remote sensing

Article

Potential of Lightweight Drones and Object-Oriented Image Segmentation in Forest Plantation Assessment

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Abstract: Forests play a vital role in maintaining ecological balance and provide numerous benefits. The monitoring and managing of large-scale forest plantations can be challenging and expensive. In recent years, advancements in remote sensing technologies, such as lightweight drones and object-oriented image analysis, have opened up new possibilities for efficient and accurate forest plantation monitoring. This study aimed to explore the utility of lightweight drones as a cost-effective and accurate method for mapping plantation characteristics in two 50 ha forest plots in the Nayla Range, Jaipur. By combining aerial photographs collected by the drone with photogrammetry and limited ground survey data, as well as topography and edaphic variables, this study examined the relative contribution of drone-derived plantation canopy information. The results demonstrate the immense potential of lightweight drones and object-oriented image analysis in providing valuable insights for optimizing silvicultural operations and planting trees in complex forest environments.

Keywords: forests; ecological balance; remote sensing technologies; lightweight drones; forest plantation monitoring

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Citation: Dixit, J.; Bhardwaj, A.K.; Gupta, S.K.; Singh, S.K.; Meraj, G.; Kumar, P.; Kanga, S.; Singh, S.; Sajan, B. Potential of Lightweight Drones and Object-Oriented Image Segmentation in Forest Plantation Assessment. *Remote Sens.* **2024**, *16*, 1554. https://doi.org/10.3390/rs16091554

Academic Editor: Arturo Sanchez-Azofeifa

Received: 6 March 2024
Revised: 21 April 2024
Accepted: 26 April 2024
Published: 27 April 2024

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1. Introduction

The importance of forests in maintaining ecological balance, providing habitats for diverse species, and mitigating climate change is well recognized [1,2]. Forest plantations play a significant role in meeting the global timber demand and providing economic and social benefits [3]. However, monitoring and managing large-scale forest plantations can be challenging because of their vast extent and complex terrain. Traditional methods of forest monitoring often rely on ground-based surveys, which are time-consuming, expensive, and have limited spatial coverage. For the purpose of monitoring the forest, identifying changes, and creating effective conservation plans, high-quality forestry data on plant distributions must be collected and integrated with other factors [4,5]. However, the Rajasthan Forest Department's conventional field surveys may be costly and time-consuming. For instance, a field crew of 7–8 people had to work for 15 days to conduct a plantation inventory for a 50-hectare plot. Additional measurements and monitoring of tree height, canopy openness, forest disturbance, and other characteristics are further constrained by the lack of available human labor and financial resources [6]. Thus, the analysis and monitoring of short- and long-term changes are not performed using ground-based surveys, as frequently as required. Therefore, a significant challenge lies in finding ways to collect forest attribute data in a timely and cost-effective manner. In recent years, advancements in remote sensing technologies, particularly lightweight drones and object-oriented image analysis, have opened up new possibilities for efficient and accurate forest plantation monitoring [7]. Lightweight drones, also known as unmanned aerial vehicles (UAVs), offer several advantages over traditional monitoring approaches. They can capture high-resolution images from different perspectives and altitudes, covering large areas in a relatively short time [8,9]. Furthermore, drones equipped with various sensors can provide valuable information beyond visual imagery, such as LiDAR data, for precise terrain modeling.

Compared to satellite and airborne remote sensing techniques, drones have the advantage of flying at low altitudes and slow speeds, allowing them to capture ultra-high spatial resolution imagery (2.5–10 cm) and collect near-earth data on plant and biophysical variables [10]. Drones also overcome several limitations associated with satellite data, such as insufficient spatial resolution to detect and measure critical biophysical properties, including forest canopy gaps and individual tree identification [11]. In addition, they can provide the necessary temporal resolution to detect changes in phenology and stand structure caused by disturbance events. Moreover, the cost of equipping drones with cameras is relatively low. Despite these advantages, cost-effective drones have limited spatial coverage per flight, small payloads, and moderate spectral resolution [12]. Consequently, this technology has not yet received much attention from forest departments, especially in long-term studies. Although ground-based long-term datasets have value, there are still many data gaps [13]. First, ground-based monitoring sites cover only a small fraction of the total work required and may suffer from geographic biases, sometimes leading to overrepresentation [14]. The high cost associated with monitoring and maintaining these sites is a major reason for their scarcity. Second, challenges persist in linking broad-scale remote-sensing data with local-scale ground data. Mismatches at spatial scales limit the monitoring and prediction of species distribution and dynamics, and similar mismatches can occur at temporal scales. Broad-scale remote sensing data are often insufficient to address various pressing monitoring questions [15].

The data obtained from the drone undergo various preprocessing and post-processing challenges. Object-oriented image analysis (OBIA) is an innovative approach that utilizes spatial relationships and contextual information within images to extract meaningful objects and features [16]. Unlike pixel-based analysis, OBIA focuses on the identification and classification of objects based on their size, shape, texture, and contextual attributes [17]. This approach allows for more accurate and detailed information extraction, making it suitable for analyzing complex forest ecosystems and plantation areas [18]. The combination of lightweight drones and OBIA has shown immense potential for various applications related to forest plantation monitoring [19]. This integration enables rapid and cost-effective data collection, detailed vegetation mapping, accurate tree counting, and the early detection of pests and diseases. Additionally, it facilitates the assessment of forest health, growth rate, and biomass estimation, all of which are crucial for effective forest management and sustainable plantation practices.

Several studies have explored the benefits of using lightweight drones and OBIA to monitor forest plantations. Tang and Shao (2015) explored the growing use of drones in remote sensing, with a particular focus on their application in forestry. The authors emphasize that drones offer a cost-effective, flexible, and high-resolution alternative to traditional remote sensing methods, filling data gaps and enhancing the capabilities of manned aircraft and satellite systems. They outlined the benefits of drone remote sensing, including its low operational costs, customizable spatial and temporal resolution, and high-intensity data collection without risking human safety. The authors also discussed various forestry applications of drones, such as forest surveying, canopy gap mapping, canopy height measurement, wildfire tracking, and intensive forest management support [20]. Ahmed et al. (2021) investigated real-time object detection and segmentation in drone-based remote sensing. By employing the deep learning-based U-Net model, they evaluated multiple object segmentation with various base architectures, including VGG-16, ResNet-50, and MobileNet. To enhance model efficiency, data augmentation and transfer learning were utilized. The study revealed that the MobileNet-based U-Net achieved the best results, attaining segmentation accuracies of 92% with VGG-16, 93% with ResNet-50, and 95% with MobileNet. These findings indicate that deep learning techniques can significantly improve drone-based real-time object detection and segmentation [21].

Srivastava et al. (2022) discussed the potential of drones in environmental monitoring for forest inventories, particularly in private native forests. Their research highlighted how drone-derived images combined with digital photogrammetry can effectively estimate tree height, thereby enhancing forest inventory accuracy and reducing reliance on labor-intensive field assessments [22]. Natesan et al. (2019) examined the classification of tree species in forest management utilizing deep learning with high-resolution RGB images obtained from a UAV platform. Specifically, this study aimed to differentiate red pine and white pine from other species using Residual Neural Networks (ResNets). The researchers trained the network with UAV images collected over a period of three years, considering variations in season, time, illumination, and angle. Using this approach, the study achieved a classification accuracy of 80% when using data from all three years and 51% accuracy when using data from just one year. This research contributed towards a unique, high-resolution dataset of labeled tree species for further deep neural network studies in forestry [23]. Nduji et al. (2023) combined object-based image analysis (OBIA) with super-resolution mapping (MRF-SRM) to detect individual trees from satellite images in Mali. This approach addresses challenges such as spectral mixture and background class interference, enhances detection accuracy, and offers valuable insights for urban and ecological planning [24]. Zhou et al. (2021) reviewed the application of infrared thermal imagery in precision agriculture to assess crop water stress. They discussed the potential of integrating deep learning techniques with thermal imaging to refine crop stress detection, underscoring the growing importance of thermal sensors in efficiently managing agricultural resources [25]. Bāders (2022) compared the effectiveness of lightweight drones and ground-based surveys in monitoring pest infestations in pine plantations. The researchers found that drone-based monitoring detected pest outbreaks earlier than ground-based surveys, enabling timely intervention and minimizing damage to plantations [25]. Lausch et al. (2013) investigated the vulnerability of spruce forests in the Bavarian Forest National Park, Germany, to bark beetle infestations (*Ips typographus* L.) caused by climate change or emissions. The researchers employed hyperspectral remote-sensing methods using HyMAP data at ground resolutions of 4 m and 7 m to assess the biochemical and biophysical characteristics of the forest. The study revealed that specific spectral bands in the 450–890 nm range, which correspond to chlorophyll absorption, were effective in classifying spruce vitality and detecting the early stages of green attack. However, the 64% accuracy rate is insufficient for practical forestry applications. The results indicated that hyperspectral data with a resolution of 4 m provided better insights into spruce vitality than 7 m data. This study suggests that early warning signs for bark beetle outbreaks may be linked to pre-existing forest vulnerabilities [26].

Despite the promising results and advantages of lightweight drones and OBIA, several challenges and limitations remain to be addressed. Issues related to image processing, data storage, and the development of automated algorithms for object detection and classification require further refinement. Furthermore, all the research carried out is limited to the classification of images and identification of attributes, but no one deals with its implications, such as forest plantations in complex ecosystems. The objective of this study was to explore the utility of lightweight UAVs as a flexible, cost-effective, and accurate method for mapping plantation characteristics in two 50-hectare forest plots in the Nayla Range, Jaipur by combining aerial photographs collected by the drone with photogrammetry and utilizing limited ground survey data and topography and edaphic variables. Furthermore, we examined the relative contributions of the drone-derived canopies.

2. Materials and Methods

2.1. Study Area

The study site for this investigation was the Nayla Plantation Site, which encompasses an area of 50 ha within the Bassi Range of the Rajasthan Forest Department, India. Established approximately 15 to 20 years ago, based on information gathered from local sources and forest guards, this site presents a mature forest environment with well-established tree species, making it an ideal location for advanced forestry research (Figure 1). The climate of the Nayla area is categorized under the Köppen climatic classification as hot, semi-arid (BSh) [27]. This region is distinctly impacted by the Indian monsoon season, leading to specific climatic patterns that influence the local ecosystem. Winters here are relatively short and can range from mildly to very cold conditions, while the summers extend longer, characterized by extreme heat and dryness. Annually, the area receives more than 601 mm of precipitation, predominantly during the monsoon months of July and August. These months generally experience lower average temperatures compared to the hotter, drier months of May and June. Although the region is subjected to heavy rainfall during the monsoon season, significant flooding is rare; however, the season is marked by frequent heavy rainfall and thunderstorms. Temperature extremes have been recorded with a maximum of 48.5 °C (119.3 °F) during May and a record low of 2.2 °C (28.0 °F) in the winter months, which are typically pleasant, dry, and moderate.

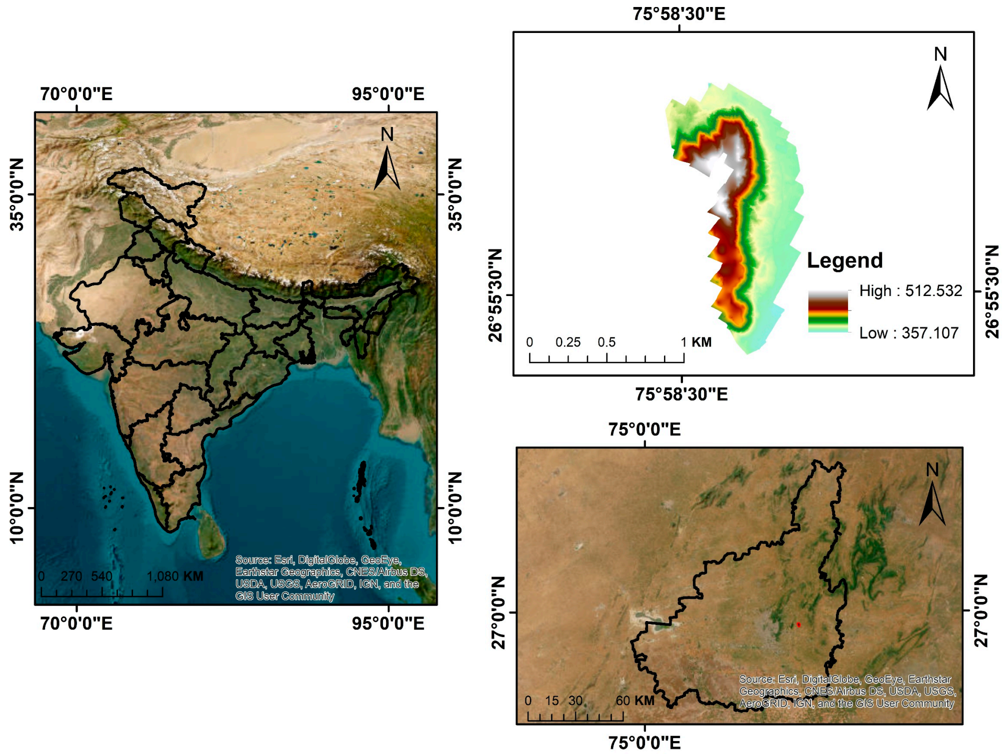


Figure 1. Nayla Plantation Sites in the Jaipur District. Displaying two 50-hectare plots managed by the Rajasthan Forest Department, this image highlights the study area for drone-based forest assessment.

The forest composition at the Nayla Site includes predominant species such as Churel, Sheesham (*Dalbergia sissoo*), and Neem (*Azadirachta indica*). Additionally, the area hosts other significant species like Ronj, Akesia, Ber (*Ziziphus jujube*), and Desi Babool (*Vachellia nilotica*). These species add to the ecological diversity and complexity of the site, providing varied habitats and contributing to the overall ecological dynamics of the region. Despite the rich biodiversity and established forestry at the Nayla Plantation Site, there are gaps in the historical data records, including the absence of initial inventory records or subsequent re-census data at the district forest officer's office. This lack of historical data presents challenges for conducting comparative analyses over time but also underscores the importance of implementing advanced monitoring techniques like those proposed in this study.

This research employs lightweight drones integrated with object-oriented image analysis (OBIA) to monitor and assess forested areas effectively. OBIA works by segmenting images into distinct objects using a multi-resolution segmentation approach, which clusters pixels based on spectral, spatial, and textural similarities. Initially treating each pixel as a separate entity, the method merges them progressively based on their homogeneity. Following segmentation, feature extraction is conducted to determine attributes such as the shape, size, texture, and average spectral values of these objects. These extracted features are then utilized in a supervised classification process to differentiate between various forest types, vegetation densities, and other pertinent ecological categories. This technique is especially adept at dissecting complex forest structures, providing more precise and detailed environmental assessments than traditional pixel-based analysis methods. The innovative application of this methodology is expected to yield profound insights into the forest structure, health, and dynamics, which are crucial for effective management and conservation. This comprehensive approach, merging advanced remote sensing technologies with conventional forest assessment techniques, is depicted in Figure 2 of the study documentation and aims to deepen the understanding of forest ecosystems and refine management strategies in these intricate environments.

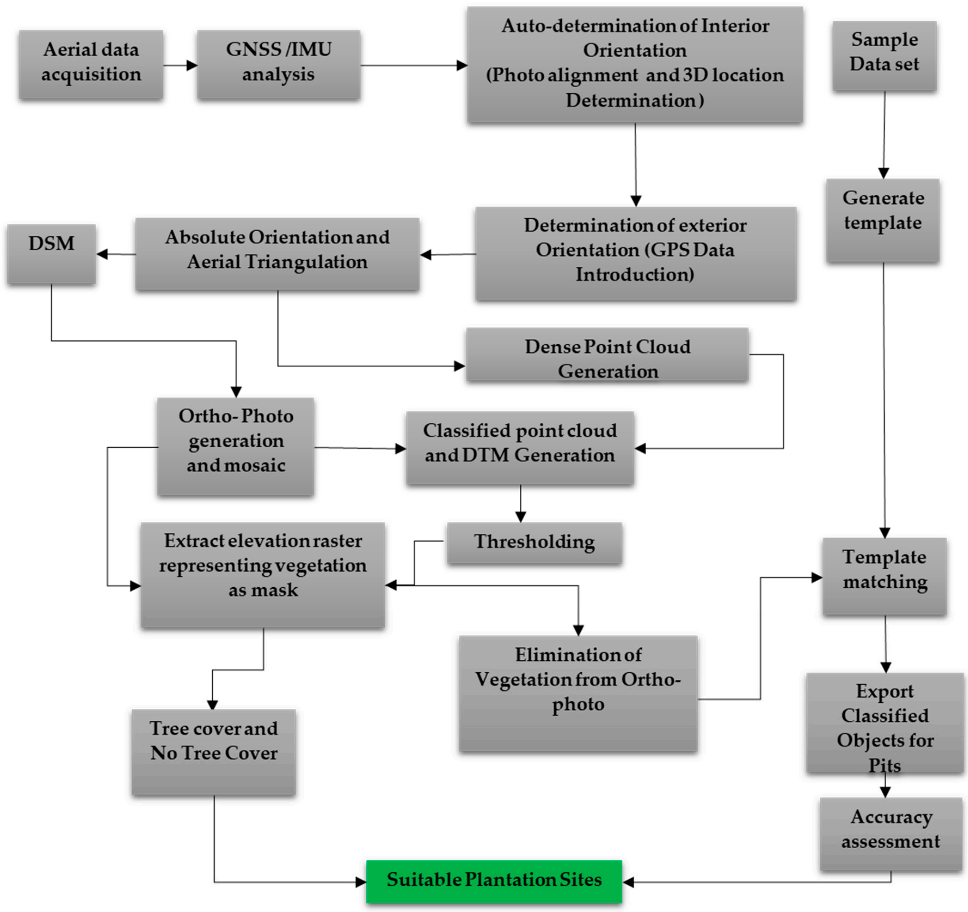


Figure 2. Flowchart of the Methodology for Forest Assessment. It outlines the sequence from data capture by drones to analysis through OBIA at Nayla Plantation.

2.2. Control Point Survey

A control point survey was conducted at both sites to establish correlations between image coordinates and real-world ground coordinates for aerial triangulation, thereby enhancing the accuracy. This was performed in conjunction with geo-tagging the aerial photographs using the on-board Global Navigation Satellite System (GNSS), as shown in Figure 3. The survey refers to marking and identifying points (control points) on the ground, observing and measuring the points using GeoMax dual-frequency DGPS Model Zenith 35 PRO to acquire coordinates with less than 10 cm level accuracy. In this project, six control points were surveyed for Nayla (Table 1): Technology-perceptive higher-ranked officials from the forest department oversaw and observed the surveying team, provided advice, and discussed work procedures on the site. Each control point was photographed during aerial data acquisition from different flight line viewpoints and was identified later at the time of photogrammetric processing. The control points were properly marked on the ground using Chuna (baked limestone) powder, while ensuring that they could be easily identified among individual aerial photographs overlapping with each other (Figure 4). The points were further triangulated and the results were within the permissible limit of the desired accuracy.

Figure 3. UAV aerial image showing marking of ground control points with number.

Figure 4. Field photographs showing field-based discussion. DGPS measurement on printed GCP.

Table 1. Ground control points, Nayla Plantation Site.

			UTM Coordinates			Geographic Coordinates	
Point ID	**Date**	**Description**	**Northing**	**Easting**	**Elevation (m)**	**Longitude**	**Latitude**
1	6 February 2023	BASE-1	2,978,882	597,205.9	402.6608	75°58′44.762	26°55′42.269
2	13 February 2023	GCP-1	2,978,850	597,219.4	397.1401	75°58′45.241	26°55′41.220
4	20 February 2023	GCP-2	2,978,456	597,218.2	407.881	75°58′45.088	26°55′28.405
8	27 February 2023	GCP-3	2,979,172	597,392.7	387.494	75°58′51.615	26°55′51.642
9	6 February 2023	GCP-4	2,979,429	597,313.4	399.0403	75°58′48.814	26°56′0.0279
10	5 March 2023	GCP-5	2,978,855	597,394.5	378.6349	75°58′51.591	26°55′41.352
12	5 March 2023	GCP-6	2,978,977	597,311.5	391.3266	75°58′48.616	26°55′45.339

2.3. Aerial Data Acquisition

Quad-rotor systems enhance flight stability by minimizing vibrations and eliminating the need for large, movable rotor units. The quadrotor UAV utilized for data collection in this study was the DJI Mavic 2 PRO, with specific details on its specifications and imagery provided in Table 2 (Figure 5). The DJI Mavic 2 PRO quadcopter is designated as "micro" under the Directorate General of Civil Aviation (DGCA) proposed regulation of drone operations and is only permitted to fly at altitudes of less than 200 feet [28]. In accordance with these recommendations, the maximum flying height was set at 200 ft above sea level [29].

Table 2. Specifications of DJI Mavic 2 PRO used in this study.

Takeoff Weight	**Mavic 2 Pro: 907 g** **Mavic 2 Zoom: 905 g**
Dimensions	Folded: 214 × 91 × 84 mm (length × width × height) Unfolded: 322 × 242 × 84 mm (length × width × height)
Diagonal Distance	354 mm
Max Ascent Speed	5 m/s (S-mode) 4 m/s (P-mode)
Max Descent Speed	3 m/s (S-mode) 3 m/s (P-mode)
Max Speed (near sea level, no wind)	72 kph (S-mode)
Maximum Takeoff Altitude	6000 m
Max Flight Time (no wind)	31 min (at a consistent 25 kph)
Max Hovering Time (no wind)	29 min
Max Flight Distance (no wind)	18 km (at a consistent 50 kph)
Max Wind Speed Resistance	29–38 kph
Max Tilt Angle	35° (S-mode, with remote controller) 25° (P-mode)
Max Angular Velocity	200°/s
Operating Temperature Range	−10 °C to 40 °C
Operating Frequency	2.400–2.483 GHz 5.725–5.850 GHz

Table 2. *Cont.*

Takeoff Weight	**Mavic 2 Pro: 907 g** **Mavic 2 Zoom: 905 g**
Transmission Power (EIRP)	2.400–2.483 GHz FCC: $\leq$26 dBm CE: $\leq$20 dBm SRRC: $\leq$20 dBm MIC: $\leq$20 dBm 5.725–5.850 GHz FCC: $\leq$26 dBm CE: $\leq$14 dBm SRRC: $\leq$26 dBm
GNSS	GPS+GLONASS
Hovering Accuracy Range	Vertical: $\pm$0.1 m (when vision positioning is active) $\pm$0.5 m (with GPS positioning) Horizontal: $\pm$0.3 m (when vision positioning is active) $\pm$1.5 m (with GPS positioning)
Internal Storage	8 GB

Figure 5. Ground operation of DJI DJI Mavic 2 PRO during the study.

2.4. Close Range Photogrammetry: Data Processing

The demand for accurate surveying and mapping methods is increasing because of the availability of high-resolution aerial data. Close-range photogrammetry is a popular choice for monitoring and surface modeling because it can measure a large number of points with high accuracy without interfering with the subject. It can determine coordinates in local or global reference systems, is economical and fast, and can create permanent records through photographs. The workflow for the photogrammetric process involved using Agisoft PhotoScan Professional version 1.4.0. The main steps included loading the aerial photographs, removing irrelevant photos (criteria for irrelevance included factors such as image blur, inadequate overlap, and poor lighting conditions, which affect the quality and usability of the images for analysis), aligning the photos to determine camera positions and generate tie points, building a dense point cloud model, creating a 3D mesh (TIN) by connecting adjacent points with triangular faces, building texture by mapping the object surface, and generating a Digital Surface Model (DSM) and ortho-photo mosaic (Figure 2). The DSM and DTM (Digital Terrain Model) were computed with a ground pixel size of 9 cm. Ortho-rectification was performed based on the mesh and DSM, and a seamless ortho-mosaic was prepared with a spatial resolution of 2.5 cm (Figure 2).

2.5. Object-Based Image Analysis (OBIA)

The main goal of this project was to classify vegetation at the individual plant level. Ten data layers, including ortho-rectified images and three topography layers (elevation, DSM, DEM, and slope), were loaded into the eCognition Trial program. The program automatically resampled these layers to the maximum resolution, even though they had different ground sample distances (GSDs). The topographic layers were resampled from a 9.0 cm pixel size to 2.5 cm. Based on extensive trial-and-error of different scale parameter values, we identified three sets of suitable parameters for segmentation. A scale parameter of 500 was used for the first level to define shadows, 250 for the second level to separate tree cover from other land cover categories, and 120 for the third level to focus on species categorization. For all three segmentation levels, eCognition's other parameters were set as color/shape weight of 0.8/0.2 and a smoothness/compactness weight of 0.5/0.5. After segmentation, the segmented images were classified into the tree class using the nearest neighbor classification. Some image objects were selected as training samples visually, and the algorithm was applied to the entire tree crown map. In subsequent steps, wrongly classified objects were added to the correct classes of training samples to improve the accuracy of the ground-truth map.

2.5.1. Object-Based Feature Extraction for Pits

Automatic feature extraction from images continues to represent a challenge and has received substantial attention for decades. This study presents an object-based and machine learning-based approach for automatic pit detection from UAV high-resolution ortho-rectified images. We carried out vegetation elimination which involved the systematic removal and isolation of vegetation elements from our dataset, which we derived from Drone LiDAR technology. LiDAR datasets consist of points in the three-dimensional space, each containing X, Y, and Z coordinates along with other attributes. Initially, a Digital Surface Model (DSM) was generated from the LiDAR data. Simultaneously, a Digital Terrain Model (DTM) was created, representing the bare ground surface devoid of any above-ground features like vegetation. The process of vegetation elimination consisted of subtracting the DTM from the DSM, resulting in a dataset that primarily captured above-ground features (termed as DSM minus DTM). This dataset contained information predominantly related to vegetation, as it excluded the ground surface and other non-vegetation elements. Various techniques, such as thresholding or segmentation algorithms, were then applied to isolate and remove vegetation points from this dataset, effectively performing vegetation elimination. The resultant dataset after vegetation elimination provided a clearer view of the terrain, without the influence of vegetation, which enabled more accurate analysis and interpretation for applications of urban planning, forestry management, and environmental assessment. We also carried out template matching-based object detection, which is the simplest and easiest method for object extraction, as shown in the methodology flowchart in Figure 2. This category of approaches involved two main steps, First, a template for each to-be-detected object class was manually created. Secondly, we carried out similarity measurements. This step matched the stored templates onto the source image at each possible position to find the best matches according to the maximum correlation or minimum difference.

2.5.2. Dataset Composition

The training set consisted of 70% of the aerial images from the Nayla Range, which ensured a diverse representation of forest conditions. The validation set comprised 15% of the images, used for tuning model parameters during the training phase. The remaining 15% served as the test set for final model evaluation to assess the performance and generalizability.

2.6. Stream Network Extraction and Pit Density Mapping

The study undertook comprehensive methodologies for stream network extraction and pit density mapping at the Nayla Plantation Site. Stream network extraction from a Digital Surface Model (DSM) was crucial for water management, erosion control, and riparian zone preservation. The process involved utilizing the ArcGIS spatial analyst module to compute the stream network, with various pre-processing and processing algorithms applied to identify minor non-perennial streams. The results delineated both primary and secondary stream networks, with the latter primarily developed in the depositional piedmont area due to high runoff from higher slopes. Pit density mapping was conducted using ArcGIS spatial analyst to compute the magnitude-per-unit area from point features within a defined neighborhood (Figure 6). High- and very high-density areas were identified as suitable for future plantation endeavors, while very low-density areas indicated dense canopy cover, demonstrating an inverse relationship between pit density and tree density. The object-based image analysis (OBIA) methodology was employed to delineate a total of 4508 pits. Pre- and post-monitoring activities such as pit repairing, hoeing, weeding, and preparatory work were conducted based on the classification results, resulting in 74 correctly identified sites across various categories out of a total of 95 reference sites, achieving an overall accuracy of 77.9%. The methodologies detail the processing procedures for stream network extraction and pit density mapping, with discussion and interpretation focusing on the distinction between primary and secondary stream networks and the relationship between pit density and tree density. Table 3 shows the fishnet ID and the corresponding no. of pits in the Nyla forest boundary used for pit density mapping.

Table 3. Fishnet ID and the corresponding no. of pits for the evaluation of pit density.

Fishnet ID	No. of Pits	Fishnet ID	No. of Pits	Fishnet ID	No. of Pits	Fishnet ID	No. of Pits
1	4	44	Nil	21	12	64	Nil
2	63	45	Nil	22	292	65	Nil
3	Nil	46	55	23	290	66	Nil
4	Nil	47	296	24	Nil	67	Nil
5	Nil	48	67	25	Nil	68	Nil
6	69	49	Nil	26	23	69	11
7	Nil	50	Nil	27	433	70	123
8	11	51	Nil	28	383	71	Nil
9	8	52	Nil	29	Nil	72	17
10	60	53	Nil	30	Nil	73	58
11	Nil	54	224	31	9	74	Nil
12	Nil	55	142	32	232	75	Nil
13	8	56	Nil	33	240	76	Nil
14	247	57	Nil	34	63	77	49

Table 3. *Cont.*

Fishnet ID	No. of Pits	Fishnet ID	No. of Pits	Fishnet ID	No. of Pits	Fishnet ID	No. of Pits
15	Nil	58	Nil	35	Nil	78	22
16	Nil	59	Nil	36	Nil	79	1
17	2	60	Nil	37	Nil	80	Nil
18	204	61	8	38	1	81	Nil
19	16	62	139	39	175	82	10
20	Nil	63	92	40	214	83	31
43	Nil	86	9	41	91	84	5
87	23	89	Nil	42	Nil	85	Nil
88	Nil	90	Nil				

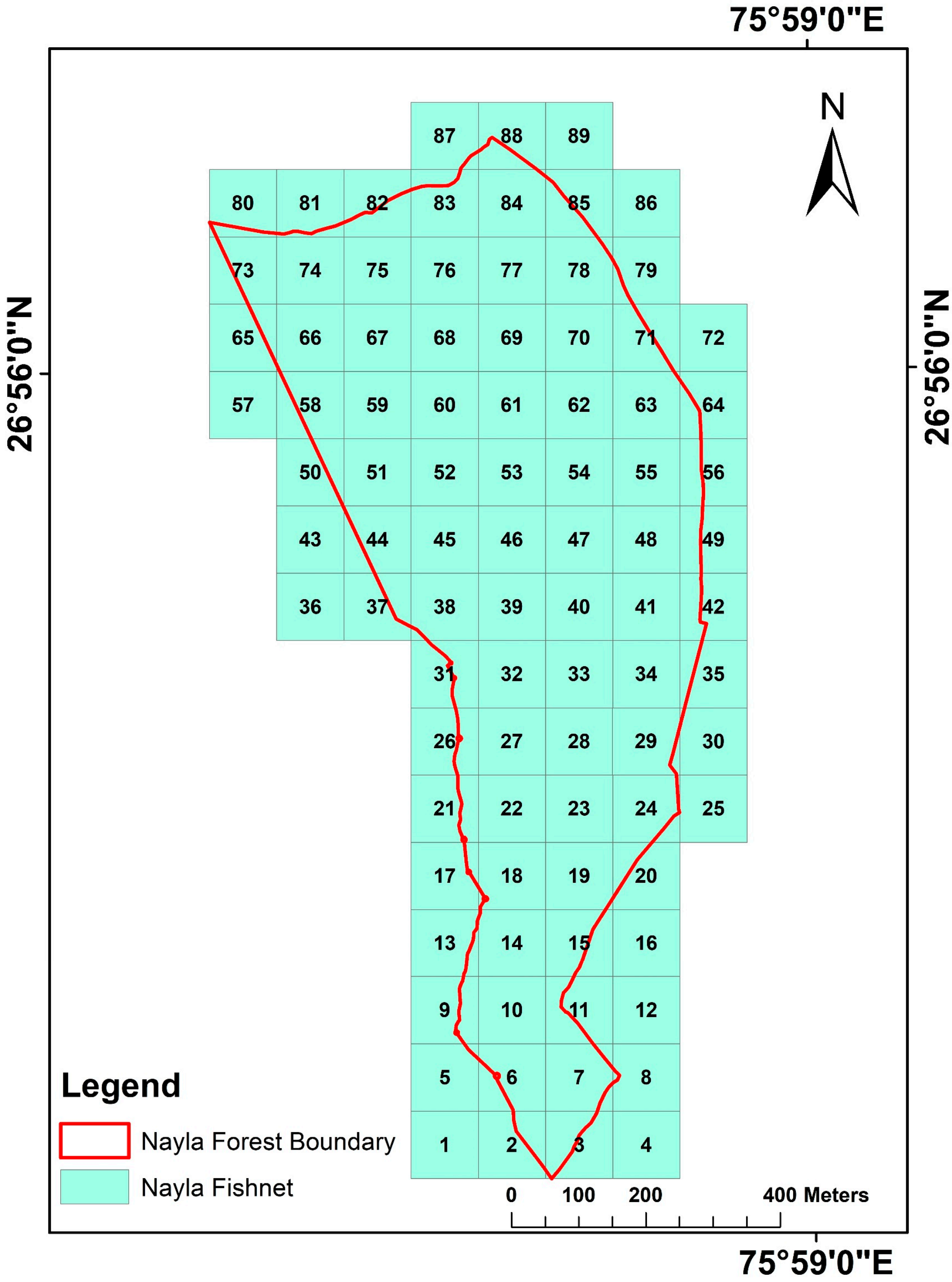


Figure 6. Fishnet method used to calculate the pit density.

2.7. Accuracy Assessment

2.7.1. Reference Data Collection and Sampling Procedure

Accuracy assessment in remote sensing is crucial for validating the classification results obtained from image analysis against the actual ground situation [30]. To ensure that the reference data accurately represent the area being studied, a structured sampling procedure was implemented, which includes random sampling, stratified random sampling, and cluster sampling. These methods ensure comprehensive coverage of the study area, addressing variations in land cover, vegetation, and elevation. In this study, we carried out the cluster sampling technique, owing to the fact that the forest was dense at places, and this method provided the best sampling solution. In this method, we divided the area into clusters, and the samples were randomly taken from the selected clusters, as shown in the following schematic diagram (Figure 7).

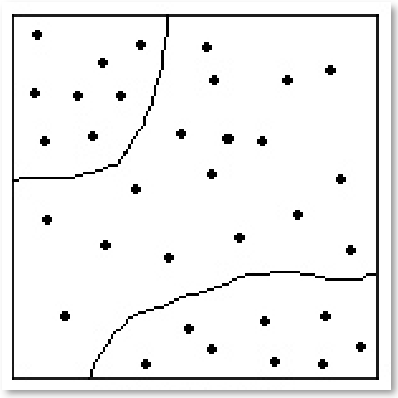


Figure 7. Stratified sampling method also referred as layer-based random point selection.

2.7.2. Error Matrix Construction and Accuracy Metrics

The collected reference data are compared against the classified data using an error matrix/contingency table (Table 4), which provides a fundamental basis for calculating accuracy metrics.

Table 4. Error matrix demonstrating the accuracy of the classification.

	Grid-1 (Ref)	Grid-2 (Ref)	Grid-3 (Ref)	Total
Grid-1 (Classified)	29	2	4	35
Grid-2 (Classified)	1	31	3	35
Grid-3 (Classified)	0	1	25	26
Total	30	34	32	96

We calculated the overall accuracy as the ratio of the sum of correctly classified points (diagonal elements) to the total number of reference points. For this study,

$$\text{Overall Accuracy} = \frac{29 + 31 + 25}{96} \times 100 = 88.54\%$$

2.7.3. Kappa Coefficient Calculation

The Kappa coefficient is an additional measure that we used to evaluate the accuracy of classification, accounting for the agreement occurring by chance. The following formula was used to determine the kappa coefficient:

$$\kappa = \frac{Po - Pe}{1 - Pe} = \frac{0.8854 - 0.3483}{1 - 0.3483} \approx 0.828$$

In this study, the Kappa value equaled 0.828, which indicated substantial agreement, suggesting that the classification accuracy obtained was significantly higher than what would be expected by chance alone.

3. Results

Long-term forest monitoring using the combination of unmanned aerial vehicle (UAV) survey and object-oriented image analysis (OOIA) has produced important outcomes and findings [31]. Utilizing these methods has allowed for effective data collection, processing, and interpretation, while also revealing important information about forest ecosystems.

3.1. Elevation Profile

Here, the slope is generated mainly from DSM data processed from lightweight drones (Figure 8). Slope data from DSMs generated by lightweight drones are crucial for forest plantation management, enabling better planning, soil erosion management, and tree species selection [32,33]. It aids in identifying suitable areas, implementing erosion control measures, and ensuring long-term stability and growth of the plantation.

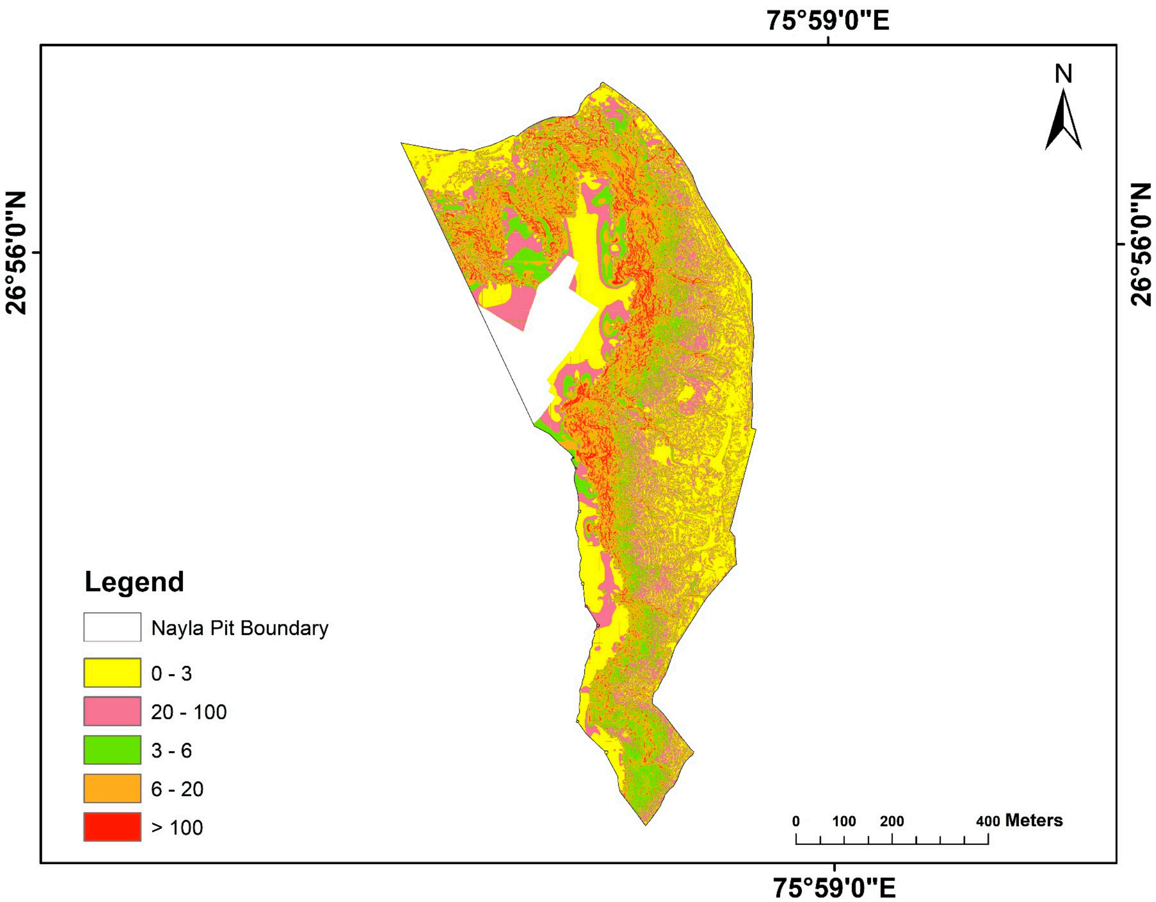


Figure 8. Slope map of Nayla Plantation Site.

Table 3 provides information on the distribution of slope classes and their corresponding area percentages. The slope classes are categorized based on the percentage of slope within each range. Slope Class 1 represents slopes ranging from 0% to 3%. The area covered by this slope range in Nayla is 0.90%. It indicates that a relatively small portion of the surveyed area consists of very gentle slopes. Slope Class 2 ranges from 3% to 6%. The area covered by this slope range is 2.33% in Nayla. While still relatively small, it indicates a slightly larger portion of the surveyed area, with slightly steeper slopes compared to the previous range. Slope Class 3 ranges from 6% to 20%. The area covered by this slope range is 19.81% in Nayla. It suggests that a significant portion of the surveyed area has moderate slopes, indicating a varied terrain with more pronounced changes in elevation. Slope Class 4 ranges from 20% to 100%. The area covered by this slope range is 69.14% in Nayla. It indicates that the majority of the surveyed area consists of steep to very steep slopes. This can have implications for various activities, such as construction, agriculture, or land management. Figure 9 shows the stream network extraction from the DSM of the Nayla Plantation Site.

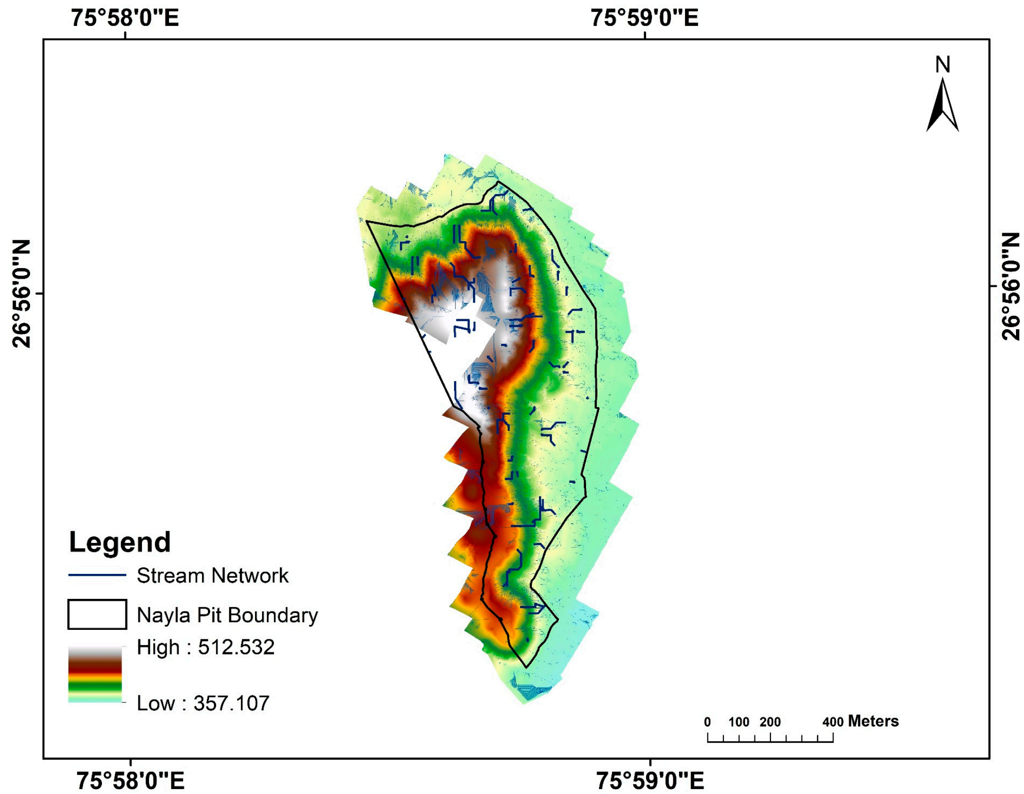


Figure 9. Stream network extraction from DSM of the Nayla Plantation Site.

Slope Class 5 represents slopes greater than 100%. The area distribution is 16.643% and the area covered by this slope range is 7.83% in Nayla. This suggests that a considerable portion of the surveyed area consists of very steep or near-vertical slopes. Table 5 provides a clear distribution of slope classes and their corresponding area percentages, indicating the prevalence of different slope ranges within the surveyed area. This information is valuable for various applications, such as land management, infrastructure planning, and environmental assessments, where understanding the terrain's slope characteristics is essential.

Table 5. Slope distribution, Nayla Plantation Site.

No.	Slope Range (%)	Area Covered (%)
1	0–3	0.90
2	3–6	2.33
3	6–20	19.81
4	20–100	69.14
5	>100	7.83

3.2. *Stream Network Extraction from DSM, Nayla Plantation Site*

Stream network extraction from a DEM or DSM is essential for water management, erosion control, and riparian zone management in plantation sites [34,35]. It helps identify stream channels, drainage patterns, and water flow paths, enabling effective water resource planning and mitigating erosion risks. The extracted stream network aids in managing water distribution, implementing erosion control measures, and preserving riparian zones, ensuring the overall health of the ecosystem. Streams have been computed using the ArcGIS spatial analyst module (Figure 9). A number of pre-processing and processing algorithms were applied in order to find the minor non-perennial stream network. The primary and secondary stream network is well depicted. The secondary stream network is developed on the depositional piedmont area because of high runoff from higher slopes.

3.3. Pit Density Map and Pit Extraction

The pit density map was derived using ArcGIS spatial analyst (Figure 10). It computes a magnitude-per-unit area from point features that fall within a neighborhood around each cell [36]. Upon initial observation, areas classified as high and very high density are presumed suitable for future plantation endeavors, whereas those categorized as very low density suggest dense canopy cover. This implies an inverse relationship between pit density and tree density. Utilizing the OBIA methodology, a total of 4508 pits were delineated. We conducted pre- and post-monitoring activities such as pit repairing, hoeing, weeding, and other preparatory work, as shown in Figure 11. The classification process yielded 74 correctly identified sites across various categories, out of a total of 95 reference sites, resulting in an overall accuracy of 77.9%.

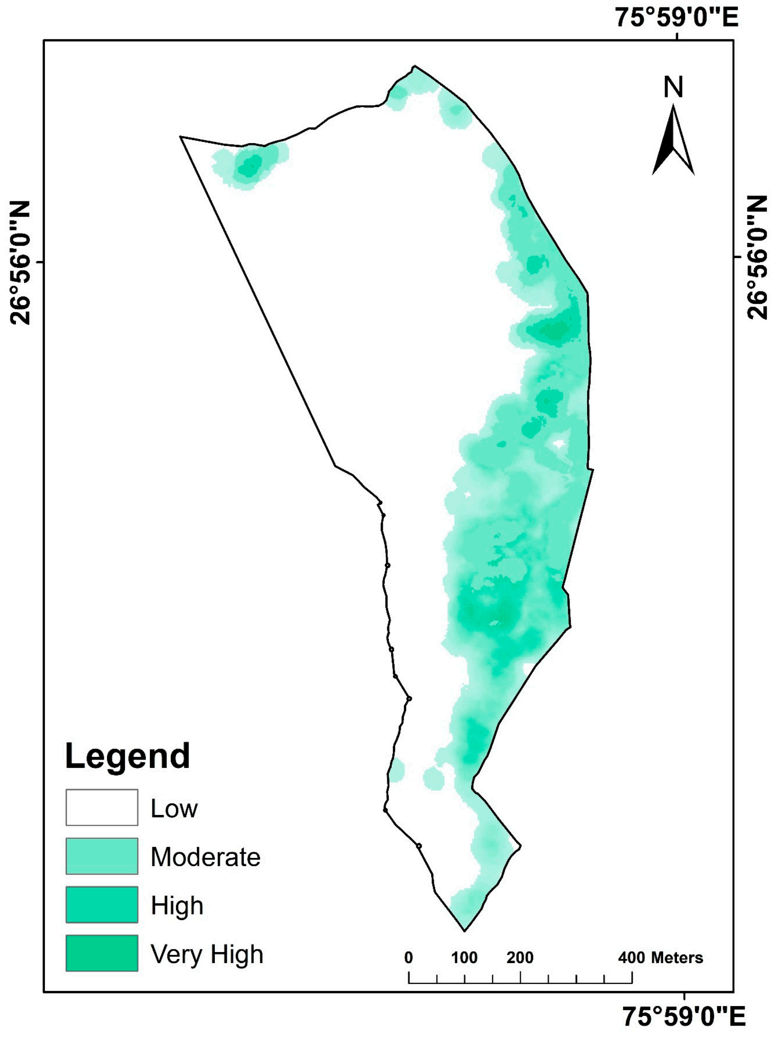


Figure 10. Pit density map, derived using ArcGIS spatial analyst.

(**a**) (**b**)

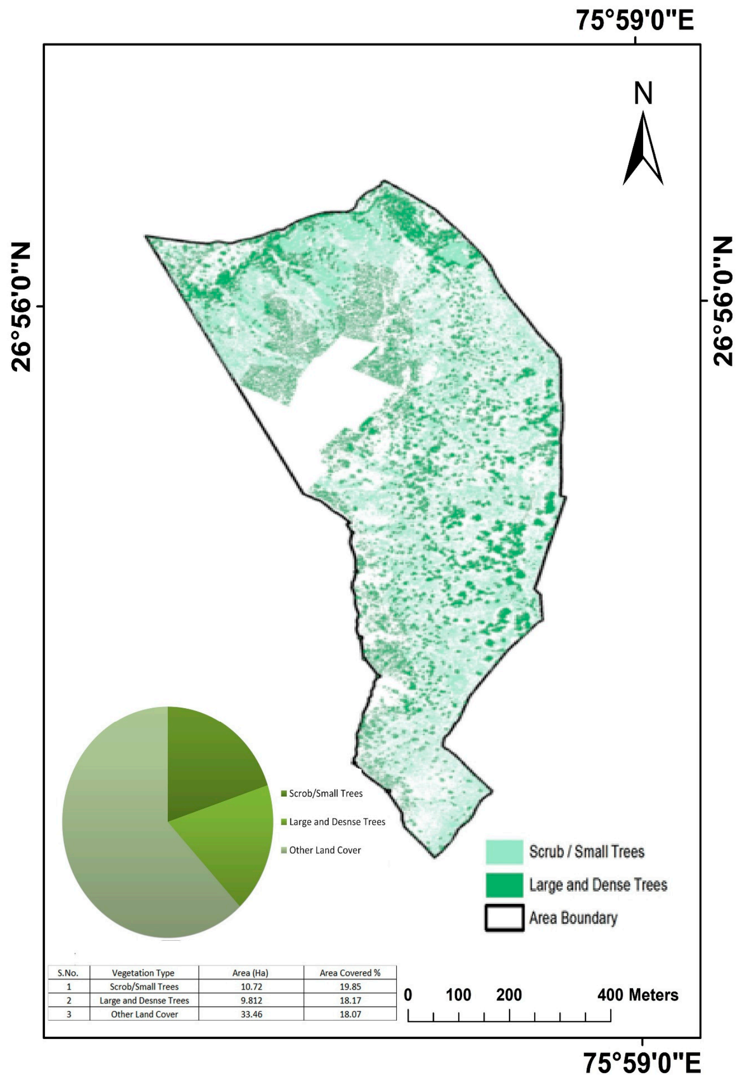
(**c**) (**d**)

Figure 11. (**a**) Pit repairing is not completed, but weeding is completed; (**b**) small pits occurring under a shady tree; (**c**,**d**) weeding, hoeing, and pit repairing are not completed. Such cases cannot be depicted using manual/automated object-based image analysis.

4. Discussion

4.1. Vegetation Cover Monitoring

The results of the vegetation cover analysis in the Nayla Site, as shown in Figure 12, indicate the distribution and extent of different vegetation types. The methodology employed for preparing the vegetation cover map, as described in Figure 2, has provided valuable insights into the composition of the site. According to the results, the scrub forest covers an area of 10.72 hectares, indicating the presence of vegetation characterized by low-lying shrubs, bushes, or sparse trees. On the other hand, the dense trees occupy an area of 9.8 hectares, representing areas with a higher concentration of trees and denser canopy cover. The total plantation site area is reported as 54 hectares, which encompasses both the scrub forest and dense trees areas. It is important to note that the remaining area within the plantation site might include other land cover types such as open spaces, water bodies, or non-vegetated areas. These results provide valuable information for assessing the existing vegetation composition and can aid in making informed decisions regarding future management and planning strategies for the Nayla Site. The distribution and extent of different vegetation types within the plantation site help in understanding ecological dynamics, identifying areas for potential restoration or enhancement, and formulating appropriate management interventions [37–39].



S.No.	Vegetation Type	Area (Ha)	Area Covered %
1	Scrob/Small Trees	10.72	19.85
2	Large and Desnse Trees	9.812	18.17
3	Other Land Cover	33.46	18.07

Figure 12. Vegetation distribution, Nayla Plantation Site.

4.2. Nayla Plantation Sites

The results indicate that pits were generated based on the vegetation cover information obtained from the previous analysis. These pits were placed in areas where the canopy gaps were large and suitable for plantation (Figure 13). The selection of plantation sites followed the rule that high- and very high-density areas on the pit density maps represent suitable areas for future plantation. By targeting areas with high- and very high-density pits, the plantation efforts focus on locations where the tree density is relatively low or where there are significant gaps in the canopy cover [40]. This approach ensured that the newly planted trees can fill in these gaps, contribute to increasing overall tree density, and enhance the ecological functions of the forested area [41–43]. The selection of suitable pits based on the density of existing pits is a practical and efficient method for identifying areas where the establishment of new plantations would yield the most significant impact, allow for optimized land use, and promote effective resource allocation by concentrating efforts on areas with the greatest potential for the successful establishment and growth of new trees [44–46]. These results and the associated approach provide valuable guidance for decision-making in forest management, enabling efficient utilization of available resources and maximizing the success of plantation efforts.

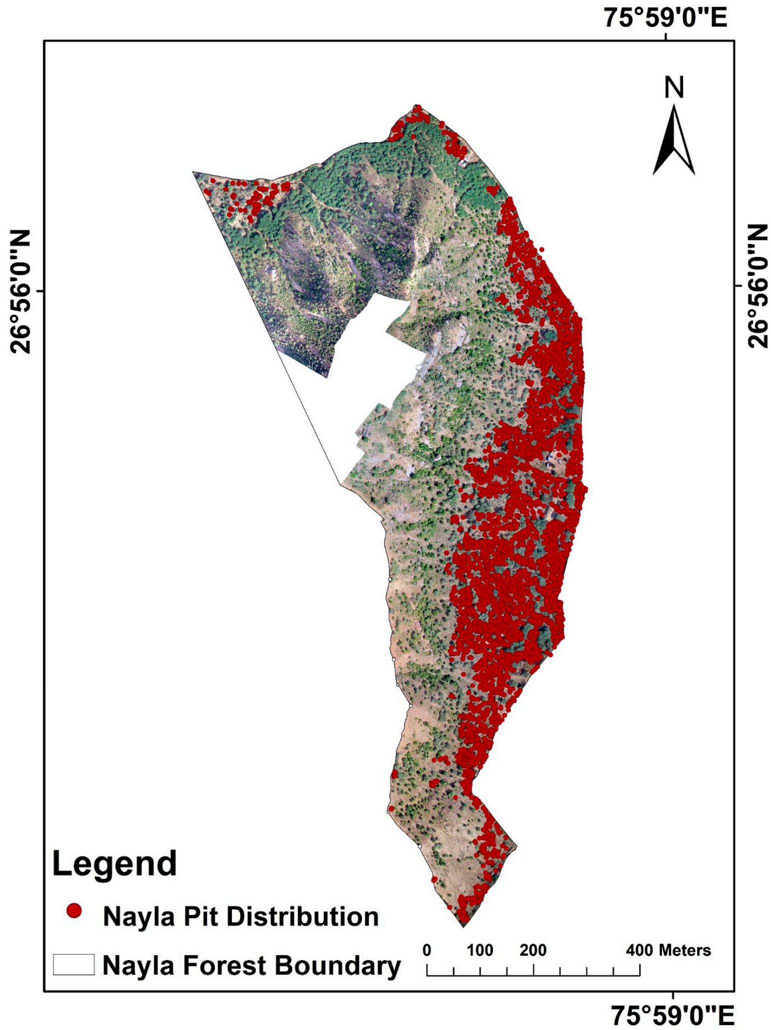


Figure 13. Distribution of pits for plantation over study area and detailed view of identified pits.

5. Conclusions

The incorporation of lightweight drones and object-oriented image analysis presents significant advantages for the monitoring of forest plantations. This study demonstrated the usefulness of employing lightweight drones to map plantation characteristics in the Nayla Range, Jaipur. By combining aerial photographs, photogrammetry, and limited ground survey data, accurate assessments of canopy information and forest biomass estimations were obtained. The findings from this study offer valuable insights for optimizing silvicultural operations, detecting pest infestations at an early stage, and supporting effective forest management practices.The utilization of lightweight drones and object-oriented image analysis provides a cost-effective and efficient approach to collect high-resolution data over vast areas, which can be applied for detailed vegetation mapping, accurate tree counting, and early detection of pests and diseases. Moreover, the assessment of forest health, growth rates, and biomass estimation is crucial for sustainable plantation practices and carbon accounting for climate change mitigation efforts. Despite the promising outcomes, challenges and limitations still need to be addressed. Issues related to image processing, data storage, and the development of automated algorithms for object detection and classification require further refinement. Furthermore, the implications of employing this technology in complex ecosystems, beyond image classification and attribute identification, need to be explored in future research.

Author Contributions: Conceptualization, J.D., A.K.B., S.K.G., G.M. and P.K.; methodology, J.D., A.K.B. and S.K.G.; validation, J.D., A.K.B., S.K.G., S.K.S., G.M., P.K., S.K., S.S. and B.S.; formal analysis, J.D. and A.K.B.; investigation, J.D., A.K.B., S.K.G., S.K.S. and G.M.; resources, J.D. and A.K.B.; data curation, J.D., A.K.B., S.K.G., S.K.S., G.M., P.K., S.K., S.S. and B.S.; writing—original J.D. and A.K.B.; writing—review and editing, J.D., A.K.B. and G.M.; visualization, J.D., A.K.B., S.K.G. and S.K.S.; supervision, J.D., A.K.B., S.K.G., S.K.S., G.M. and P.K.; project administration, J.D. and A.K.B.; funding acquisition, S.K. and P.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data shall be available from the corresponding authors upon reasonable request.

Acknowledgments: We acknowledge the help from the three anonymous reviewers whose critical comments improved the quality of this manuscript. The author G.M. acknowledges the support of Japan Society for the Promotion of Science for JSPS KAKENHI (Grant Number 23KF0024).

Conflicts of Interest: The authors declare no conflicts of interest with Geo planet solution Pvt Ltd.

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