

Integrating UAV Photogrammetry and Object-Based Image Analysis for Fine-Scale Vegetation Classification

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Abstract: Classification of vegetation cover is a fundamental aspect of environmental monitoring by remote sensing, offering crucial information on ecosystem structure, land use, and resource management. This research merges unmanned aerial vehicle (UAV) photogrammetry and object-based image analysis (OBIA) to develop a semiautomatic framework for vegetation mapping at hyper-spatial resolution. Using a DJI Mavic Pro UAV, RGB high-resolution images were captured; these were then processed for orthomosaics and Digital Surface Models (DSM). Vegetation was first extracted using the GCC index while vertical structure was calculated as a normalized DSM. Image segmentation, feature engineering, and rule-based classification created a hierarchical classification based on thresholding height. Results from the study demonstrate that the study area is covered with about 45% vegetation, most grassland, and low shrubs below 1 meter, and mid-canopy and high canopy plants are fewer in number. The results prove that OBIA outperforms traditional pixel-based methods of image analysis for very high-resolution images obtained from UAV systems. It also enhances its precision as well as its ecologic significance. There are definite challenges in terms of RGB-only sensor issues as well as processing requirements, although the proposed UAV-OBIA methodology is an excellent viable alternative for in-depth monitoring of plant life in data-poor regions.

Keywords: UAV, Vegetation Classification, GCC, OBIA, nDSM, High-resolution imagery

Introduction

The capacity for utilizing high-resolution data with access to geographical information systems (GIS) has experienced rapid growth with enhancements and developments in technologies associated with remote sensing and GPS. The cumulative effect of this data and technological framework provides the basis upon which Geographic Information Science (GISc) operates. Evaluating and exploring data with this framework has been

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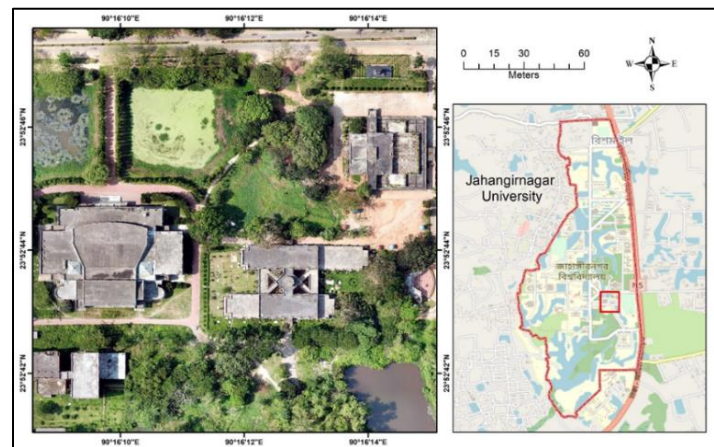
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significantly enhanced by the incorporation of Unmanned Aerial Vehicle (UAV) technologies. Such a framework has proven effective due to the accuracy with GPS and the capacity for collecting detailed spatial data. Compared with satellite remote sensing imagery, the image obtained by UAV devices offers much higher resolution, with considerably more flexibility in terms of the scheduling of the imagery for the purpose of study. Though it is true that high-end resolution obtained with UAV devices makes use of RGB imagery rather than the multi-spectral kind, its availability and the high level of detail offered with it make it much more beneficial for the purpose of study, especially for urban ecological research (Cleve et al., 2008). However, the higher spatial resolution can create problems for traditional pixel-based image classification because individual objects are often shown by many different pixels. Object-Based Image Analysis (OBIA) helps to overcome these challenges by grouping pixels into meaningful image objects and using spectral, spatial, textural, and contextual information in the classification process (Blaschke et al., 2014). Many studies have shown that OBIA works better than pixel-based methods when used with high- and very high-resolution imagery, especially for mapping land use and vegetation (Yu et al., 2006; Myint et al., 2011). Despite this, not many studies have systematically used OBIA on UAV-derived datasets for classifying fine-scale vegetation height. In this context, the current study uses UAV-acquired hyper-spatial resolution imagery and OBIA techniques to classify vegetation cover based on structural height within the Jahangirnagar University campus. The goal is to show a reliable, low-cost, and scalable method for automated vegetation classification that is suitable for monitoring small areas of the environment.

Study area

The study was conducted within a selected portion of the Jahangirnagar University (JU) campus, located in Savar, Dhaka District, Bangladesh. The study area extends from $90^{\circ}16'8.32''\text{E}$ to $90^{\circ}16'15.30''\text{E}$ longitude and from $23^{\circ}52'40.86''\text{N}$ to $23^{\circ}52'47.77''\text{N}$ latitude, covering approximately 3.84 hectares. The area includes academic buildings (Cafeteria, TSC, and Auditorium), paved surfaces, water bodies, and heterogeneous vegetation comprising grasslands, shrubs, and trees. This mixed land-cover composition makes the site suitable for evaluating UAV-based object-oriented vegetation classification.

Figure 1: Study Area Map

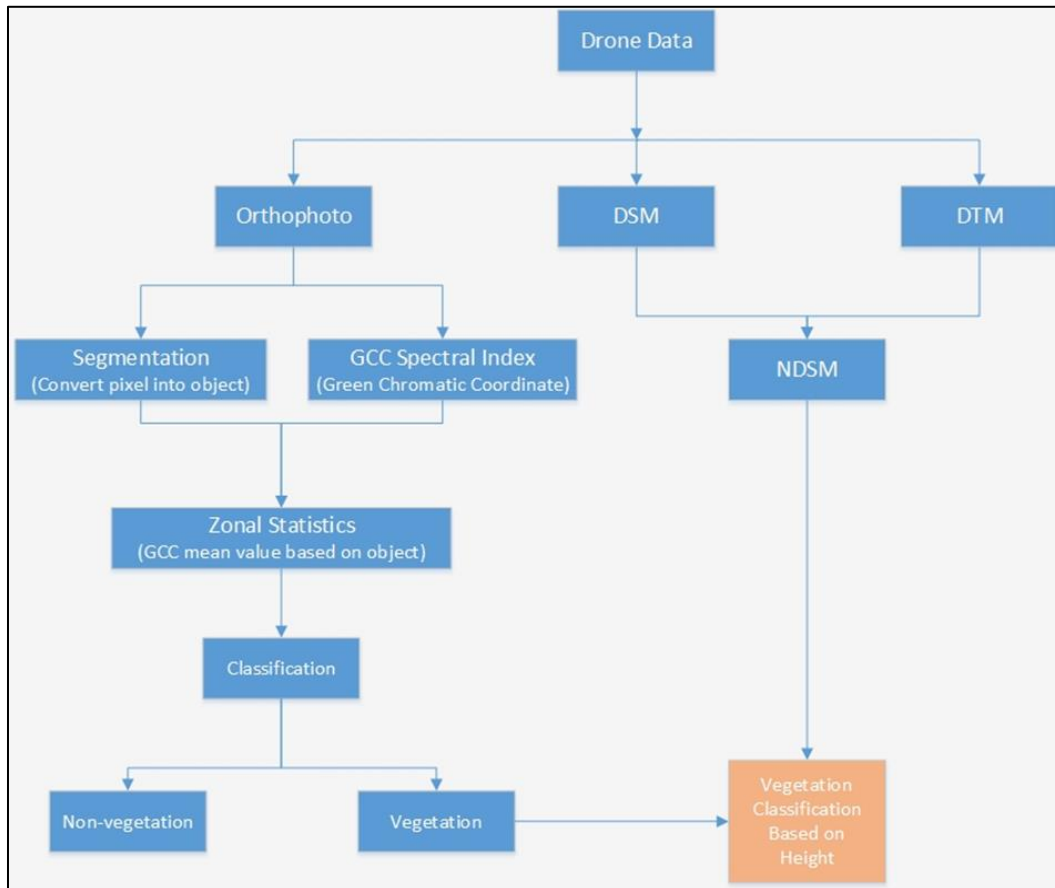


Source: Authors, 2025

Methodology

The overall methodological workflow comprised UAV data acquisition, photogrammetric processing, image segmentation, vegetation extraction using GCC, height estimation using nDSM, and rule-based object classification. This integrated UAV–OBIA framework enables automated, fine-scale vegetation mapping with high spatial accuracy and limited dependence on multispectral sensors. A schematic overview of the methodology is presented in Figure 2.

Figure 2: Methodological flow chart.



Source: Authors, 2025

UAV Data Acquisition and flight Planning

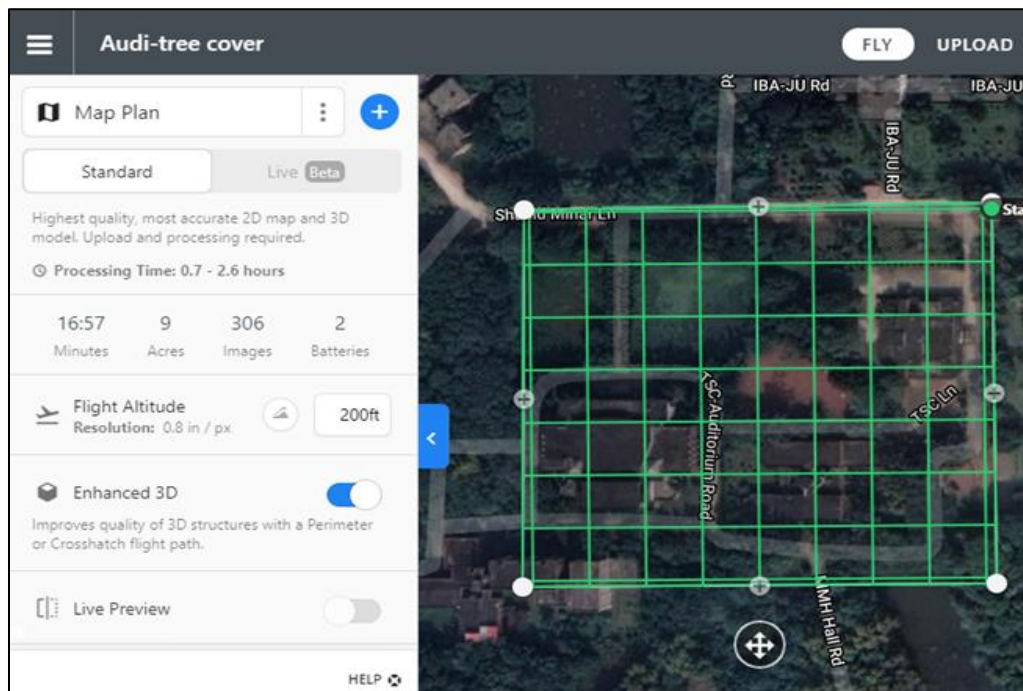
High-resolution aerial images were captured with a DJI Mavic Pro drone that has a consumer-grade RGB camera. We planned the flight and carried out the mission using DroneDeploy software on an Android device. The UAV survey took place in clear weather to reduce changes in light and shadow effects. A total of 306 straight-down images were taken at a flight height of 200 ft (about 61 m) above the ground. We set the image overlap to 80% in the forward direction and 60% on the sides to provide enough redundancies for

reconstruction. The resulting ground sampling distance (GSD) of the images was about 2 cm, which allowed for detailed spatial analysis suitable for object-based classification.

Key flight parameters are summarized as follows:

- Number of images: 306
- Flight altitude: 200 ft
- Forward overlap: 80%
- Side overlap: 60%
- Dense point cloud size: ~799,510 points
- Ground resolution: ~2 cm.

Figure 3: Flight plan of the study area.



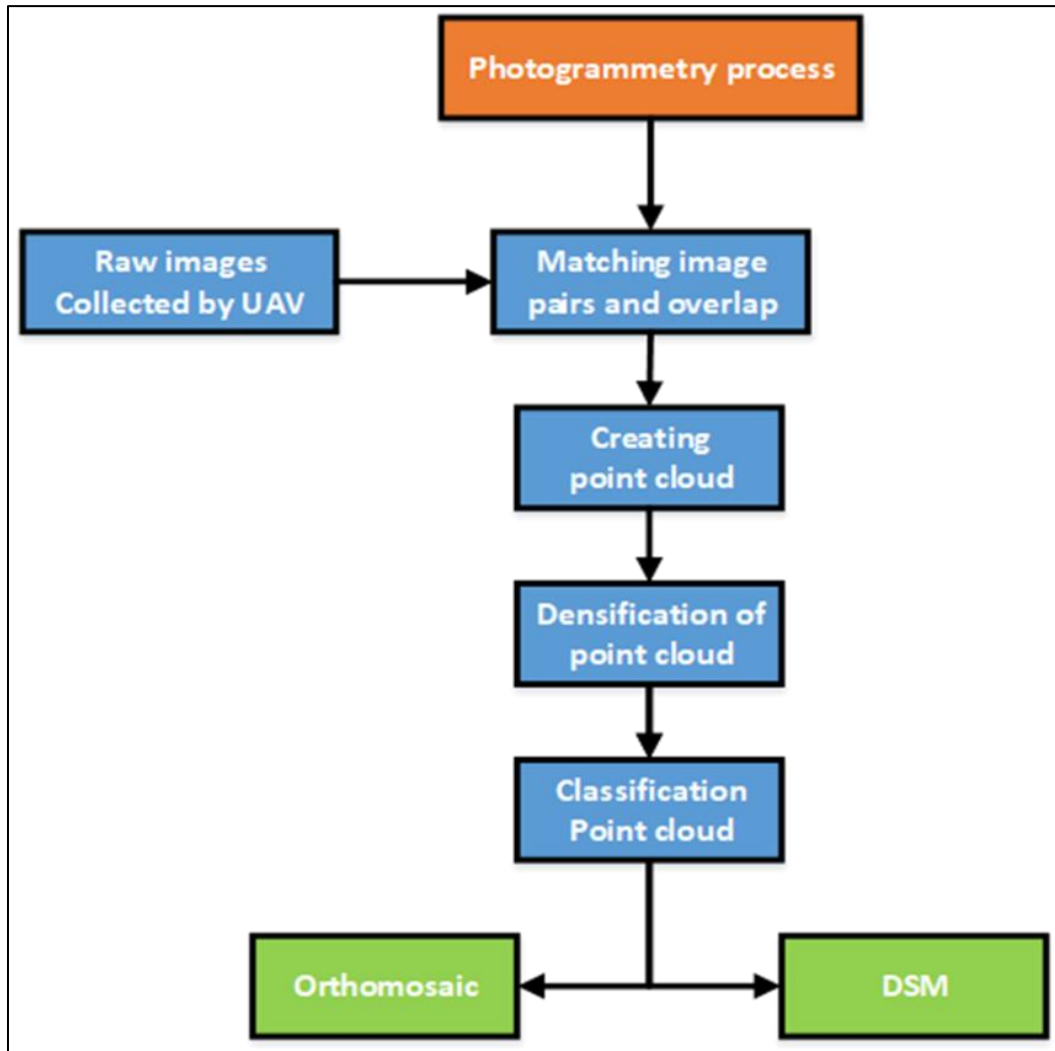
Source: Authors, 2025

Photogrammetric Processing and Surface Model Generation

We conducted the photogrammetric processing using Pix4D Mapper, following the standard SfM-MVS workflow. It consisted of image alignment, camera calibration, sparse point cloud generation, dense point cloud reconstruction, and surface interpolation. From the dense point cloud, we created DSM and a high-resolution orthomosaic. The DSM with its elevations of natural and artificial surface features like vegetation canopies and man-made structures like buildings is shown above. The process of orthorectification was used to remove geometric distortions related to terrain, camera tilt, and perspective effects. The

outcome was a true-to-scale orthophoto, ready to be used in measurements and analyzed in GIS systems.

Figure 4: Flow chart of the process of Orthomosaic and DSM



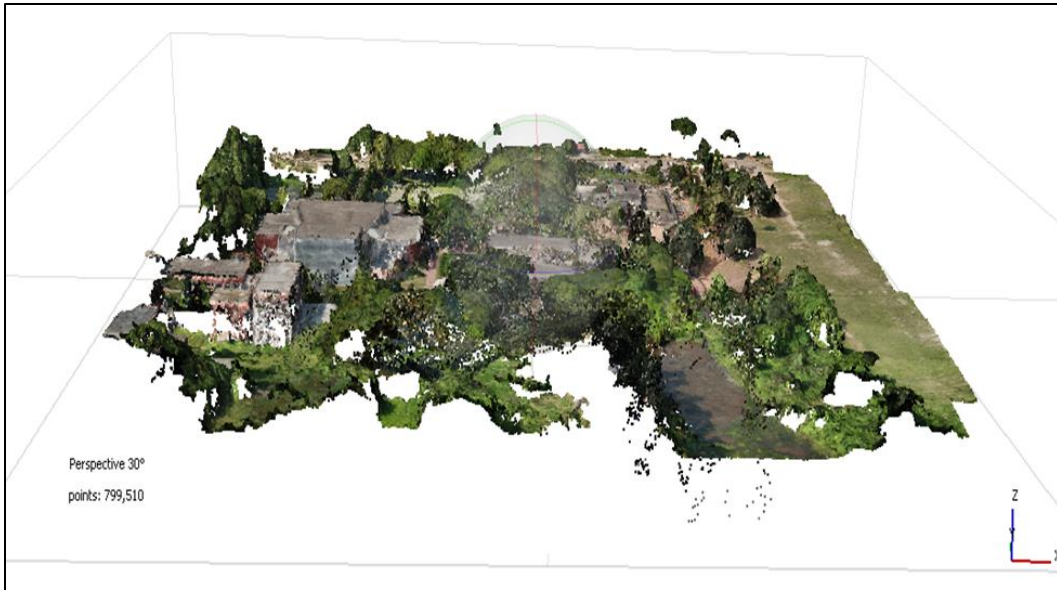
Source: Authors, 2025

Figure 5: Point cloud density.



Source: Author, 2024

Figure 6: 3D mesh with point cloud.



Source: Authors, 2025

Image Segmentation

To overcome the disadvantages of pixel-based classification with very high resolution UAV images, the Object-Based Image Analysis (OBIA) technique was adopted for the study area. The first step in an OBIA workflow is segmentation, which converts groups of homogeneous pixels to meaningful groups of pixels referred to as objects in an image. Mean Shift segmentation was carried out for the obtained ortho-mosaic, wherein the segments of the images would be spectrally or spatially homogeneous. However, the quality of the segmentation was enhanced using an unsupervised evaluation strategy for the F-measure.

F-measure unifies normalized area-weighted variance, denoted by WV_norm , with Moran's I normalized measure, denoted by MI_norm , to assess the within-object consistency and differences between objects.

The segmentation scale parameters used are carefully selected to maximize the object's coherence while maintaining the importance of the vegetation structure for the next step of the classification process.

The multi-resolution segmentation strategy helped to identify vegetation objects of appropriate scale for ecological study.

Equation can be used to get the F-measure value for estimating the ideal MS of an application:

$$F - measure = (1 + \varphi^2) \frac{MI_{norm} \times WV_{norm}}{\varphi^2 \cdot MI_{norm} + WV_{norm}}$$

where WV_{norm} (the over-segmentation measure) and MI_{norm} (the under-segmentation metric) stand for the normalized area-WV and Moran's I, respectively. The scene-independent factor (φ) regulates the relative weights of WV_{norm} and MI_{norm} .

Figure 7: Image after segmentation.

Source: Authors, 2025

Vegetation Extraction Using Spectral Index

Vegetation pixels were initially identified using the Green Chromatic Coordinate (GCC) index, which is particularly suitable for RGB-only imagery. The GCC index enhances green vegetation by normalizing the green band relative to the total visible spectrum and was computed as:

$$GCC = \frac{G}{R + G + B}$$

where R , G , and B represent the red, green, and blue digital numbers, respectively. Thresholding of GCC values enabled the separation of vegetated and non-vegetated image objects prior to height-based classification.

Normalized Digital Surface Model (nDSM)

To quantify vegetation height, a Normalized Digital Surface Model (nDSM) was derived by subtracting the Digital Terrain Model (DTM) from the DSM:

$$nDSM = DSM - DTM$$

Where,

nDSM = Normalized Digital Surface Model

DSM = Digital Surface Model

DTM = Digital Terrain Model

The generated DTM was filtered from the ground points represented by the dense point cloud, depicting bare-earth elevation. The obtained nDSM gives relative height values above the ground level of the features of the surface, which allows discrimination between grass, shrubs, and tree canopies.

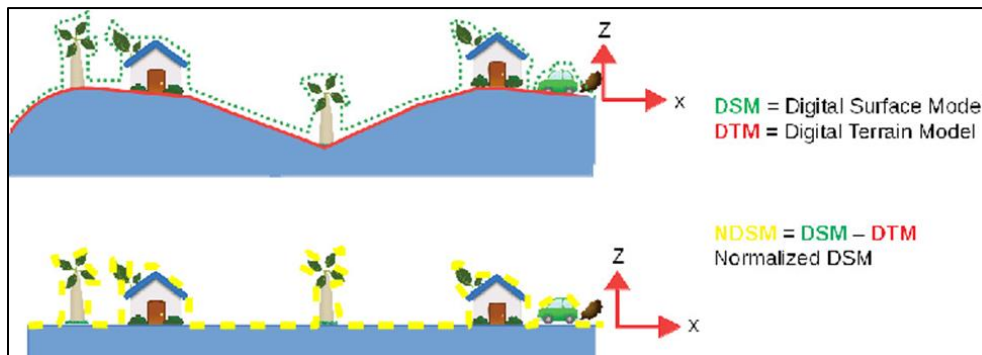
Rule-Based Vegetation Classification

In the classification of vegetation types, a rule-based Object-Based Image Analysis was used to integrate object spectral (GCC) and object structural (nDSM) information. The vegetated objects were classified at different height levels as follows:

- < 1.0 m (grassland and low shrubs)
- 1.0–4.0 m (shrubs and small trees)
- 4.0–8.0 m (medium canopy trees)
- 8.0–12.0 m (tall trees)
- 12.0 m (very tall trees)

For this study, classification rules were created based on figures provided by nDSM statistics. The rules were designed to easily interpret while keeping classification rules straightforward.

Figure 8: Normalized Digital Surface Model



Results and Discussion

UAV-Derived Orthomosaic and Surface Models

The orthomosaic imagery generated by UAV had adequate resolutions with a ground sampling distance of approximately 2 cm in landscape features such as shrubs, pathways, water bodies at smaller scales, and building features or rooftops. Usually, these features are not visible in satellite images at resolutions from medium or high resolutions. The information generated in such resolutions indicates that it becomes important or feasible in site-specific analysis when detailed object information needs to be identified at smaller altitudes by UAVs in analyzing the environment within a particular site. The information generated by the photogrammetric process in the DSM precisely identified natural features such as vegetation cover and man-made features such as building rooftops compared to

satellite imagery with resolutions in elevation data at levels from 10 or 30 meters or even greater scales following the implementation with the use of UAVs in acquiring detailed information in an environment. When considering the accuracy in resolving the information regarding the various levels within vegetation covers, it needs to have resolutions comparable or even finer in elevation data and objects or features in an environment. These results match earlier studies that show UAV-based photogrammetry can be an effective alternative to airborne LiDAR for small-area projects, especially when cost and data availability are concerns.

Figure 9: Digital Orthophoto of study area.



Source: Authors, 2025

Vegetation Detection Using GCC Index

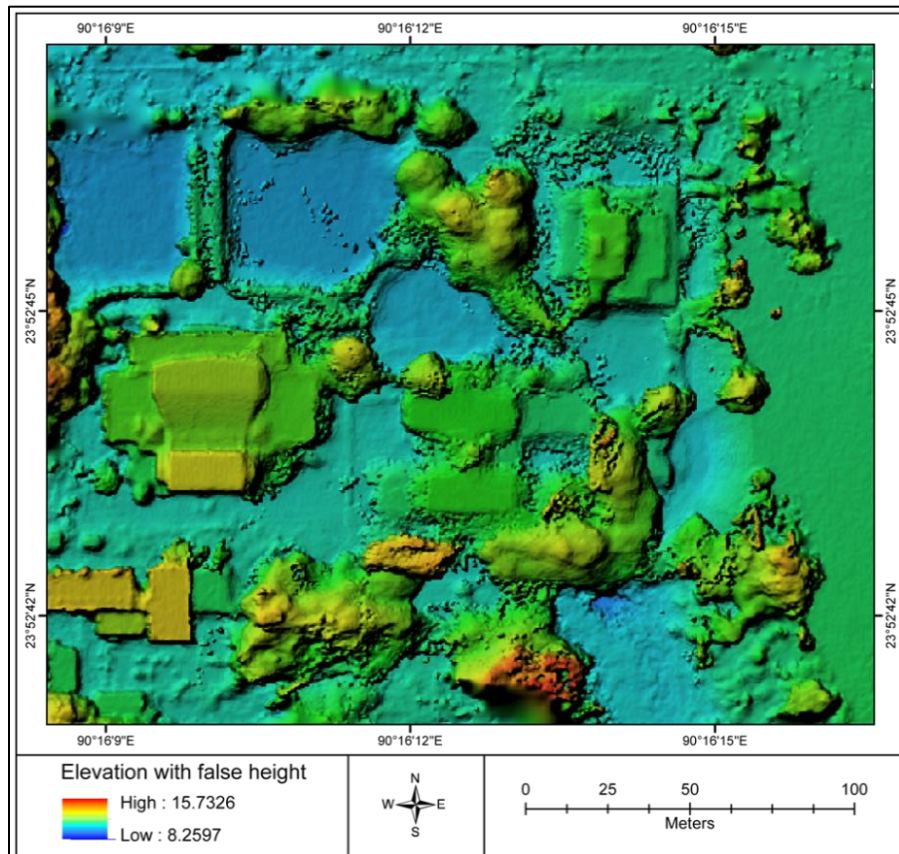
The GCC index was able to successfully distinguish between vegetated and non-vegetated surfaces using purely RGB imagery. Vegetation returned higher values compared to impervious surfaces, bare soil, and water bodies, allowing for threshold-based discrimination in a reliable way. Although multispectral vegetation indices such as NDVI are popular, results indicate that GCC works for the general extraction of vegetation in UAV imagery under constant light conditions. Comparable studies using UAVs with RGB sensors have also found GCC to serve as an efficient alternative to multispectral methods. However, limitations were encountered in the shaded regions as well as the edges of

vegetation, soil, etc., owing to the corresponding overlapped values of the GCC. This highlights the complexity of weighing the simplicity of a sensor with the ability to spectrally discriminate between the relevant features, especially with the application of combined spectral indices within the OBIA domain.

Height-Based Vegetation Stratification Using nDSM

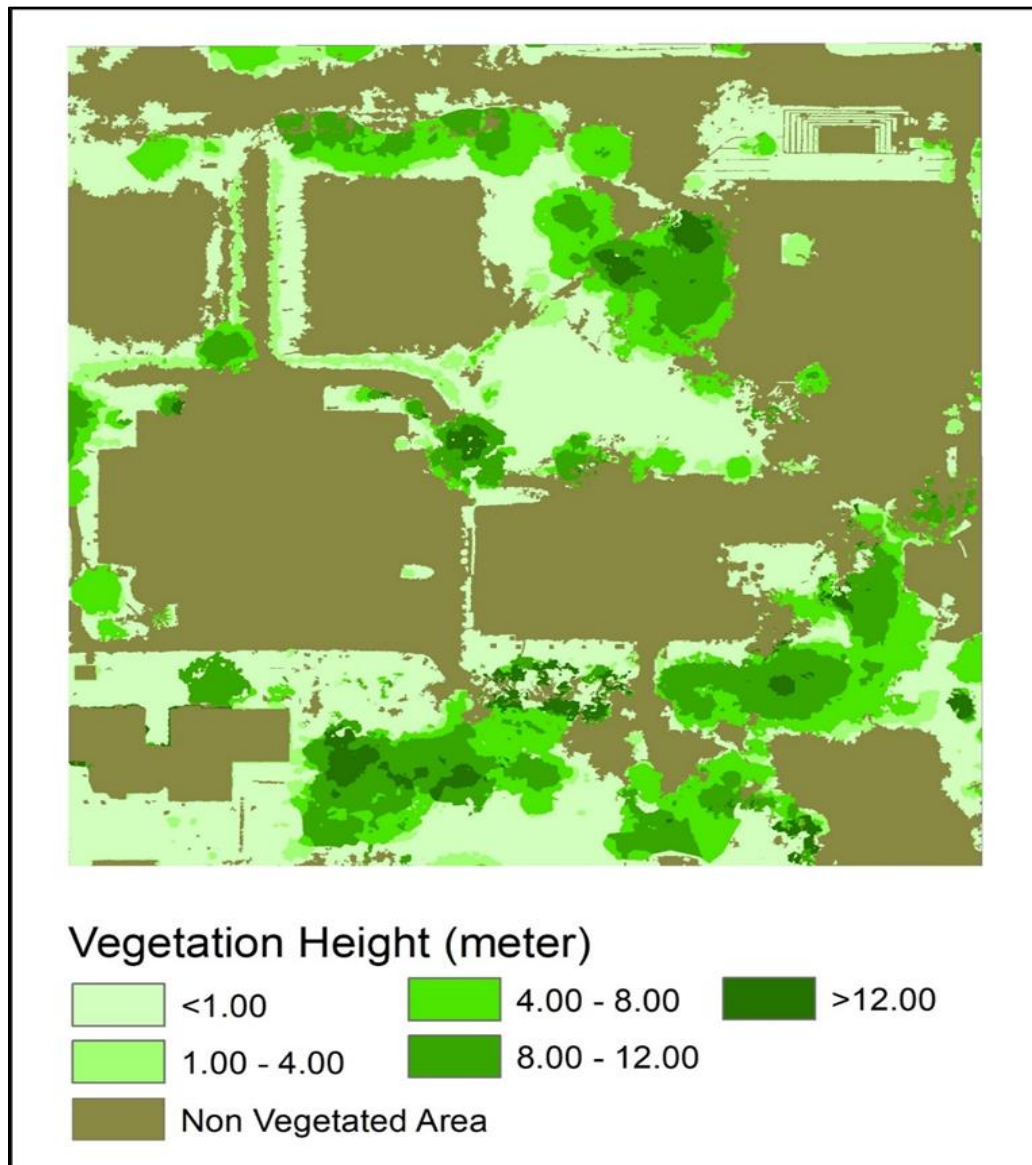
nDSM allowed for the quantification of the canopy height in the study area by subtracting DTM from DSM to get object-oriented canopy height, which helped in the classification of the hierarchical structure of vegetation.

Figure 10: Digital Surface Model of study area



Source: Authors, 2025

Figure 11:Vegetation Classification Scheme of study area (Based on height).



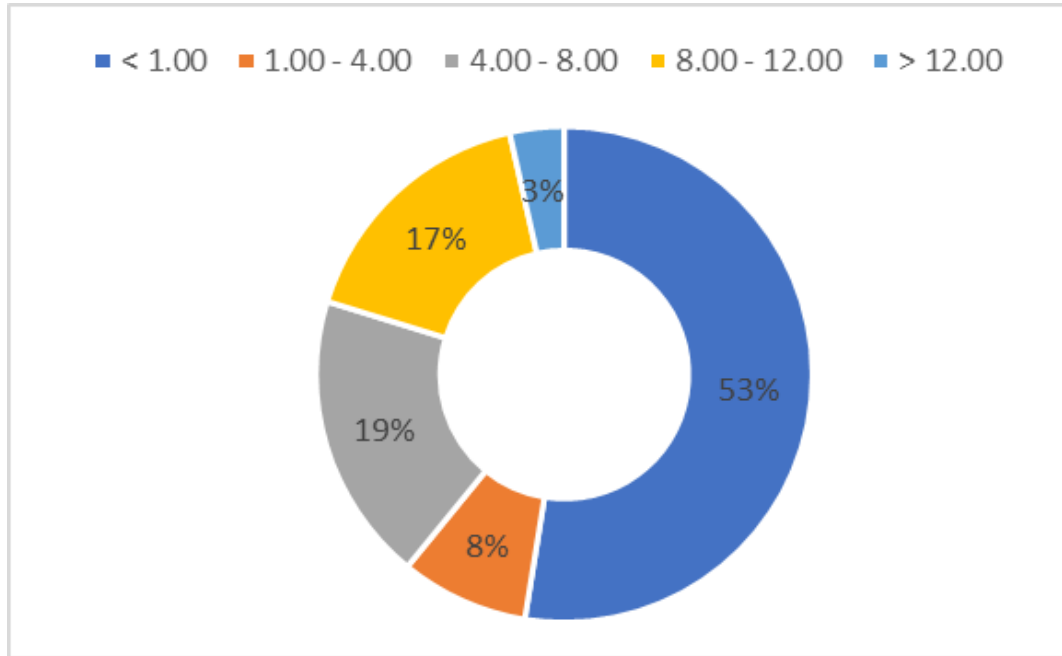
Source: Authors, 2025

The total area studied covered around 38,440 m², with 17,454 m² (~45%) of it vegetated. Remaining area comprised built-up, paved, bare lands, and water features, covering ~55%. Vegetation Heights Distribution: Strong dominance of low-height vegetation is indicated in the vegetation height distribution.

- Vegetation < 1.0 m accounted for **9,173 m² (~53%)** of the total vegetated area
- Vegetation between 1.0–4.0 m occupied **1,455 m² (~8%)**
- Vegetation between 4.0–8.0 m covered **3,294 m² (~19%)**

- Vegetation between 8.0–12.0 m represented **2,914 m² ($\approx 17\%$)**
- Vegetation > 12.0 m comprised only **618 m² ($\approx 3\%$)**

Figure 12: Area distribution percentage of the classified vegetation cover.



Source: Authors, 2025

This distribution reflects the land-cover composition of a university campus, characterized by prevailing grasslands, ornamental shrubs, and medium-height trees, while mature tall trees are spatially limited. Similar vegetation height distributions have been obtained in studies using UAV-based nDSM analysis within urban green-space areas, confirming the robustness of the adopted approach.

Performance of OBIA Compared to Pixel-Based Approaches

The object-based classification method demonstrated obvious advantages in comparison with traditional "pixel-based" techniques when utilized with HR UAV imagery. In "pixel-based" techniques, there may be certain limitations at extremely high resolutions due to the occurrence of "salt and pepper" noise in images, as objects are made up of multiple pixels with different values.

Also, the advantages of OBIA lie in its ability to integrate spectral, spatial, and structural information. To find features in images while minimizing the amount of user input required in the feature extraction process. Within this study, segmentation-based input objects were seen as suitable in comparison with real-world vegetation patches, thus enabling effective classification with regard to the application of image classification using rules. Use of both GCC image information with characteristics of nDSM enabled enhanced separability of certain classes, particularly between low vegetation areas and built-up structures, thus

validating existing studies that demonstrated effective suitability of OBIA in comparison with pixel-based image classification in urban/real-world ecological applications, where elements of shape and height are taken into account.

Implications for UAV-Based Vegetation Monitoring

The results indicate the potential for using UAV-based RGB images with OBIA and surface modeling to create an efficient vegetation classification system without the requirement for expensive hardware like multispectral or LiDAR devices. This is essential for vegetation monitoring in areas with no available resources or data. Classification of vegetation by height aids in the detailed mapping of the area beyond the general category of vegetation or bare ground. Apart from that, it is possible to use flexible revisit intervals of the UAV platform, which allows rapid response to vegetation cover changes, a problem that is present when one is forced to use satellite images that have a restricted orbital path, coupled with the problem of cloud cover interference. The approach, however, is influenced by segment parameters that need extensive computation during photogrammetry processing.

Comparison with Previous Studies

Compared to other vegetation classification studies carried out by means of satellites, this method has shown more precise results in terms of spatial resolution. Although, it has to be acknowledged that satellite images must always be used in regional studies, whereas with this method, it can be used in local studies with much more precise results. Previous studies related to UAV have confirmed advantages in applying nDSM and OBIA in vegetation and urban analysis. The similarities with previous research further prove that UAV-OIBA frameworks can always be used in conjunction with other methods in a helpful way.

Accuracy Assessment

Accuracy assessment is a crucial component of image classification research. Accuracy assessment methods provide quantitative as well as qualitative information on image classification accuracy. In this paper, accuracy assessment for image classification utilizing object-based classification methods was performed to compare object-based classification accuracy with those obtained by methods of visual interpretation, consistency checks, and comparisons with reference datasets at high resolution that were obtained using UAV imagery. Because we didn't use any information on reference measurements collected on-site, this method used UAV ortho-image datasets for accuracy assessment. The datasets provide reliable accuracy assessment for object-based classification used for assessing image classification accuracy for those situations when imaging conditions at very high resolution are possible. The object-based classification was validated by selecting representative image objects from different classes of vegetation height (<1 m, between 1 m to 4 m, between 4 m to 8 m, between 8 m to 12 m, and ≥ 12 m) as well as non-vegetated classes using a stratified sampling method. The performance of classification was validated by visually inspecting classification results at an object level against nDSM to check for thematic consistency as well as structural consistency. The classification results obtained

using object-based classification matched highly with results obtained from visual interpretation for all main vegetation height classes. Low vegetation height objects (<1 m), dominating most of our area of interest, were classified well with minimal confusion with impervious surfaces. Taller vegetation classes matched well with nDSM-derived height ranges, confirming that height-based rules effectively distinguish shrubs from tree canopies. Misclassifications occurred in transitional zones, such as densely vegetated areas next to buildings and shaded regions, where spectral similarity and elevation changes created uncertainty. Although we did not create a formal confusion matrix or calculate accuracy metrics (like overall accuracy, user's and producer's accuracy, and Kappa coefficient) because we lacked independent ground reference data, the classification results show high internal consistency and strong spatial agreement with UAV-derived reference products. Similar validation methods have appeared in previous UAV-based OBIA studies, especially when the goal is to show methodological feasibility rather than operational use. Future work should include field-measured vegetation height data or independent reference datasets to allow a full quantitative accuracy assessment. Adding ground truth measurements would enable the calculation of standard accuracy metrics and allow for direct comparisons with different classification methods.

Conclusion

This study shows how effective it can be to combine UAV-derived high-resolution images with Object-Based Image Analysis (OBIA) for classifying vegetation cover in mixed land-use areas. By merging RGB-based color information with structural details from a Normalized Digital Surface Model (nDSM), the proposed system allowed for automated vegetation mapping and height-based classification at a level of detail that conventional satellite images cannot achieve.

It is observed from the results that UAV-based photogrammetry can generate high-quality ortho-mosaics and surface models, which are appropriate for highly detailed vegetation analysis. Approximately 45% of the test area fell into the vegetated class, with low-height vegetation under 1 meter dominating the landscape. This was followed by smaller quantities in both the shrub and tree canopy classes. This kind of classification based on height is going to provide more useful data compared to simple vegetation maps and will support uses that need structural vegetation data, like assessing urban green spaces and ecosystem monitoring.

The object-based approach has been found very useful for very high-resolution UAV images, given that the pixel-based methods may not handle noise and variation within the same class. Focusing attention on objects, OBIA allowed for the integration of spectral, spatial, and height features, making vegetation objects sharper and closer to real-world elements. Using a Green Chromatic Coordinate index shows that proper vegetation extraction is possible with just RGB sensors and hence decreases the dependence on expensive multispectral or LiDAR. However, some limits should also be taken into consideration. The fact that RGB images are being utilized limits the capacity to identify different types of vegetation and determine their health. The determination of segmentation parameters also becomes subjective, and this can influence the end result of the classification. Furthermore, considerable computational capacities are needed for

photogrammetric processing and OBIA workflows, and this may present another limitation.

The conclusions drawn are that UAV-OBIA technology provides an effective, inexpensive, and flexible tool for examining vegetation with detail at the local scale, and this would particularly be effective for regions with minimal data. Future research should aim to incorporate multispectral or LiDAR data to improve vegetation characterization, develop ways to optimize segmentation automatically, and include accuracy assessments using field reference data. These improvements would enhance how UAV-based object-oriented vegetation mapping can be used in environmental and urban studies.

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