A Comparative Study of Machine Learning Classification Algorithms for Benthic Habitat Mapping in West Bali National Park

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Abstract *The West Bali National Park (Taman Nasional Bali Barat/TNBB) comprises a variety of ecosystems, including coastal regions that support different habitats such as mangroves, seagrass, and coral reefs. This distinctive conservation area, situated in the Jembrana and Buleleng Districts, encompasses roughly 3,415 hectares and fosters the development and preservation of diverse species, including benthic ecosystems. Benthic habitats are vital elements of coastal ecosystems, including seagrass, coral reefs, macroalgae, and diverse substrate types. This study seeks to evaluate the efficacy of two machine learning classification algorithms, Random Forest (RF) and Support Vector Machine (SVM), in delineating benthic habitat composition in the Teluk Terima region of TNBB, utilizing 3-meter resolution PlanetScope imagery encompassing visible and near-infrared (NIR) spectral bands. The classification emphasizes four principal benthic habitat categories: predominant seagrass, predominant coral, predominant macroalgae, and predominant substrate. The RF algorithm achieved an overall accuracy (OA) of 59.1%, delineating 27.3 ha of predominant seagrass, 35.9 ha of coral, 0.5 ha of macroalgae, and 40.2 ha of substrate. In contrast, the SVM method achieved a diminished OA of 47.3%, delineating 35.4 ha of seagrass, 43.9 ha of coral, 15.5 ha of macroalgae, and 9.2 ha of substrate. Comparative accuracy assessments reveal that Random Forest (RF) exhibits more stability in classifying seagrass and substrate categories, whereas Support Vector Machine (SVM) has superior performance in identifying coral and macroalgae, notwithstanding discrepancies in user and producer accuracy. The results indicate that the selection of classification method substantially influences benthic habitat mapping results, with Random Forest providing more reliable conclusions in shallow water settings characterized by intricate substrate compositions.*

Keywords: Benthic Habitat, Conservation, Random Forest, Support Vector Machine, Machine Learning

Introduction

Benthic habitats are crucial to marine ecosystems, functioning as the foundation of the food chain and providing habitat for diverse marine creatures. The presence of robust benthic habitats signifies high marine ecosystem quality. Nonetheless, these ecosystems frequently confront the peril of degradation resulting from anthropogenic activity and environmental alterations. Consequently, it is crucial to preserve benthic ecosystems sustainably (Sugara et al., 2020). One of the primary phases in conservation include monitoring, which commences with precise habitat mapping. This mapping seeks to furnish fundamental data regarding habitat characteristics applicable for the development and management of conservation areas (Putra, 2023).

Mapping and monitoring a benthic habitat necessitates the application of classification methods using machine learning for analysis. The manual classification of data is inefficient and labor-intensive for processing and interpretation. Remote sensing data frequently constitutes big data, necessitating machine learning programs that can efficiently and effectively interpret substantial volumes of information, hence enhancing its utilization (Pillay et al., 2021). In studies on benthic habitats, including Wicaksono et al. (2019), the Random Forest (RF), Classification Tree Analysis (CTA), and Support Vector Machine (SVM) algorithms were employed to differentiate substrates across benthic habitats, including seagrass, algae, coral reefs, and other substrates.

The West Bali National Park (TNBB) encompasses diverse ecosystems, including a coastline region characterized by mangrove, seagrass, and coral reef habitats. This distinctive conservation area in the seas of TNBB is situated in the districts of Jembrana and Buleleng, including an area of 3,415 hectares, which facilitates the growth and protection of biodiversity, including benthic habitats. Classification was conducted on four primary benthic habitat categories: seagrass-dominant, coral reef-dominant, macroalgae-dominant, and substrate-dominant. The RF and SVM algorithms are widely utilized for classifying spatial data on benthic habitats; however, a thorough comparison of their performance is necessary to achieve optimal conservation outcomes (Hartoni Siregar, 2022).

Benthic habitats in West Bali National Park (TNBB) are crucial for sustaining coastal ecosystem equilibrium and enhancing blue carbon sequestration. Nevertheless, data concerning the spatial distribution of benthic ecosystems within the park remains insufficient. Conversely, advancements in remote sensing technology and machine learning provide expedited and precise mapping of benthic habitats; nonetheless, the efficacy of each classification approach requires more investigation. Consequently, it is essential to analyze the precise distribution of benthic habitats and assess the relative efficacy of two machine learning classification techniques in mapping these habitats.

Literature Review

Benthic habitats are ecosystems that serve as habitats for benthos, organisms residing on the sediment at the bottom of a body of water. Shallow marine habitats or benthic habitats possess both ecological and economic functions that are beneficial for the management of coastal regions and tiny islands. Benthic habitats in Indonesia denote environments located at the substrates of aquatic bodies, particularly marine settings. Indonesia is an archipelagic nation, with approximately 75% of its territory comprised of coastal regions across more than 13,000 islands. Indonesia's waterways host marine biota ecosystems, including benthic habitats. The state of benthic habitats in Indonesia is highly varied and affected by multiple factors, including geography, anthropogenic activity, and environmental alterations (Sari & Syah, 2021).

Remote sensing technology is recognized as an effective means of rapidly acquiring information about things in extensive and inaccessible regions. It also offers benefits in the geographical and temporal updating of data, encompassing information on benthic ecosystems at the bottoms of aquatic environments. Satellite photography enables the rapid and economical detection and monitoring of alterations in the status of shallow water benthic ecosystems. Remote sensing technology, capable of capturing the appearance of objects through multispectral channels and possessing high spatial resolution, enables the acquisition of information regarding benthic habitat cover at the water's bottom, constrained by optical depth and the requirement of clear water. Remote sensing in clear shallow waters enables the image sensor to penetrate to a depth of 30 meters.

The classification system utilized in benthic habitat mapping is typically segmented into two tiers: the major classification scheme (level 1) and the detailed classification scheme (level 2) (Mumby & Harborne, 1999; Wicaksono, 2016). This study used a level 2 benthic habitat classification scheme, utilizing machine learning classification algorithms such as RF and SVM, which function most well with more specific class. The selection of this comprehensive approach was tailored to the attributes of PlanetScope imagery, which possesses a spatial resolution of around 3 meters, hence enabling detailed item detection based on the available visual information.

Random Forest Classification

RF is a machine learning methodology employed to enhance the precision of classification models. A study (Ginting et al., 2023) demonstrated the effective application of RF classification for categorizing benthic habitats, such as coral reefs, seagrass, macroalgae, and substrates, achieving an OA between 62.72% and 73%. The study demonstrated that optimal parameter configurations, including the utilization of 500 trees with a root mean square function for variable selection, yielded superior outcomes in the classification of benthic habitats. Ariasari et al. 2019 utilized RF to accurately map the composition and proportion of seagrass cover, achieving an OA in seagrass species classification ranging from 83.52% to 85.71%.

Support Vector Machine Classification

SVMs is a widely utilized and efficient classification approach in machine learning due to its capacity to handle data exhibiting both deep linear and non-linear correlations (Raychaudhuri et al., 2017). SVM seeks to identify a hyperplane that delineates data classes while minimizing the distance between them. Joutsijoki (2013) conducted a study utilizing SVM to categorize benthic habitats, which are crucial for evaluating water quality. The application of SVM in this instance yielded exceptional accuracy and exhibited proficiency in handling intricate data sets. The SVM use the Radial Basis Function (RBF) kernel attained an accuracy of 96.1% in the classification of benthic area.

Methodology Research Location

The research site is situated within the West Bali National Park (WBNP), Buleleng Regency, as illustrated in Figure 1. It is situated in the northern region of Bali Island and possesses significant marine potential. The shoreline in this region extends to 157.05 km. The coastal region of Buleleng Regency possesses significant tourism potential, characterized by an extensive coastal expanse suitable for optimization. The research site features a relatively flat topography, distinctive black sand beaches typical of Bali's northern coast, and is situated within a sheltered bay with comparatively tranquil waves. The research site was selected because to its significant benthic habitat potential, particularly for coral reefs, seagrass beds, and seabed substrates (Negara, 2020).

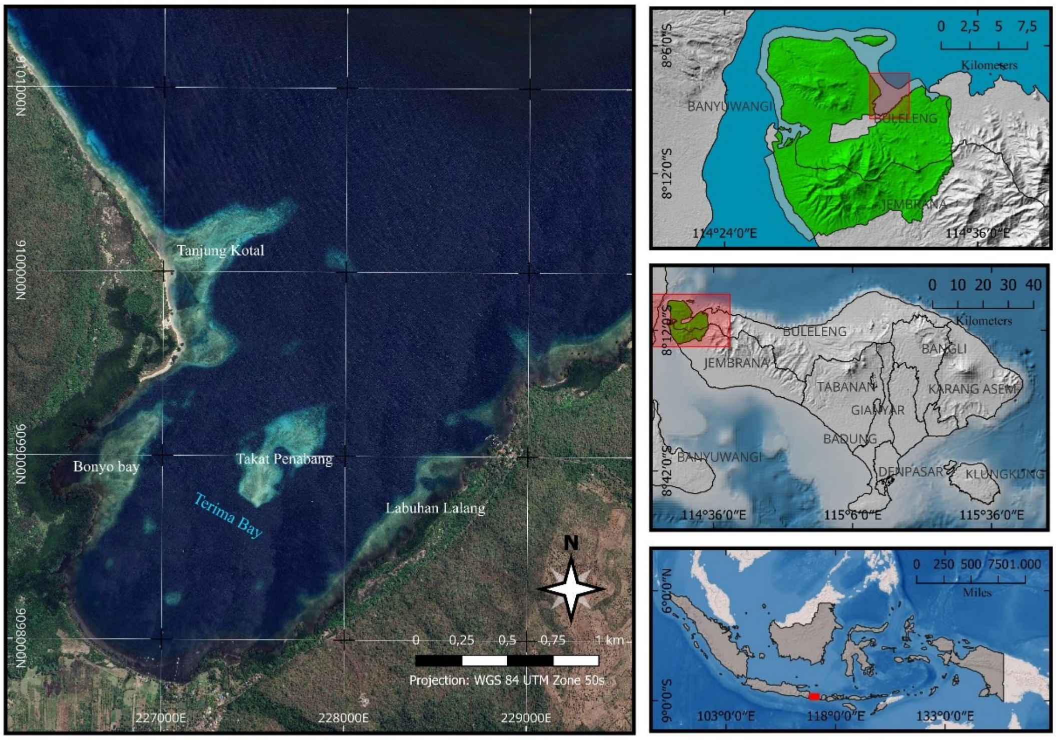

Figure 1: Study Area Map

Data Source

Based on the research conducted, the data used is shown in table 1.

Table 1: Research Data Source

Material	Data Description	Acquisition Date
PlanetScope SuperDove Imagery	Multispectral satellite imagery consisting of 8 spectral bands (coastal blue, blue, green I, green II, yellow, red, red edge, and near-infrared), used for benthic habitat classification and spectral analysis.	7 April 2025
Field Samples	A total of 3,893 georeferenced underwater photographs collected for ground-truth validation and training data.	2 - 3 July 2025

Research Flow

According to Figure 2, flow research of data collection through the field survey process in this study included preliminary data processing, sunglint correction, and water column correction of PlanetScope imagery, culminating in data processing to generate benthic habitat classification data through unsupervised ISODATA classification. Prior to executing the field survey, transects were established for field activities through on-screen digitization, utilizing the classification overlay and high-resolution imagery, in addition to formulating a field sampling timetable aligned with the anticipated tide schedule at the research site. During the data collection phase, GPS facilitated navigation to the transect line locations, and data collection responsibilities were allocated to each team member. Subsequently, photos were captured of each transect for the purposes of validation and training sample data, along with images of the field locations were utilized as supplementary data for analysis.

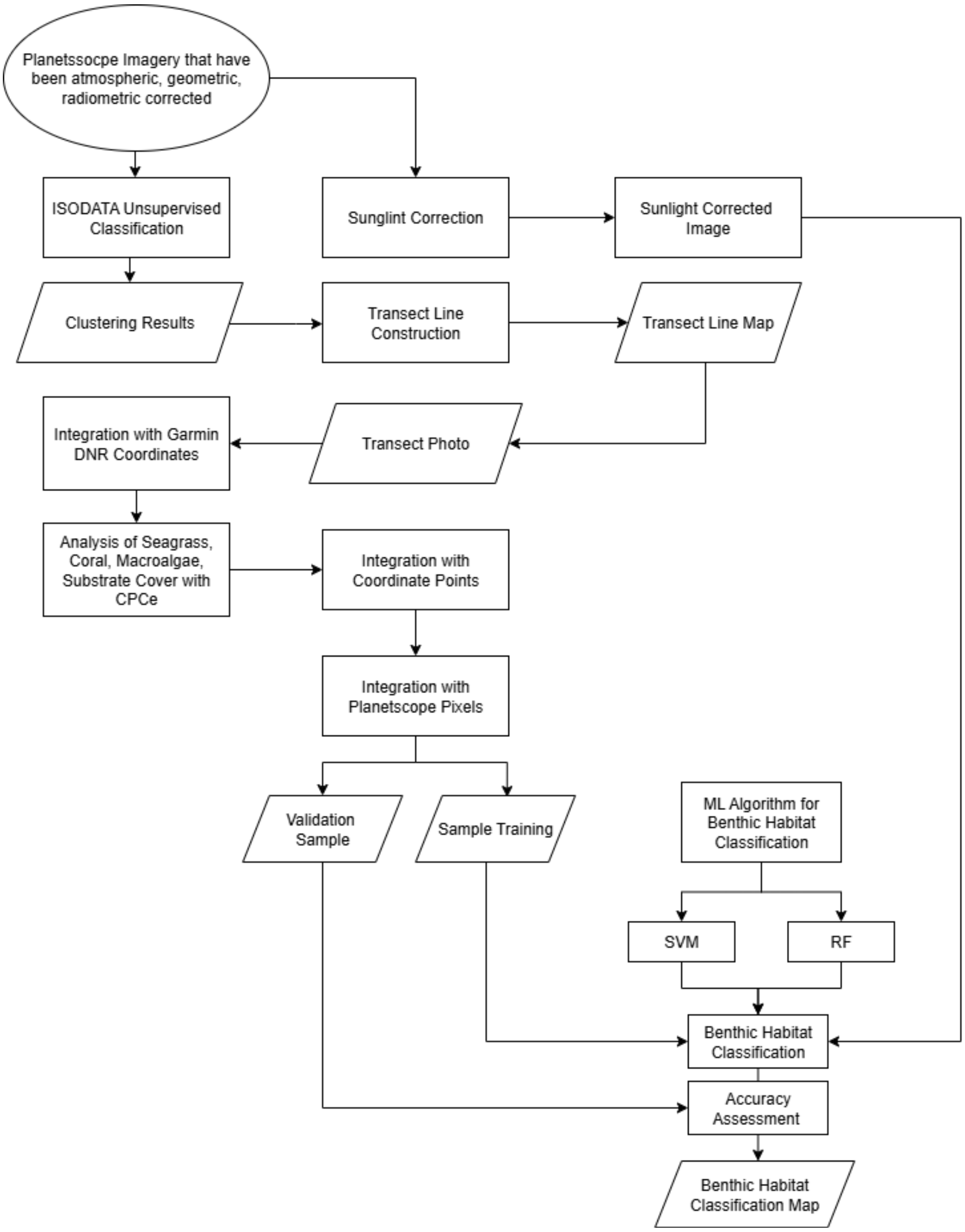

Figure 2: Research Flow

Data Processing

After collecting the data, photo transect data processing is conducted utilizing software for the validation and training samples derived from field survey results, followed by classification processing employing RF and SVM machine learning techniques by inputting the processed validation and training sample data into the Coral Point Count with Excel extensions (CPCe) software. After concluding the validation and training sample, accuracy assessment of the classification outcomes a benthic habitat map was created.

Results and Discussion

Field data gathering occurred over two days, from July 2 to July 3, in the seas of Teluk Terima to gather samples for validation and training data. Sampling was conducted using the photo transect approach at four distinct shallow marine sites: Tanjung Kotal, Teluk Bonyo, Takat Penabang, and Pelabuhan Labuhan Lalang. A total of 3,237 field samples were collected, however only 2,493 photographs persisted following the geotagging procedure, including GPS coordinates documented during the photo transect. Figure 3 illustrates an example of a field sample photograph. The photographs were subsequently analyzed utilizing CPCe software to ascertain the percentage coverage of each category of benthic habitat objects identified at the research site. Upon determining the percentage coverage, the sample photographs were categorized into two types training samples and validation samples.

a) b) c) d)

Figure 3: Sample Result Photos

a) Seagrass, b) Coral, c) Coral and Substrate, and d) Substrate and Algae

The samples were transformed into spatial data for application in the spatial analysis process through the spatial join feature, which integrates the percentage cover values from the field samples with the ISODATA classification polygons previously generated using PlanetScope SuperDove imagery. The outcomes of this sample integration were subsequently utilized as input for classification employing the RF and SVM algorithms to generate a benthic habitat mapping model with a specified level of precision.

Mapping Benthic Habitat Using Random Forest (RF)

A benthic habitat classification map for the Teluk Terima area was generated through the RF technique to map benthic habitat calssification. PlanetScope SuperDove imagery obtained on April 7, 2025, along with field samples, used as input data for the RF algorithm, generating a map illustrating the spatial distribution of benthic habitats in Teluk Terima, categorized into four distinct benthic habitat classes.

The variations in benthic habitat classes were visualized using distinct colors to illustrate the differences between each class in Figure 4. The distribution of seagrass specimens is predominantly observed along the shoreline of the study area. Mapping results show the presence of seagrass objects throughout the sites of Tanjung Kotal, Teluk Bonyo, Takat Penabang, and Pelabuhan Labuhan Lalang. The length of the transects created for sampling from the edge to the coastline shows a pattern of variation in benthic habitat composition. Many seagrass specimens were found along the coast, several types of substrate and algae were found throughout the waters of Teluk Terima, and a significant number of corals were identified throughout Takat Penabang.

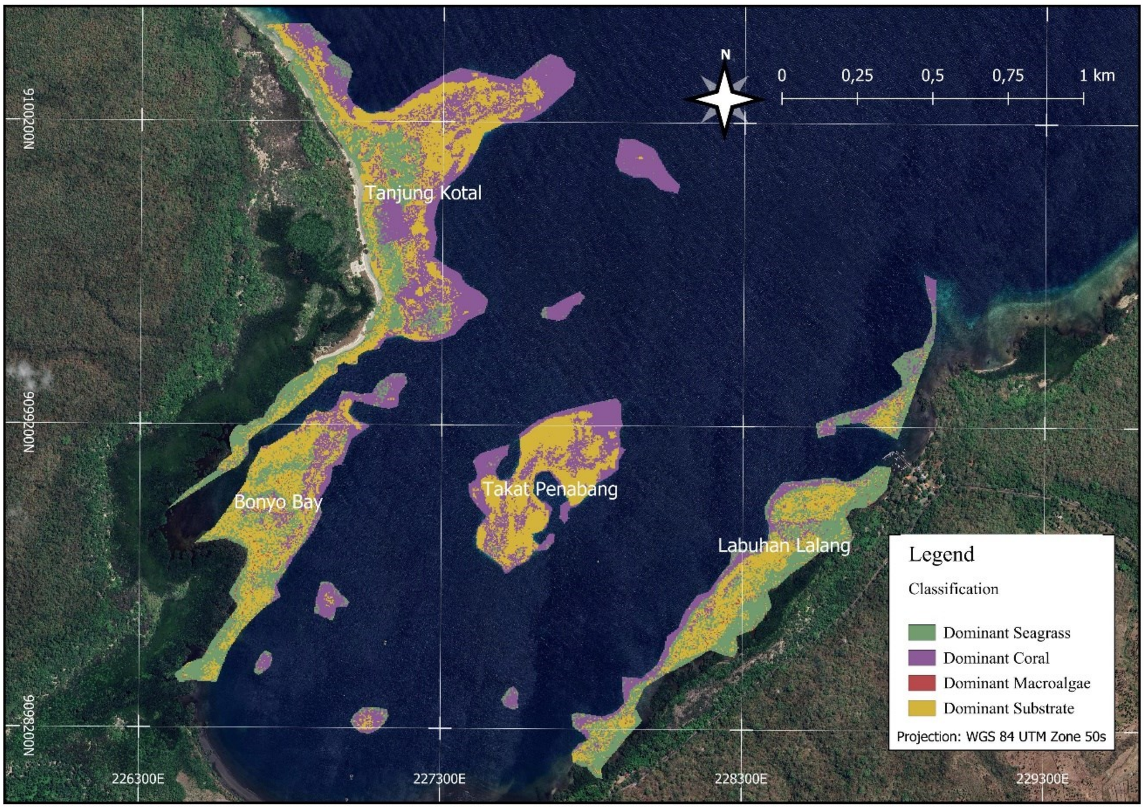

Figure 4: Benthic Habitat Map of Teluk Terima Using the RF Algorithm

Accuracy assessment was conducted utilizing a Confusion Matrix on RF classification model data, comprising 433 validation samples that were previously segregated during the data processing phase. The comprehensive outcomes of the accuracy assessment are presented in Table 2.

Table 2: Accuracy Assessment of benthic habitat maps using the RF (RF) algorithm

Class	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)
Dominant Seagrass	59.4	66.6	59.1
Dominant Coral	62.8	58.9	
Dominant Macroalgae	0	0	
Dominant Subtrate	56.8	57.7	

Table 2 presents the accuracy assessment outcomes for the benthic habitat classification derived from the Random Forest (RF) algorithm. The overall accuracy (OA) of 59.1% indicates that the classification performance remains within a moderate-to-low reliability range, suggesting that further refinement of the input data or additional feature enhancement is required to improve model precision. This moderate level of accuracy reflects the inherent complexity of discriminating spectrally similar benthic classes using medium-resolution multispectral imagery.

Examining class-specific accuracies provides further insight into the model's performance. In the Dominant Seagrass category, the User's Accuracy (UA) of 59.4% indicates that approximately 59% of pixels classified as seagrass correspond to true seagrass observations in the field. Meanwhile, the Producer's Accuracy (PA) of 66.6% reveals that roughly one-third of the actual seagrass cover was incorrectly assigned to other classes. These findings suggest that although seagrass is relatively well identified, the classification still experiences considerable omission errors, likely due to spectral overlap with neighboring classes such as macroalgae or sandy substrates.

In the Dominant Coral category, the UA of 62.8% and PA of 58.9% imply a moderate classification performance. While a substantial proportion of coral pixels are correctly identified, notable misclassifications persist. This issue may be attributed to the spectral similarity between coral and other benthic substrates, particularly sandy areas or coral regions partially covered by macroalgae, which obscure their spectral distinctiveness.

For the Dominant Substrate class, the UA and PA values of 56.8% and 57.7%, respectively, indicate a balanced yet moderate level of reliability, with approximately 40% of substrate pixels being misclassified. Such misclassifications are common in benthic mapping, especially where substrate textures vary spatially or are confounded by water column effects.

The Dominant Macroalgae class exhibits the poorest classification performance, with both UA and PA recorded at 0%. This complete absence of correct classification suggests that the RF model failed to distinguish macroalgae from other categories. The misclassification may stem from insufficient or imbalanced training samples, spectral confusion with seagrass, or the presence of small macroalgae patches that fall below the detection threshold of the PlanetScope SuperDove imagery. Consequently, this result emphasizes the need for targeted improvement through additional ground truth data or the integration of higher-resolution or hyperspectral imagery.

Spatially, the classification map reveals that the Dominant Substrate class occupies the largest area (40.2 ha), followed by Dominant Coral (35.9 ha), Dominant Seagrass (27.3 ha), and Dominant Macroalgae (0.5 ha). The predominance of substrate and coral areas indicates that these two classes constitute the major benthic components within the Teluk Terima region. Meanwhile, the considerable extent of seagrass coverage highlights the presence of a well-established seagrass ecosystem, particularly in nearshore zones. These spatial patterns collectively reflect the benthic community composition and provide valuable baseline information for future monitoring and management of coastal habitats in the study area.

Mapping Benthic Habitats Using Support Vector Machine (SVM)

The SVM algorithm was employed to map the benthic habitat in the Teluk Terima area, resulting in a benthic habitat classification map. PlanetScope SuperDove imagery obtained on April 7, 2025, along with field samples, served as input data for the SVM method, resulting in a map that delineates the spatial distribution of benthic habitats in Teluk Terima, categorized into four distinct benthic habitat classes. The variations in benthic habitat classes were visualized with distinct colors in Figure 5: the dominant seagrass class in green, the dominant coral reef class in purple, the dominant macroalgae class in red, and the dominant substrate class in yellow.

The distribution of seagrass habitat is predominantly observed along the shoreline of the study area, indicated in green on the map. The mapping results revealed a limited number of seagrass specimens at the Takat Penabang site, situated in the bay's central area. However, upon collection of field samples at that site, no seagrass specimens were identified, leading to the assumption that a classification error occurred at this location. The transect extending from the seashore to the beach's edge revealed a pattern of variations in the characteristics of the benthic habitat composition. Seagrass specimens were located along the Labuhan Lalang area, substrate materials were identified in the Takat Penabang at central area Teluk Terima, and corals were discovered adjacent to the boundary other than Labuhan Lalang area.

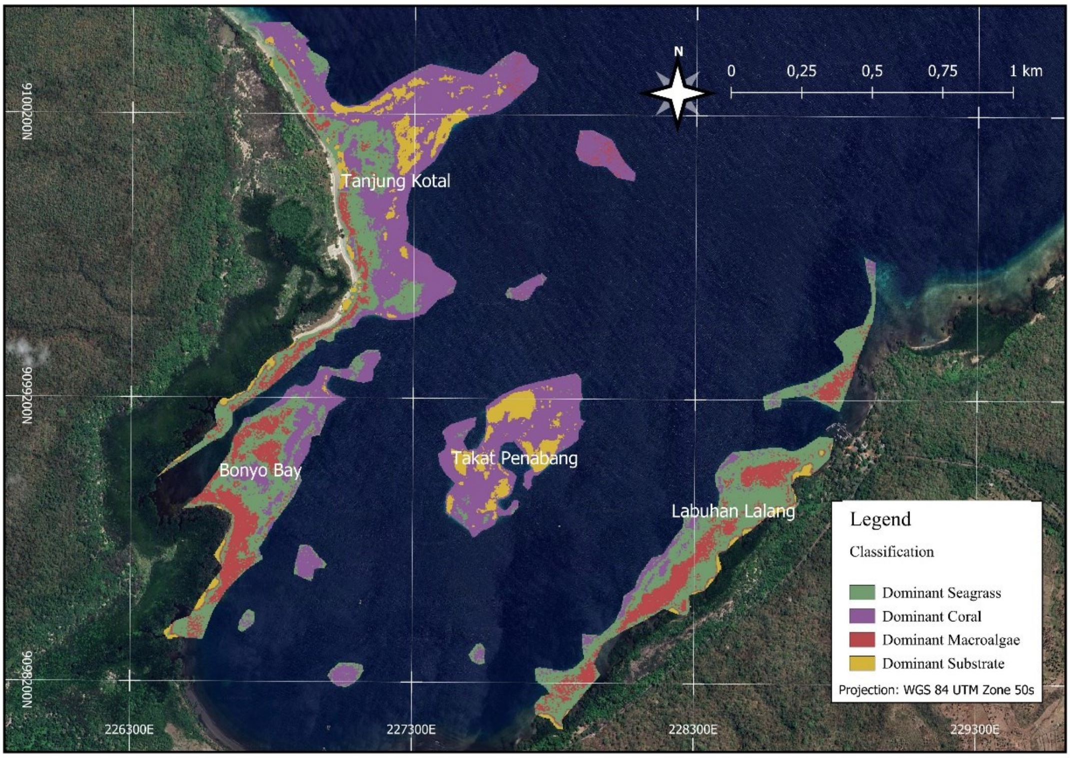

Figure 5: Benthic Habitat Map of Teluk Terima Using the SVM Algorithm

The comprehensive findings of the accuracy assessment are presented in Table 3. According to Table 3, the benthic habitat classification results utilizing the SVM technique exhibit an OA of 47.3%, signifying that the classification precision for this category is comparatively inadequate and requires enhancement. The accuracy of benthic habitat class identification differs among classes. In the Dominant Seagrass class, the User's Accuracy value of 50.9% signifies that almost half of the pixels identified as seagrass correspond with the reference data collected in the field. Meanwhile, the Producer's Accuracy of 56.7% signifies a substantial omission error, since over 40% of the seagrass cover field was inaccurately identified. The OA for the seagrass class is 47.3%, signifying that the classification accuracy for this category is rather poor and requires enhancement.

Table 3: Accuracy assessment of benthic habitat maps using the SVM algorithm

Class	User's Accuracy (%)	Producer's Accuracy (%)	Overall Accuracy (%)
Dominant Seagrass	50.9	56.7	47.3
Dominant Coral	52.5	81.4	
Dominant MacroAlgae	0.8	75	
Dominant Substrate	83.3	18.2	

In the Dominant Coral class, the user's accuracy of 52.5% reflects a moderate degree of confidence, whereas the producer's accuracy attains 81.4%. The elevated producer value signifies that the majority of coral regions in the field were accurately identified. Conversely, the Dominant Macroalgae class exhibits a minimal user's accuracy of merely 0.8%, while demonstrating a relatively high producer's accuracy of 75%. This suggests that while the majority of macroalgae in the field are identified (resulting in a low omission error rate), numerous pixels classified as macroalgae do not correspond to actual macroalgae in the field, leading to a significantly high commission error rate.

The Dominant Substrate class exhibits a contrasting trend, characterized by a high User's Accuracy of 83.3% and a low Producer's Accuracy of 18.2%. This indicates that nearly all pixels identified as substrate correspond to actual substrate in the field (low commission error), yet a significant portion of substrate areas in the field are not classified as substrate (high omission error). This pattern signifies the model's constraint in identifying all substrate regions, despite the predictions produced for this category being comparatively dependable.

Following the execution of accuracy assessments, the classification model can elucidate the distribution of diverse benthic habitat classifications in the Teluk Terima region. The classification results indicate that Dominant Coral encompasses the largest area, approximately 43.9 hectares, followed by Dominant Seagrass at 35.4 hectares, Dominant Macroalgae at 15.5 hectares, and Dominant Substrate at 9.2 hectares. The prevalence of coral and seagrass in the study area signifies that the ecosystem remains relatively abundant in biotic cover, with these organisms crucial for sustaining coastal ecosystem.

Comparison of Benthic Habitat Mapping Results Using Random Forest and Support Vector Machine Algorithms

Table 4 presents the mapping outcomes utilizing RF and SVM in the benthic habitat investigation in Teluk Terima, revealing notable discrepancies in accuracy and class distribution. Overall, RF exhibits a superior accuracy of 59.1%, whilst SVM attains just 47.3%. This enhances the stability of RF in overall classification, particularly within the seagrass and substrate categories, despite the presence of significant classification mistakes. In the seagrass classification, RF attained a user's accuracy of 59.4% and a producer's accuracy of 66.6%, surpassing SVM, which recorded 50.9% and 56.7%, respectively. In contrast, within the coral classification, SVM demonstrated dominance with a producer's accuracy of 81.4%, correctly detecting the majority of corals in the field, despite a user's accuracy of just 52.5%. In the macroalgae classification, RF (RF) exhibited a total failure with 0% accuracy, but SVM successfully identified the majority of macroalgae, achieving a producer's accuracy of 75%. However, the credibility of these results was significantly compromised, as the user's accuracy was at 0.8%. In the substrate class, RF achieved moderate accuracy, approximately 57% for both indicators, whereas SVM exhibited a contrasting trend, demonstrating a high user's accuracy of 83.3% but a low producer's accuracy of 18.2%. This indicates that a significant portion of the substrate areas in the field remained unclassified, despite the reliability of the predictions made.

In terms of area distribution, RF indicates the predominance of substrate and coral, whereas SVM emphasizes the existence of biotic components with extensive expanses of coral, seagrass, and macroalgae. Consequently, RF excels in mapping that necessitates consistency and stability among classes, whereas SVM is more advantageous for targeted detection, such as coral or macroalgae; however, the results must still be corroborated with field validation to avoid biased ecological interpretations

Table 4: Comparison of Benthic Habitat Mapping Results Using RF and SVM

Aspect	Random Forest (RF)	Support Vector Machine (SVM)
Overall Accuracy (OA)	59.1%. Classified within a moderate–low accuracy range; overall performance relatively higher compared to SVM.	47.3%. Lower overall accuracy, indicating relatively poor classification reliability.
Seagrass	UA: 59.4%; PA: 66.6%. Demonstrates relatively stable performance with balanced omission and commission errors.	UA: 50.9%; PA: 56.7%. Lower classification accuracy with notable omission errors.

Coral	UA: 62.8%; PA: 58.9%. Moderate performance, yet with evident misclassification among benthic classes.	UA: 52.5%; PA: 81.4%. Exhibits strong capability in detecting coral (high PA) but with moderate classification consistency.
Macroalgae	UA: 0%; PA: 0%. Complete failure in detecting macroalgae presence.	UA: 0.8%; PA: 75%. Successfully detects most macroalgae occurrences, yet highly unreliable due to extreme commission errors.
Substrate	UA: 56.8%; PA: 57.7%. Moderate and balanced predictive capacity between user and producer accuracy.	UA: 83.3%; PA: 18.2%. Highly reliable predictions (high UA), but substantial omission of actual substrate areas (low PA).
Class Area Distribution	Substrate (40.2 ha) > Coral (35.9 ha) > Seagrass (27.3 ha) > Macroalgae (0.5 ha). Indicates substrate dominance across classified habitats.	Coral (43.9 ha) > Seagrass (35.4 ha) > Macroalgae (15.5 ha) > Substrate (9.2 ha). Reflects biotic dominance (coral and seagrass) in classification outcomes.

Conclusion and Recommendation

The RF method classified benthic habitats into four categories: seagrass-dominant, coral reef-dominant, macroalgae-dominant, and substrate-dominant. Each benthic habitat encompasses 27.3 ha for seagrass dominance, 35.9 ha for coral reef dominance, 0.5 ha for macroalgae dominance, and 40.2 ha for substrate dominance. UA for the seagrass class was 59.4%, surpassing the SVM's 50.9% for the same class, however the RF achieved 56.8% for the substrate class, which is inferior than SVM 83.3%. SVM classification yields a distinct distribution of regions, with seagrass covering 35.4 ha, coral 43.9 ha, macroalgae 15.5 ha, and substrate 9.2 ha, alongside an OA of 47.3%, which is inferior to RF 59.1%. This disparity signifies that RF is superior in differentiating benthic habitat classification.

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