cover -serve as critical sources of timber, fuelwood, and food security in developing economies like India. These ecosystems enhance environmental resilience and strengthen community livelihoods, necessitating precise spatial analysis. This study applied Object-Based Image Analysis (OBIA) to Google Earth imagery to map woody vegetation across Ayodhya District, Uttar Pradesh. A systematic stratified random sampling design guided field survey point selection, object classification, and thematic map validation using ground-truth data. Vegetation features were classified as patches, linear arrangements, or isolated trees; notably, forested areas exhibited exclusively patch-based distributions. The standardized delineation methodology involved: (1) initial pixel segmentation into image objects, followed by (2) application of spatial-property rules for crown/cluster detection – establishing the object-based framework. The resultant spatial inventory provides vital baseline data for sustainable management of woody vegetation resources.

Keywords*: Object-Based Image Analysis (OBIA), Geospatial Vegetation Mapping, Woody Vegetation Systems classification, tree-based and shrub-dominated land cover classification, Geographical information System, Sustainable Environment, Uttar Pradesh.*

INTRODUCTION:

Forests and trees form integral components of various landscapes, including tree-based and shrub-dominated land cover, and often serve as the primary source of tree-related resources for rural populations, particularly in developing countries. Growing a lot of trees outside of forest regions would be one of the management strategies since it would help to preserve the natural balance while also giving the surrounding population access to fuel, fodder, and timber (A. A. Wani, Basira Mehraj, T. H. Masoodi, A. A. Gatoo, andJ. A. Mugloo, 2021). It also plays an important role in combating greenhouse gases as a carbon storage sink (Him Lal Shrestha, Anu Rai and Puspa Dhakal, 2020).

Government sustainable development strategies recognize trees as vital contributors to quality-of-life enhancement in both rural and urban landscapes. Beyond aesthetic enrichment, trees provide critical ecological services: they act as natural air filters by trapping particulate matter (dust, smoke) and absorbing gaseous pollutants through foliar and bark systems. Through photosynthetic carbon sequestration, trees mitigate greenhouse effects by removing atmospheric CO_2 while releasing oxygen. Their multifunctional environmental roles include microclimate regulation, water cycle conservation, soil stabilization, and biodiversity habitat provision – collectively sustaining healthier ecosystems for human communities.

Through photosynthesis, plants and trees sequester atmospheric carbon dioxide while releasing oxygen as a metabolic byproduct. In territorial forests, trees also serve a crucial function in reducing pollution and regulating temperature, but they also do this outside of forests (Anubha Srivastav, Hari Om Shukla, 2021). Trees are likewise a viable sound wall and can restrain noise pollution. Trees in themselves advantage the earth and the landscape, yet they are additionally a necessary part of the biological community giving advantages to natural life and biodiversity. Trees, particularly older or veteran trees give living habitats to native ground flora and fauna. Tree-Based and Shrub-Dominated Land Cover are specific trees and tiny collections of trees in non-forest habitats that are regarded as a fundamental resource internationally (Dacia M. Meneguzzo, Greg C. Liknes & Mark D. Nelson, 2012). A significant portion of land—whether on agricultural fields, in densely populated regions, fruit tree plantations, or home gardens—is often covered with trees. In urban settings, trees offer crucial aesthetic and environmental benefits that enhance the livability of cities and contribute to the energy efficiency of farmsteads.

Tree-Based and Shrub-Dominated Land Cover refers to areas of land where the dominant vegetation consists of trees (either naturally occurring or planted) and shrubs (woody plants smaller than trees, typically with multiple stems). These landscapes include forests, orchards, groves, plantations, hedgerows, and scattered trees or shrubs across agricultural fields, urban spaces, and rural homesteads. Such land cover plays a vital role in providing timber, fuelwood, food, carbon storage, biodiversity habitat, and contributes to ecosystem services like soil conservation, climate regulation, and air purification.

According to the 2021 biennial assessment by the Forest Survey of India (FSI) under the Ministry of Environment, Forest and Climate Change (MoEFCC), India's total forest cover spans 7,13,789 km2 (21.71% of the geographical area), while tree cover extends over 95,748 km2 (2.91%). Uttar Pradesh contributes 14,817 km2 of forest cover (6.15% of its geographical area) and 7,421 km2 of tree cover (3.08%), yielding a combined forest-and-tree cover of 22,238 km2 (9.23%). Notably, Ayodhya Social Forestry Division retains 89.30 km2 of forest cover, constituting 3.81% of its 1,282 km2 geographical area (FSI, 2021).

Digital image classification is the most often used image analysis method for tree-based and shrub-dominated land cover extraction. There are two main categories of categorization processes, and each is used in the remotely sensed image processing (Jesus Aguirre-Gutiérrez, Arie C. Seijmonsbergen, Joost F. Duivenvoorden, 2012). The first is called unsupervised classification, and the second is called supervised classification. While they can be used independently, they are often integrated into hybrid approaches that combine multiple methods. The conventional pixel-based classification method, widely used for classifying multispectral images, has been effective particularly with low-resolution imagery. However, as newer satellite images offer higher spectral and spatial resolution, traditional pixel-based methods often struggle to deliver satisfactory classification results. To address these limitations, the advancement of remote sensing technologies has introduced a novel approach called Object-Based Image Analysis (OBIA). This method segments imagery into homogeneous objects based on properties such as spectral values, shape, and texture—enabling a more accurate and context-aware classification.

Unlike pixel-based techniques that rely solely on spectral data, object-based classification integrates both spatial and contextual information. In this approach, images are first segmented into groups of spectrally similar pixels, forming objects. These objects are then classified using their combined spectral and spatial characteristics (e.g., size, shape, texture). This method mimics the human visual system, which processes high-resolution imagery more effectively by recognizing patterns and contextual clues.

This study used ERDAS Imagine 2016 Object-Based Image Analysis (OBIA) to map trees and shrubs in Ayodhya District, Uttar Pradesh. The method worked well for identifying vegetation in mixed areas like residential-commercial zones and suburban communities. Mapping of Ayodhya District is important because it helps protect cultural heritage, support sustainable development, and manage religious tourism.

MATERIALAND METHODOLOGY:

2.1 STUDY AREA:

Ayodhya Division (26°24′26″N to 26°53′17″N latitude and 81°32′36″E to 82°28′55″E longitude), with its administrative headquarters at Ayodhya city situated along the Saryu River, area covered to **2751.749 sq. km**. Revered as the birthplace of **Lord Ram** and recognized as one of the **Mokshdayini Sapt Puris**, this ancient city positioned at an elevation of **93 meters**. Administratively, the division comprises **12 blocks**, **5 tehsils**, **835 gram panchayats**, and **1,272 villages**. Bounded by the districts of **Basti, Ambedkar Nagar, Sultanpur**, and **Barabanki**, the region experiences a **humid subtropical climate** with summer temperatures ranging between **22°C and 46°C**, winter temperatures between **5°C and 15°C**, and an average annual rainfall of **700.6 mm**. The **Ayodhya Forest Division**, consisting of **five forest ranges** namely Bikapur Range, Faizabad Range, Kumarganj Range, Maya Range, and Rudauli Range. The study area and its spatial extent are illustrated in Figure 1 Location Map of Ayodhya District, Uttar Pradesh, India.

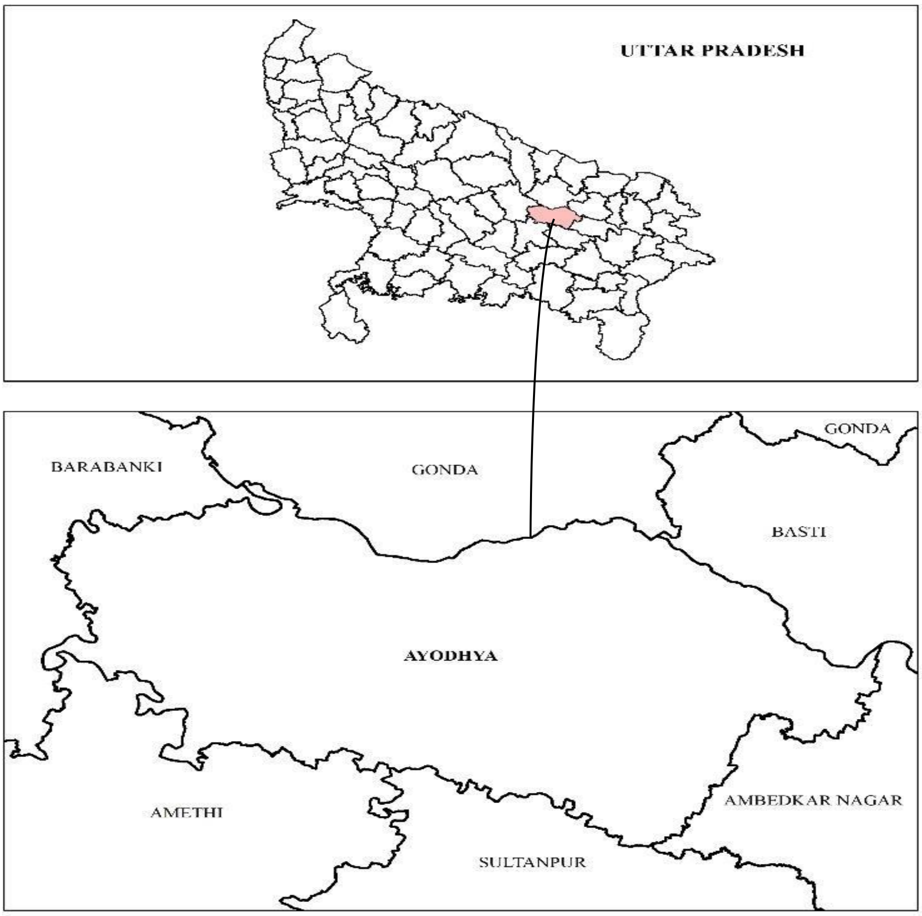

Figure 1: Location Map of Ayodhya District.

2.2 DATA LOADING AND DATA SOURCE:

Georeferenced and projected high-resolution Google Earth imagery was downloaded in *.img format using SAS Planet (SAS.Planet. Release.191221) and processed using ERDAS Imagine 2016 and ArcGIS 10.2 for digital image analysis and thematic mapping. The study utilized a combination of primary data (field observations), secondary or collateral data (such as administrative boundaries, topographic maps, and forest records), along with appropriate hardware and software tools. Following data acquisition, the imagery was prepared through geospatial processing techniques to support the mapping and estimation of Tree-Based and Shrub-Dominated Land Cover in Ayodhya District, Uttar Pradesh, using the Object-Based Image Analysis (OBIA) methodology.

METHODOLOGY:

3.1 PROCEDURE:

Provide the following procedure for estimating Tree-Based and Shrub-Dominated Land Cover in this paper. The steps were as follows: (i) the data was obtained from a free online source; (ii) the data was prepared for classification; (iii) the classification procedure; (iv) ground truth validation and verification; (v) the classified data was refined after ground truth; (v) data integration and statistical analysis; and (vi) the final report was prepared. Figure 2 shows the basic process for mapping and evaluating Tree-Based and Shrub-Dominated Land Cover.

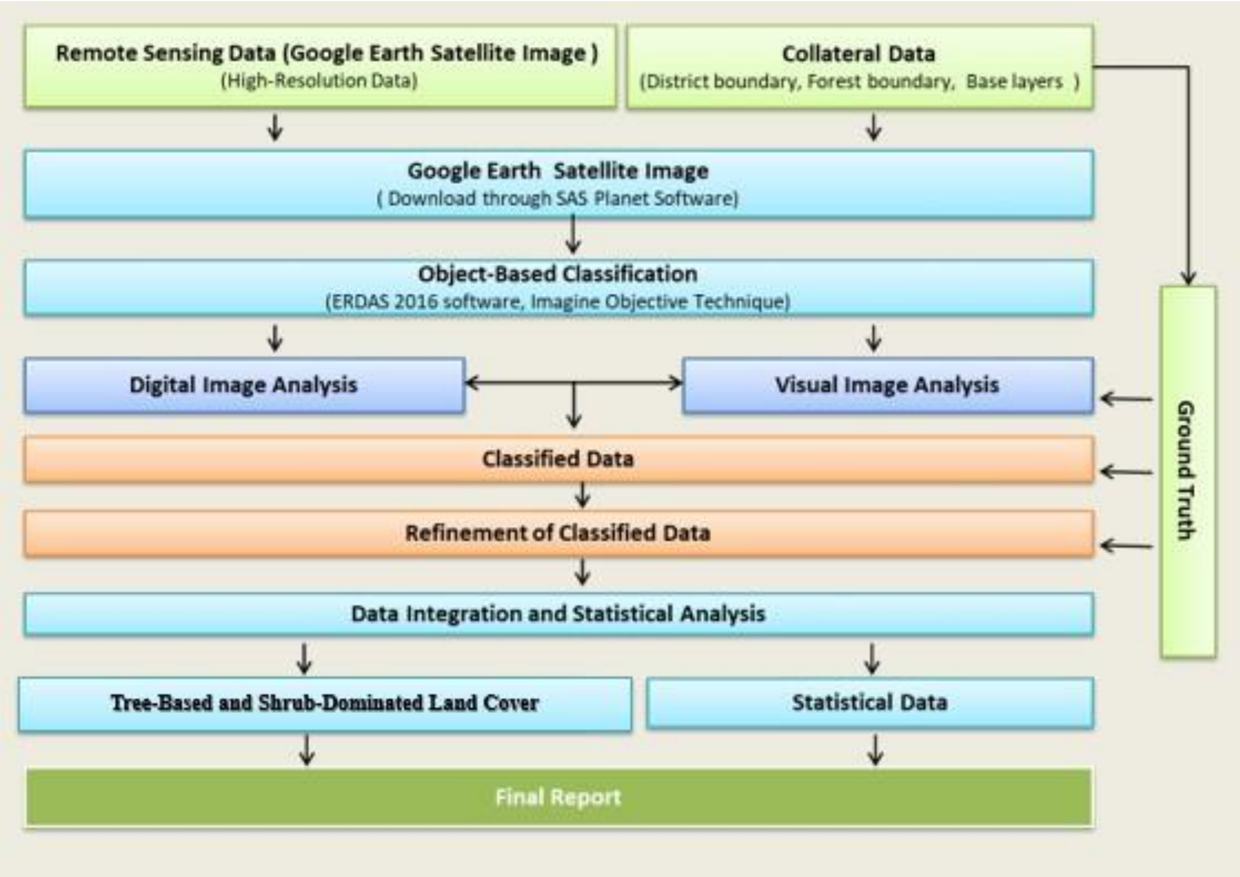

Figure-2: Methodology for Mapping and Assessment Tree-Based and Shrub-Dominated Land Cover

3.2 OBJECT BASE IMAGE CLASSIFICATION:

In this study, object-based analysis employing an ERDAS Imagine software module is used to classify images. The Imagine Objective framework is intended to streamline the feature extraction process from images. The way that images are interpreted by the visual system of humans is the basis of this design. To do this, each prominent visual image interpretation cue for a feature is quantified, used to train machine learning components, and the imagery is processed so that the learned cues can be applied. The field of image interpretation has established that color, tone, texture, size, shape, shadow, site location, pattern, and association are the cues that humans use to manually evaluate imagery. These cues need to be measurable before they can be used in an automated Imagine Objective system. Cue algorithms that produce cue metrics that are applicable in this situation are used to quantify the cues. To do this, nevertheless, one needs to understand the data that these cues are gauging and that they inevitably fall into two different categories: cues at the pixel level and cues at the object level.

Pixel-level cues have to be measurable as pixel values, or dimensionless. One-dimensional lines or two-dimensional polygons are measured by object level cues. They can also quantify the spatial association between a feature object and other feature objects, or the connections between the distributional patterns of an object inside a feature class. Therefore, a system needs two distinct machine-learning components, one for training, one for learning, and one for searching for clues at both levels of cues, in order to fully utilize all of the cues that humans interpret. The method must also be able to transition information across the levels, particularly from the pixel level to the object level, in order for these cues to work together in a single framework.

The per-pixel technique is more likely to generate allocation confusion even though it tends to commit materials with similar radiometric responses. However, the object-based approach has made use of enhanced clumping pixel image processing, which is then followed by shaped-based classification utilizing an image with high resolution. It is feasible to improve the accuracy of classification by including a sufficient number of photographs of ground truth classes. There are benefits to the object-based method in two areas. First, within-class spectral variance is decreased by changing from pixels to image objects as the classification unit. Secondly, provides additional information to the spectral observations made

directly, an enormous number of features characterizing the spatial, textural, and contextual qualities of objects can be generated, potentially increasing the classification accuracy.
There are typically two kinds of errors in the object-based analysis approach. These errors could have one of two effects on the ensuing classification procedure: Two types of image objects exist: (1) those that cross several classes, which result in classification mistakes since the pixels of every mixed object have to be allocated to the same class; and (2) features that are taken from image objects, but if chosen incorrectly, may not be helpful or may decrease classification accuracy since they don't precisely reflect the size and shape of actual objects on Earth. Consequently, there are positive and negative effects on the final performance of object-based classification that arise from using imagine objects as classification units and using object features in the classification process. Specifically, the assessment is divided into two sections: first, we develop a new accuracy metric to measure the potential impact of errors on object-based classification; second, we quantify the overall effects of the benefits and drawbacks of object-based classification concerning features and classification units to evaluate the trade-off between them. Figure -3 shows the popup window and step-up of processing Imagine Objective.

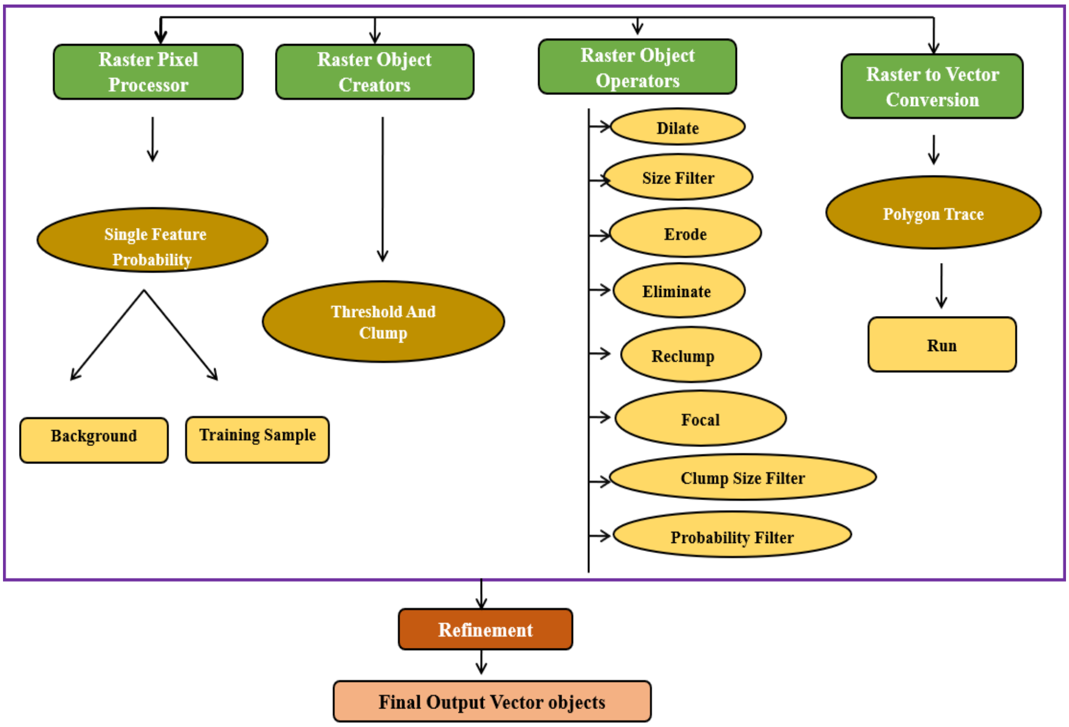

Figure-3: Popup window and Start-up Process of Imagine Objective in ERDAS Imagine

3.3 RASTER PIXEL PROCESSOR:

The Raster Pixel Processor implements multiple classification approaches, including Normalized Difference Vegetation Index (NDVI), Single Feature Probability (SFP), shadow, and texture, by utilizing the Pixel cue classifiers found in the Object-Based Image Analysis (OBIA) software. The trees in this study were extracted using the SFP function. Using various feature detection and extraction techniques from the satellite imagery, the individual tree model was defined by the classification of each tree using SFP Imagine Objective (figure-4a). The extraction was based on a "feature model," which was composed of seven consecutive "process nodes." Constructing a feature-based model is simpler and more logical. Furthermore, the feature models are more transferable to different images when they are constructed because they permit both training under supervision and the classifier's own evidentiary learning. These nodes can automatically arrange a given set of algorithms in terms of settings and order.
In the area of image interpretation, Imagine Objective also makes use of cues, which are characteristics that human beings manually employ to analyze images. Pixel-level signals and object-level cues are two different kinds. Color/tone, texture, and site/situation cues are examples of pixel level cues that need to be dimensionless, or quantifiable as pixel values. Object level cues, such as size, shape, orientation, shadow, and background, can be used to measure the characteristics of two- or one-dimensional polygons as well as the relationships between an object's spatial association with other features and its distributional

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patterns within a feature class. A key factor in the result is the definition of training zones for background pixels and individual trees. It was necessary to carefully select training zones that excluded all background pixels (figure-4b). During the training phase, representative pixels for each individual tree were submitted in order to compute pixel cue metrics and train the pixel classifier. In the automated extraction stage, the pixel classifier receives applicant pixels from the images and queries it to find out how much they resemble the training pixels. These training pixels were located in the imagery using training polygons.
At this point, the result is the pixel probability layer, where every value of a pixel denotes the likelihood that the pixel is the item of interest—in this case, the trees displayed in figure 4c. This layer serves as the foundation for a number of operators that can operate in the vector domain, convert from the raster domain to the vector domain, and then continue in the vector domain. These operators create vector objects or vector object properties from the data in the pixel probability layer, which are then utilized in all downstream processing.

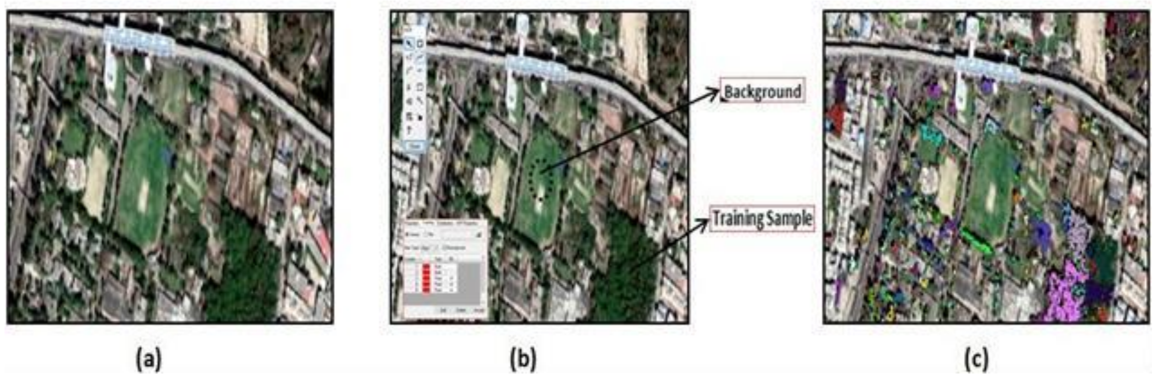

Figure-4: (a) Satellite image (b) The Area Enclosed by the Dotted Polygon used as the Single Training Sample and Background (c) Output of Raster pixel processor

3.4 RASTER OBJECT CREATORS:
The Raster Pixel Processor was used to obtain the Pixel Probability Layer, which was then scaled from 0 to 1 for true/false binary images. The raster object Layer was then converted using clumping. In this stage, a pixel probability layer was threshold using the function "threshold/clump," which kept only pixels whose probability was greater than or equal to the threshold value. The remaining pixels are converted to binary (0, 1), and the binary values of 1 are then subjected to a contiguity operation (clump). After that, the pixel probability layer is transformed into a raster object layer with grouped pixels that make up raster objects.
3.5 RASTER OBJECT OPERATORS:
Pixel objects that have a high probability and just a specific amount of pixels can be kept using the probability and size filters. Size filters allow one to limit the collection of raster items to those that are suitable for each specific tree by eliminating raster objects that are excessively big or little. The model's performance was increased by filtering out items because fewer objects were handled in later phases. Raster object operators use the following procedures: dilate, erode, eliminate, clump size filter, focal, probability filter, reclump, and size filter.
3.6 RASTER TO VECTOR CONVERSION:
The process of transforming raster object moving between the vector and raster domains, known as "polygon trace," was carried out automatically. Consequently, Polygon Trace is a raster-to-vector converter that transforms raster objects into vector objects by tracing their outlines (figure-5).

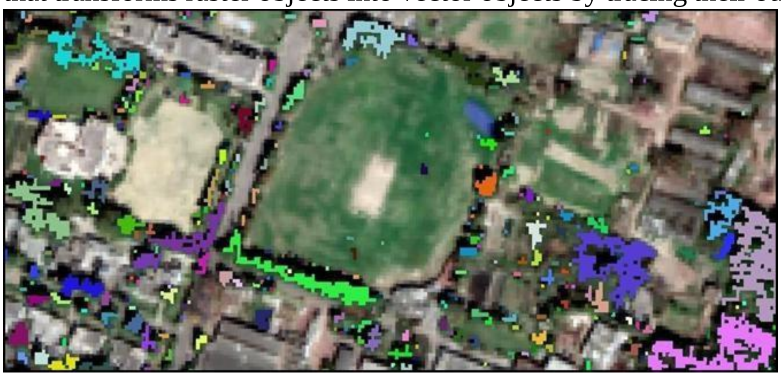

Figure-5: Raster to Vector Conversion of Polygon

3.7 FIELD SURVEY/GROUND TRUTH:

The rectified Google Earth imagery was classified into Tree-Based and Shrub-Dominated Land Cover using an object-based image classification technique. This classification was further enhanced through on-screen visual interpretation, based on a defined interpretation key utilizing standard image interpretation elements such as colour, tone, size, shape, texture, pattern, association, and location.

To ensure accuracy, a field survey was conducted to identify and verify the Tree-Based and Shrub-Dominated Land Cover areas interpreted from the pre-field images/maps. During this survey, GPS coordinates and other essential field information were collected to assist in the validation and correction of the classified map.

A stratified random sampling method was used for the survey. This approach is crucial for both the classification accuracy assessment and validation of thematic maps, based on ground truth data. The methodology adopted is illustrated in Figure-6.

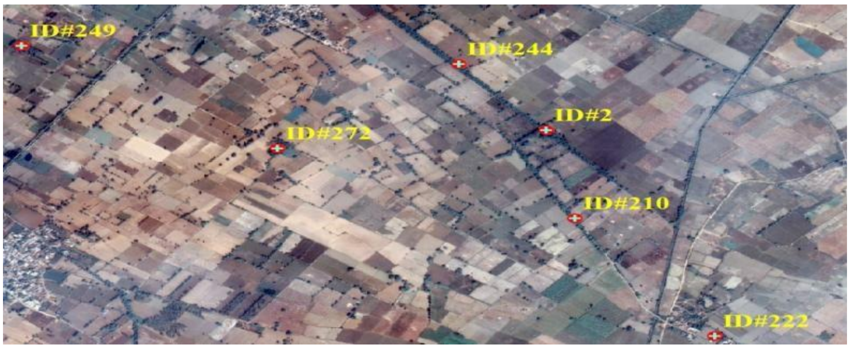

Figure-6: Maps of Field Survey

3.8 DATA ANALYSIS:

Based on information collected during ground truthing, necessary corrections were incorporated. The final thematic raster image was processed using the Clump and Eliminate functions in ERDAS IMAGINE 2016. Subsequently, this refined raster was converted to a polygon feature class within the ArcGIS environment. Figure-7(a) illustrates the raster output after refinement, while Figure-7(b) shows the final vector layer output following this conversion.

To prepare the final thematic vector layer, several GIS processes were applied, including editing, eliminating sliver polygons, attribute assignment, Intersect, Union, Dissolve, and area calculation. Following these procedures in ArcGIS 10.2, the resulting vector data delineates Tree-Based and Shrub-Dominated Land Cover classes.

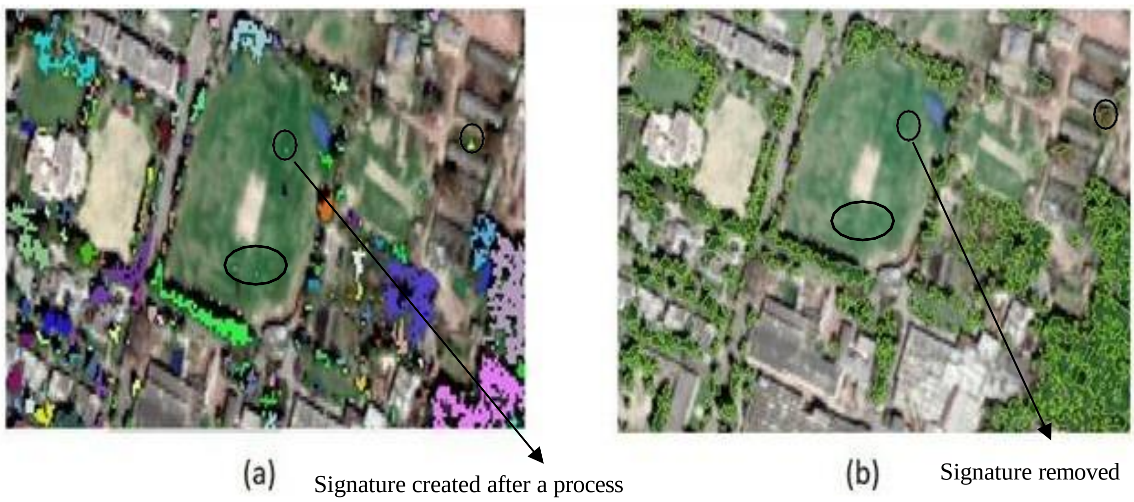

Figure-7: (a) Output Comes After Refinement (b) Final Output after Refinement

RESULT AND DISCUSSION:

Satellite remote sensing, integrated with Geographic Information Systems (GIS) and Global Positioning Systems (GPS), has been widely employed by researchers for accurate forest and tree mapping. This study utilizes high-resolution Google Earth imagery to map **Tree-Based and Shrub-Dominated Land Cover** using object-based classification techniques, supported by field validation.

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Tree canopy objects within the imagery were identified and delineated using polygon-based feature extraction models implemented in Imagine Objective software. These models demonstrated strong compatibility with Google Earth imagery, requiring primarily adjustments to the training datasets rather than fundamental model changes. A significant advantage of Imagine Objective is its inherent **model portability**; it avoids storing absolute file path references within models, facilitating efficient transfer and reuse.

However, a key limitation observed was the **misclassification of agricultural areas** as target land cover classes, affecting approximately 45% of relevant areas. Despite this, the study confirmed the high **transferability** of the feature models. Training sets derived from individual tree samples enabled successful application to other images and regions with minimal or no adjustments. This makes the approach particularly valuable for processing large volumes of **multi-temporal imagery**.

Imagine Objective provided an adaptable framework for developing **open, adjustable, and expandable feature models** leveraging object-based extraction of individual trees. Rectified raw input images are presented in Figures 8(a) and 9(a). The resulting classified maps of Tree-Based and Shrub-Dominated Land Cover for Ayodhya District, generated using Imagine Objective, are shown in Figures 8(b) and 9(b).

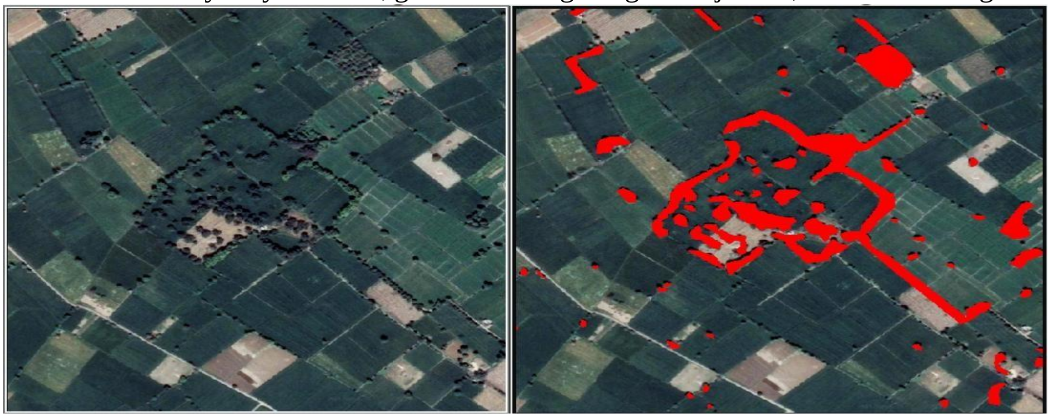

Figure-8: (a) Rectified Raw Image (b) Classified Image of Trees base

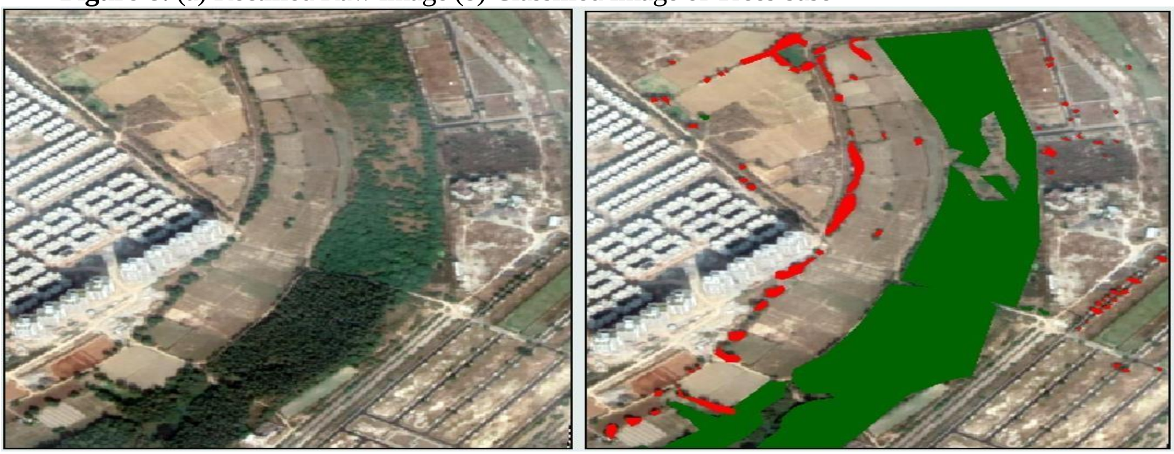

Figure-9: (a) Rectified Raw Image (b) Classified Image of Tree-Based and Shrub Dominated Land Cover

CONCLUSIONS:

The information generated on Tree-Based and Shrub-Dominated land cover through this research provides valuable insights into their spatial distribution. The study demonstrates the effectiveness of object-based image analysis (OBIA) techniques for detecting individual tree objects. We employed Single Feature Probability (SFP), a probabilistic method, for efficient quantitative tree extraction. SFP enables rapid identification of small tree units and proves particularly effective for mapping trees within settlement areas, achieving a minimum accuracy of 85%.

These advanced techniques facilitate precise mapping and measurement of TBSDL. The resulting geospatial information supports evidence-based planning at local to global scales, guiding sustainable management practices. To safeguard vital TBSDL resources, government and management agencies should develop reforestation initiatives aligned with Forest Department standards and regulations.

Future research will focus on developing an integrated Forest Management Plan using high-resolution satellite imagery combined with socioeconomic parameters. "Consequently, the accurate mapping and area estimation of TBSDL achieved in this study provide valuable data to support environmental protection, sustainable resource management, and evidence-based policy formulation.

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