Pertanika Proceedings 1 (7): 67 - 75 (2025)

PERTANIKA PROCEEDINGS

Journal homepage: http://www.pertanika.upm.edu.my/

Object-based Image Analysis (OBIA) for Bamboo Area Classification using Unmanned AerialV (UAV): A Case Study in Koperasi Kariah Masjid Kundur Ulu (KOMASKU), Rembau

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ABSTRACT

Bamboo cultivation in Rembau, Peninsular Malaysia, presents opportunities for community-based marketing, particularly as a food supply for Giant Pandas, with the potential to enhance local income. Bamboo plantations can serve as both productive landscapes and leisure spaces for villagers and visitors, underscoring the need for accurate area assessment. In Model 1 (“vegetation” vs. “non-vegetation”), subsets A, B, and C achieved overall accuracies of 97.79%, 94.10%, and 99.08%, with Kappa values of 0.60, 0.84, and 0.84, respectively. In contrast, Model 2 (“bamboo” vs. “non-bamboo”) showed poor performance, with accuracies of 85.71%, 56.71%, and 52.50%, and Kappa values of 0.67, 0.15, and –0.01. The results highlight UAV based on OBIA as effective for general vegetation mapping but less robust for bamboo-specific classification and larger area. Spectral similarity by other landscaped combined with bamboo and mixed vegetation, infrastructure reduce the stability, reliability, and consistency of the classification conducted in the study. Conclusively, bamboo classification maps are valuable not only for methodological advancement but also for supporting agricultural and agroforestry planning, including plantation management, yield estimation, and land-use mapping.

Keywords: Bamboo, community, fibre strength, vegetation indices, world fibre

ARTICLE INFO

Article history:
Received: 27 October 2025
Published: 10 December 2025

DOI: https://doi.org/10.47836/pp.1.7.012

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INTRODUCTION

To begin with, bamboo, widely known as the “poor man’s timber” or “green gold,” is a key forest resource distributed across tropical and subtropical regions (Alamerew et al., 2024). Specifically, most of the bamboo resources in Asia originates from

e-ISSN: 3083-9475

South and Southeast Asia which amounted to 17.87 million hectares followed by East Asia about 7.00 million hectares (Tahir et al., 2023). Meanwhile, bamboo is planted around the globe because its unusual fibre characteristics and longevity. In terms of growing capability, bamboo is known as multifunctional and fastest-growing plant on Earth (Ahmad et al., 2021). Beyond Asia, bamboo is distributed mainly in Brazil, Columbia, Venezuela, Panama, Argentina, and many more countries located in tropical region countries (Ruiz-Sanchez et al., 2021).

Due to its huge benefits and rapid growth small holders are adopting bamboo in their small plantation nearby their home. To date, UAV-based image classification has become well established, frequently being applied for segmenting forest, non-forest, agricultural, and urban tree canopy. In terms of methodology, the best digital land cover maps to date have been produced using OBIA, which usually achieves good accuracies. In fact, the study highlighted that the lack of direct transferability is an important limitation of OBIA methods since, once calibrated for one image, the OBIA settings are not directly portable to other images (e.g., to different areas, extensions, radiometric calibrations, background colour, spatial and spectral resolutions, or different sizes or shapes of the target objects).

As a result, this research aims to evaluate imaging classification techniques for bamboo monitoring to provide up-to-date mapping tools. Specifically, to develop an efficient bamboo classification model for distinguishing bamboo from non-bamboo vegetation. Finally, the study assessed the accuracy of the classification model compared for smallholder bamboo plantation mapping, that indicate land use types for the study area.

MATERIALS AND METHODS

Study Area

This study was conducted in the Betong (*Dendrocalamus asper*) bamboo plantation area in Rembau District, Peninsular. The study received prior consent and cooperation from the cooperatives, which manages the plantation as part of its community-based economic activities. The plantation is owned by Koperasi Khariah Masjid Kundur Ulu (KOMASKU), a local cooperative comprising residents of Kampung Kundur Ulu, which manages small-scale economic activities such as a local food restaurant and the *Pusat Jualan Produk IKS Kundur* Figure 1. showed study site for this study.

Data Acquisition

UAV flights were implemented to obtain high-resolution raw raster data on RGB cameras in the study area in May 2024. For this purpose, the DJI Matrice 300 RTK (M300 RTK), using Zenmuse L2 camera, that integrate LiDAR sensor with an integrated RGB camera for 3D mapping and forestry applications (DJI, 2025) was deployed. This UAV is a professional-grade quadcopter that integrates Real-Time Kinematic (RTK) positioning

Figure 1. (Left) Orthomosaic of the KOMASKU bamboo plantation site; (Middle) Exact location of the OBIA classification area; (Right) Team set-up the UAV flight

technology, enabling centimetre-level accuracy in aerial surveys, which assists farmers to obtain accurate information Figure 2 showed the team setting up the flight mission, with the UAV positioned for launch.

OBIA Workflow

Geographic OBIA also can be referred to OBIA, as explain in (Chen et al., 2018). Accurately, it refers as a classification technology sets adjacent pixels as an objects to identify interested spectral elements, and makes full use of spatial, texture and spectral information of high-resolution panchromatic and multi-spectral data to segment and classify, and outputs high-precision classification results or vectors (Zhao et al., 2020). OBIA is particularly valuable as it moves beyond a land-cover centric view that relies only on the spectral characteristics of pixels and instead integrates both spectral and spatial (contextual) information (Blaschke, 2010; Ma et al., 2017). Classification is carried out using OBIA through CATALYST Professional Version 2 (Figure 2). Segmentation is the important steps in this technique, where it refers to as a bridge between raw pixel data and meaningful interpretation (Riabko, 2023). The segmentation process was completed using the defined parameters (Scale = 150, Shape = 0.5, Compactness = 0.5), after that attribute calculations were subsequently performed (Figure 3). The classification model was developed for Model 1: General vegetation (vegetation and non-vegetation) and Model 2: Bamboo (bamboo and non-bamboo). The main objective of the model segmentation process is to remove irrelevant features such as roads, rivers, houses, shops, and mosques. by site visit information and ground-truth validation.

For this study, Support Vector Machine (SVM) algorithm was employed. The study employed Radial Basis Function (RBF/Gaussian kernel) (Sawarkar et al., 2023). The details of the training site editing process was presented in Figure 4. The selection of classes is based on attribute information calculation conducted prior of the training site editing. The SVM is well known classifier and produced an overall accuracy of 85%

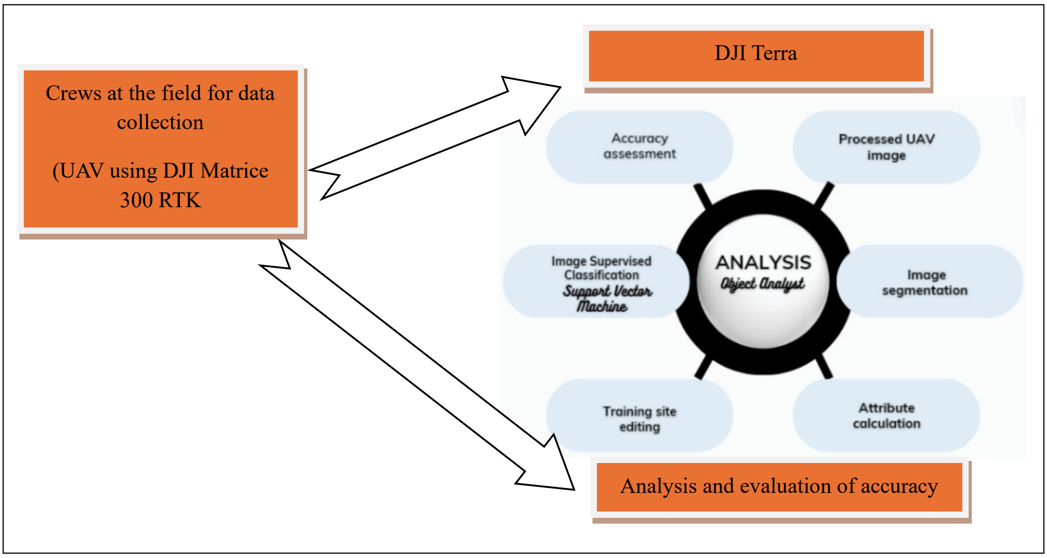

Figure 2. Workflow of UAV bamboo mapping at the KOMASKU plantation site

and kappa coefficient value of 0.74 when compared with conventional classifier (Kamarulzaman et al., 2022). These results highlight the distinct spectral separability of structured plantation crops compared to heterogeneous vegetation types (Razali & Lion, 2021), such as demonstrated in the study.

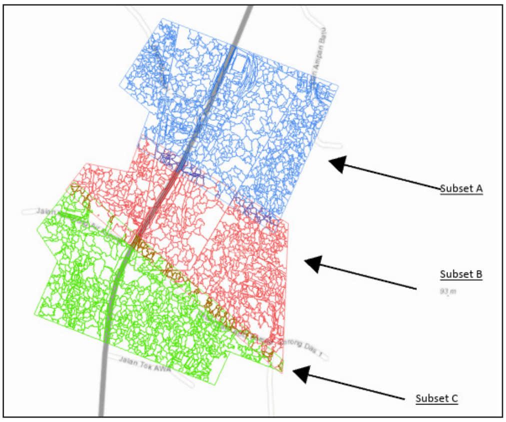

Figure 3. Overview of all the segmentation segmentation into three subsets (A – blue, B – green, and C – red) to facilitate image analysis

RESULTS AND DISCUSSION

The segmentation is evaluated based on visual evaluation with expert judgment, based on ArcGIS Pro base maps. Field reference employed as supports materials for features identification during overlaid process. Based on Figure 3, the subsets produced reveal that, for Model 1, the data show a strong skew toward the "vegetation" land-use category, which comprises most entries—approximately 95%. This suggests that "vegetation" is the dominant category within this subset A. The results show that "vegetation" dominates the category with 31,907 counts, while "non-vegetation" has only 323 counts, indicating a strong ability of discrimination between the two classes. Meanwhile, subset C showed the bar chart has a significantly higher count of 17,817 for "vegetation", compared to "non-vegetation", which has a count of 181.

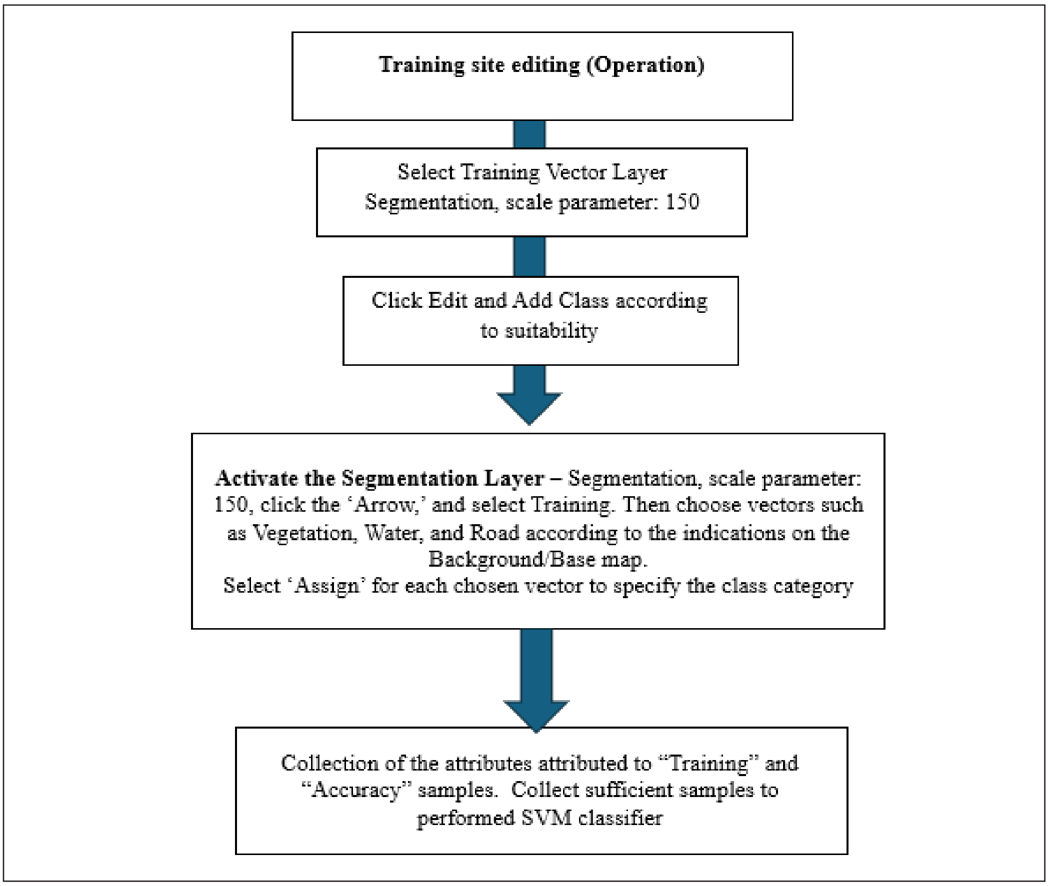

Figure 4. Workflow of the training site editing for the classification

Models' Classification Scheme and Data Sampling

The model classification was developed for the models. The designed scheme outlined rules and criteria for selecting training samples for training site editing, which the study employed SVM techniques for classification (Table 1).

To evaluate the effectiveness of this classification framework, an accuracy assessment was conducted that presented in table below (Table 2). Training and accuracy samples collected in the training site editing procedure.

Data Accuracy Assessment

The kappa coefficient, like most correlation measures, can range between -1 and +1 (Chicco et al., 2021). When measuring the accuracy, a value of Kappa greater than 0.75 might be deemed (arbitrarily) as "excellent" agreement, whereas a value less than 0.4 indicates "poor" agreement (Table 3).

Table 1
Classification rule for training site editing

Model	Land use type	Classification rules
1	Vegetation	All vegetation features selected are other than infrastructure such as houses and shops. They also do not include rivers and main roads or village roads.
	Non-vegetation	Including all non-vegetation features using a combination of true colour UAV visualization of the image.
2	Bamboo	Perform pre-collection before non-bamboo features to avoid overlapping feature selection. Most of the bamboo trees seen in this UAV data have shadows. Shadows are selected as non-bamboo. Bamboo shows small leaf opening and clumps therefore the clump shape is easy to see from above.
	Non-bamboo	This sample is easier for non-plant types, such as roads, village roads, rivers, buildings including village houses and mosques. Plants other than bamboo are easier to sample by only picking bamboo that shows the shape of "broccoli" and is present without grouping.

Table 2
Training sample collected for the accuracy assessment

Model	Land use type	Training	Accuracy
1	Vegetation	5915	3360
	Non-vegetation	151	194
2	Bamboo	579	258
	Non-bamboo	482	287
Total sample	7127		4099

Table 3
Accuracy assessment of Model 1 and Model 2 across polygon subset area (A, B, and C), showing overall accuracy, allocation disagreement, and Kappa coefficients

Model	Subset area	A	B	C
1	Overall accuracy (%)	97.70	94.10	99.05
	Allocation disagrees (%)	0.90	28.12	0.78
	Kappa	0.60	0.84	0.84
2	Overall accuracy (%)	85.71	56.77	52.50
	Allocation disagrees (%)	10.88	28.13	40.00
	Kappa	0.67	0.15	- 0.01

The accuracy assessment indicates Model 1 demonstrates high overall accuracy across all polygon subsets, with percentages ranging from 94.10% to 99.05%. Its Kappa coefficients (0.60 to 0.84) indicate moderate to excellent agreement, particularly for subsets B and C, which show strong agreement (Kappa > 0.75). In contrast, Model 2 showed more variable and generally lower performance. Subset A achieved reasonable accuracy (85.71%) with a Kappa value of 0.67, showed a moderate agreement. However, performance declined significantly found in Subset B (56.77% accuracy, Kappa = 0.15) and Subset C (52.50% accuracy, Kappa = –0.01), indicating little to no agreement between classification and ground reference. The final map for "bamboo" and "non-bamboo are presented below (Figure 5).

These lower accuracies can be attributed to spectral confusion between bamboo and other vegetation types, as well as shadow effects from UAV imagery that obscure bamboo clump structures (Blaschke, 2010; Ma et al., 2017). These findings highlight a key limitation in applying Model 2 for bamboo classification. The low performance of the Model 2 particularly in subsets B and C, can be attributed to spectral confusion between bamboo and other vegetation types, especially in heterogeneous landscapes. In this aspect, based on other study higher classification accuracy was recorded in the case study of UAV data *Fallopia japonica* and *Portulacaria afra* due to higher availability of training (Soltani et al., 2022) data, which unlike the Model 2. Lower training and accuracy samples mislead the classification and results in inappropriately identified the "bamboo" and "non-bamboo" across the subset. Consequently, the homogeneity of bamboo species could also be due to low overall accuracy, hence low kappa statistics for Model 2 in subset C. This task is very challenging to bamboo area with similarity to forest understory (Liu et al., 2021) , bushes and various herbs and lianas, that occurred in the study area.

RELEVANCE TO AGRICULTURE APPLICATION

In particular, the bamboo classification maps are not only important from a methodological perspective but also have direct implications for agricultural and agroforestry applications. The Table 3 the high accuracy observed in Model 1 ("vegetation" vs. "non-vegetation") demonstrates the reliability of UAV-based OBIA in delineating cultivable land versus non-productive areas, for example "banana" and "non-banana". In addition, the models

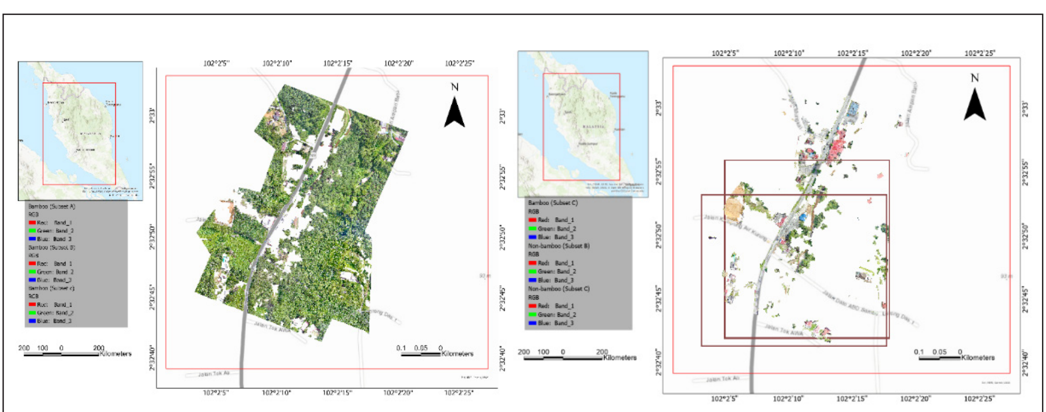

Figure 5. Bamboo final maps based developed based on OBIA classification techniques for the study area

developed from the study is fundamental in plantation establishment and expansion planning that can be employed in agricultural company such as SD Gutherie for Sime Darby Plantation for oil palm plantation area mapping.

However, when the focus shifts to bamboo-specific mapping (Model 2), the results reveal limitations. The lower overall accuracy and Kappa values in Subset C suggest that bamboo is not easily distinguished from other woody vegetation. In the meantime, now a days new methodology of Convolutional neural network (CNN)-based methods have been widely used to predict crop types according to UAV remote sensing imagery, which has excellent local feature extraction capabilities (Dersch et al., 2023; Xiang et al., 2023; Zhang et al., 2022).

CONCLUSION

This study demonstrates the potential of OBIA for bamboo mapping in both productive landscapes and leisure spaces for villager's areas. Model 1 successfully differentiated vegetation from non-vegetation with consistently high accuracy, which confirmed by many studies. However, Model 2 revealed the limitations of bamboo-specific classification, where spectral similarity with low growth from surrounding vegetation and subset variability reduced classification stability. Despite these challenges, the findings is so practical and relevance for the forestry, agricultural and agroforestry sectors.

ACKNOWLEDGEMENT

The study was funded by Ministry of Higher Education, GP-IPM (No. Vot 9733500) under Institute of Tropical Forestry and Forest Products (INTROP), and the project also funded by Universiti Driven Research Program (UDRP), Universiti Putra Malaysia. Appreciation also goes to Universitat fur Bodenkultur Wien or University of Natural Resources and Life Sciences (BOKU), Vienna, Austria, as a host for long-term research attachment January 2024.

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