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ARTICLE

Determination of Coral Distribution Using Multispectral Images from an Unmanned Aerial Vehicle in Bach Long Vy Island, Vietnam

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ABSTRACT

Coral reefs are among the world's most valuable marine ecosystems, providing critical ecological functions, supporting biodiversity, and protecting coastlines. Accurate mapping of coral reef distribution is essential for effective conservation and management, particularly within Marine Protected Areas (MPAs). This study mapped coral distribution in the northwestern waters of Bach Long Vy Island, Vietnam, using ultrahigh-resolution multispectral imagery acquired by a DJI Phantom 4 Multispectral Unmanned Aerial Vehicle (UAV). The imagery comprised five multispectral bands and RGB with a spatial resolution of 7 cm/pixel over an area of approximately 492,360 m^2. Water-column effects were corrected using the Lyzenga method, and benthic habitats were classified using a supervised maximum likelihood algorithm. A total of 259 field survey points are used for training and validation of the classification results. Three major benthic substrate classes were identified: coral, sand, and rock. Coral reefs covered 199,410 m^2 (40.50%) of the surveyed area, while sand and rock occupied 66,100 m^2 (13.43%) and 226,850 m^2 (46.07%), respectively. The classification achieved an overall accuracy of 86.87% with

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a Kappa coefficient of 0.78, demonstrating good agreement between image classification and field observations. The results confirm that UAV-based multispectral remote sensing provides an accurate and cost-effective approach for mapping shallow coral reef habitats. The proposed workflow offers an efficient tool for routine reef monitoring and supports evidence-based conservation, adaptive management of MPAs, and long-term assessment of coral reef responses to increasing environmental pressures and climate change.

Keywords: Coral Reef Mapping; UAV Multispectral Imagery; Water-Column Correction; Lyzenga Method; Maximum Likelihood Classification; Marine Protected Area

1. Introduction

Coral reefs are among the most productive and biologically diverse marine ecosystems worldwide, providing essential ecological functions and ecosystem services. They support high levels of biodiversity, provide habitats and nursery grounds for numerous marine organisms, sustain fisheries resources, contribute to nutrient cycling, and protect coastlines from wave action and erosion [1–4]. Consequently, coral reefs play a crucial role in maintaining marine ecosystem stability and supporting the socioeconomic development of coastal communities. However, coral reef ecosystems are increasingly threatened by both natural and anthropogenic pressures, including ocean warming, ocean acidification, climate change, coastal development, and other human activities, resulting in coral degradation and loss in many regions worldwide [5–7].

Effective monitoring of coral reef distribution and spatial dynamics is therefore essential for evaluating ecosystem status, detecting environmental changes, and supporting conservation and management efforts. Traditional monitoring approaches based on diving surveys and underwater observations provide detailed ecological information but are often labor-intensive, time-consuming, expensive, and spatially limited [8–10]. Over the last two decades, remote sensing technologies have become important tools for monitoring coastal and marine ecosystems because they allow rapid assessment over large spatial areas [11–14]. Remote sensing data have been widely applied to map and monitor coral reefs, seagrass beds, mangrove forests, and other coastal habitats [15,16]. In particular, recent studies have demonstrated the growing capability of remote sensing techniques for coral reef mapping and long-term ecosystem monitoring [11,15,17,18].

Satellite remote sensing provides valuable information for coastal ecosystem monitoring; however, its application is often constrained by cloud cover, revisit frequency, acquisition costs, and limited spatial resolution when detailed habitat mapping is required [19–22]. However, when detailed mapping of shallow reef habitats is required, UAV platforms provide significant advantages over conventional satellite imagery. Recent advances in unmanned aerial vehicle (UAV) technology have created new opportunities for environmental monitoring [23–26]. UAVs can acquire ultrahigh-resolution imagery at user-defined locations and times while maintaining relatively low operational costs and rapid deployment capability [27–30]. The integration of multispectral sensors with UAV platforms enables the collection of detailed spectral information that can improve the discrimination of benthic habitats in shallow coastal waters [31–33]. Previous studies have successfully applied UAV-based imagery to mapping seagrass beds, macroalgae, and coral reef habitats, demonstrating its potential for marine ecosystem monitoring and management [34–36].

Despite these advances, accurate mapping of coral reefs from multispectral imagery remains challenging. The optical properties of the water column modify the spectral signals reflected from benthic substrates through absorption and scattering processes, making it difficult to distinguish between coral, rock, and sand habitats, particularly in deeper waters [37–39]. Furthermore, many recent studies have focused on high-resolution satellite imagery, hyperspectral sensors, or advanced classification approaches, which often require extensive datasets, complex processing workflows, or substantial computational resources [17,40,41]. Consequently, there remains a need for practical, cost-effective, and operationally efficient methodologies that can be readily implemented for routine coral reef monitoring in marine protected areas and coastal management programmes.

Bach Long Vy Island, located in the central Gulf of Tonkin, hosts one of the most important coral reef ecosystems in northern Vietnam. The island supports high coral species richness and serves as a critical habitat for numerous marine organisms [42–44]. Since the establishment of the Bach Long Vy Marine Protected Area (MPA), the conservation and monitoring of coral reef ecosystems have become increasingly important. However, coral reefs in this region continue to be exposed to multiple environmental pressures associated with climate change and human activities [6,7,45,46]. Reliable and timely information on coral distribution is therefore essential for supporting conservation planning and ecosystem management.

The objective of this study was to develop and evaluate an operational workflow of coral reefs in the northwestern waters of Bach Long Vy Island using ultrahigh-resolution multispectral imagery acquired by a DJI Phantom 4 Multispectral UAV. Water-column correction based on the Lyzenga method and supervised maximum likelihood classification were applied to discriminate coral, rock, and sand substrates. In addition to providing updated information on coral distribution within the study area, this study demonstrates a practical UAV-based workflow for high-resolution coral habitat mapping that can support routine monitoring and management of coral reef ecosystems in marine protected areas.

2. Materials and Methods

2.1. Study Area

This study was conducted in the northwestern coastal waters of Bach Long Vy Island, located in the central Gulf of Tonkin, northern Vietnam (**Figure 1**). Geographically, the island is situated between 20°07′35″–20°08′36″ N and 107°42′20″–107°44′15″ E. Bach Long Vy is an isolated offshore island located approximately 110 km from the Vietnamese mainland and plays an important ecological and strategic role in the Gulf of Tonkin. The surrounding waters are generally shallow, with seabed depths gradually increasing away from the coastline and providing suitable habitats for the **development** of coral reef communities [42–44].

Bach Long Vy Island supports one of the most important coral reef ecosystems in northern Vietnam. Previous surveys have recorded 118 coral species belonging to 32 genera and 15 families of hard corals (Scleractinia), together with one species of soft coral (Alcyonidae) [42–44]. Coral reefs are distributed around the island, although their extent and coverage vary considerably among locations. The northwestern coast contains the largest and most continuous coral reef area, exhibiting relatively high coral cover and species richness. Most coral communities occur at depths between approximately 3–8 m, where environmental conditions are favorable for coral growth and development [42–44]. For this reason, the northwestern reef zone was selected as the focus area for UAV-based coral mapping in the present study.

Since 2013, the island and its surrounding waters have been protected under the Bach Long Vy Marine Protected Area (MPA), which covers approximately 27,009 ha (270,090,000 m^2). The MPA was established to conserve coral reefs, fisheries resources, and marine biodiversity of regional importance [45,46]. Despite its protected status, the coral reef ecosystem remains exposed to multiple environmental and anthropogenic pressures. These include increasing sea-surface temperatures and ocean acidification associated with climate change, as well as local impacts from fishing activities, vessel anchoring, marine pollution, and socio-economic development on the island [6,7,46]. Consequently, Bach Long Vy Island represents an ideal natural laboratory for evaluating UAV-based approaches for coral reef mapping and long-term ecological monitoring in shallow marine protected areas.

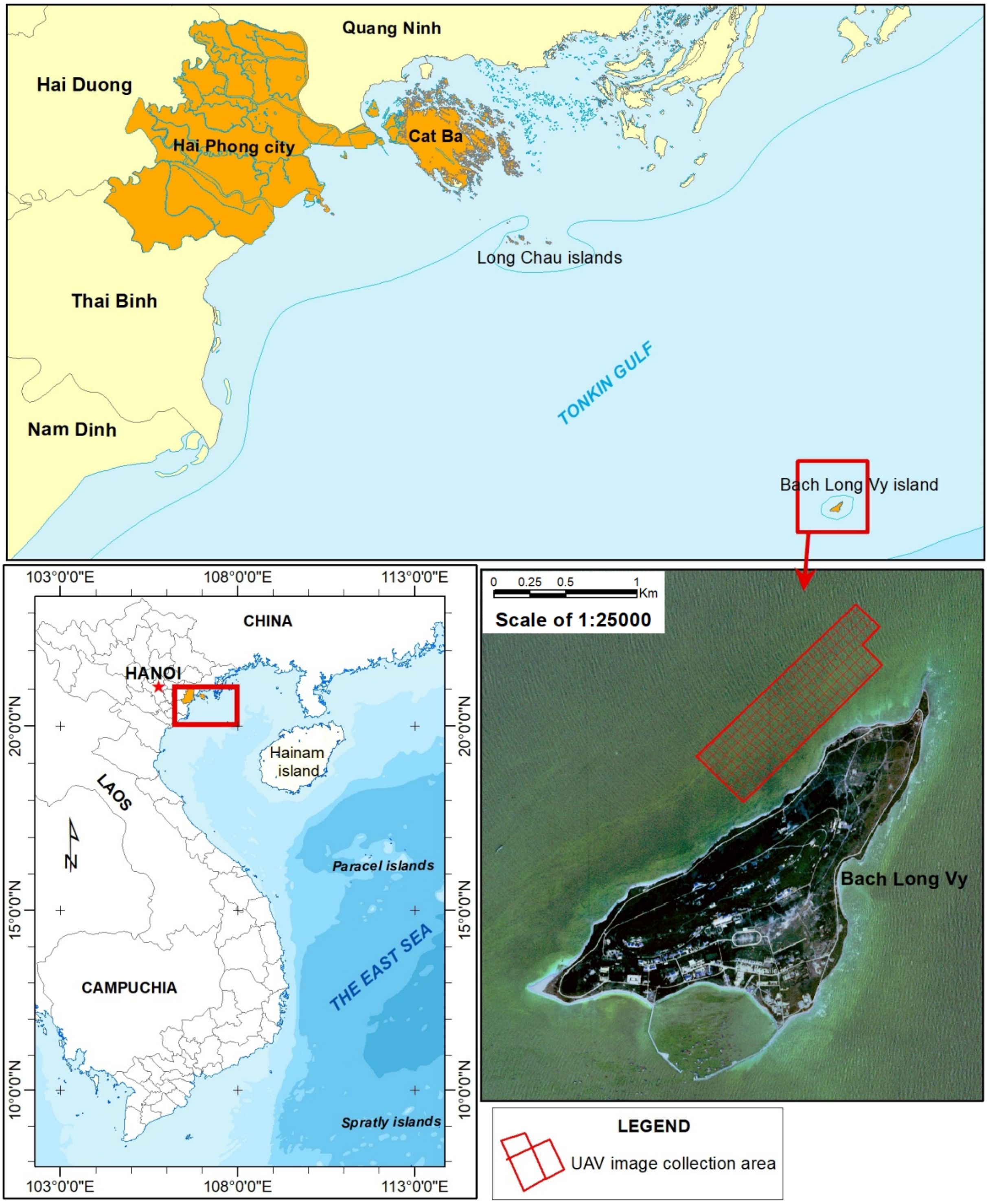


Figure 1. Location of the study area.

2.2. Obtained Image

Multispectral imagery was acquired using a DJI Phantom 4 Multispectral UAV, which includes two components. It has a maximum flight altitude of 500 m, up to 7 km of distant flight, and a maximum flight time of approximately 27 min. The multispectral camera has six channels: blue (B) 450 nm ± 16 nm; green (G) 560 nm ± 16 nm; red (R) 650 nm ± 16 nm; red edge (RE) 730 nm ± 16 nm; near-infrared (NIR) 840 nm ± 26 nm;

and an RGB camera. The low-altitude multispectral imaging flight in Northwest Bach Long Vy Island was conducted from 6:00 to 7:00 (GMT+7) to avoid direct reflection of sunlight from surface water under favorable weather conditions (wind speeds less than 5 m/s, cloudless skies, and small waves).

2.3. Field Survey

Field surveys were conducted concurrently with the UAV image acquisition campaign in June 2021 to provide ground-truth data for image interpretation, training sample selection, and accuracy assessment. A total of 259 survey points were established within the UAV coverage area, extending from the shoreline to approximately 8 m water depth along transects oriented perpendicular to the coast (**Figure 2**).

At each survey point, the dominant benthic substrate was visually identified using Self-Contained Underwater Breathing Apparatus (SCUBA) observations and underwater photography. Geographic coordinates were recorded using a Garmin GPS 76CSx receiver, while water depth was measured using a Hondex PS-7 echo sounder. The observed substrates were categorized into three primary classes: coral, rock, and sand. Among the 259 survey points, 95 points corresponded to coral habitats, 143 points to rocky substrates, and 21 points to sandy substrates (**Table 1**).

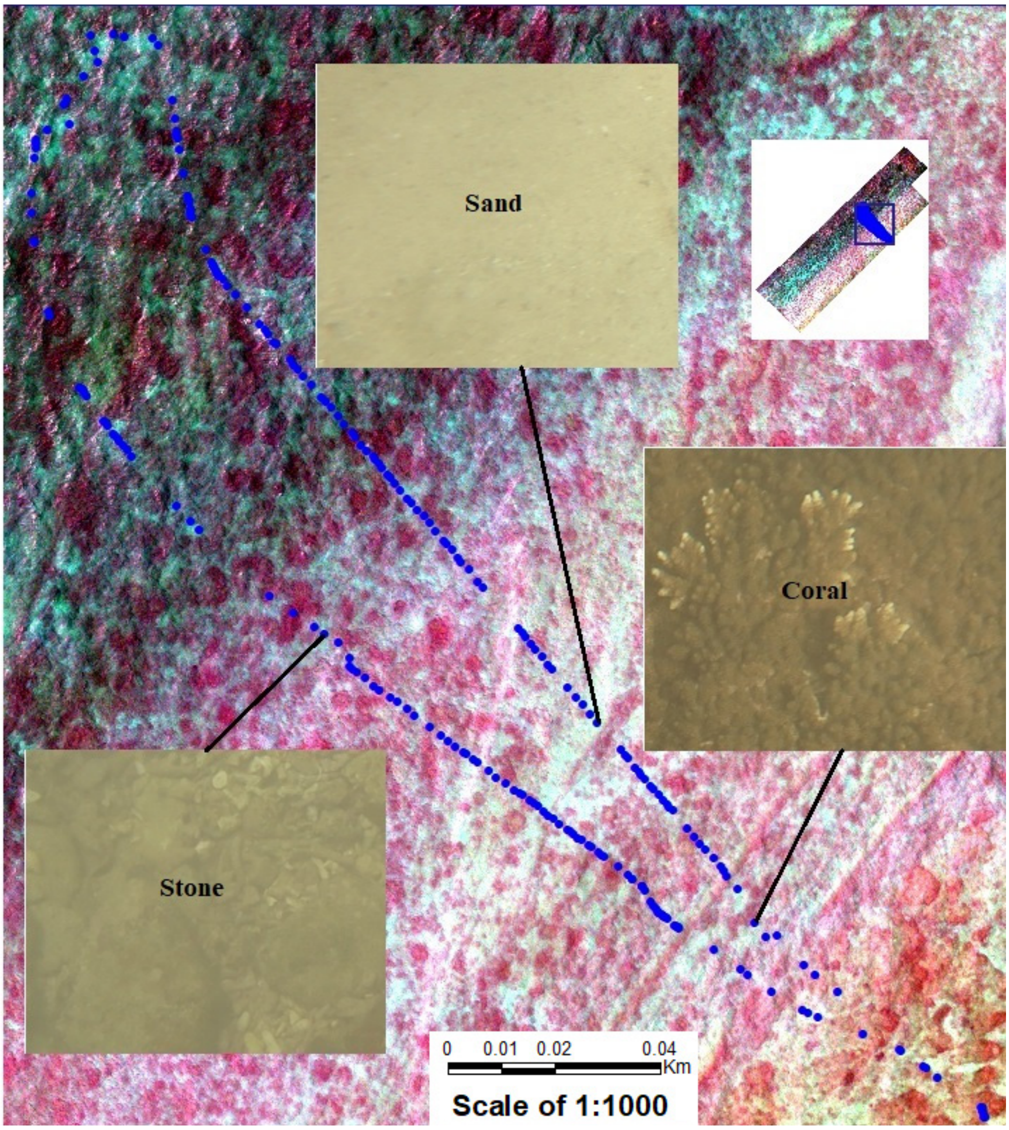


Figure 2. Locations of seabed survey points.

Table 1. Survey results of the bottom substance.

No.	Bottom Substance	Number of Survey Points
1	Coral	95
2	Rock	143
3	Sand	21
	Total	259

To support image classification, 100 survey points were randomly selected as training samples for developing the interpretation key and defining spectral classes. The remaining 159 survey points were reserved as independent validation data for accuracy assessment. In addition, several environmental parameters, including seawater temperature, salinity, pH, turbidity, water transparency, and wind speed, were measured during the survey period to characterize environmental conditions at the time of image acquisition (**Table 2**).

2.4. Low-Altitude Multispectral Imaging

The data obtained from the camera after the end of the flight process were approximately 3,000 images (area about 1,800 m^2 below ground/photo) that were used to construct an orthomosaic image and then exported to a low-altitude multispectral image with a ground area of 50 ha (492,360 m^2). Agisoft Metashape Professional software was used to perform image compositing (**Figure 3**).

Table 2. Environmental survey results.

No.	Environmental Parameters	Value	Measuring Device
1	Sea water temperature	Surface layer = 27.3 °C Bottom layer = 26.0 °C	Custom NIR-01
2	Salinity	33‰	Master-S/Mill Alpha
3	pH	8.2	HANNA Instruments
4	Turbidity	5 mg/L	Sample analysis in the lab
5	Transparency	12 m	Sechi Disc
6	Wind speed	4.8 m/s	EXTECH instrunents

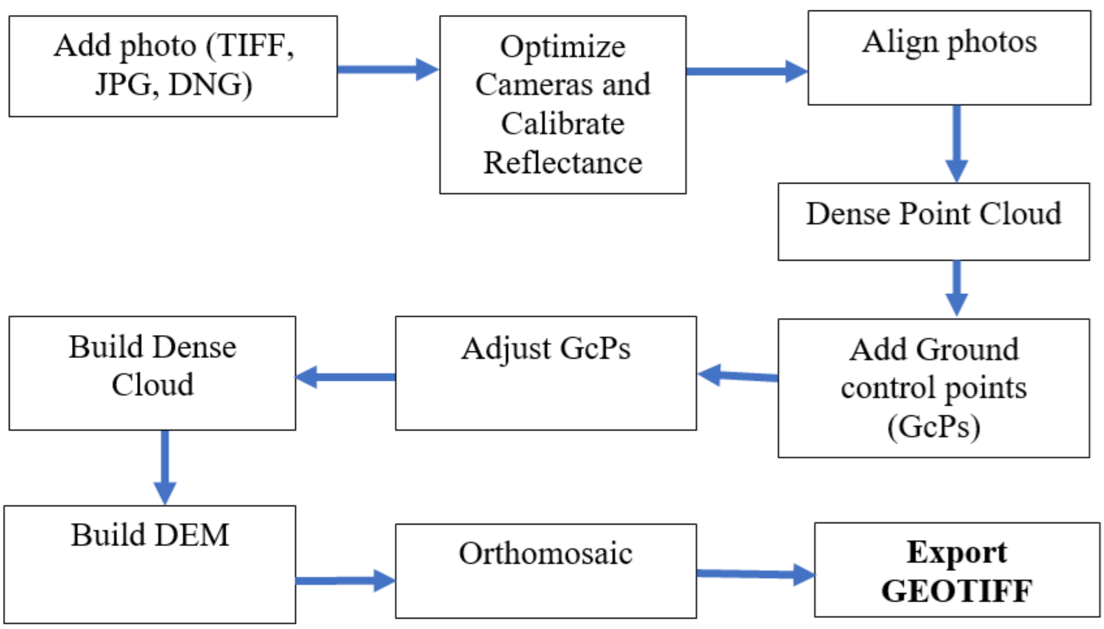


Figure 3. Diagram of a building orthomosaic image process via Agisoft Metashape Professional software [47].

A multispectral image scene was captured by DJI Phantom 4 multispectral UAV at an altitude of 120 m above sea level in the northwest area of Bach Long Vy Island in June 2021. The spatial resolution of the image is 7.0 cm/pixel, and the image area covers 50 ha (492,360 m^2), which is parallel to the shoreline of the island and has a depth ranging from one to seven meters (**Figure 4**).

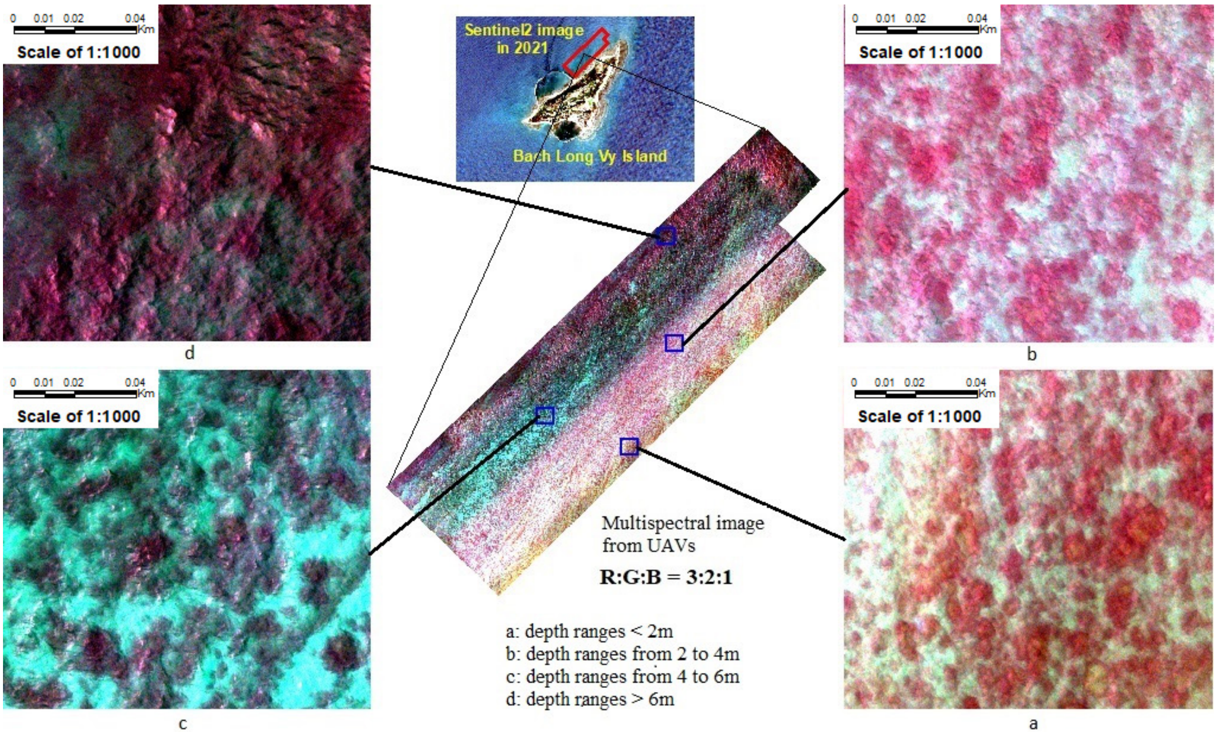


Figure 4. Multispectral image captured by a DJI Phantom 4 multispectral unmanned aerial vehicle.

2.5. Water Column Correction

Water column effect correction is required for remote sensing data processing for the mapping and assessment of aquatic ecosystems. The sunlight shines interact with the water surface before reaching the bottom substrate. In addition, upon reflection from the substrate, the light also interacts with the water, so the signal received by the camera has undergone scattering and absorption from the water [37,48,49].

There are many methods of water column correction, and the method with the highest accuracy is the method of directly measuring the light absorption coefficient of the water environment in the study area. This method requires a photometric device in the water column that captures light scattering and absorption data at high resolution and is computationally demanding [50]. The Lyzenga method is often used for water column correction because it is easy to apply and has acceptable accuracy [38,51]. A total of 33 survey points with rocky bottoms out of 71 survey points in 2007 in shallow water around Bach Long Vy Island were used to calibrate the water column for IKONOS multispectral images collected in 2005 (**Figure 5**). The calculated absorption ratios are (k_2/k_3) = 0.3529, (k_1/k_2) = 0.3331 and (k_1/k_3) = 0.1497. The spectral bands of IKONOS images are similar to the spectral bands of multispectral images collected by UAVs in June 2021. Therefore, the water column calibration results for the IKONOS images were used for multispectral images collected by UAVs (**Figure 6**).

Because direct measurements of inherent optical properties were unavailable during the UAV survey, previously validated attenuation coefficients represented the most appropriate practical solution.

Because the study area, water depth range, substrate type, and water environment characteristics (**Table 3**) changed little between surveys (2007 and 2021), the light attenuation coefficients were considered suitable for water column correction. Nevertheless, this assumption introduces uncertainty and should be verified through direct measurements of inherent optical properties during future UAV campaigns.

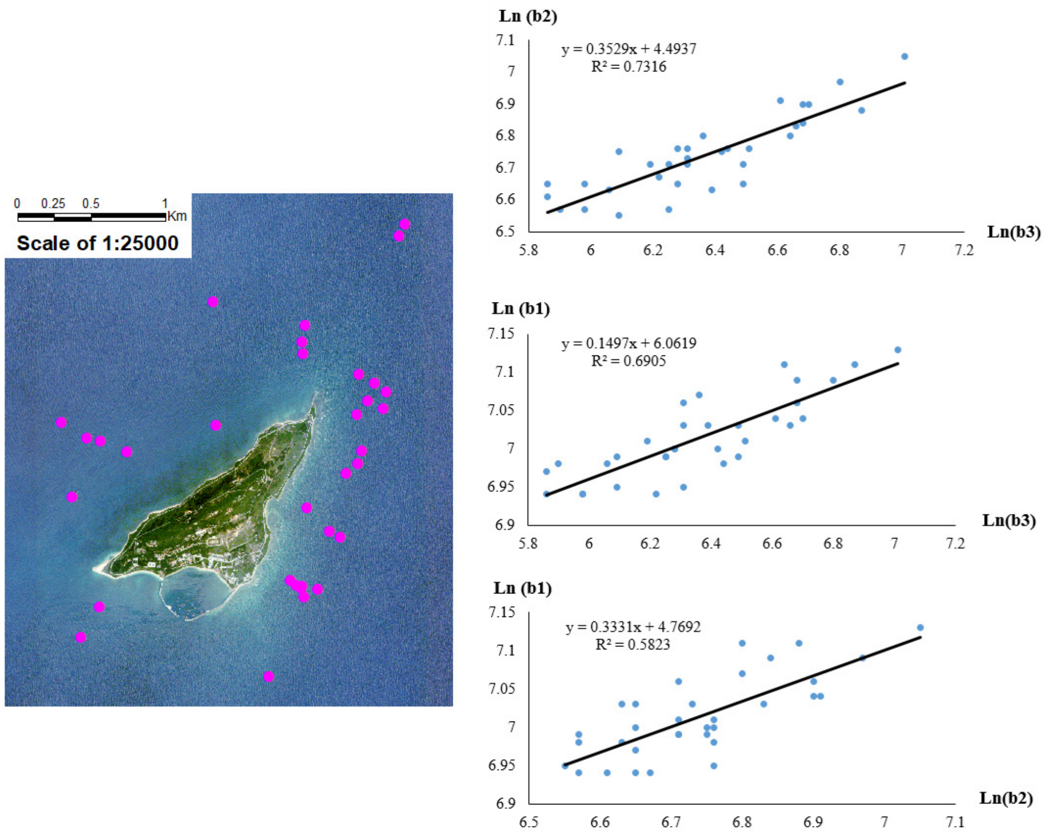


Figure 5. IKONOS 2005 image, 33 bottom matter survey points in 2007 and the relationship between the absorption coefficients of channel 1 (blue), channel 2 (green), and channel 3 (red) of IKONOS images in the waters around Long Vy Island [52].

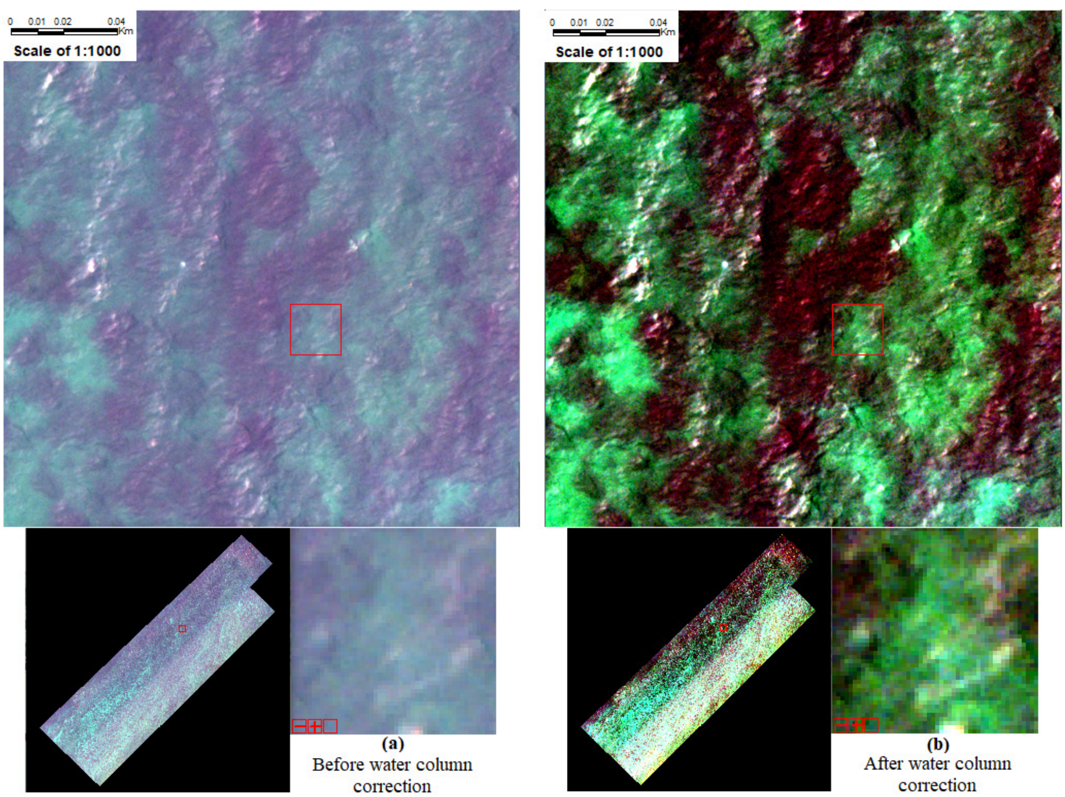


Figure 6. Water column correction results for low-altitude multispectral images according to the combination R:G:B = 3:2:1.

Table 3. Several water quality parameters along the coast of Bach Long Vy Island affect the absorption and scattering of light [53].

No.	Parameter	Unit	Value	
			6/2007	6/2021
1	DO	mg/L	6.01	5.96
2	COD	mg/L	1.16	1.10
3	TSS	mg/L	4.56	5.0
4	$N\text{-}NH_4^+$	µg/L	40.03	41.46
5	$P\text{-}PO_4^-$	µg/L	12.23	12.82
6	Coliform	CFU/100 mL	270	276
7	Chl-a	mg/m^3	0.25	0.27

2.6. Development of the Interpretation Key

Three major benthic substrate categories were identified in the study area, namely coral, sand, and rock. However, preliminary examination of the multispectral imagery and field observations indicated that substrate reflectance varied substantially with water depth because of absorption and scattering effects within the water column. Consequently, identical substrate types located at different depths often exhibited different spectral characteristics despite representing the same benthic habitat.

To reduce spectral confusion and improve classification accuracy, each substrate category was subdivided into depth-dependent spectral classes during the training stage. Coral habitats were divided into four spectral classes according to their depth distribution: Coral 1 (1–2 m), Coral 2 (2–4 m), Coral 3 (4–6 m), and Coral 4 (6–8 m). Similarly, sandy and rocky substrates were each separated into two depth-related classes, corresponding to shallow-water (0–4 m) and deeper-water (4–8 m) environments.

It is important to note that these subclasses do not represent different ecological habitat types or coral assemblages. Instead, they were established solely to account for depth-related spectral variability and to improve the separability of training samples during supervised classification. Following classification, all coral subclasses were merged into a single coral habitat class, while the sand and rock subclasses were merged into their respective substrate categories.

Representative image characteristics and depth ranges of each spectral class are summarized in **Table 4.**

Table 4. The key for decoding multispectral images at low altitudes via the color combination R:G:B = 3:2:1 to determine the distribution of bottom matter in the northwest area of Bach Long Vy Island.

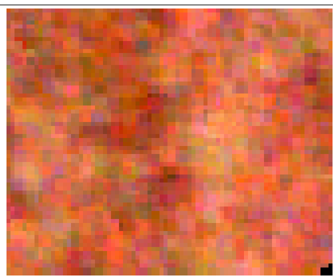
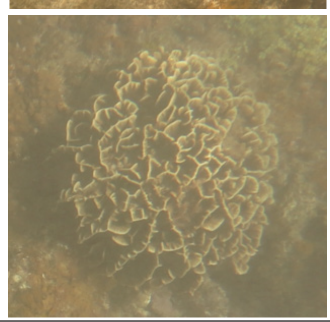
No.	Bottom	Multispectral Images	Depth	Picture
1	Coral 1		Depth ranges from 1 m to 2 m	
2	Coral 2		Depth ranges from 2 m to 4 m	

Table 4. *Cont.*

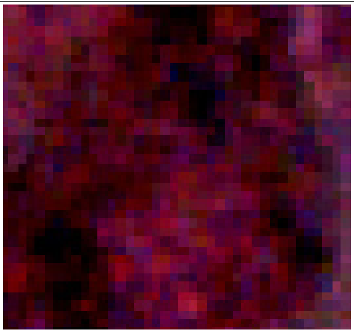
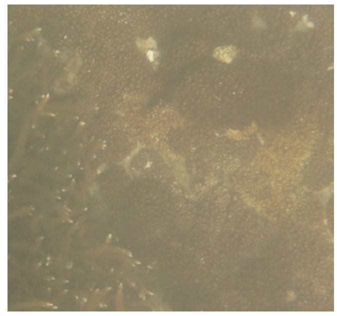
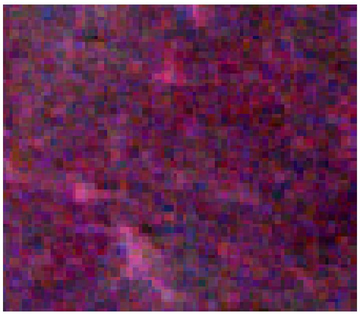
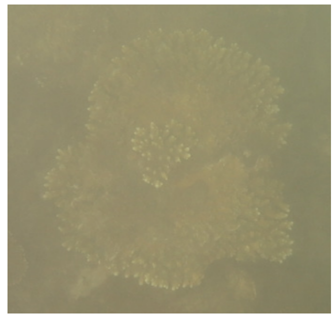
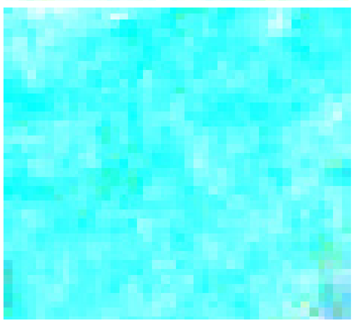
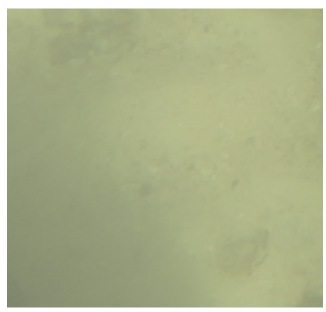
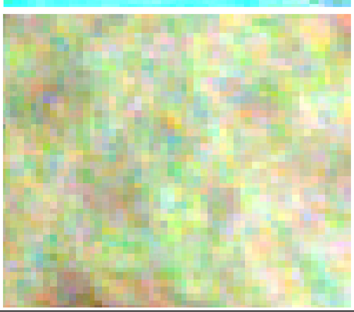
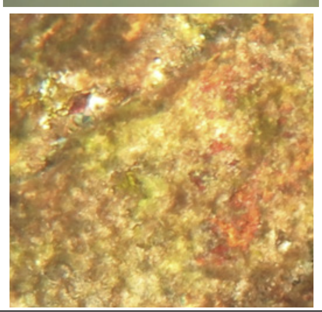
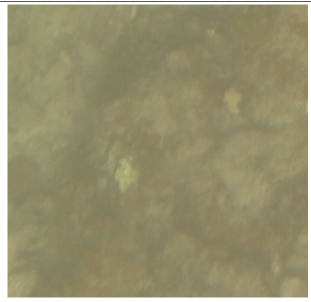
No.	Bottom	Multispectral Images	Depth	Picture
3	Coral 3		Depth ranges from 4 m to 6 m	
4	Coral 4		Depth ranges from 6 m to 8 m	
5	Sand 1		Depth ranges from 0 m to 4 m	
6	Sand 2		Depth ranges from 4 m to 8 m	
7	Rock 1		Depth ranges from 0 m to 4 m	

Table 4. *Cont.*

No.	Bottom	Multispectral Images	Depth	Picture
8	Rock 2		Depth ranges from 4 m to 8 m	
9	Outside		No-sign area	

2.7. Training Sample Selection

Training samples were selected on the basis of the interpretation key developed from field observations and multispectral image characteristics. For each spectral class, representative regions of interest (ROIs) were carefully delineated to ensure spectral homogeneity and minimize overlap among classes.

The subdivision of coral, sand, and rock substrates into depth-dependent spectral classes was specifically designed to reduce spectral confusion caused by water-column attenuation. For example, shallow corals (Coral 1) exhibited considerably higher reflectance than deeper corals (Coral 4), despite belonging to the same benthic habitat. Similar depth-related spectral differences were observed for sandy and rocky substrates. Therefore, treating each depth interval as an independent spectral class improved the discrimination capability of the classifier and reduced classification errors.

The separability between training samples was evaluated using spectral distance metrics. Following the recommendation of Lillesand et al. [54], all selected classes exhibited spectral overlap values below 3%, indicating satisfactory separability for supervised classification (**Table 5**). These training samples were subsequently used in the maximum likelihood classification procedure.

Table 5. Results of sample area selection.

Comparing Sample Area	Sample Area	% Pixel of Nonseparation
	Coral 1	
Coral 2		0.77608346
Coral 3		1.10998149
Coral 4		1.57875550
Sand 1		1.99914683
Sand 2		1.99610510
Rock 1		1.98869654
Rock 2		1.89005478
Outside		0.000
	Coral 2	
Coral 3		1.13355567
Coral 4		1.57240934
Sand 1		1.99972098
Sand 2		1.99703429
Rock 1		1.99648057

Table 5. *Cont.*

Comparing Sample Area	Sample Area	% Pixel of Nonseparation
	Coral 2	
Rock 2		1.92951763
Outside		0.000
	Coral 3	
Coral 4		0.35614729
Sand 1		1.99187607
Sand 2		1.99879878
Rock 1		1.97468060
Rock 2		1.97982399
Outside		0.000
	Coral 4	
Sand 1		1.99415083
Sand 2		1.99897854
Rock 1		1.97612052
Rock 2		1.98871912
Outside		0.000
	Sand 1	
Sand 2		1.90663770
Rock 1		1.64286639
Rock 2		1.94027604
Outside		0.000
	Sand 2	
Rock 1		1.91995379
Rock 2		1.51088674
Outside		0.000
	Rock 1	
Rock 2		1.70838167
Outside		0.000

2.8. Supervised Classification Method

A supervised classification method in which the maximum likelihood method was used to classify the substrate of the low-altitude multispectral image was employed. After classification, the independent distribution and small-scale substrate were removed, and the images were merged with the classified objects [55]. In this study, only substrates that are independently distributed and have an area of less than 5 × 5 pixels are imported into the adjacent object. This results in combining Coral 1, Coral 2, Coral 3, and Coral 4 objects into 1 coral substrate; Sand 1 and Sand 2 combine to form a sandy substrate; Rock 1 and Rock 2 combine to form a rock substrate. This procedure resulted in the merging of Coral 1–4 into a single coral class, Sand 1–2 into a sand class, and Rock 1–2 into a rock class.

2.9. Accuracy Assessment

An accuracy assessment is conducted according to 2 groups of indices. The index group calculates the accuracy on the basis of the sample area selection data. They include the following parameters: overall accuracy, accuracy of each bottom matter and the Kappa coefficient. The index group calculates the accuracy between the classification results and the field data. This is the correlation between the interpretation results and the survey reality. These index groups are calculated according to the confusion matrix algorithm in remote sensing data interpretation software [56,57].

3. Results

3.1. Classification of Corals from Low-Altitude Multispectral Images

The results of decoding coral distribution from low-altitude multispectral images are shown in **Table 6** and **Figure 7**.

Table 6. Area of substrates in the northwestern area of northern Bach Long Vy Island from low-altitude multispectral image processing.

Bottom Objects	Total Pixels	Area (m^2)	Percent of Area (%)
Coral	40,695,371	199,410	40.50
Sand	13,490,368	66,100	13.43
Rock	46,296,558	226,850	46.07
Total	100,482,297	492,360	100.00

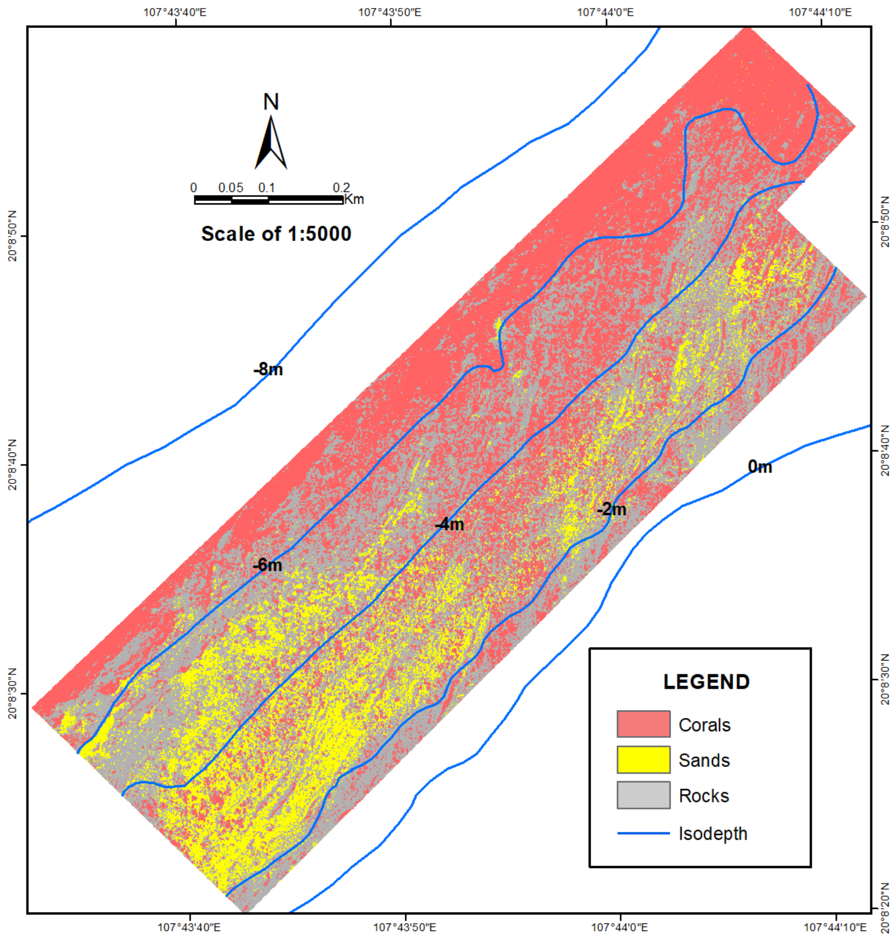


Figure 7. Results of interpreting substrates in the northwest region of Bach Long Vy Island from a low-altitude multispectral image.

The results presented in **Table 6** demonstrate that the classification derived from low-altitude multispectral imagery effectively delineates the primary benthic substrates. Notably, coral distribution was successfully identified and distinguished from rocky substrates, a task that remains challenging in remote sensing applications due to the frequent co-occurrence of corals on hard rock surfaces. This spectral similarity between coral and rock has historically posed limitations for substrate discrimination using conventional remote sensing techniques [18,19].

3.2. Accuracy Assessment

The post-classification results were compared with the selected sample area and the field survey results to evaluate the accuracy of the low-altitude multispectral data in determining the distribution of bottom matter. Comparison with the classification results with the sample area selection showed that the accuracy of Coral 1 was the highest (96.7%); the lowest were Sand 1 and Sand 2 (91.5%) (**Table 7**).

The comparison between the classified map and the independent validation dataset demonstrated a high overall classification accuracy of 86.87%, with a Kappa coefficient of 0.78 (**Table 8**). Among the three substrate categories, rock exhibited the highest classification accuracy (89.26%), followed by coral (83.91%) and sand (82.61%).

The relatively lower accuracies observed for coral and sand classes are likely related to spectral similarity among benthic substrates and the influence of water-column attenuation. Coral colonies frequently occur on rocky substrates, resulting in partial spectral overlap between coral and rock classes. Similarly, deeper coral habitats exhibited reduced spectral contrast because of increased light absorption and scattering within the water column. Nevertheless, the classification performance remained sufficiently robust for coral habitat mapping, as demonstrated by the strong agreement between image-derived classifications and field observations.

The relationship between classified and observed substrate classes yielded a coefficient of determination (R^2) of 0.739 (**Figure 8**), indicating a strong correspondence between UAV-derived classifications and ground-truth survey data.

Table 7. Classification results of bottom matter compared to sample area.

No.	Bottom Matter	Overall Accuracy (%)	Kappa
1	Coral 1	96.7	0.96
2	Coral 2	95.2	0.94
3	Coral 3	94.8	0.94
4	Coral 4	93.3	0.92
5	Sand 1	91.5	0.90
6	Sand 2	91.5	0.90
7	Rock 1	91.7	0.90
8	Rock 2	91.8	0.90

Table 8. Evaluation of the classification results compared with the field survey.

No.	Accuracy Metric	Coral (%)	Sand (%)	Rock (%)
1	Classification accuracy	83.91	82.61	89.26
2	Overall accuracy		86.87	
3	Kappa coefficient		0.78	

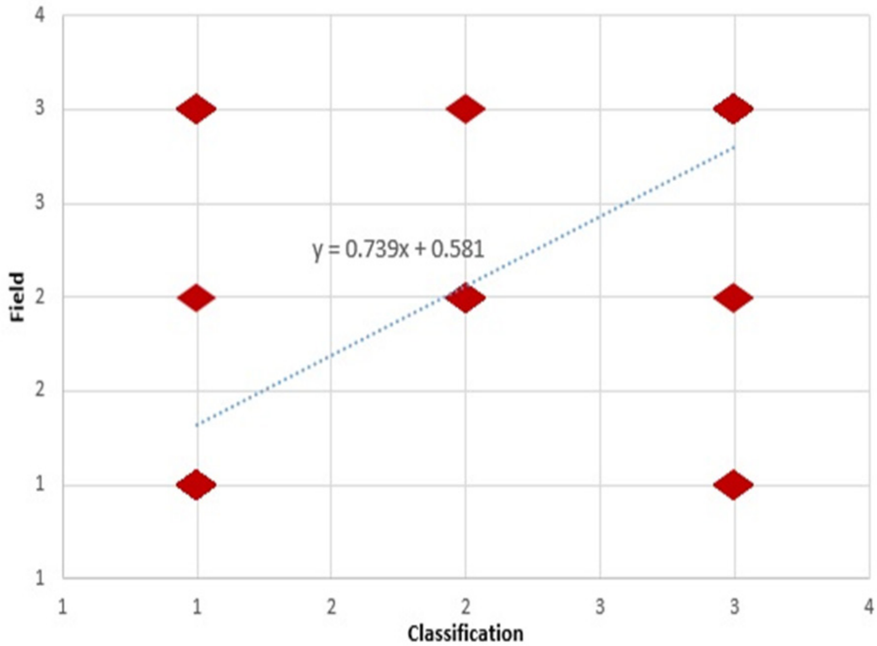


Figure 8. Correlation between the image interpretation results and field survey data.

4. Discussion

4.1. Coral Distribution Patterns in the Northwestern Waters of Bach Long Vy Island

The UAV-derived habitat map revealed that coral reefs occupied approximately 199,410 m^2, accounting for 40.5% of the surveyed area. This result confirms that the northwestern coast of Bach Long Vy Island supports one of the most extensive coral reef habitats within the island's coastal waters. The predominance of coral habitats in this area is consistent with previous ecological surveys, which reported relatively high coral cover and species richness in the northwestern sector of the island [42–44].

The predominance of coral communities in the northwestern sector is likely controlled primarily by hydrodynamic conditions. Bach Long Vy is a small offshore island (2.33 km^2) located in the central Gulf of Tonkin, where monsoon-driven wave regimes strongly influence coastal environments. During the northeast monsoon, prevailing winds originate from the mainland, resulting in relatively short fetch distances and reduced wave energy reaching the northwestern coast. Conversely, during the southwest monsoon, wave energy accumulates across the open South China Sea before reaching the southeastern coast of the island, exposing this area to substantially stronger wave action. Consequently, the northwestern coast remains comparatively sheltered throughout the year.

This hydrodynamic contrast provides a plausible explanation for the observed coral distribution pattern. Although hard rocky substrates suitable for coral settlement occur around much of the island, extensive coral development is concentrated on the sheltered northwestern side. In contrast, no comparable coral assemblages were identified along the southeastern coast despite the presence of suitable substrate. Previous studies have demonstrated that chronic exposure to high wave energy can reduce coral recruitment, increase colony breakage, alter community composition, and limit long-term reef accretion [58–60]. Therefore, wave exposure rather than substrate availability appears to be one of the primary factors controlling coral distribution around Bach Long Vy Island.

Most coral assemblages mapped in this study occurred within the depth range of 3–8 m, a zone generally subjected to strong wave-induced disturbance in shallow-water reef environments. The occurrence of extensive coral communities within this depth interval on the northwestern coast further supports the hypothesis that natural sheltering from monsoon-driven wave energy is a critical factor promoting reef development. The uniformly low turbidity observed during the survey period and the island's location more than 100 km from major river mouths suggest that water clarity is consistently favorable throughout the island and is unlikely to explain the marked spatial differences in coral distribution. Instead, the combination of suitable hard substrate, adequate light availability, and reduced hydrodynamic stress creates optimal conditions for coral growth and persistence [44,61].

These findings have important implications for management of the Bach Long Vy Marine Protected Area. The northwestern reef system should be considered a priority conservation zone because it contains the largest and most diverse coral habitats documented around the island. Coral reefs play critical roles in maintaining biodiversity, supporting fisheries resources, and enhancing ecosystem functioning [1]. Furthermore, the structural complexity of coral reefs contributes substantially to coastal protection by dissipating wave energy and reducing shoreline erosion [2]. As climate change is expected to increase sea-surface temperature, storm intensity, and other environmental stressors affecting coral reef ecosystems worldwide [5], long-term monitoring of these sheltered reef habitats will be essential for assessing ecosystem resilience and supporting adaptive conservation strategies.

4.2. Classification Uncertainty and Sources of Error

Although the overall classification accuracy was high, several sources of uncertainty should be considered. The primary source of classification error arises from the spectral similarity between coral colonies and adjacent rocky substrates. Because many coral colonies develop directly on hard rocky surfaces, their spectral responses can partially overlap, particularly in areas where coral cover is sparse or fragmented.

A second source of uncertainty is related to water-column attenuation. As water depth increases, absorption and scattering processes progressively reduce the spectral contrast between benthic substrates. Consequently, deeper coral habitats exhibited lower classification accuracy than shallow coral communities. Similar depth-related decreases in classification performance have been reported in previous coral reef remote sensing studies [37–39, 48–51].

Additional uncertainties may originate from water-surface conditions, including wave-induced sun glint, minor variations in water turbidity, and geometric mismatches between field survey locations and image pixels. Despite these limitations, the achieved accuracy demonstrates that UAV multispectral imagery provides a reliable approach for mapping shallow coral reef habitats in clear-water environments.

These findings indicate that the reported accuracy should be interpreted as representative of shallow, relatively clear-water reef environments rather than universally applicable conditions.

4.3. Implications of Water-Column Correction

The present study applied attenuation coefficients derived from previous investigations conducted in the waters surrounding Bach Long Vy Island [52]. This approach was adopted because the spectral characteristics of the IKONOS imagery and the UAV multispectral imagery exhibit substantial similarity within the visible wavelength range. Furthermore, environmental conditions during image acquisition, particularly water transparency and turbidity, were generally comparable to those reported in earlier studies.

Nevertheless, the use of historical attenuation coefficients represents a potential source of uncertainty. Temporal variations in water optical properties may influence the effectiveness of water-column correction and consequently affect classification accuracy. Future studies should directly measure inherent optical properties and attenuation coefficients during UAV surveys to further improve benthic habitat discrimination and reduce classification uncertainty [62].

4.4. Comparison with Recent Coral Reef Mapping Approaches

Recent advances in coral reef remote sensing have increasingly incorporated machine learning and deep learning algorithms, including Random Forest, Support Vector Machine, convolutional neural networks (CNNs), and object-based image analysis approaches [18,63,64] (**Table 9**). These methods often achieve higher classification accuracies than traditional pixel-based classifiers because they can capture complex spatial and spectral relationships within imagery. Furthermore, these studies used UAVs to photograph areas with depths below 4 m, clear water, and small waves, thus minimizing the influence of the water column and eliminating the need for water column correction, significantly increasing accuracy.

However, advanced machine learning frameworks typically require large training datasets, extensive image annotation, substantial computational resources, and expertise. In contrast, the maximum likelihood classifier employed in this study provides a relatively simple, transparent, and computationally efficient workflow while still achieving an overall accuracy of 86.87%. For routine monitoring programmes within marine protected areas, particularly in regions with limited technical and financial resources, such an approach may represent a practical balance between classification performance and operational feasibility.

These accuracy values are not directly comparable because they were obtained under different environmental conditions, sensor configurations, and classification objectives; however, they provide a general indication of the performance range achieved by recent coral reef mapping studies.

Table 9. Comparison of coral reef mapping approaches.

No.	Area	Method	Accuracy (%)	Water Correction	Reference
1	Lord Howe Island, Australia	Deep learning	96	No	Giles et al. [63]

Table 9. *Cont.*

No.	Area	Method	Accuracy (%)	Water Correction	Reference
2	Belize	UAV classification	98	No	Peterson et al. [64]
3	Heron Reef, Australia	ML approach	81	No	Carrasco Rivera et al. [18]
4	Bach Long Vy	Maximum likelihood	86.87	Yes	This study

4.5. Implications for Coral Reef Monitoring and Management

Climate change is expected to increase the frequency of coral bleaching events, alter species composition, and affect the long-term resilience of coral reef ecosystems [5–7,65]. Under these circumstances, timely and accurate information on coral distribution becomes increasingly important for conservation planning and adaptive management.

The workflow developed in this study demonstrates that UAV-based multispectral imagery can provide rapid, high-resolution assessments of coral reef distribution at relatively low cost. Compared with traditional diving surveys, UAV surveys can cover larger areas within shorter time periods and can be repeated regularly to detect changes in reef extent and condition. Although the present study focused on Bach Long Vy Island, the proposed workflow is readily transferable to other shallow-water coral reef systems where rapid, high-resolution habitat mapping is required.

5. Conclusions

This study demonstrated the applicability of UAV-based multispectral remote sensing for high-resolution mapping of shallow coral reef habitats in the northwestern waters of Bach Long Vy Island, Vietnam. By combining water-column correction using the Lyzenga method with supervised maximum likelihood classification, three major benthic substrate classes, including coral, sand, and rock, were successfully identified and mapped. Coral reefs occupied approximately 199,410 m^2, representing 40.50% of the surveyed area, whereas sand and rock accounted for 13.43% and 46.07%, respectively. The classification achieved an overall accuracy of 86.87% and a Kappa coefficient of 0.78, indicating good agreement between image-derived classifications and field observations.

The results confirm that UAV multispectral imagery can provide reliable and detailed information on coral reef distribution in shallow-water environments. The subdivision of benthic substrates into depth-dependent spectral classes effectively reduced spectral confusion caused by water-column attenuation and improved classification performance. Although some uncertainties remain due to spectral similarities between coral and rocky substrates and the use of historical attenuation coefficients for water-column correction, the proposed approach proved sufficiently robust for operational coral habitat mapping.

Beyond its application to Bach Long Vy Island, the methodology offers a practical, cost-effective, and rapidly deployable tool for routine monitoring of coral reef ecosystems in marine protected areas. The generated habitat maps can support biodiversity conservation, resource management, and environmental monitoring programmes, particularly under increasing pressures from climate change and human activities. Future studies should incorporate in situ measurements of optical water properties and evaluate advanced machine learning and deep learning approaches to further improve classification accuracy and enhance long-term coral reef monitoring capabilities.

Author Contributions

N.V.T. drafted the manuscript; N.V.T., T.D.L. and C.G. edited the manuscript; V.M.H. assisted in drafting the Bach Long Vy Island context; D.H.N. provided specific information on the natural condition of Bach Long Vy Island; N.D.V. and B.M.T. contributed to image processing; C.G. conducted critical review of the manuscript and scientific revision. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not applicable, as the study does not involve humans or animals.

Informed Consent Statement

Not applicable.

Data Availability Statement

Data will be made available on request.

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Conflicts of Interest

No potential conflict of interest was reported by the authors.

AI Use Statement

The authors used ChatGPT solely to improve the English language, grammar, and readability of the manuscript. The AI tool was not used for study design, data collection, data analysis, interpretation of results, or scientific decision-making. The authors subsequently reviewed and edited the content as necessary and take full responsibility for the final content of the published article.

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