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Mapping Shallow Water Benthic Habitats Using High Resolution Multispectral UAV Data: A Case Study of Panggang Island

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Abstract

The use of Unmanned Aerial Vehicles (UAVs) has become increasingly important for high-resolution remote sensing applications, particularly for mapping coastal and shallow-water environments. Benthic habitats in shallow marine ecosystems include seagrass meadows, macroalgae, live coral reefs, and degraded coral communities associated with sandy, muddy, and coral rubble substrates. Accurate mapping of these habitats is essential for effective coastal management and conservation. Therefore, this study aims to investigate the spatial distribution of benthic habitats in Panggang Island, Indonesia, using very high-resolution UAV multispectral imagery and to quantitatively evaluate the effectiveness of a pixel-based Support Vector Machine (SVM) classification approach for shallow-water benthic habitat mapping. Multispectral imagery was acquired using a DJI Phantom 4 Multispectral UAV with a spatial resolution of 6 cm per pixel. Seven benthic habitat classes were identified: sand, seagrass, live coral, dead coral with algae, coral with algae, rubble, and macroalgae. Habitat classification was performed using a pixel-based SVM algorithm. Classification accuracy was assessed using a confusion matrix, resulting in an overall accuracy of 87% and a Kappa coefficient of 0.84. The results demonstrate that the integration of very high-resolution UAV multispectral imagery with pixel-based SVM classification provides an effective and reliable approach for detailed benthic habitat mapping in small-island shallow-water environments.

Keywords: benthic habitat, mapping, multispectral imagery, SVM, UAV

1. Introduction

Indonesia has emerged as one of the countries with substantial adoption of Unmanned Aerial Vehicles (UAVs) for remote sensing applications, particularly in mapping-related studies (Gohari et al., 2024). The inscreasing use of UAV technology in Indonesia not only reflects advances in mapping techniques but also highlights a strong commitment to the sustainable management and conservation of marine resources. The application of UAVs for marine and coastal mapping has expanded rapidly between 2012 and 2023, indicating increased awareness of the importance of monitoring marine ecosystems, especially benthic habitats, which play a critical role in environmental sustainability. This expansion has been driven by several factors, including technological advancements, reduced operational costs, and improved accessibility of UAV platforms for benthic habitat mapping (Joyce et al., 2023).

Benthic habitats are shallow-water ecosystems that include seagrass meadows, macroalgae, seaweeds, live coral reefs, and degraded coral communities associated with sandy, muddy, and coral rubble substrates (Kurniawati et al., 2020). Ecosystems such as seagrass meadows, macroalgae, and coral reefs not only provide essential habitats for marine organisms but also support coastal sustainability through a wide range of ecological and socio-economic services, including shoreline protection, enhanced food security, and income generation through ecotourism and blue carbon initiatives (Feng et al., 2023). Given the substantial ecological and economic value of benthic habitats, continuous and systematic monitoring is required to ensure ecosystem integrity and the long-term maintenance of their functions (Hamidah et al., 2021).

Benthic ecosystems are critically important because they support diverse marine communities and contribute to maintaining the surrounding ecological balance. Continuous environmental monitoring therefore plays a vital role in conserving natural ecosystems while optimizing the sustainable use of marine resources for coastal communities (Belfiore et al., 2004). Efficient acquisition and processing of benthic habitat data have become increasingly essential to inform evidence-based management and policy-making for sustainable marine resource governance (Mohamed et al., 2020). In this context, the present study evaluates and compares the performance of RGB and multispectral band combinations for benthic habitat mapping.

Unmanned Aerial Vehicles (UAVs) have emerged as an effective and efficient technology for benthic habitat monitoring, primarily due to their ability to acquire high-accuracy, high-detail imagery of shallow-water environments. UAV platforms also offer significant advantages in data acquisition, especially in spatially limited or difficult-to-access areas (Sugara et al., 2023). However, successful UAV-based benthic habitat mapping is not solely dependent on high spatial resolution; it is also strongly influenced by the selection of appropriate image processing and analysis methods (Ventura et al., 2023).

Recent advances have highlighted the growing application of machine learning algorithms, which are well suited for handling complex and non-linear relationships in remote sensing data and have been shown to improve classification accuracy (Prentice et al., 2021). Moreover, machine learning approaches offer advantages in reducing the influence of depth-related gradients, thereby enhancing classification robustness in shallow marine environments (Hamuna et al., 2024). Therefore, this study aims to investigate the spatial distribution of benthic habitats in Panggang Island using very high-resolution UAV multispectral imagery and to evaluate the effectiveness of a pixel-based Support Vector Machine (SVM) classification approach through quantitative accuracy assessment in shallow-water environments.

2. Materials and Methods

2.1. Study Area

Field surveys were conducted from 19 to 23 May 2024 on Panggang Island, Thousand Islands, Jakarta Special Capital Region, Indonesia (**Figure 1**). Geographically, Panggang Island is located between 106°35′9.71″-106°36′17.78″ E and 5°44′13.23″-5°44′50.98″ S. Benthic habitat data were collected using a random sampling approach, in which sampling locations were selected while accounting for the spatial distribution of benthic habitat classes. Sampling was carried out evenly across the shallow-water areas surrounding Panggang Island to ensure adequate representation and to improve the reliability of classification results (Utama et al., 2023). Field data collection included geographic coordinates, acquisition times, and in situ identification of benthic habitat classes.

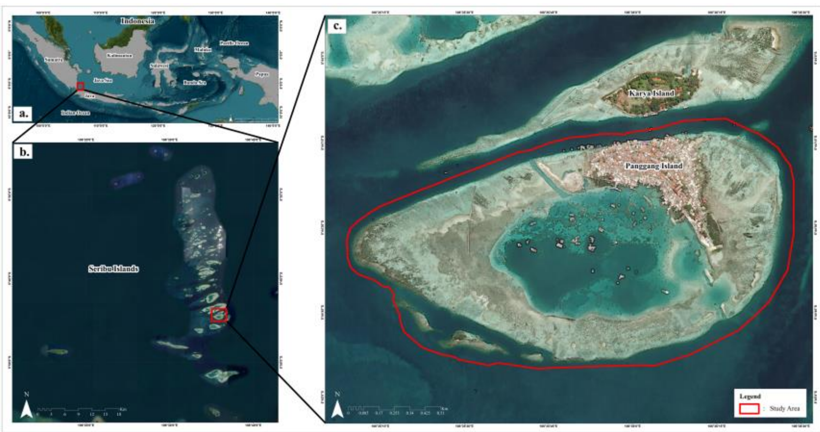

Figure 1. Geographical overview of the study area at Panggang Island illustrating the spatial extent of the research site. The map also shows the administrative boundaries and geographic coordinates that define the study area.

2.2. Data Collection

2.2.1. Benthic Habitat

Benthic habitat data were collected using a proportional random sampling approach, in which sampling locations were selected while accounting for the spatial distribution of benthic habitat classes. Sampling was conducted evenly across the shallow-water areas surrounding Panggang Island to ensure representative coverage and to enhance the accuracy of habitat classification (Utama et al., 2023). The field survey recorded georeferenced point locations, acquisition times, and in situ identification of benthic habitat classes. Benthic habitats were classified into seven categories: macroalgae (MA), coral with algae (CA), dead coral with algae (DCA), live coral (LC), seagrass (SG), sand (S), and rubble (R).

2.2.2. UAV Data Acquisition

Aerial image acquisition was conducted using a DJI Phantom 4 Multispectral UAV operated via the DJI GS PRO application. The UAV was flown at an altitude of 100 m, with the camera sensor oriented at a 90° nadir angle, and configured with 85% forward and side overlap. The flight speed was set to 53.1 km h^{-1}. A high overlap ratio was applied to minimize data gaps during image acquisition, as missing coverage may adversely affect subsequent image processing and reduce overall data quality. Aerial surveys were carried out from 07:00 to 09:00 local time, a time window selected to account for favorable weather and illumination conditions, particularly to reduce the effects of low solar angles and surface reflectance variability (Utama et al., 2023).

2.3. Image Pre-processing

Image processing and orthomosaic generation were performed using Agisoft Metashape Professional. This processing stage aimed to integrate multiple geometrically corrected images into a single seamless product in the form of an orthomosaic. Orthomosaic generation followed several sequential steps, including photo import, image alignment, reflectance calibration, dense point cloud generation, digital elevation model (DEM) construction, orthomosaic generation, and final export. The resulting orthomosaic represents a continuous, georeferenced image of the study area and served as the primary dataset for subsequent analyses.

Image classification was conducted using a machine learning approach. The Support Vector Machine (SVM) algorithm was selected due to its widespread application in classification tasks. In this study, classification was performed using a pixel-based approach, in which individual pixels were classified based on their spectral characteristics without prior image segmentation. SVM offers multiple kernel functions, including linear, polynomial, radial basis function (RBF), Gaussian, and sigmoid kernels, allowing flexibility to accommodate different data characteristics (Cervantes et al., 2020). Kernel selection plays a critical role in optimizing classification performance. Among the available options, the RBF kernel has been shown to be particularly effective for underwater and benthic habitat classification, as it performs well with complex, non-linearly separable data distributions (Mansor et al., 2024).

2.4. Accuracy Assessment

Accuracy assessment was performed using a confusion matrix approach (Prabowo et al., 2018). The confusion matrix compares benthic habitat classes derived from image classification with corresponding field reference data, allowing the calculation of standard accuracy metrics such as Overall Accuracy (OA) and the Kappa coefficient (K). In addition, class-specific accuracy measures were derived, including Producer's Accuracy (PA), which indicates the extent to which reference data classes are correctly represented in the classification results, and User's Accuracy (UA), which reflects the probability that a pixel assigned to a given class corresponds to that class in the field. The UA and PA metrics are fundamental components of the confusion matrix and are widely applied in remote-sensing image classification accuracy assessments. User's Accuracy describes the reliability of classification results from a map user's perspective; higher UA values indicate lower commission errors, which occur when pixels are incorrectly assigned to classes to which they do not belong into reality (Gunathilaka and Fernando, 2022).

This is consistent with the view that User's Accuracy (UA) plays a critical role in assessing the reliability of classification results from the perspective of end users of thematic maps. In contrast, Producer's Accuracy (PA) emphasizes the extent to which classes present in the field are correctly identified by the classification model; therefore, higher PA values indicate lower omission errors, which occur when reference features are not detected in the classified output. According to Lillesand et al. (2015), PA is particularly important as it reflects the sensitivity of the model to actual ground conditions and indicates the consistency with which a class can be recognized.

Overall classification performance is expressed using Overall Accuracy (OA), which represents the proportion of correctly classified samples relative to the total number of validation samples. OA is calculated as the ratio of the sum of diagonal elements in the confusion matrix to the total number of samples. In addition, the level of agreement between classification results and reference data is evaluated using the Kappa coefficient (K), which accounts for the agreement that could occur by chance. The Kappa statistic is derived by comparing the observed agreement with the expected agreement under random classification. Kappa values approaching one indicate a very strong level of agreement between the classified map and ground reference data, whereas values close to zero suggest agreement no better than random chance.

The formulas used to calculate the percentage accuracy metrics based on the confusion matrix are presented as follows (Gunathilaka and Fernando, 2022):

a. Producer's Accuracy (PA)

$$PA = \frac{Y}{X1+} x\ 100\% \tag{1}$$

b. User's Accuracy (UA)

$$UA = \frac{Y}{X+1} x\ 100\% \tag{2}$$

c. Overall Accuracy (OA)

$$OA = \frac{\sum Y}{N} x\ 100\% \tag{3}$$

d. Koefisien Kappa (K)

$$K = \frac{N \sum Y - \sum x\ (X_{1+}\ X_{+1})}{N^2 - \sum x\ (X_{1+}\ X_{+1})} X100\% \tag{4}$$

Here, X_{1+}denotes the number of pixels classified as benthic habitat class 1, and X_{+1}represents the number of reference samples for the same class. $P_{1+}$and P_{+1}indicate the classified and reference data categories for class 1, respectively, while Yrefers to the number of reference samples of class 1 that are correctly classified. The index $i$denotes the row or column in the confusion matrix, $r$is the total number of benthic habitat classes, Nrepresents the total number of samples, and K denotes the Kappa coefficient.

3. Results and Discussion

3.1. UAV Image Acquisition

The UAV image acquisition resulted in a spatial resolution of 6 cm per pixel (**Figure 2**), providing a high level of detail for representing shallow-water surface conditions and benthic habitat variability around Panggang Island. Image acquisition was conducted from 07:00 to 09:00 local time at a flight altitude of 100 m, a time window considered optimal for minimizing the effects of low solar angles, cloud shadows, and surface sun glint. Under these illumination conditions, bottom reflectance could be recorded more consistently and reliably, thereby supporting more accurate spectral information extraction and benthic habitat classification (Elma et al., 2024).

The spatial coverage of the UAV survey was deliberately focused on the shallow-water areas surrounding Panggang Island, with limited inclusion of terrestrial areas and deeper waters. This strategy was adopted to ensure that the acquired data were directly relevant to the primary objective of the study, namely benthic habitat mapping, while also reducing data complexity, file size, and computational requirements. In addition, constraining the flight coverage contributed to optimizing UAV battery performance, allowing image acquisition to be conducted efficiently and reliably without compromising data quality within the main area of interest. Similar approaches have been widely applied in UAV-based benthic habitat mapping studies, particularly in small-island environments characterized by high habitat heterogeneity (Ventura et al., 2023).

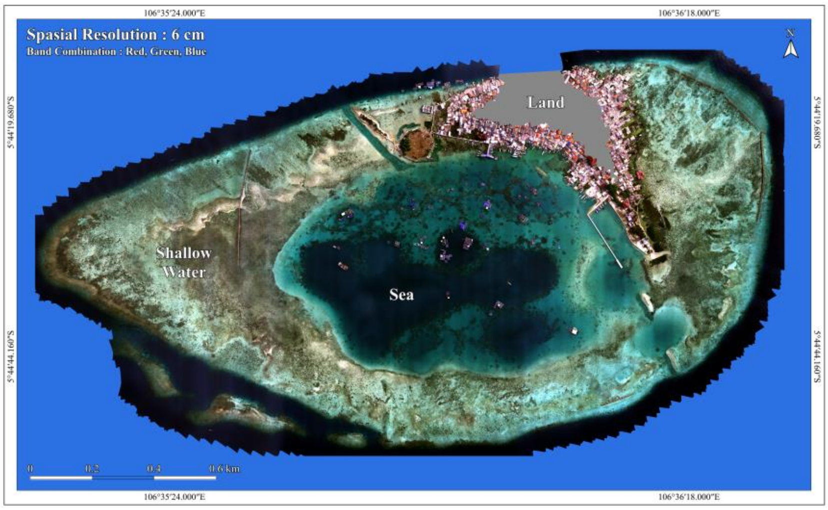

Figure 2. High-resolution UAV orthomosaic imagery of Panggang Island was acquired using the DJI Phantom 4 Multispectral and processed using the red, green, and blue (RGB) band combination to generate a true-color representation of the study area. The high spatial resolution of the imagery enhances the ability to distinguish fine-scale habitat variations, supporting detailed mapping and classification analyses.

3.2. Benthic Habitat Classification Results

Benthic habitat classification was derived from UAV imagery processed using the Support Vector Machine (SVM) algorithm. A total of seven benthic habitat classes were identified on Panggang Island, including sand (S), seagrass (SG), live coral (LC), dead coral with algae (DCA), coral with algae (CA), rubble (R), and macroalgae (MA) (**Figure 3**). Visual interpretation indicates that sand is the dominant and most continuous substrate across the lagoon area, serving as a primary foundation for the development and persistence of other benthic habitats.

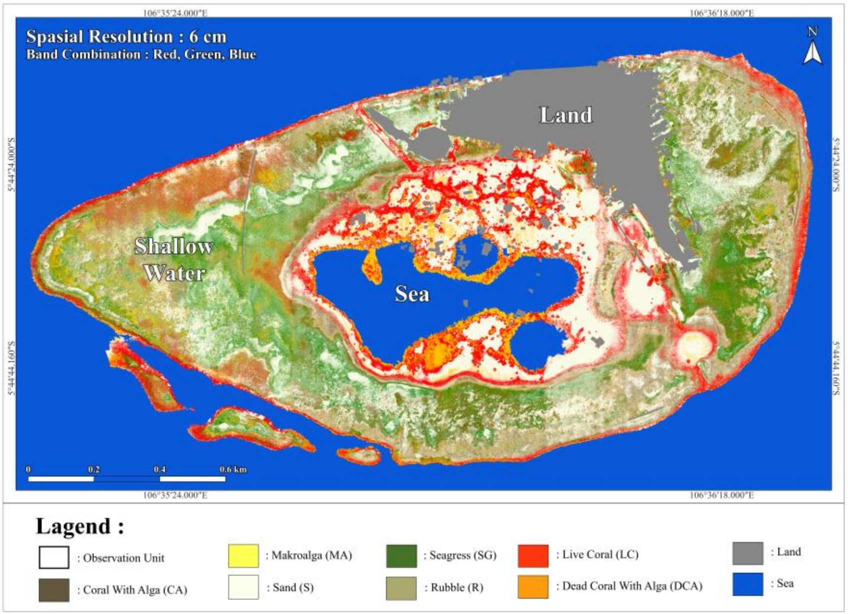

Figure 3. The spatial distribution of benthic habitats derived from UAV imagery using the Support Vector Machine (SVM) classification algorithm. The identified habitat classes consist of macroalgae (MA), seagrass (SG), live coral (LC), coral with algae (CA), dead coral with algae (DCA), sand (S), and rubble (R), each represented by distinct colors in the legend.

Habitats characterized by higher biological complexity, particularly seagrass and live coral, exhibit heterogeneous and spatially fragmented distribution patterns, typically occurring as discrete patches. Despite their fragmented appearance, these patches play a critical ecological role as centers of marine biological activity and as key contributors to biodiversity within the waters of Panggang Island. In contrast, habitats representing transitional or degraded conditions, such as coral rubble and dead coral with algae, are predominantly concentrated along reef margins, areas that are subject to higher hydrodynamic energy and increased physical disturbance.

The ability of the classification map to clearly and consistently delineate boundaries between benthic habitats indicates a high level of spatial coherence, reflecting the effective performance of the SVM algorithm when applied to high-resolution UAV imagery. Although spectral differences among classes such as live coral, algae-covered coral, and seagrass are relatively subtle, the SVM classifier was able to optimally exploit both spectral and textural information to accurately discriminate between these habitats. These findings are consistent with previous studies demonstrating that high-resolution UAV imagery enables more detailed identification of benthic habitat diversity compared to medium-resolution satellite data, thereby supporting more comprehensive assessments of coral reef ecosystem conditions (Roelfsema et al., 2018).

3.3. Classification Accuracy Results

Accuracy assessment based on the confusion matrix (**Table 1**) for benthic habitat mapping on Panggang Island using a pixel-based Support Vector Machine (SVM) approach indicates a high classification performance. The classification achieved an Overall Accuracy of 87% and a Kappa coefficient of 0.84, reflecting a very strong level of agreement between the classification results and field reference data. These results demonstrate that the pixel-based SVM model is capable of reliably representing benthic habitat conditions within the study area.

The Producer's Accuracy (PA) values reveal variability among benthic habitat classes. The dead coral with algae class recorded the highest PA at 100%, indicating that all reference samples for this class were correctly detected in the classification results. The sand and coral classes also exhibited high PA values of 94% and 93%, respectively, suggesting that the model effectively captured these reference classes. In contrast, the rubble class showed the lowest PA at 43%, highlighting limitations in detecting the full variability of rubble habitats, likely due to limited sample availability and spectral similarity with sand and dead coral substrates.

Table 1. Confusion matrix of benthic habitat classification results derived from UAV imagery using the SVM algorithm. The table presents classification accuracy based on error distribution and overall accuracy.

	Class	Reference Data							Total	PA (%)
		A	CA	DCA	LC	SG	S	R		
Classified Data	A	11	0	0	0	0	0	0	11	92
	CA	0	22	0	0	2	0	1	25	88
	DCA	0	1	4	0	0	0	0	5	100
	LC	0	0	0	13	0	0	1	14	93
	L	0	1	0	1	23	2	0	27	82
	P	1	1	0	0	3	30	2	37	94
	R	0	0	0	0	0	0	3	3	43
Total		12	25	4	14	28	32	7	OA = 87%	
UA (%)		100	88	80	93	85	81	100		

User's Accuracy (UA) reflects the reliability of classification results from the perspective of map users. The algae and rubble classes achieved the highest UA values of 100%, indicating that all pixels assigned to these classes corresponded accurately to field conditions. The coral and seagrass classes also exhibited relatively high UA values of 93% and 85%, respectively, suggesting a high level of confidence in the classification outputs. In contrast, lower UA values were observed for the dead coral with algae class at 80% and the sand class at 81%, indicating the presence of misclassification errors likely caused by spectral overlap among benthic substrates.

These findings are consistent with previous work by (Roelfsema et al., 2018), who reported an overall accuracy of 78.6% for pixel-based SVM benthic habitat mapping and noted substantial accuracy degradation for classes such as sand, rubble, and dead coral. In this context, the UA and PA values obtained in the present study demonstrate comparable or improved performance, while also highlighting the inherent limitations of pixel-based approaches in discriminating complex benthic habitat classes.

4. Conclusions

This study demonstrates that the use of UAV imagery with a very high spatial resolution of 6 cm per pixel enables detailed and accurate representation of shallow-water conditions and benthic habitat variability on Panggang Island. Image acquisition conducted at an optimal flight altitude and time window produced consistent data quality, thereby supporting reliable spectral information extraction and benthic habitat classification. Classification using a pixel-based Support Vector Machine (SVM) algorithm successfully identified seven benthic habitat classes with consistent spatial distribution patterns, with sand dominating lagoonal areas, while seagrass and live coral occurred in spatially fragmented patches of high ecological importance. Accuracy assessment based on the confusion matrix indicated strong classification performance, yielding an Overall Accuracy of 87% and a Kappa coefficient of 0.84, which reflect a very high level of agreement between the classification results and field reference data. The Producer's Accuracy (PA) and User's Accuracy (UA) metrics further indicate that most habitat classes were reliably identified and mapped, although reduced performance was observed for classes with high spectral similarity, such as rubble, sand, and dead coral with algae. Overall, these results confirm that integrating high-resolution UAV imagery with pixel-based SVM classification provides an effective approach for benthic habitat mapping in small-island environments.

Conflicts of Interest

There are no conflicts to declare.

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AI Writing Statement

The authors did not use any artificial intelligence-assisted technologies in the writing process.

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