Volume 18, No. 3, 2025

ISSN: 1907-9931 (print), 2476-9991 (online)

COMPARATIVE PERFORMANCE EVALUATION OF MACHINE LEARNING ALGORITHMS FOR SENTINEL-2 BENTHIC HABITAT CLASSIFICATION USING GOOGLE EARTH ENGINE

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Submitted: 13 November 2025 / Revised: 17 November 2025 / Accepted: 27 November 2025

http://doi.org/10.21107/jk.v18i3.32389

ABSTRACT

This study evaluates the optimal classification methodology and analyzes temporal changes over five years across four benthic habitat classes (Seagrass, Coral Reef, Rubble, and Sand) in the shallow waters of Ohoidertawun, Southeast Maluku, using Sentinel-2 imagery and the Google Earth Engine (GEE) platform. A comparative assessment of Machine Learning (ML) algorithms revealed that Random Forest (RF) demonstrated the best classification performance compared to Support Vector Machine (SVM), Classification and Regression Tree (CART), K-Nearest Neighbors (KNN), and Minimum Distance (MD) in benthic habitat mapping, achieving an Overall Accuracy of 0.856 and a Kappa Coefficient of 0.870. The classification results and accuracy assessment using the best-performing ML model from the 2025 Sentinel-2 imagery were used to analyze temporal changes relative to the 2020 Sentinel-2 data. Temporal analysis indicated a significant ecosystem shift, marked by a 52.41% increase in seagrass cover and a 31.46% decrease in coral reef area. These findings can serve as a recommendation for conservation site selection and urge stakeholders to help mitigate coral reef loss by utilizing the results of this research. The resulting benthic habitat map can serve as a reference for effective coastal resource management and blue carbon initiatives. Based on these findings, the Random Forest ML algorithm can be considered an optimal methodology for tropical benthic habitat mapping in the study area.

Keywords: *Benthic Habitat, Sentinel-2, Machine Learning, Google Earth Engine*

INTRODUCTION

Coastal benthic habitats, such as coral reefs, seagrass meadows, and macroalgae, represent critical biodiversity hotspots that underpin numerous ecosystem services globally, yet they remain highly susceptible to anthropogenic pressures and climate change (Misiuk and Brown, 2024). Accurate and up-to-date spatial information on the distribution and extent of these habitats is paramount for effective marine spatial planning, conservation management, and sustainable resource exploitation (Burns *et al.,* 2022). Historically, mapping efforts relied heavily on expensive and time-consuming in-situ surveys, which are impractical for large geographical areas (Yeong *et al.,* 2024). Consequently, remote sensing technology has emerged as an indispensable tool, offering both efficiency and repeatability. Specifically, the open-access Sentinel-2 satellite imagery is frequently leveraged for mapping shallow water environments due to its high spatial resolution (10–20 m) and favorable temporal resolution, providing sufficient spectral information to distinguish various bottom types (Hartoni *et al.,* 2022; Zibar *et al.,* 2024).

Despite the potential of Sentinel-2, the overall mapping accuracy is fundamentally constrained by the choice of the classification algorithm, particularly when dealing with the complex spectral signatures inherent in sub-aquatic environments (Van an *et al.,* 2023). Traditional parametric statistical methods, such as Maximum Likelihood, often struggle with the non-linear relationship between spectral data and benthic classes (Wicaksono *et al.,* 2019). In contrast, Machine Learning (ML) techniques

have demonstrated superior performance, acting as robust non-parametric classifiers capable of handling the high-dimensional and non-linear characteristics of remote sensing data (Ghayour *et al.,* 2021). Algorithms like Random Forest (RF) and Support Vector Machine (SVM) are widely recognized for achieving high accuracies in marine habitat classification due to their distinct algorithmic approaches (Patil and Panhalkar, 2023; Wahidin *et al.,* 2015).

The successful application of remote sensing in mapping benthic habitats is highly dependent on effective pre-processing, most notably the Water Column Correction (WCC). The attenuation of light through the water column severely masks the true spectral signature of the seabed, necessitating robust WCC algorithms to isolate the benthic signal (Vahtmäe *et al.,* 2020). This pre-processing step is especially crucial in tropical archipelagic regions like Southeast Maluku, which are characterized by high biological complexity, varied water quality, and high conservation value. Studies targeting these complex, data-poor, but ecologically rich areas are scarce, particularly since benthic habitats with rich biodiversity in the eastern parts of Indonesia are yet to be mapped. Consequently, local decision-makers lack definitive data on the optimal classification methods, as most maps produced by government institutions often do not report accuracy assessments (Wicaksono, 2016; Thomasberger *et al.,* 2023).

Despite the success of individual machine learning applications, there remains a need for a direct and comprehensive comparative evaluation across a wider spectrum of machine learning techniques (Wicaksono *et al.,* 2019). Existing literature often focuses on comparing only two or three algorithms, leaving a gap in understanding the relative performance of other established classifiers. To fill this gap, this study systematically includes five diverse classifiers: the ensemble method (Random Forest), the hyperplane-based method (SVM), and three simpler, yet crucial algorithms, including the splitting techniques of Classification and Regression Tree (CART) and Minimum Distance (MD) as well as the proximity-based technique of K-Nearest Neighbor (KNN) (Thomasberger *et al.,* 2023). The comparative analysis is essential to provide definitive guidance on the most suitable algorithm—in terms of accuracy and robustness—for routine, pixel-based Sentinel-2 benthic mapping (Ghayour *et al.,* 2021).

The execution of a large-scale, multi-algorithmic comparison on vast Sentinel-2 datasets, alongside necessary WCC procedures, poses significant computational challenges. These are effectively mitigated by leveraging Google Earth Engine (GEE), a cloud-computing platform that offers access to the entire Sentinel-2 archive and the necessary parallel processing power to execute multiple ML algorithms simultaneously and efficiently (Patil *et al.,* 2023; Gorelick *et al.,* 2017). By implementing the comparative framework within GEE, the study ensures the methodology is highly reproducible and scalable for future applications across different geographical regions. herefore, this study aims to evaluate and identify the optimal ML classifier (RF, SVM, CART, KNN, MD) for Sentinel-2-based benthic habitat mapping using Google Earth Engine, with temporal comparison from 2020–2025. This research endeavors to provide a robust technical benchmark, identifying the optimal classifier that yields the highest accuracy and offers the best balance of computational efficiency for routine benthic habitat monitoring.

MATERIALS AND METHODS

Location and Data

This research was conducted in Ohoidertawun Southeast Maluku, field data collection (ground truthing), crucial for model calibration and accuracy assessment, was performed betweeen September and October 2025.

The primary data source was Sentinel-2B Level-2A multispectral satellite imagery, which provides a spatial resolution of 10×10 metres. The selection of Level-2A imagery ensures that the data has been automatically subjected to Atmospheric Correction by the European Space Agency (ESA), thus yielding surface reflectance data suitable for subsequent analysis. Image selection criteria required minimal cloud cover (<10%), good visual quality, and an acquisition date as close as possible to the field survey period. The spectral bands relevant for shallow water benthic habitat mapping used in this analysis include Band 2 (Blue), Band 3 (Green), Band 4 (Red), and Band 8 (NIR). All stages of image pre-processing, water column correction, and classification algorithm implementation were executed using the Google Earth Engine (GEE) platform. GEE was chosen for its capability to provide comprehensive access to the Sentinel-2 archive and to utilize planet-scale parallel processing, which is essential for the efficient and reproducible comparative analysis of multiple algorithms.

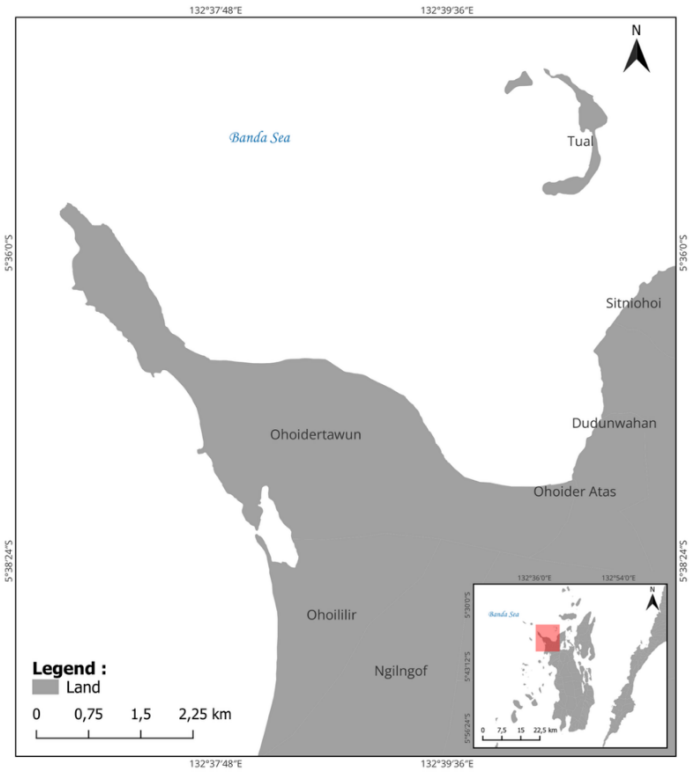


Figure 1. Map of the study area in Ohoidertawun, Southeast Maluku, Indonesia

Field Data Collection

Field data collection, a critical component for model training and classification validation, was conducted from September to October 2025. The methodology employed was Stratified Random Sampling, ensuring a representative distribution of ground truthing points across all expected benthic habitat classes within the area of interest. Data acquisition utilized the "rapid mobile" survey method, where researchers collected high-precision Global Positioning System (GPS) coordinates while simultaneously performing direct visual observation to determine the dominant substrate cover (Nugroho *et al.,* 2024). These observations were strictly categorised into four definitive benthic classes: Seagrass, Sand, Coral, and Rubble, forming the foundational truth data. Subsequently, the total collected points were independently and rigorously partitioned into two subsets: a Training Dataset used exclusively to calibrate the machine learning algorithms, and a separate Validation Dataset reserved solely for the final, unbiased assessment of classification accuracy.

Benthic Habitat Analysis and Classification

The analysis stage commenced with the pre-processing of Sentinel-2 imagery, implemented entirely within the cloud-computing environment of Google Earth Engine (GEE) (Gorelick *et al.,* 2017; Traganos *et al.,* 2018). The first critical step involved the application of Water Column Correction (WCC) to mitigate the spectral distortion caused by light attenuation within the water column (Vahtmäe *et al.,* 2020; Traganos *et al.,* 2018; Siregar *et al.,* 2018). This procedure is imperative for isolating the true benthic reflectance signal, particularly in clear tropical waters. Subsequently, pixel-based benthic habitat classification was performed to evaluate the comparative performance of five Machine Learning (ML) algorithms: Random Forest (RF), Support Vector Machine (SVM), Classification and Regression Tree (CART), Minimum Distance (MD) and K-Nearest Neighbor (KNN) (Nugroho *et al.,* 2024; Alifatri *et al.,* 2022). These five structurally diverse algorithms were trained using the meticulously collected field data, aiming to identify and map the spectral patterns corresponding to the Seagrass, Sand, Coral, and Rubble classes. The comprehensive performance comparison, ranging from the ensemble method (RF) to the proximity-based method (KNN), seeks to definitively identify the classifier that is most accurate, reliable, and computationally efficient for routine benthic habitat monitoring in the Maluku region (Thomasberger *et al.,* 2023).

The classification maps and attribute tables were subsequently processed using QGIS

software for map layouting and habitat area extraction. The statistical analysis and algorithmic performance evaluation utilized the Confusion Matrix method, which was implemented within the Google Earth Engine (GEE) environment (Gorelick *et al.,* 2017). To train and validate the algorithms, a total of 500 field data points were employed, specifically distributed across the four benthic habitat classes used in the classification (Seagrass, Coral Reef, Rubble, and Sand). These points were partitioned into two sets: 400 points were dedicated to training the five classification algorithms (RF, SVM, CART, KNN, and MD), and 100 independent points were reserved for objective validation to calculate the accuracy metrics, specifically the Overall Accuracy and the Kappa Coefficient (Landis & Koch, 1977).

Accuracy Assessment and Performance Evaluation

The reliability of the final habitat maps generated by the five Machine Learning algorithms was quantified through a rigorous Accuracy Assessment based on the Confusion Matrix (Error Matrix). This matrix compared the classified pixel category against the independent Validation Dataset derived from the field observations, thereby providing an objective measure of classification performance. The assessment focused on three key metrics, calculated in accordance with the standard methodology proposed by Congalton and Green (2009). These metrics included the Overall Accuracy (OA), representing the total proportion of correctly mapped pixels; the Producer's Accuracy (PA), which measures the completeness of the classification for individual classes; and the User's Accuracy (UA), which indicates the reliability and correctness of the classification results. Kappa Coefficient which is statistically more robust as it measures the agreement between classification and ground truth while factoring out agreement occurring by chance, served as the primary comparative metric to definitively determine the optimal algorithm that yielded the highest performance for benthic habitat monitoring in the study area.The calculation of each accuracy was performed using the following equation (Congalton and Green, 2009) :

$$Overall\ accuracy\ = \frac{\sum_{i=1}^{k} nii}{n} \quad \text{..... (1)}$$

$$Producer's\ accuracy\ = \frac{n_{jj}}{n_{+j}} \quad \text{..... (2)}$$

$$User's\ accuracy\ = \frac{n_{ii}}{n_{i+}} \quad \text{..... (3)}$$

$$Kappa\ accuracy = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} x_i + x_{+i}}{N^2 - \sum_{i=1}^{r} x_i + x_{+1}} \times 100\% \quad \text{..... (4)}$$

RESULTS AND DISCUSSION

Benthic habitat mapping utilizing satellite imagery necessitates a series of pre-processing stages to optimize image visual quality and ensure data accuracy prior to analysis. The core steps of this pre-processing routine include layer stacking, image cropping, and atmospheric correction, in addition to standard radiometric and geometric corrections. Layer stacking is fundamental as it consolidates multiple spectral bands into a single layer, enabling the user to select the appropriate Red-Green-Blue (RGB) color composites and process the data according to analytical requirements. Subsequently, image cropping is performed to delineate the study area exclusively to the waters of Southeast Maluku, thus focusing the computational analysis. Most critically, atmospheric correction is applied to eliminate errors and noise resulting from atmospheric interference, which significantly improves the clarity and brightness of the image visual, both across shallow waters and land features, thereby yielding more accurate pixel values (Digital Numbers) for subsequent classification (Kurniawati *et al.,* 2025).

The visualization of benthic habitat classification results in the waters of Southeast Maluku, reveals notable qualitative differences among the algorithms. The map produced by the Random Forest (RF) algorithm exhibits the most cohesive boundary separation between habitat classes (Seagrass, Coral, Sand, Rubble) and demonstrates minimal salt-and-pepper noise (**Figure 2**). Conversely, the map generated by the Minimum Distance (MD) algorithm appears patchy, characterized by rough class boundaries and high fragmentation. This visual discrepancy directly indicates the superior spectral discrimination capability of ensemble-based algorithms like RF compared to simple distance-based classification (Richards & Jia, 2006). The resulting variation in classification accuracy inherently leads to a disparity in habitat area estimation, a critical parameter for effective conservation management (**Table 1**).

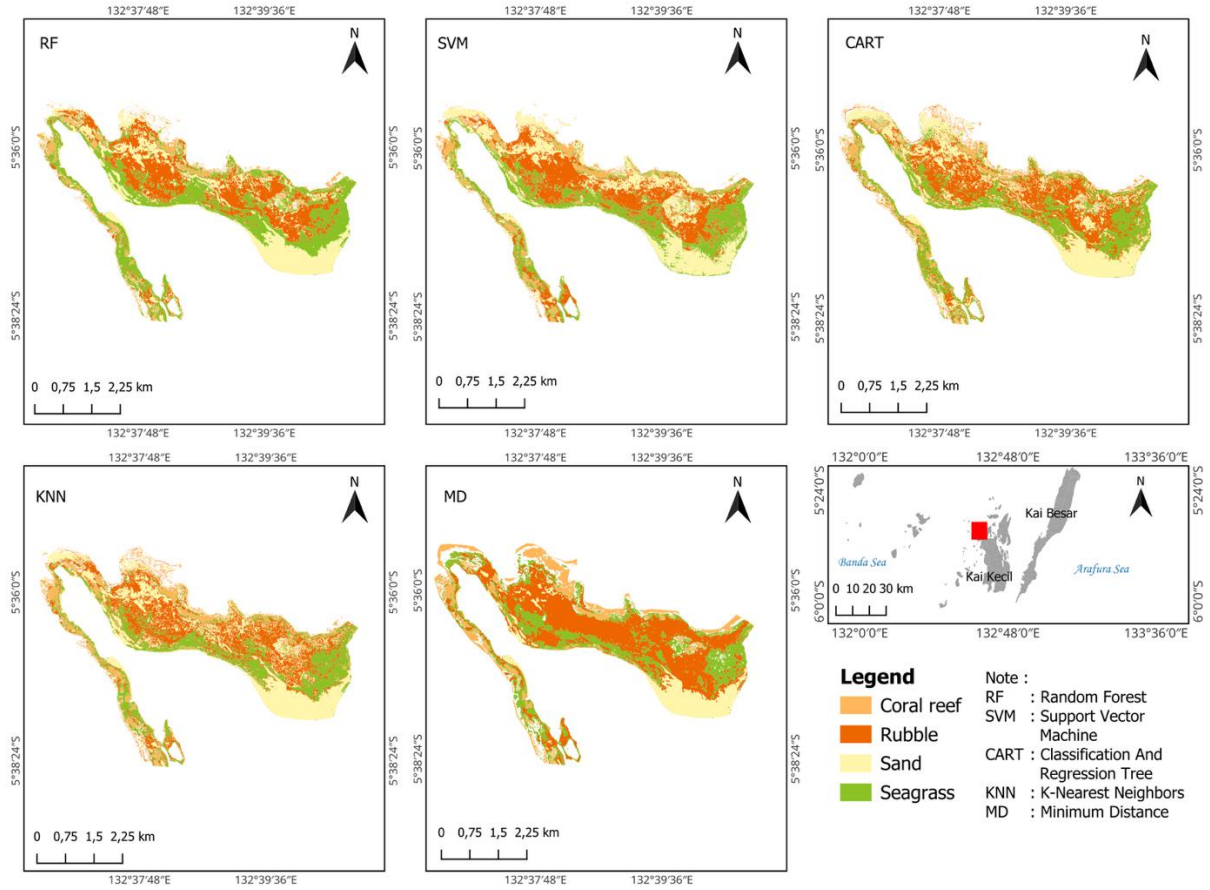


Figure 2. Classification Results of Five Machine Learning Algorithms

Table 1. Area Extent of Benthic Habitats

Benthic Objects	Area of Benthic Habitats Based on Machine Learning Algorithms (ha)				
	RF	SVM	CART	KNN	MD
Sand	379.78	426.94	449.77	429.45	198.54
Rubble	471.06	520.29	517.19	635.28	722.52
Coral Reef	112.28	128.89	138.16	168.85	225.41
Seagrass	569.66	446.07	451.61	399.12	412.28

For the Seagrass class, the area estimation varied most extremely between RF (569.66 Ha) and KNN (399.12 Ha). This substantial difference of 170 Ha (approximately 30%) suggests that algorithms with comparatively lower accuracy (such as KNN, SVM, and CART) exhibit a tendency to misclassify Seagrass as other classes (e.g., Sand or Rubble). This misclassification is primarily attributed to spectral similarity caused by sparse Seagrass cover or variations in water depth (Green *et al.,* 2000).

Regarding the Rubble and Coral classes, the MD algorithm yielded the highest area estimates for both Rubble (722.52 Ha) and Coral (225.41 Ha), while simultaneously producing the lowest estimate for Sand (198.54 Ha). This illogical pattern indicates that MD had severe difficulty distinguishing Rubble from Sand and also improperly grouped sparse Seagrass and dead Coral into the Rubble class. This failure proves that the MD algorithm is insensitive to the subtle spectral differences that determine the distinction between Live Coral (which typically occupies a small area) and Coral Rubble (Richards & Jia, 2006). Conversely, RF produced the lowest Coral area estimate and the most reasonable Sand estimate, consistent with its proven high accuracy. This comparison of area estimates affirms that accuracy metrics (Overall Accuracy and Kappa) are essential for quantitative validation. Without this vital validation, area estimations—which serve as the basis for carbon stock assessment—can be misleading and ultimately unreliable for conservation planning.

Table 2. Overall Accuracy and Kappa Values

Index	Machine Learning Accuracy				
	RF	SVM	CART	KNN	MD
Overall Accuracy	86%	78%	75%	78%	54%
Kappa	0.87	0.72	0.69	0.72	0.43

The RF algorithm led not only in logical area estimation but also statistically. RF achieved an OA of 86% (0.86) and a Kappa Coefficient of 0.87,(**Table 2**) which is classified as a "Very Good" or near-perfect agreement level (Landis & Koch, 1977). This superior performance is attributed to its ensemble learning nature, which involves the construction of hundreds of decision trees from different data subsets. This majority voting process effectively stabilizes the classification and enhances RF's ability to handle multispectral data characterized by high non-linear complexity, which is characteristic of the benthic environment (Breiman, 2001; Pal, 2005). The SVM and KNN algorithms secured the second position with identical performance (OA 78% or 0.78; Kappa 0.720), classified as "Good" agreement. The strong performance of SVM demonstrates that its hyperplane method can effectively separate classes in high-dimensional space (Mountrakis *et al.,* 2011). CART lagged slightly (OA 75% or 0.75; Kappa 0.690), reinforcing the finding that single decision trees tend to be less stable than ensemble methods.

Conversely, the Minimum Distance (MD) algorithm demonstrated significantly limited accuracy, achieving an OA of 54% (0.54) and a Kappa of 0.430. This low accuracy is primarily due to its simplistic reliance on Euclidean distance, rendering it incapable of handling the high spectral variance induced by depth gradients and water quality in Ohoidertawun's complex environment. The analysis of habitat change reveals a more critical ecological dynamic: The sharp decline of the Coral Reef area (31.46%) implies severe habitat degradation, possibly driven by sedimentation or recurrent thermal stress (Hughes *et al*., 2018). Simultaneously, the significant Seagrass expansion (52.41%) may indicate newly colonized recovery zones, which is beneficial for ecosystem function, particularly in enhancing blue carbon sequestration (Short *et al.,* 2007). This reinforces the necessity of using only sophisticated non-linear algorithms like RF to generate reliable maps that accurately inform urgent ecological interpretations.

The comparative analysis of the Shallow Water Coastal Habitat area in the waters of Southeast Maluku, between 2020 and 2025 demonstrates a significant ecosystem shift over the five-year period (**Figure 3**). This change is interpreted as resulting from a combination of natural and anthropogenic factors that influence the health and composition of the seafloor substrate (Green *et al.,* 2000). The most striking change is observed in the Seagrass area, which experienced a 52.41% expansion (increasing from 373.76 Ha in 2020 to 569.66 Ha in 2025) (**Table 3**). This increase in Seagrass coverage represents a positive indicator of marine ecosystem health. Seagrass expansion can be attributed to several factors, including enhanced area protection, improved water quality, or optimal environmental conditions for growth (such as the availability of stable Sand substrate and adequate water clarity following Water Column Correction). This increase in Seagrass is of critical importance given its vital role as a blue carbon sink and a nursery ground for marine organisms.

In contrast to Seagrass, Coral Reef area experienced the most drastic decline, amounting to 31.46% (from 163.82 Ha down to 112.28 Ha). This substantial reduction over a five-year period indicates serious ecological stress within the waters. Dredging, destructive fishing practices, or mass bleaching events caused by rising sea surface temperatures are the primary drivers frequently associated with the rapid global decline of coral cover. The change in the area of the Rubble (Coral Rubble) class showed a decrease of 9.44% (from 520.17 Ha to 471.06 Ha). This reduction can be linked to the decline in Coral Reefs. However, the significantly larger reduction in Coral (31.46%) compared to Rubble (9.44%) suggests two possibilities: first, that older coral rubble material has been eroded into Sand; or second, that the lost Coral was not entirely detected as Rubble, but rather as newly established Seagrass or Sand. The Sand class experienced only a marginal increase in area of 1.78% (from 373.13 Ha to 379.78 Ha). The relatively stable change in Sand, despite potential conversion from Rubble, indicates that Sand serves as a relatively permanent basal substrate supporting Seagrass expansion.

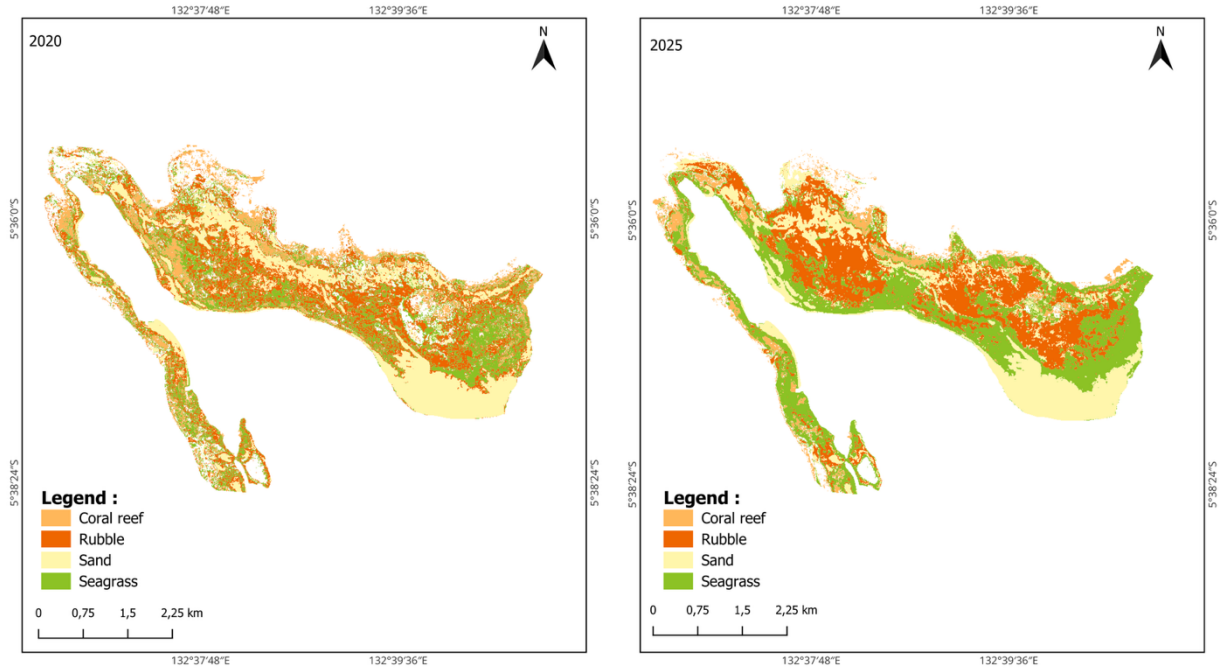


Figure 3. Comparison of Benthic Habitat Conditions in 2020 and 2025

Overall, the Ohoidertawun data indicates a concerning and pressing ecosystem shift (habitat shifting). The sharp decline in Coral Reefs signifies the loss of complex habitat structure, while the expansion of Seagrass beds either fills the resulting ecological void or expands into shallow water zones previously occupied by other substrates. The 2025 map must serve as a primary reference for the Southeast Maluku Regency Government to immediately implement conservation intervention measures focused on protecting the remaining Coral Reefs and managing the expanding Seagrass beds.

Table 3. Changes in the Extent of Benthic Habitats From 2020 to 2025

Object name	Changes in Benthic Area (ha)			
	Year 2020	Year 2025	Area Change	Percentage of Change
Sand	373.13	379.78	+6.65	+1.78%
Rubble	520.17	471.06	-49.11	-9.44%
Coral Reef	163.82	112.28	-51.54	-31.46%
Seagrass	373.76	569.66	+195.90	+52.41%
Total Luas	1430.88	1532.78	+101.9	+7.12%

The finding that Random Forest (RF) is the superior classifier for shallow marine habitat mapping is highly consistent with similar studies involving medium or high-resolution satellite data. For instance, Pal (2005) found that RF consistently outperformed other conventional algorithms, such as Maximum Likelihood and Support Vector Machine (SVM), in land classification with higher accuracy and better stability. Similarly, research by Mountrakis *et al.* (2011) positioned SVM as one of the leading classifiers due to its ability to handle complex non-linear data, a finding that aligns with the performance of SVM in southeast maluku (kappa 0.720) which secured the second position after RF. The failure of Minimum Distance (MD) in this study, which was unable to handle spectral overlap, is also supported by the literature emphasizing the need to shift from simple distance-based classification to probabilistic or machine learning methods for modern remote sensing data (Richards & Jia, 2006). This consistency reinforces the validity of the methodology used in this study and supports the conclusion that RF is the recommended gold standard for mapping Seagrass ecosystems in the Southeast Maluku region.

CONCLUSIONS AND SUGGESTION

The benthic habitat mapping study conducted in the waters of Ohoidertawun, Southeast

Maluku Regency, concluded that among the five evaluated Machine Learning algorithms, Random Forest (RF) achieved the best classification performance, with an Overall Accuracy of 0.856 and a Kappa Coefficient of 0.870, outperforming Support Vector Machine (SVM), Classification and Regression Tree (CART), K-Nearest Neighbors (KNN), and Minimum Distance (MD). Based on the classification results produced by the RF algorithm, temporal analysis of benthic habitat areas from 2020 to 2025 revealed a significant ecosystem shift, characterized by a 52.41% increase in seagrass beds and a 31.46% decrease in coral reefs. These findings highlight areas that require conservation attention. The RF method proved to be a robust Machine Learning approach for benthic habitat mapping using Sentinel-2 satellite imagery in 2025 for the Ohoidertawun waters of Southeast Maluku. The results of this study can serve as a baseline for marine spatial planning focused on coral reef rehabilitation and leveraging seagrass expansion for blue carbon initiatives. Future researchers are advised to integrate bathymetric data to further enhance classification accuracy.

ACKNOWLEDGEMENT

Special gratitude is extended to all parties who provided vital support throughout this research. Thanks are specifically directed to the survey team from Pattimura University (UNPATTI) for their dedicated effort in data acquisition, the Department of Marine and Fisheries of Southeast Maluku Regency for their collaboration and local facilitation, and particularly to the Samudera Indonesia Timur Foundation (YASIT) for initiating and fully facilitating this research project.

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