Mapping Coral Reef Habitat Using High-Resolution Satellite Imagery and Temporally Disparate In-Situ Data: A Multi-Depth Analysis

Che Azani B.[1], Mohd Zaki N.A. [1,2*], Zainal M.Z. [3], Che Hasan R. [3] and Razak T.R. [4,5]

[1]Faculty of Built Environment, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia

[2]Institute for Biodiversity and Sustainable Development, Universiti Teknologi MARA, Shah Alam, 40450, Malaysia

[3]School of Engineering and Technology, Jalan Sultan Yahya Petra, Universiti Teknologi Malaysia, 54100 Kuala Lumpur, Wilayah Persekutuan Kuala Lumpur, Malaysia

[4]College of Computing, Informatics and Mathematics, Universiti Teknologi MARA, Shah Alam, Malaysia

[5]Department of Architecture and Built Environment, University of Nottingham, United Kingdom

*nurulain86@uitm.edu.my

Abstract: *Over the past few years, coral reefs have faced multiple threats from environmental and anthropogenic stressors. It is beyond doubt that monitoring coral reefs is crucial particularly for habitat changes detection. Despite that, matching the date for both satellite images with field data oftentimes can be challenging. Therefore, this study used Pleiades high-multi resolution satellite image of Pinang Island, Terengganu, Malaysia for coral reef habitat classification and in situ data from CPCe photo quadrats and underwater photographs collected in 2024 which are temporally delayed. The satellite image, limited to surface reflectance, was processed to extract spectral and texture indices. In situ data, including 376 georeferenced quadrats with depth and substrate composition from 40 locations, were integrated and stratified by depth (≤5 m and >5 m) to assess classification performance across varying optical conditions. Furthermore, random forest algorithm classification will be applied as machine learning classifiers with underwater photographs as visual reference to address the four-year temporal gap. This approach aims to demonstrate how older satellite data can support coral reef mapping when recent or up-to-date imagery is unavailable through the integration with more recent field observations, from several years later.*

Keywords: coral reef mapping, temporal mismatch, Pleiades satellite, machine learning classification

Introduction

Coral reefs is a complex ecosystem that are built by tiny animals, that made up less than 0.1% of the ocean floor yet managed to house at least 25% of marine species (Coral Reef Alliance, 2021). They are crucial in our ecosystem due to its ability to support a vast array of marine life and provide crucial benefits to both ocean and human communities. They offer both shelter and foods for juvenile fish populations (Rivera et al., 2020), and protection from predators which boost healthy food chain (Rogers et al., 2017). In addition, irregular structure and rough surface of coral reef create fiction which slow water movement, thus making it a great natural breakwater and reducing coastal erosion, protecting shorelines from storms and tsunamis (Ferrario et al., 2014).

Coral reefs also act as ocean health indicators. They are sensitive toward changes of ocean, be it temperature or its chemical level. Bleaching events indicate ocean warming and marine heatwaves, while abnormal pace in reef growth indicate changes in ocean chemistry which may cause by ocean acidification (Burke & Wood, 2021).

These days, the decline of coral reef has been a global problem. It happens due to environmental and anthropogenic activity. To monitor coral reef, a large monitoring system needs to be set up. On the flip side, remote sensing technology has been the pioneer for large monitoring and mapping while detecting any changes in the environment (Foo & Asner, 2019). Sensor used for remote sensing can capture wavelengths that will be used to distinguish spectral signature. Spectral signature is distinctive between objects. Hence different species of coral and other benthic habitat can be identify using this way (Mustapha et al., 2014). Remote sensing technology also offers temporal resolution depending on the research need. Thus, making remote sensing technology the best choice for coral reef monitoring and habitat change detection.

Nonetheless, despite these advantages, satellite imagery cannot avoid nature circumstances. (The University of Queensland, 2025). For instance, during rainy season, some areas may be covered by clouds. This could also happen during sunny days. Also depending on the sensor use, the imagery may not be available on certain date, resulting in temporal gaps between image acquisitions and field data that affect habitat mapping accuracy. Obtaining up-to-date satellite images for specific dates and specifications to map coral reefs is often hard. Inevitably, field work usually was done post-date with the available imagery which further increased the temporal gaps.

This study aims to explore the potential of older high-resolution Pleiades imagery (19 July 2024), combined with recent in situ observations (22 August 2025), to overcome temporal mismatch challenges and assess coral reef habitats in Pinang Island, Terengganu, Malaysia.

Literature Review

a. Remote sensing applications in coral habitat mapping

Over the year, remote sensing applications has proven to be irreplaceable in mapping coral habitat. Not only it can cover a large area, it also can create map while monitoring changes happen on coral reefs. Over the years, a variety of techniques have been applied to map coral habitats, including satellite-based remote sensing, benthic terrain modeling, acoustic surveys, ground-truth observations, and machine learning approaches. While each method offers valuable insights on its own, combining these techniques can yield more comprehensive and reliable results. Some studies that were to be noted are Rivera-Sosa et al. (2025) that combined remote sensing and acoustic data to monitor coral reef and Nomenisoa et al. (2024) with the used of free and accessible satellite imagery and object-based image analysis (OBIA) to create coral reef habitat mapping. In addition, a study by White et al. (2021) proved machine learning can be used to detect coral reefs on Landsat imagery. When integrates with hyperspectral data, it can create a more detailed map of coral reef (Schürholz & Chennu, 2022). In 2025, Moustafa et al. publish a review on global coral bleaching survey methodologies that use satellite and AI to improve monitoring accuracy. Not only that, even a health index for coral reef could be created using open-source remote sensing data and statistical techniques (Hafizt et al., 2023). All these studies highlight the perks of using remote sensing application in mapping coral reef habitat.

b. Machine learning and classification techniques

Classification techniques can be divided into two, pixel based, and object based. For decades, pixel based has been used for classification. Supervised and unsupervised classification are the examples of it. Supervised classification used training sample with algorithms while unsupervised classification used algorithms only to classify the pixels (Kudale et al., 2018). Random Forest (RF), Support Vector Machine (SVM), Maximum Likelihood (MLH) and k-Nearest Neighbor (k-NN) are some of the examples of algorithms used. MLH is the commonly used pixel-based classification algorithm followed by RF and SVM (Burns et al., 2022). MLH used statistics to estimate the parameters of the model by maximizing the likelihood function. This allows user to observe the given data with specific parameters values. SVM is a supervised machine learning technique that finds the optimal line or hyperplane that maximizes the distance between each class in an N dimensional space to classify the data, and RF uses ensemble method where multiple classifiers predict the outcome. It increases the accuracy rate and reduces overfitting (Burns et al., 2022b). With recent advancement in technologies, machine learning (ML) has become the core to process complex remote sensing data. Study by White et al. (2021) achieved 90% overall accuracy using MLH as algorithm. Van An et al. (2023) achieved 90.55% and 90.95% overall accuracy using RF and SVM respectively, during unsupervised classification.

c. Spectral and texture for benthic habitat

In remote sensing, each object is identify using their unique pattern of reflectance or emittance that is called spectral signature (Goware, 2016). Hence, using spectral signatures, it helps differentiate between coral reef composition. Using spectral signatures, band ratio and spectral indices such as NDVI, NDWI and NDMI ca be calculated. Which will help to enhance coral and substrate detection. There was a study by Hochberg et al., (2003), where they created a spectral library of 13,100 reflectance spectra d using data across the world for coral reefs identification. Mustapha et al., (2014) also discover that factors like calcium carbonate composition and presence of benthic microalgae can affect the spectral signature of coral habitats. It is important to have background knowledge on coral's spectral signature to avoid mismatch between class.

On the contrary, texture features can capture the spatial heterogeneity and patterns (roughness or grain) using Gray Level Co-occurrence Matrix (GLCM). It increases the ability to distinguish between class in heterogeneous coral reef (Nguyen et al., 2021).

d. Temporal and spatial challenges in reef monitoring

In general, monitoring coral reefs are tricky due to its high spatial heterogeneity and temporal dynamics. (Rivera-Sosa et al., 2025b). Seasonal changes, anthropogenic impact and climate event could happen between the date, effecting coral reefs health and structure. Ultimately leading to inconsistencies between data. Not to mention, satellite imagery has their own limitations. Cloud cover, water turbidity and sun glint are some of the spatial distortions that require correction.

e. Depth-related limitations and water column effects

To assess coral reefs, one needs to consider the water conditions. Its transparency, depth and movement can affect the data. Ligh attenuation and scattering are some of the effects that disturb spectral signals, as its increase with depth and water turbidity. Study by Foo and Asner (2019) noted that depth and water turbidity can influence optical remote sensing accuracy.

This causes spectral signal to weaken, thus reducing classification accuracy. Some proposed the need for refined water column correction to enhance mapping accuracy of benthic habitat (Zoffoli et al., 2014), while Huang et al. (2025) emphasized on performing atmospheric correction especially polymer to compensate the depth related light attenuation for better coral reef map accuracy.

Methodology

a. Study Area

This study was conducted at Pinang Island, Terengganu, Malaysia, a small island within the Redang Island archipelago. This island is affected by northeast monsoon which impacting its water clarity (Marine Park & Resources Management, 2021). It causes different levels of turbidity that effect benthic clarity in satellite image. Using data from study done in 2021 (Muhamad et al., 2021), 40 locations had been marked for possibility of coral reef existence.

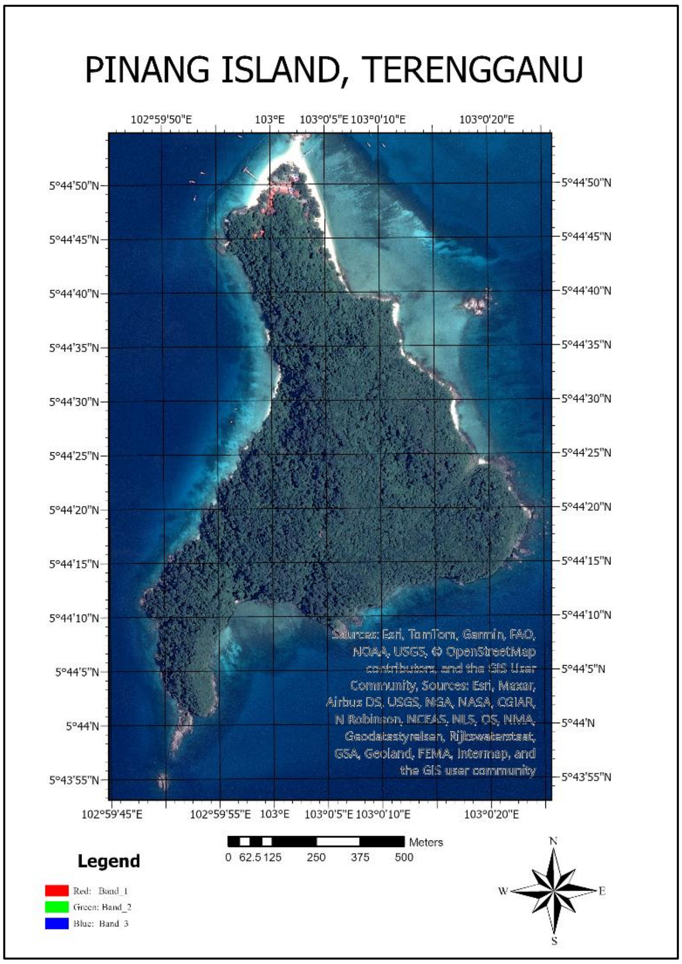

Figure 1: Study area

On 21 and 22 August of 2024, fieldwork for in situ data collection was conducted. The main priority is collecting georeferenced videos (which will be screenshot for photo quadrats per

10 seconds). InstaX360 camera was attached to custom-built bracket together with NANO transponder for Micro-Ranger 2 Ultra Short Baseline (USBL) and torchlight (Figure 2). This is to record the position of coral when videos were taken. Once arrived at the marked zone, the bracket was thrown into sea and let it sit for about 2-3 minutes. Approximately 376 images were collected across 40 sites. Each image was then linked to its coordinate using GeoSetter software, from data by USBL.

a b

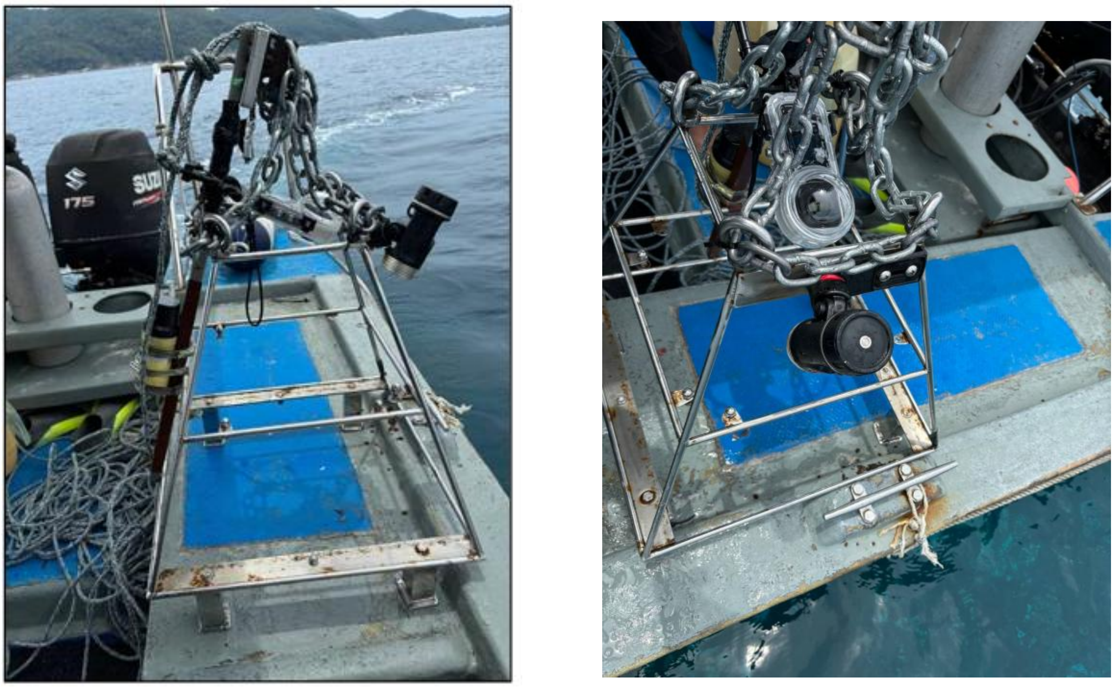

Figure 2: a) Side view of the bracket b) Upper view of the bracket

b. Methodology Flowchart

The methodology for this study is split into two to cater different data. In situ data was obtained through underwater survey, which later being process using GeoSetter and CPCe software. Satellite image, on contrary was acquired through Malaysian Space Agency (MYSA) and processed in ArcGIS Pro. From then on, ArcGIS Pro and Jupyter were used to classify each class. Below is the methodology flowchart for this study

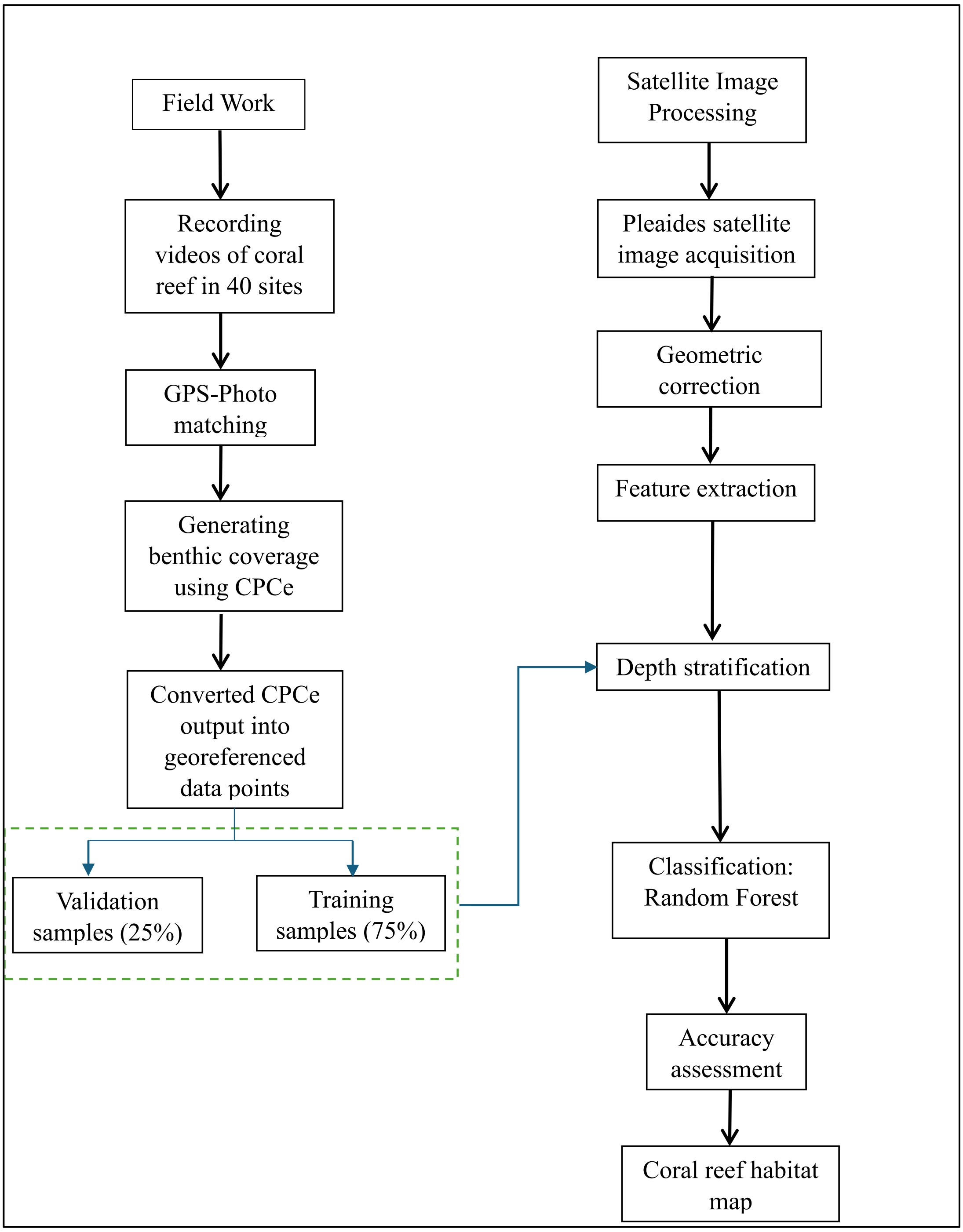

Figure 3: Methodology Flowchart

c. Field Data Collection and Processing

During the field survey, a total of 376 underwater photo-quadrat images (screenshots from videos recorded) were extracted using the Insta360 camera and saved as individual images for analysis. It was collected across 40 survey sites distributed within the study area. Image acquisition was conducted on 25 and 26 August 2024 using an Insta360 X4 camera, which provides high-resolution, wide-angle underwater imagery suitable for benthic habitat assessment. The survey uses drop camera method where bracket (with camera attached) was dropped into water and let sink. At each station, the camera was positioned consistently to minimize bias and maintain comparability between sites. Each photograph was subsequently processed and annotated to extract substrate composition data, specifically the percentage cover of hard coral, rubble, sand, and rock. These categories were selected as they represent dominant benthic substrates relevant for coral reef habitat classification and monitoring. In addition to substrate information, depth measurements were recorded alongside each photo-quadrat, providing essential environmental context and enabling stratified analysis of shallow versus deeper reef areas.

Table 1: Description on field data

Total quadrants	376 photos
Sites	40
Camera used	Insta360 X4
Collection method	Drop camera & Underwater survey
Date collected	25 and 26 August 2024
Parameter annotated	Substrate composition (hard coral, rubble, sand, rock), depth

i. Benthic cover assessment from geotagged photos

For this study, it focuses on four substrates namely, Coral (C), Rubble (RB), Rock (RK), Sand (S) Tape, Wand, And Shadow (TWS). Using CPCE software, it allows user to analysed photo quadrates and assess the benthic cover present. 20 random points were generated on each photo, and user need to assign it accordingly. Using those points, its estimate the benthic coverage and exported the data into Excel file.

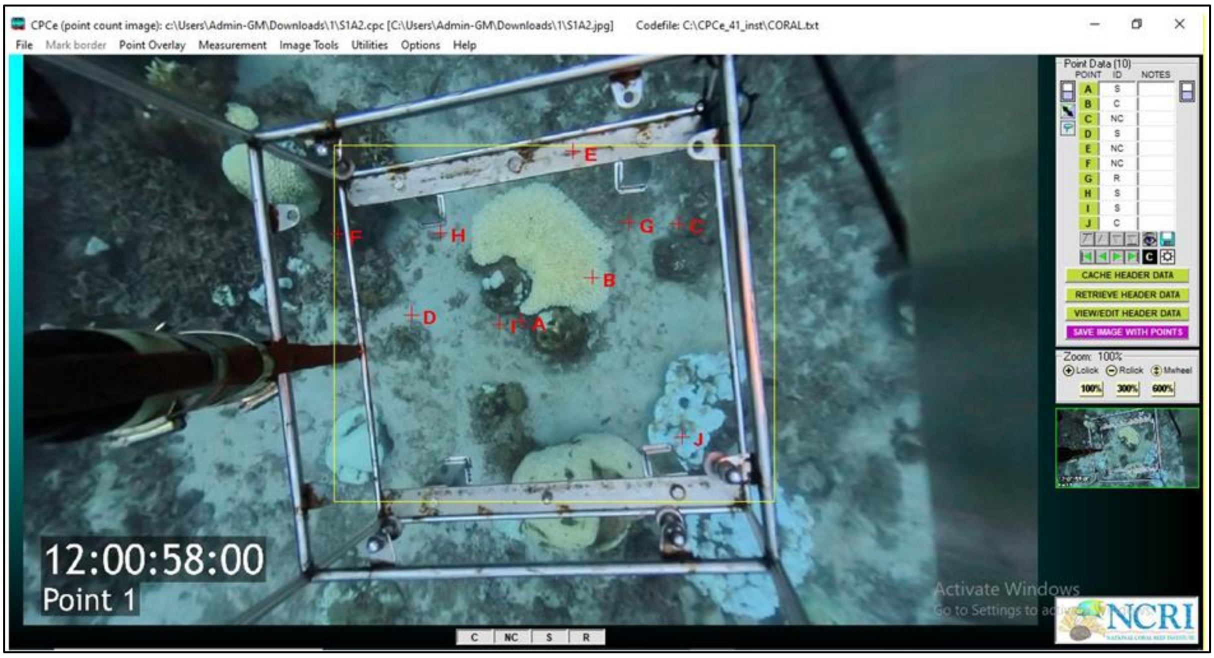

Figure 4: CPCe classification

Table 2: CPCe summary chart

Results Summary Chart	# Points	%	Sw Index	Simpson (1-D)
Coral (C)	3500	40.36	0.37	0.16
Rock (Rc)	774	8.93	0.22	0.01
Rubble (Rb)	1175	13.55	0.27	0.02
Sand (S)	3223	37.17	0.37	0.14
Tape, Wand & Shadow (Tws)	1378	13.71		
Totals	10050	100.00	1.22	0.67

ii. Conversion of CPCe data into sample points

As mentioned earlier, USBL capture the coordinate of each image while CPCe exported benthic coverage result into excel. Thus, by combining both data into a single sheet, it allows user to export points into ArcGIS Pro to be overlay with Pleiades satellite image. Dominant class of each point can also be done. The data were then split into 75/25 ratio for training and validation sample, respectively using ArcGIS Pro.

Figure 5: Points with coordinate

d. Satellite image processing

Pleiades imagery was used for this research. Pleiades satellite imagery offers high spatial resolution for multispectral resolution of 2m which allows a detailed observation of the Earth's surface. These features are essential in coral habitat mapping. It is retrieved on 19 July of 2020. These images consist of 4 bands (blue, green, red, near infra-red). There are 25966 rows and 24252 columns for this image.

Table 3: Description of Pleiades 1B data

Satellite	Pleiades 1B
AOI	Pinang Island, Terengganu
Resolution	2 m
Number of bands	4
Projection	UTM 47N (EPSG:32647)
Sensor bands	Multispectral (red, blue, green, near-IR)
Acquisition date	19 July 2020

i. Image preprocessing and feature extraction

To avoid geographic distortion and enable spatial analysis, the imagery was reprojected to Universal Transverse Mercator (UTM) Zone 47N, WGS84 (EPSG:32647). This step ensures consistency between all datasets.

Then from the imagery, both spectral features (raw reflectance, NDVI, depth-invariant indices) and texture measures were extracted. Texture was derived using the Gray-Level Co-occurrence Matrix (GLCM) with metrics such as contrast, entropy, and homogeneity.

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

NIR = Near-Infrared Band (e.g., Sentinel-2 Band 8, Landsat Band 5)

Red = Red Band (e.g., Sentinel-2 Band 4, Landsat Band 4)

Interpretation:

NDVI > 0.2 → Presence of vegetation (seagrass, macroalgae).

NDVI < 0.2 → non-vegetated surfaces (sand, coral, water).

$$Homogeneity = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P(i,j)}{1 + |i-j|}$$

- Measures how uniform the texture is.
- Higher values indicate smoother textures (e.g., sand).

Classification

For this study, Random Forest classifier was used. This is due to its ability to handle multi-dimensional data and differentiate class better. RF use spectral bands, spectral indices and texture features to analyse. It uses ensemble method where multiple classifiers predict the outcome which increases the accuracy rate and reduces overfitting (Burns et al., 2022). Moreover, using underwater photograph, it serves as tools for verification purpose to avoid misclassification. 75% of the data was used as training and 25% for validation. In addition, another set of 75/25 split for depth stratified (<5 m and > 5 m) was also created.

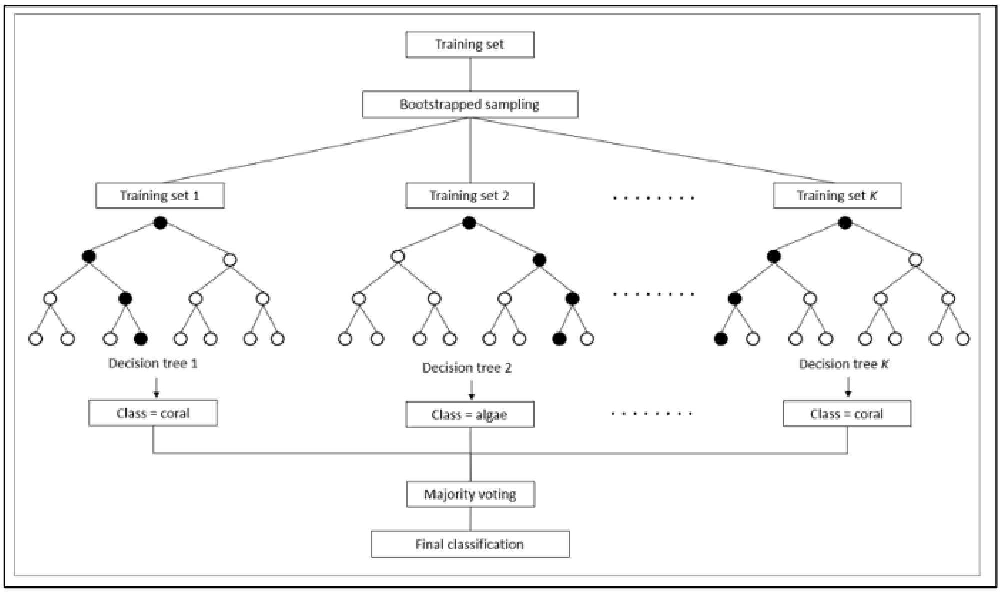

Figure 6: RF conceptual (Burns et al., 2022)

Accuracy Assessment

For accuracy assessment, confusion matrix was generated to calculate overall accuracy (OA), kappa coefficient and class-wise accuracy (user and producer). It was further stratified by depth to determine its performance under different water column.

OA shows the general performance of classifications. Below shows the formula used to calculate it.

$$OA = \frac{\sum Correctly\ Classified\ Samples}{Total\ Samples}$$

Kappa coefficient (K) is used to measures agreement between the classified map and the reference data, while correcting for chance agreement.

$$k = \frac{p_O - p_e}{1 - p_e}$$

Where:

Po = observed agreement (same as OA)

Pe = expected agreement by random chance

Interpretation:

- k = 1 → perfect agreement
- k = 0 → no better than random chance
- k < 0 → worse than random

User's accuracy is the probability that a sample predicted as a certain class belongs to that class. It measures commission errors when extra pixels are wrongly included in a class.

$$UA_i = \frac{Correctly\ Classified\ Samples\ i}{Total\ Predicted\ Samples\ of\ Class\ i}$$

Producer's accuracy is the probability that a reference sample is correctly classified. It measures omission errors when a reference class is omitted from prediction.

$$PA_i = \frac{Correctly\ Classified\ Samples\ i}{Total\ Reference\ Samples\ of\ Class\ i}$$

Results and Discussion

a. Classification Map

The Random Forest classifier produced distinct habitat maps of Pinang Island's coral reefs using the year 2020 Pleiades image and year 2024 CPCe quadrats as reference data. Classified reef habitats included coral, rubble, sand, and rock, with clear spatial differentiation in shallow reef flats and more uncertain classification in deeper reef slopes. Texture indices contributed notably to improving boundary delineation between sand and rubble, which are spectrally similar in shallow waters.

i. Randomly assign

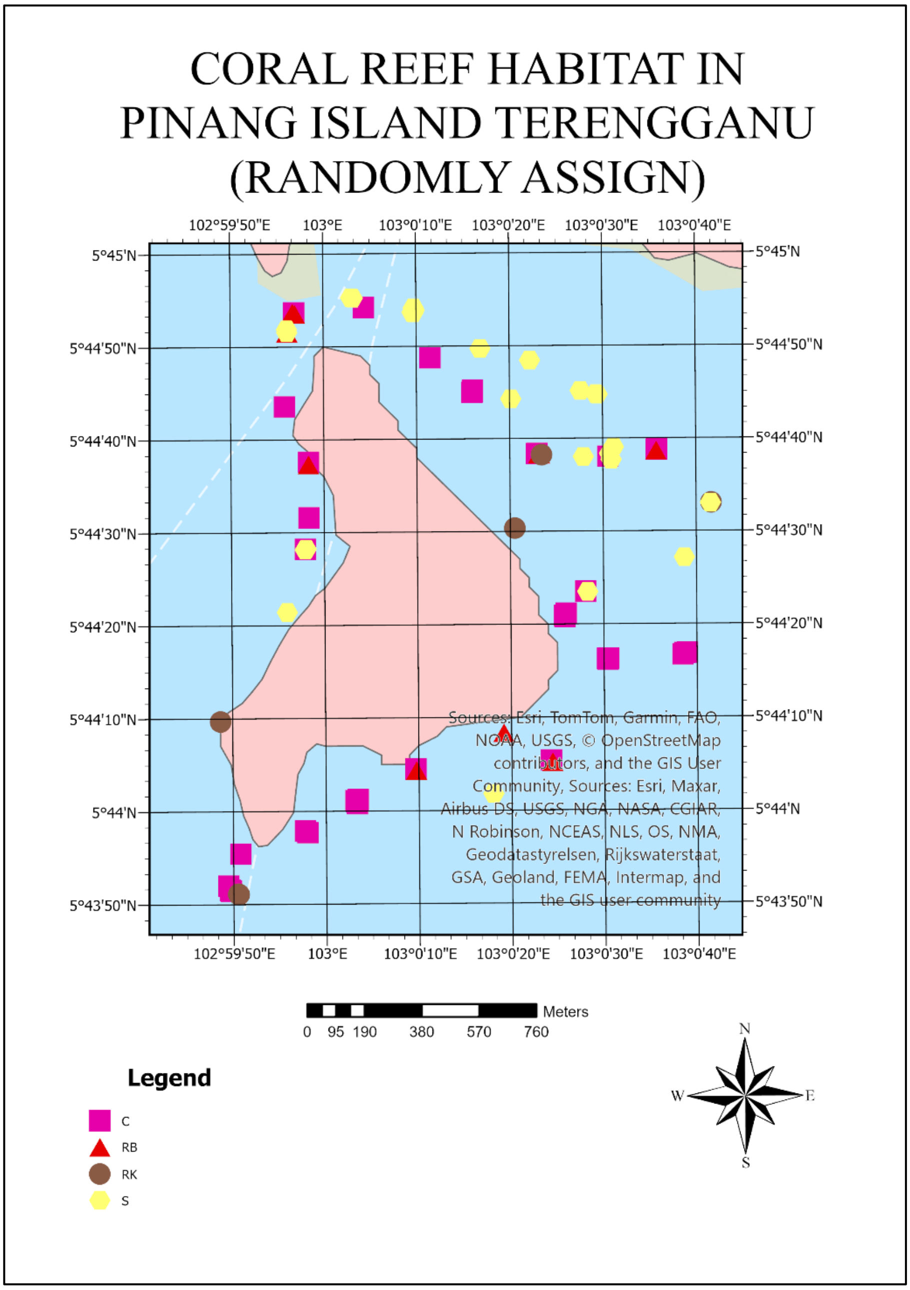

Figure 7: Coral reef habitat map of Pinang Island (Randomly assign)

ii. Assign based on stratified depth

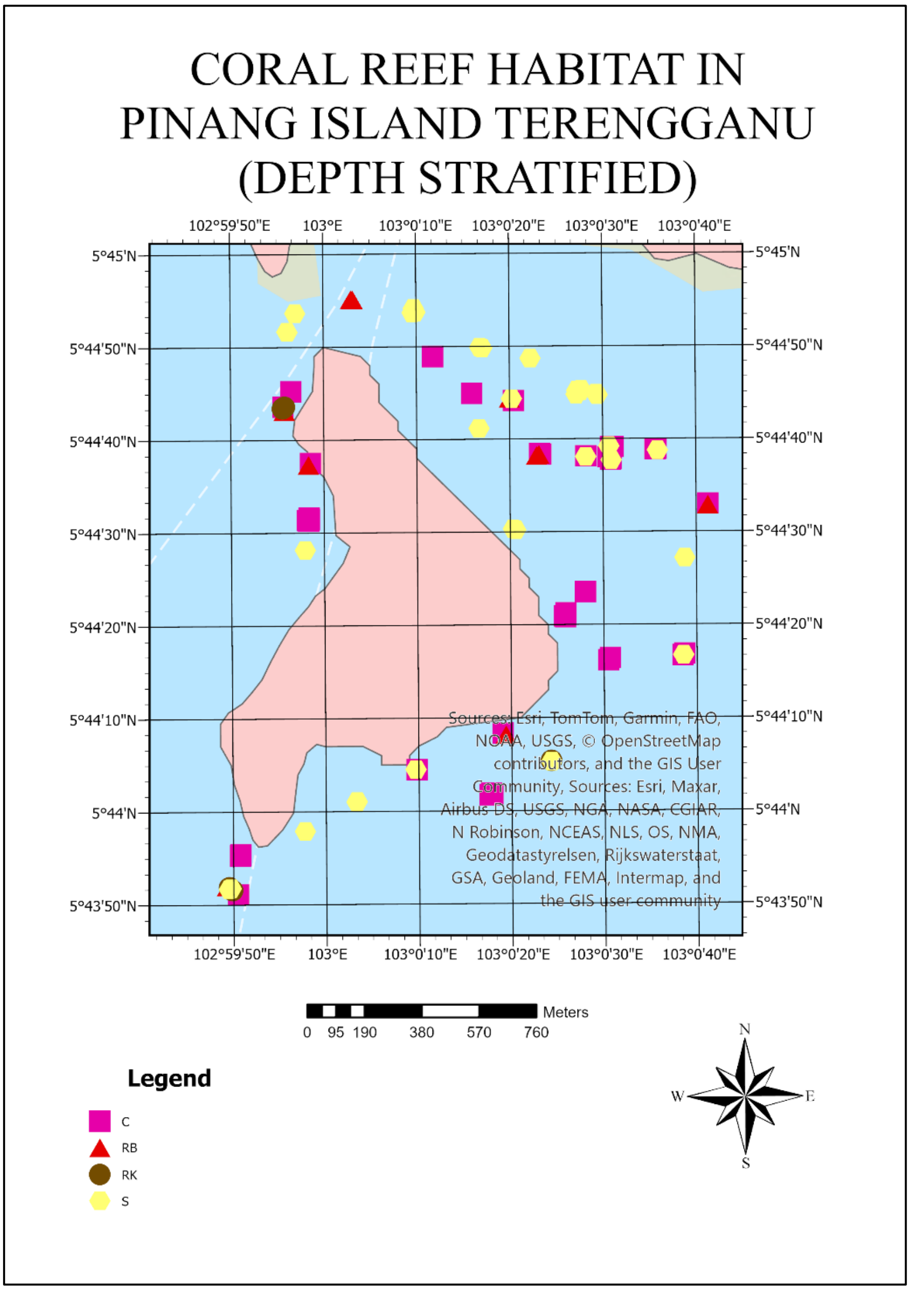

Figure 8: Coral reef habitat map of Pinang Island (Depth stratified)

b. Accuracy Assessment

i. Randomly assign

This study achieved overall classification accuracy of 75.8% with kappa coefficient of 0.557. Rock has the weakest performance in both PA and UA, while other classes (Coral, Rubble, Sand) perform relatively well. On average, Coral and Rubble have high scores for both producer's and user's accuracy

Table 4: Confusion matrix

Row Labels	C	RB	RK	S	Grand Total
C	30	1	0	7	38
RB	3	10	1	0	14
RK	4	0	2	1	7
S	5	2	4	25	36
Grand Total	**42**	**13**	**7**	**33**	**95**

Table 5: Producer's and user's accuracy result

Class	Producer's Accuracy (%)	User's Accuracy (%)
Coral	78.9	71.4
Rubble	71.4	76.9
Rock	28.6	28.6
Sand	69.4	75.5

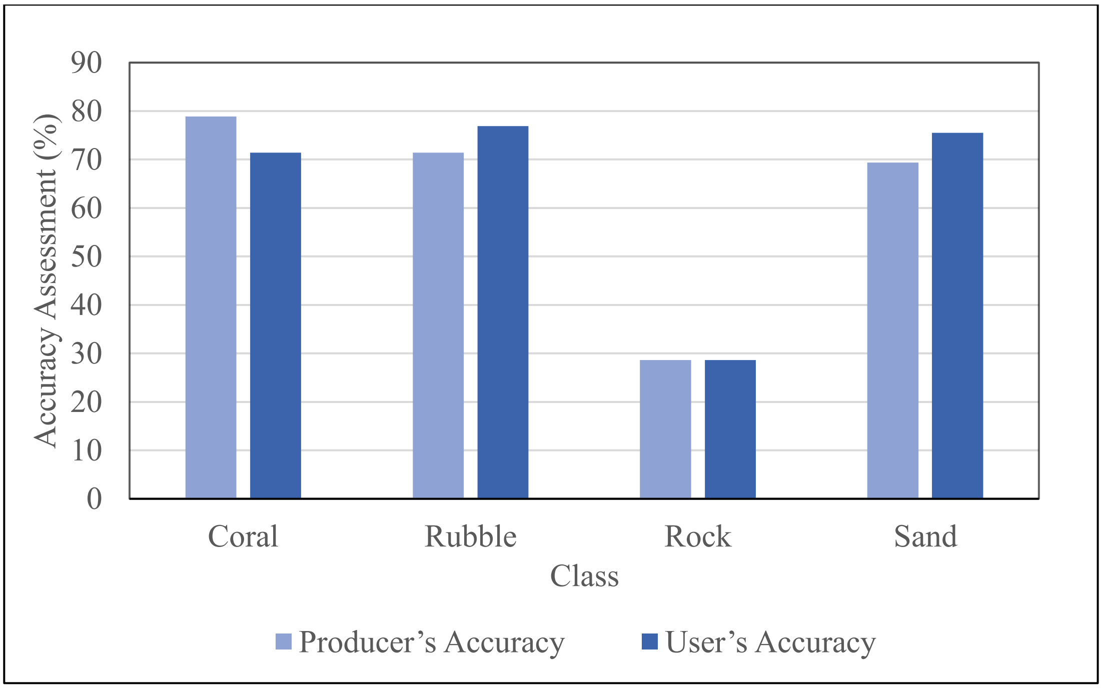

Figure 9: Graph of Producer's and User's accuracy assessment.

ii. Assign based on depth stratified

This study achieved overall classification accuracy of 62.5% with kappa coefficient of 0.430. Rock has the weakest performance in both PA and UA, while other classes (Coral, Rubble, Sand) perform relatively well. Among classes, Coral and Sand showed the highest producer's and user's accuracies, while Rubble and Rock had more frequent misclassifications, reflecting both spectral overlap and temporal differences between the datasets.

Table 4: Confusion matrix

Row Labels	**C**	**RB**	**RK**	**S**	**Grand Total**
C	31	1	2	9	43
RB	6	5	0	2	13
RK	2	4	2	2	10
S	5	2	1	22	30
Grand Total	44	12	5	35	96

Table 5: Producer's and user's accuracy result

Class	Producer's Accuracy (%)	User's Accuracy (%)
Coral	72	70.4
Rubble	38.4	41.6
Rock	20	40
Sand	73.3	62.8

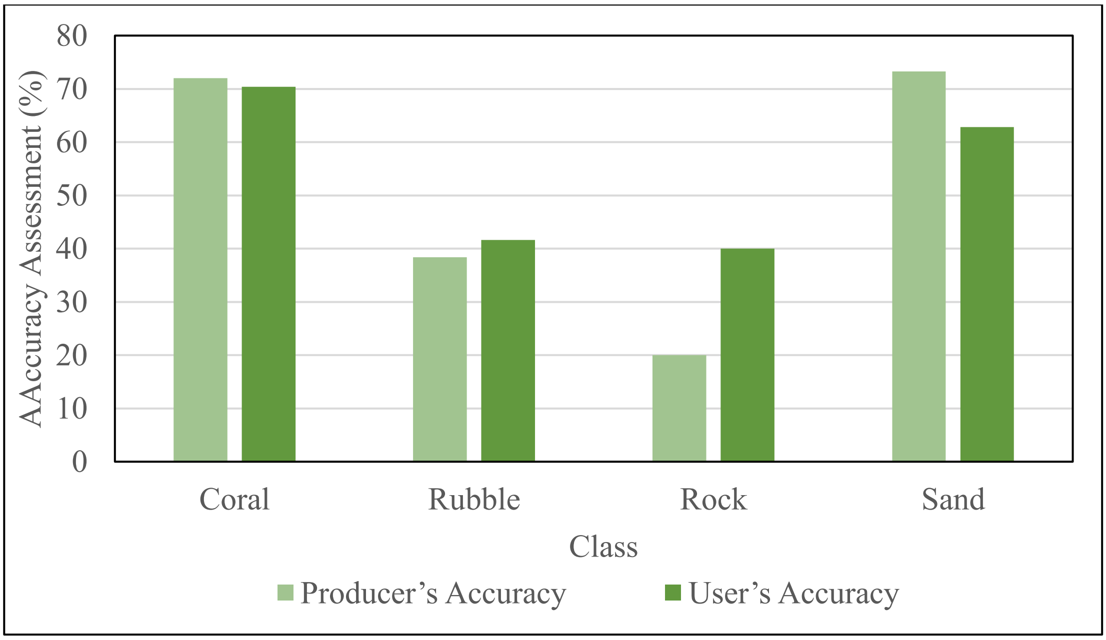

Figure 10: Graph of Producer's and User's accuracy assessment.

Conclusion and Recommendation

From the result, it shows the integration between older high-resolution Pleiades imagery and recent field observations can be used for coral reef habitat mapping. It also achieved high accuracy during classification. This proves the reliability of older imagery spectral and texture features for surface level habitats. Although coral cover may have changed during the interval, spatial patterns of major habitat types remained sufficiently consistent for effective classification. The integration of high-resolution CPCe quadrats and underwater photographs provided reliable training and validation data. It also acts as visual references helps in decision making for areas where satellite images cannot penetrate

Depth-stratified analysis highlighted the challenges of reef mapping in optically complex environments. In shallow waters, RF classification effectively distinguished substrate types, aligning closely with in situ observations. In deeper areas, accuracy declined due to limited penetration of visible bands and higher turbidity. This suggests that supplementary approaches, such as physics-based water column correction or integration with acoustic/bathymetric data, may be needed to enhance classification reliability beyond 5 m depth.

These results demonstrate the potential of combining older satellite imagery with recent in situ observations to support reef monitoring in data-limited contexts. In cases where recent satellite acquisitions are unavailable, past imagery that coupled with detailed field surveys can provide valuable insights into habitat composition and distribution. This approach is particularly relevant for regions with restricted image archives or where acquisition costs limit frequent updates.

This study demonstrated the feasibility of integrating temporally delayed satellite imagery and field observations for coral reef habitat mapping at Pinang Island, Terengganu, Malaysia. Using a 2020 Pleiades image in combination with CPCe quadrats and underwater photographs collected in 2024, the Random Forest classifier produced reliable habitat classifications, with higher accuracy in shallow reef areas compared to deeper zones. Although temporal mismatch and water column effects introduced challenges, the results highlight that legacy satellite data, when complemented with recent in situ surveys, can still provide valuable information for reef monitoring. This approach offers a practical solution in data-limited scenarios where up-to-date imagery is unavailable, and it underscores the importance of integrating multi-source datasets for long-term reef assessment and conservation planning.

Not only will it help in monitoring coral reef habitat, but it will also help achieving the United Nations Sustainable Development Goals (SDGs). SDG 14 (Life Below Water) focuses on protecting marine ecosystems and ensuring sustainable use of reef resources. This can be attained by long-term monitoring where changes in coral cover and bleaching event can be detected. In addition, it also indirectly contributes to SDG 13 (Climate Action) where monitoring allows researchers to document the effect of climate changes, thus helping them to create a countermeasure. Hence the importance of coral reef monitoring, fr both biodiversity and our sustainable development

Acknowledgements

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