Hybrid Random Forest and Support Vector Machine Classification for Benthic Habitat Mapping using Sentinel-2 Imagery

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***Abstract*:** *Accurate benthic habitat mapping is essential for coastal management and ecosystem monitoring. However, remote sensing-based classification faces challenges due to the small size of benthic objects and their submerged nature, which increases the risk of misclassification. Machine learning algorithms such as Random Forest (RF) and Support Vector Machines (SVM) have been widely used to address these limitations, yet each has its drawbacks—RF may overfit. At the same time, SVM can misclassify and is sensitive to complex samples. This study proposes a hybrid classification method to overcome these limitations by fusing RF and SVM outputs within Google Earth Engine. The study area is located along the coast of Bontang City, East Kalimantan, Indonesia. Sentinel-2 imagery was classified using RF (ntree=50, 100), SVM (gamma=10, cost=10), and a hybrid RF-SVM approach. The fusion rule applied in the hybrid model is as follows: if RF and SVM predictions agree, the shared class label is accepted. If the predictions differ, the final class is determined using a 3×3 majority neighborhood filter to resolve the disagreement and assign the benthic habitat class. Three benthic classes were mapped: coral/macroalgae, seagrass, and bare substrate. RF yielded an overall accuracy range from 78.19 to 78.50%, while SVM reached 72.27 to 81.93%. Based on four scenarios, three of them showed that the hybrid method outperformed both RF and SVM individually. The hybrid method achieved the highest overall accuracy of 82.24% with a Kappa value of 0.70, with producers' and users' accuracy outperforming both individual classifiers in most classes. The use of varied parameters for RRF and SVM demonstrated the effectiveness of the hybrid approach. Spatially, this method reduced salt-and-pepper noise and improved consistency across benthic habitats. These findings indicate that the hybrid fusion method enhances the accuracy of benthic habitat mapping. Moreover, the hybrid RF-SVM approach effectively addressed key limitations encountered in single-algorithm classifications, such as the inability to accurately map coral/macroalgae in SVM and RF's "salt and pepper" effect.*

Keywords: benthic habitat, random forest, remote sensing, support vector machine, hybrid classification

Introduction

Accurate and detailed mapping of benthic habitats is vital for effective coastal and marine management and long-term ecosystem monitoring. Indonesia is home to an exceptionally diverse and expansive benthic environment, with its coral reefs harboring approximately 70% of the coral species found in the Indo-Pacific region (Wicaksono et al., 2019b; Hidayah et al., 2021). Despite this ecological richness, benthic habitat maps in Indonesia are limited at both local and regional scales. Remote sensing offers a promising solution to address this gap by providing imagery with a range of spatial and spectral characteristics that enable wide-area coverage, rapid mapping, and temporal monitoring (Wicaksono, 2015; Hedley et al., 2016). Remote sensing facilitates more scalable habitat assessments than traditional field surveys, which can be labor-intensive, costly, and spatially constrained.

Nonetheless, several challenges persist. Benthic features are generally small, submerged, and can often be obscured by water column effects, sunglint, limited spatial resolution, and narrow spectral sensitivity. These complications heighten the risk of misclassification, underscoring the need for careful consideration in remote sensing-based habitat mapping (Wicaksono, 2015; Wicaksono & Aryaguna, 2020).

Sentinel-2 is a prominent choice for benthic habitat studies among satellite platforms, thanks to its advantageous spatial and spectral resolution that enhances the identification of underwater objects (Hafizt, 2024; Traganos & Reinartz, 2018). Its open-access nature and compatibility with cloud-based platforms like Google Earth Engine (GEE) further facilitate large-scale and reproducible analyses (Fakhrurrozi, 2024; Traganos & Reinartz, 2018). Numerous studies conducted in Indonesia have demonstrated the effectiveness of Sentinel-2 imagery for classifying benthic habitats, achieving accuracy levels exceeding 65% (Alifatri, 2022; Fakhrurrozi, 2024; Hafizt, 2024; Hamuna, 2023; Hartoni, 2021; Yarmazen, 2024). These studies typically utilize machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM), both renowned for their efficacy in remote sensing applications. Nevertheless, each method has limitations—RF is prone to overfitting, while SVM can be sensitive to complex samples and may struggle with limited training data.

This research proposes a hybrid classification approach that integrates RF and SVM within the GEE environment to enhance the accuracy and reliability of benthic habitat mapping. Combining RF's robustness with SVM's generalization capabilities, the hybrid method aims to overcome individual weaknesses and comprehensively classify diverse benthic ecosystems (Syeykhmousa, 2020). Importantly, improving benthic habitat mapping involves reducing classification errors and ensuring that the mapped classes reflect the actual spectral characteristics of benthic features (Wicaksono et al., 2019b). Therefore, the classification method, scheme, and imagery choice are critical. The coastal region of Bontang City in East Kalimantan was chosen as the study site because of its diverse benthic habitats and notable human activities. This area encompasses sea-based settlements, is near industrial zones, experiences intensive fishing activity, and includes zones dedicated to seaweed farming, making it an ideal location for assessing variations in benthic habitats.

Literature Review

In the last three decades, remote sensing has become essential for studying coastal and benthic habitats, providing scalable and efficient alternatives to traditional field surveys. Conventional methods for collecting benthic data are often constrained by accessibility, environmental conditions, and the complex nature of underwater ecosystems (Wicaksono & Hafizt, 2013). In contrast, remote sensing allows for the extraction of surface information without direct contact. It utilizes electromagnetic wave reflections to detect and classify features on the Earth's surface (Campbell & Wyne, 2011).

Among satellite platforms, Sentinel-2 imagery has emerged as a preferred source for benthic habitat mapping due to its favorable spatial resolution (10 m GSD) and diverse spectral bands—from visible wavelengths (blue 0.49 µm, green 0.56 µm, red 0.665 µm) to near-infrared (NIR 0.842 µm). Its accessibility via platforms like Google Earth Engine (GEE) further supports large-scale, reproducible analysis. Sentinel-2 has been successfully applied across various spatial scales, including local (Fauzan et al., 2021; Wicaksono et al., 2022a; Wicaksono et al., 2022b; Wijaya & Wicaksono, 2024), regional and national (Lee et al., 2023; Traganos et al., 2022a; Traganos et al., 2022b), and global contexts (Li et al., 2021; Lyons et al., 2020), consistently yielding acceptable classification accuracy.

A range of classification methods has been employed in benthic mapping, including supervised and unsupervised approaches. Standard techniques include Maximum Likelihood, RF, SVM, ISODATA, K-Means, and object-based classification. Maximum Likelihood remains widely used in supervised classification, particularly under the assumption of normally distributed data (Chang & Bai, 2018), and often outperforms other parametric methods (Koedsin et al., 2016). Machine learning algorithms such as RF and SVM have gained prominence due to their adaptability and performance across diverse datasets. RF, an ensemble method based on decision trees, constructs multiple trees using randomly selected data subsets. It is known for its robustness, resistance to overfitting, and independence from data distribution assumptions (Chang & Bai, 2018). RF performs well with large datasets and is relatively easy to implement (Syeykhmousa et al., 2020). In benthic mapping using WorldView-2 imagery, RF achieved up to 88.54% accuracy across 14 classes in Kemujan Island (Wicaksono et al., 2019b). Class generalization into four categories improved model accuracy and overall accuracy using the validation samples.

Subsequent RF applications in the Karimunjawa Islands yielded stable and consistent results (Wicaksono et al., 2019a), while RF-based classification in Tunda Island reached 69.86% accuracy across five classes (Fakhrurrozi et al., 2024). Comparative studies also suggest RF slightly outperforms SVM in Sentinel-2-based benthic classification, though differences are modest (Hamuna et al., 2023; Hartoni et al., 2021).

SVM, another widely used machine learning algorithm, classifies data by calculating distances and separating them using hyperplanes. It is particularly effective in filtering noise during training and handling limited sample sizes (Syeykhmousa et al., 2020). Although SVM may struggle with multi-class classification, kernel function tuning—such as the radial basis function (RBF)—can mitigate this limitation (Chang & Bai, 2018). Traganos et al. (2018) demonstrated SVM's effectiveness in Sentinel-2-based benthic mapping, achieving strong quantitative and qualitative results. Hamidah et al. (2021) combined SVM with object-based image analysis (OBIA) to classify four benthic classes, reaching 74.29% accuracy. In Kemujan Island, SVM achieved 75.98% accuracy (Wicaksono et al., 2019b), though some seagrass classes were poorly classified. These findings suggest that SVM performance varies with site complexity and object characteristics. Furthermore, SVM has been successfully applied to seagrass species classification, achieving 76.11% accuracy using RBF kernel tuning (Wicaksono et al., 2021a).

Methodology

a. Study Area:

The study area is located along the coastal region of Bontang City, East Kalimantan, on the eastern side of Kalimantan Island. Geographically, it spans from 0.197884° to 0.038307° N latitude and from 117.477279° to 117.569772° E longitude. The socio-economic conditions in this region are notably active, driven primarily by community-based fishing activities (Irawan et al., 2019). In addition to intensive fisheries, seaweed farming is a dominant livelihood, particularly in the Bontang Lestari sub-district of South Bontang District (Lesmana et al., 2023).

Mangrove ecosystems play a significant ecological role along the Bontang coastline, forming a continuous fringe along the shore. Seagrass beds in the area often grow adjacent to mangrove zones and are also found around offshore islands beyond the administrative boundaries of Bontang City. Faunal composition within the seagrass meadows is dominated by fish species such as rabbitfish (*Siganus* spp.), emperor fish (*Lethrinidae* spp.), squid (*Loligo* spp.), and sea urchins (*Echinometra* spp.) (Oktawati et al., 2018).

Satellite imagery and field surveys identified at least seven seagrass species in the study area, with *Enhalus acoroides* (Ea) and *Thalassia hemprichii* (Th) being the most dominant. The benthic habitat mainly consists of extensive reef flat zones, which are surrounded by fore reef and reef slope (wall) formations in shallow marine areas. The substrate near mangrove zones is typically composed of muddy sand and experiences turbid water conditions, while areas further offshore are characterized by carbonate sand substrates and clearer waters. During low tide, seagrass beds and reef flat substrates are often exposed. Figure 1 illustrates the satellite imagery utilized, the spatial extent of the study area, and the distribution of samples.

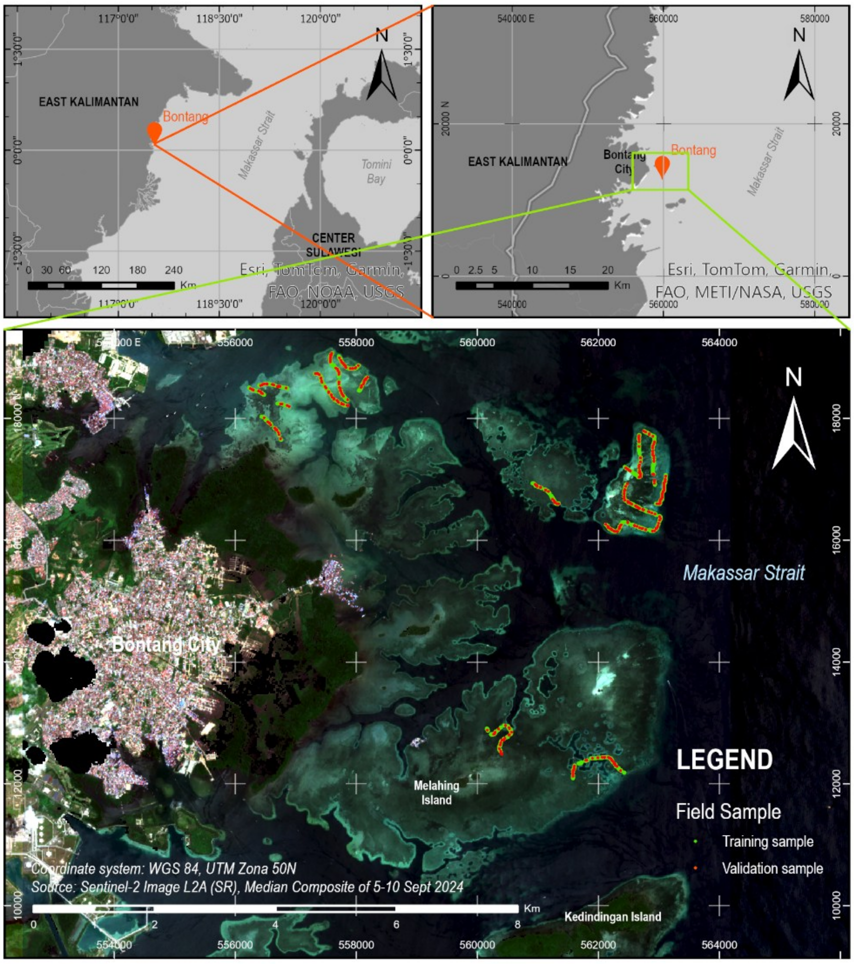

Figure 1: Study Area and Field Sample Distribution.

b. Field Data:

A field survey was conducted from August 5 to 8, 2024, along the coastal area of Bontang City using the georeferenced photo transect method. The observed benthic habitats included reef flat zones, fore reefs, seagrass beds, sparse macroalgae, and carbonate sand and mud substrates. The georeferenced photo transect technique followed the steps outlined by

Roelfsema and Phinn (2009, 2010). Photo transects were analyzed to identify benthic habitat classes using the Coral Point Count with Excel (CPCe) software (Kohler & Gill, 2006). The resulting habitat class samples were adjusted to match the 10-meter ground sample distance (GSD) of Sentinel-2 imagery. The classification scheme consisted of three generalized categories: (1) coral/macroalgae, (2) seagrass, and (3) bare substrate. Habitat class assignments were based on the dominant cover type, which was defined as covering at least 80% of the area within a single photo frame.

Previous studies have shown that using dominant or generalized class schemes consistently yields higher classification accuracy than more detailed schemes (Wicaksono et al., 2019b). Macroalgae were grouped with coral due to their similar spectral appearance and low dominance in the study area, particularly where macroalgae coloration blended with dead coral. A total of 1,070 field samples were classified, with 70% allocated for model training and 30% for validation.

c. Satellite Imagery:

The satellite imagery utilized in this study was obtained from Sentinel-2 and processed to Surface Reflectance (SR) level (Level-2A), including geometric and radiometric corrections. The images were sourced from the Google Earth Engine (GEE) catalog and composited using the median values from acquisitions recorded between September 5 and September 10, 2024. This date range was chosen based on cloud cover and sunglint conditions in the Bontang coastal area, which is typically cloudy. Additionally, it was selected to ensure temporal proximity to the field survey dates. Aligning the satellite acquisition date with the field survey period helps minimize discrepancies between ground conditions and satellite observations (Wicaksono et al., 2021b; Wicaksono et al., 2022a, 2022b, 2023). The imagery had a GSD of 10 meters, and the spectral bands selected for benthic habitat classification included the blue (Band 2), green (Band 3), and red (Band 4) wavelengths.

d. Benthic Habitat Classification:

This study utilized three classification algorithms: Random Forest (RF), Support Vector Machine (SVM), and a hybrid RF-SVM model. For RF, hyperparameter tuning was conducted by setting the number of variables randomly selected at each split (mtry) to the square root (sqrt). Trials were performed using 50 and 100 trees (ntree). The selected range for *ntree* was based on findings from previous studies by Wicaksono et al. (2019b; 2021b) and Ginting Br et al. (2023), which showed that increasing *ntree* from 100 to 500 did not significantly improve classification accuracy.

For SVM, hyperparameter tuning was done using a Radial Basis Function (RBF) kernel, with gamma values set to 5 and 10, and cost parameters tested at 5 and 10. The choice of RBF kernel, along with tuning of the kernel width and complexity parameters, is known to affect classification performance (Mountrakis et al., 2010). Previous applications in benthic habitat mapping informed the selected hyperparameter values, particularly studies by Traganos et al. (2018) and Wicaksono et al. (2019b), which successfully used gamma and cost values of 10. The hybrid classification method combines the outputs of RF and SVM for each trial, organized into four distinct scenarios (see Table 1).

Table 1: Classification and RF-SVM Hyperparameter Tuning Scenarios

Scenario 1	RF (ntree = 50) SVM (gamma= 10, cost =10)
Scenario 2	RF (ntree = 50) SVM (gamma= 5, cost =5)
Scenario 3	RF (ntree = 100) SVM (gamma= 10, cost =10)
Scenario 4	RF (ntree = 100) SVM (gamma= 5, cost =5)

The fusion rule applied in the hybrid model is as follows: if RF and SVM predictions agree, the shared class label is accepted. If the predictions differ, the final class is determined using a 3×3 majority neighborhood filter to resolve the disagreement and assign the benthic habitat class. Figure 2 shows the research framework for the benthic habitat classification using RF, SVM, and hybrid RF-SVM. To evaluate the performance of the Hybrid method, comparisons were conducted through visual inspection of the classification results and accuracy assessment using a confusion matrix from the validation samples, focusing on overall accuracy (OA) and kappa value.

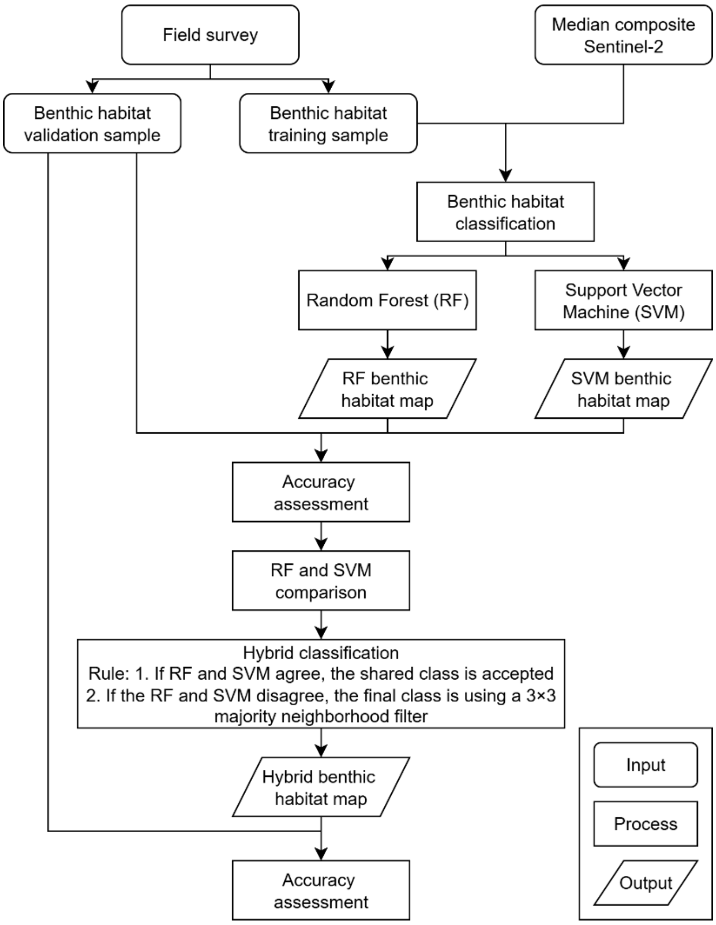

Figure 2: Research Framework.

Results and Discussion

Benthic habitat classification and mapping were conducted using Sentinel-2 imagery, employing RF, SVM, and a hybrid RF-SVM algorithm. This approach aimed to optimize each method's strengths to enhance classification accuracy and improve overall map quality. Figure 3 compares the classification results from the RF and SVM algorithms. Generally, the benthic habitats along the coast of Bontang are predominantly characterized by seagrass meadows. The RF classification results in Figures 3a and 3b reveal similar spatial patterns, with seagrass dominating most areas, bare substrates common in the northern region, and coral cover found in the eastern part near the Makassar Strait—likely representing a fore reef zone.

Based on field observations, the benthic habitat maps produced by RF are relatively representative, although there is evidence of overestimation in coral coverage in the eastern region. This may be attributed to spectral similarities between dead coral and other objects like seagrass, affecting classification accuracy. Meanwhile, the SVM classification results in Figures 3c and 3d show noticeable differences due to variations in the gamma and cost hyperparameters. Specifically, Figure 3d, which used gamma and cost values 5, failed to identify coral features in the eastern fore reef zone. Figure 3c better represented seagrass and bare substrate distribution, although coral classification remained suboptimal.

When compared, RF tends to produce "salt and pepper" effects or spatial noise, while SVM yields more generalized and realistic results despite being pixel-based classification (Wicaksono et al., 2021b). This contrast is particularly evident in the northern region, where SVM more clearly delineates the boundaries between seagrass and bare substrate. At the same time, RF introduces scattered misclassifications within the bare substrate area. Field validation confirms that bare substrate is the dominant habitat in the northern section. Such misclassification is likely due to the low spectral reflectance characteristics of the area, which complicate object differentiation.

Furthermore, although multispectral imagery such as Sentinel-2 is theoretically capable of distinguishing objects based on specific spectral reflectance characteristics, disturbances such as the water column can hinder the sensor's ability to capture spectral differences among benthic habitat types, thereby affecting mapping accuracy (Lyons et al., 2011; Joyce et al, 2013; Wicaksono et al., 2021b). The background of bare substrate can also influence the reflectance values of seagrass, and the spectral similarity among objects such as seagrass, substrate, and dead coral can increase misclassification (Lazuardi et al., 2021).

A hybrid RF-SVM approach was implemented based on each algorithm's classification results across four different scenarios (see Table 1). Overall, the variations in classification outcomes among scenarios 1 to 4 were minimal. Table 2 presents the varying areas (in hectares) of benthic classes from all scenarios of hybrid classification. There were minimal differences among the classes across all scenarios. The seagrass class predominated the study area, followed by bare substrate and the coral/macroalgae class. Most differences were observed at the pixel level, suggesting that all four scenarios effectively represented the spatial distribution of benthic habitats within the study area.

Table 2: Area of Benthic Habitat Classes in Hybrid Classification (in Hectares)

Class	coral/macroalgae	seagrass	bare substrate
Scenario 1	324	4356	1004
Scenario 2	319	4377	989
Scenario 3	327	4343	1015
Scenario 4	322	4362	1000

A more straightforward comparison can be made by referring to Figures 3 and 4, which showcase the differences between the classifications produced by the single algorithms (RF and SVM) and the hybrid method. In the single SVM classification, corals in the eastern fore reef zone were not successfully identified, and the Random Forest (RF) method produced noticeable "salt and pepper" noise in the northern region. However, the hybrid classification effectively addressed both of these issues. It consistently identified corals in the eastern zone across all four scenarios and reduced the spatial noise in the northern bare substrate area.

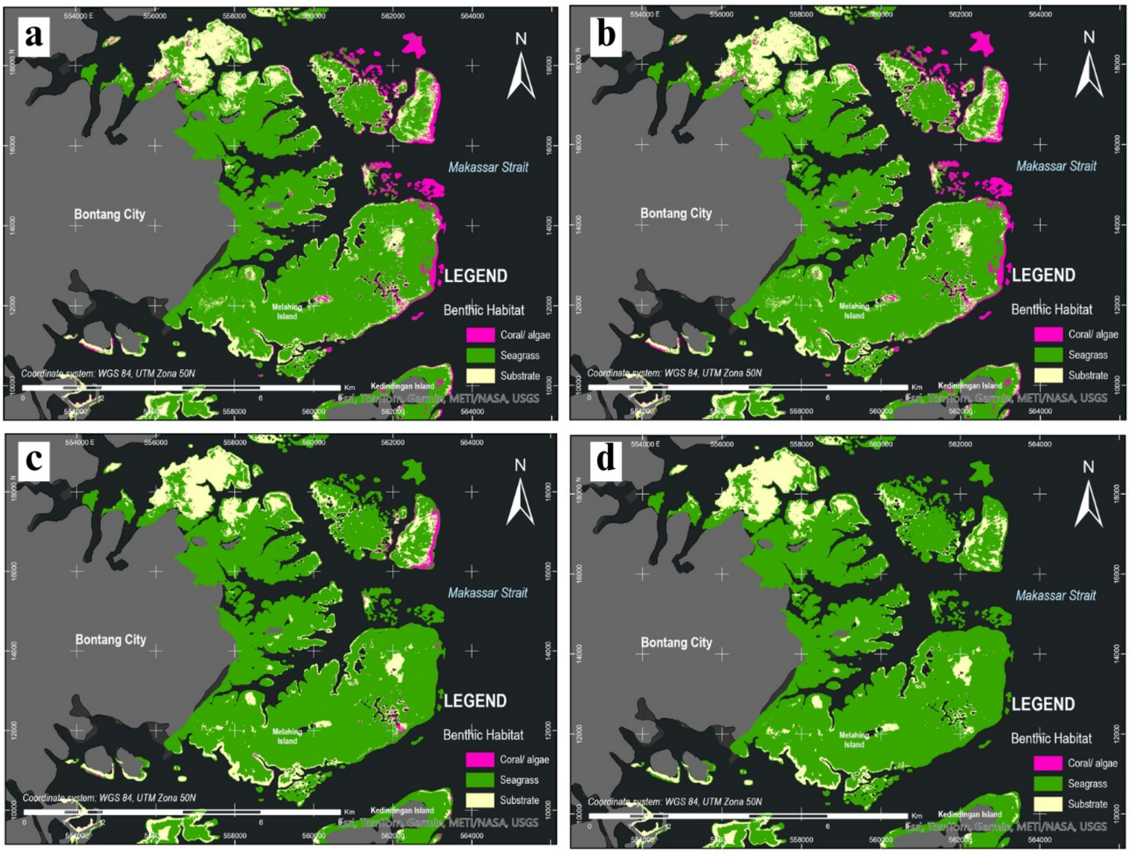

Figure 3: The Results of Benthic Habitat Classification a) RF *ntree*=50, b) RF *ntree*=100, c) SVM gamma = 10 and cost = 10, d) SVM gamma = 5 and cost = 5

When Figure 4 is examined closely, it is evident that the northern part of the bare substrate area in scenarios 1 and 2 contains more coral/macroalgae than in scenarios 3 and 4. The classifications of these classes are consistent with the results obtained from the RF model using *ntree* 50. Additionally, when analyzing the coral reef on the eastern side of Figure 4 based on the hybrid classification, all scenarios exhibit a similar pattern. This indicates that when there is disagreement between the RF and SVM, the 3×3 majority filter plays a significant role. Due to the large area classified as coral and macroalgae in the RF model, this classification ultimately leads to greater coverage of coral and macroalgae in the eastern region. Visually, the hybrid method provided a more accurate mapping of benthic habitats, aligning well with field observations. Nevertheless, careful consideration of the classification schemes and parameter tuning in the individual algorithms—particularly for RF and SVM—remains essential to achieve optimal results reflecting benthic habitats' spectral characteristics along the Bontang coastline.

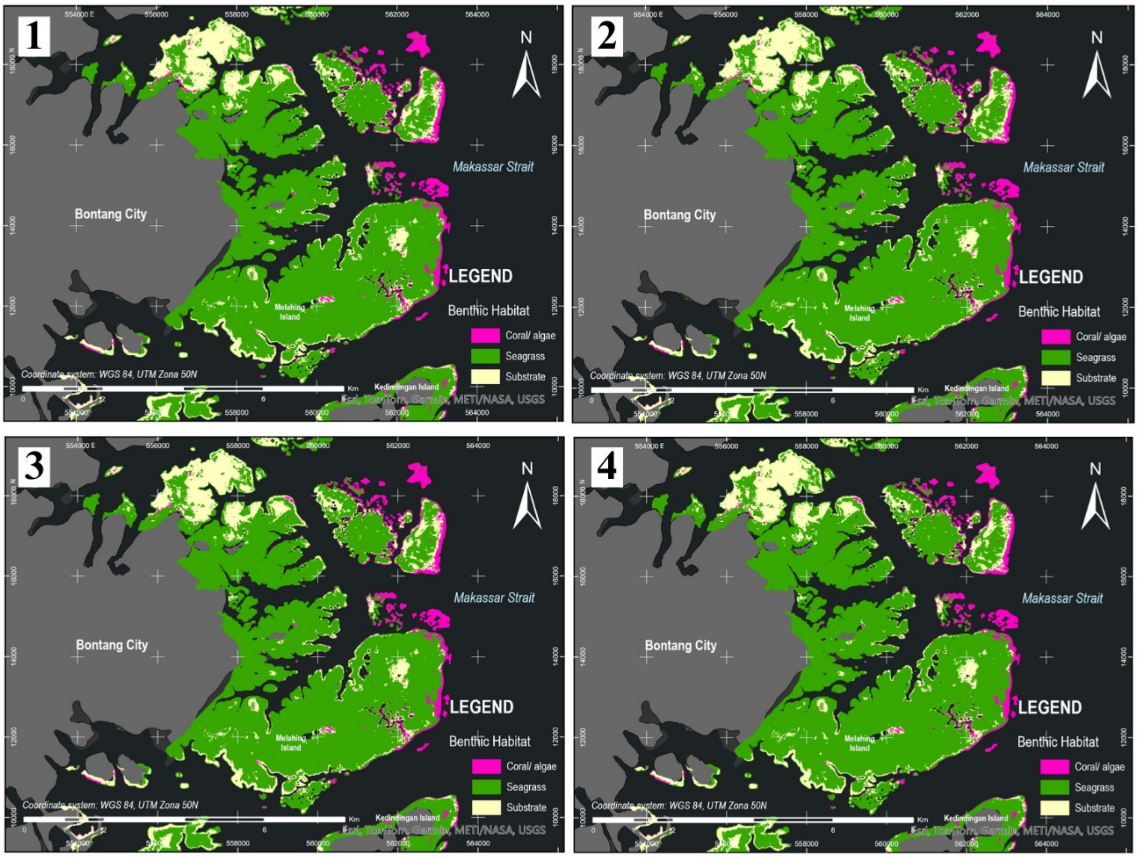

Figure 4: Hybrid RF-SVM Benthic Habitat Classification Result

The accuracy assessment results indicate that all scenarios—both single-algorithm classifications (RF and SVM) and the Hybrid RF-SVM method—achieved overall accuracy values exceeding 60%. This meets the minimum threshold established by the Indonesian National Standard SNI 7716:2011 (Ginting Br et al., 2023). In comparing overall accuracy across the four scenarios, three of them demonstrated that the hybrid method outperformed both RF and SVM when used individually. However, Scenario 3 was the exception, where the hybrid method yielded slightly lower accuracy than the SVM classification, which was configured with a gamma of 10 and a cost of 10.

Figure 5 provides a graphical comparison of the overall accuracy values for each scenario. In Scenario 3, RF achieved an overall accuracy (OA) of 78.19%, SVM reached 81.93%, and the

Hybrid RF-SVM method attained 81.62%, with a Kappa coefficient of 0.69. This scenario illustrates that while the hybrid method does not always produce the highest accuracy, its performance remains comparable to that of single-algorithm approaches. Additionally, the hybrid method can enhance the accuracy of RF classification.

Among the four scenarios, the hybrid method achieved the highest OA in Scenarios 1 and 2, reaching 82.24% with a Kappa value 0.70. These scenarios demonstrated greater accuracy than the RF and SVM methods individually. However, in Scenario 1, the difference between the hybrid method and the SVM results was insignificant. As illustrated in Figure 5, the hybrid method notably improved OA in Scenarios 2 and 4 compared to the single classifications using RF and SVM.

In Scenario 2, with a *ntree* of 50, the RF accuracy was 78.50%, achieving a Kappa of 0.64. In Scenario 4, where *ntree* was increased to 100, the RF accuracy slightly decreased to 78.19%, with a Kappa of 0.63. The SVM classification used in Scenarios 2 and 4 was the same, yielding an accuracy of 72.27% and a Kappa of 0.50. Notably, these SVM results were the only ones with Kappa values below 0.6, indicating "moderate agreement," according to Landis & Koch (1977), which defines a Kappa coefficient above 0.6 as representing "substantial agreement."

Further analysis of the SVM classification presented in Figure 3d reveals that the coral/macroalgae class was poorly identified. The accuracy metrics showed a producer's accuracy (PA) of only 2.5% for the coral/macroalgae class, while the user's accuracy (UA) was 100%, indicating a substantial underestimation of coral/macroalgae presence. In contrast, the RF classification resulted in a PA of 72.5% and a UA of 76.32%, suggesting that coral/macroalgae was classified reasonably well. With the hybrid method, the coral/macroalgae class achieved a PA of 70% and a UA of 84.85%. Scenarios 2 and 4 results demonstrate that the hybrid method can quantitatively enhance classification accuracy and improve the visual representation of benthic habitat maps to reflect field conditions better.

Comparative studies of RF and SVM classification methods have been extensively conducted in remote sensing, particularly for benthic habitat mapping. Each algorithm presents unique advantages and limitations. In terms of hyperparameter tuning for RF, adjustments to the number of trees (ntree = 50 or 100) have not demonstrated a significant improvement in classification accuracy, as noted by Ginting Br et al. (2023) and Wicaksono et al. (2019c). On the other hand, SVM classification is generally more sensitive to its hyperparameter settings and the number of classes utilized. For example, Tamondong et al. (2018) achieved an accuracy of 72% using two classes with gamma and cost values of 10, while Wicaksono et al. (2019b), using the same parameter settings but with 14 classes, achieved an accuracy of 75.98%.

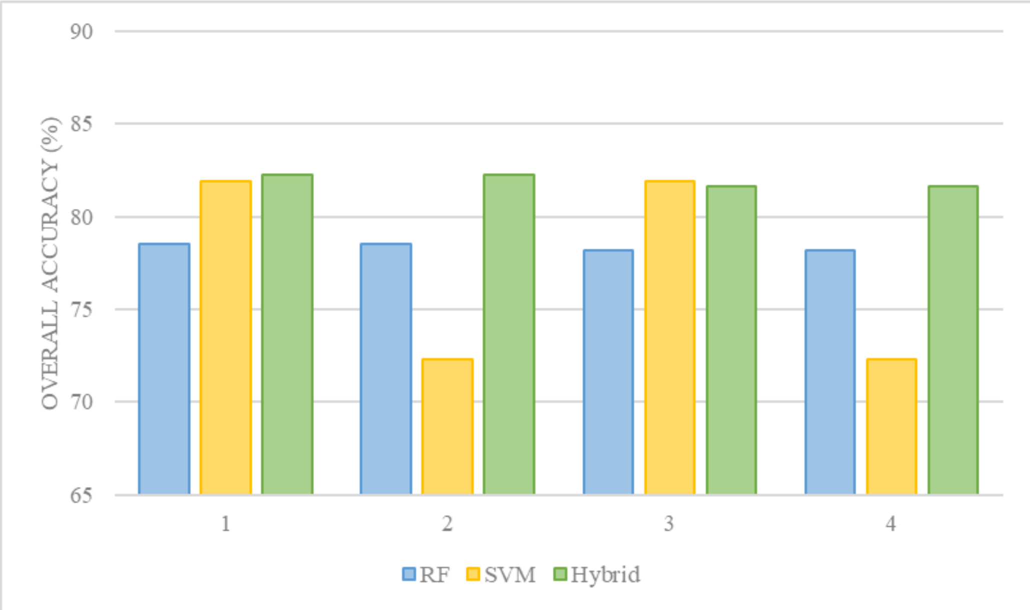

Figure 5: Comparison of Overall Accuracy (Scenario 1 – 4)

These variations in hyperparameter tuning should be carefully considered when preparing input data for hybrid classification methods. In this study, the hybrid approach used was relatively straightforward—class agreement between RF and SVM, followed by a 3×3 majority neighborhood filter. Consequently, the hybrid method may not have reached its full potential. Alternative fusion rules could involve probability-based class selection or weighted voting based on the performance of individual classifiers. Further exploration of additional scenarios and comparative methods could enhance classification outcomes.

Beyond the classification approach, one inherent challenge in using remote sensing imagery for benthic habitat mapping is the complexity of the habitats. Benthic features are often small and heterogeneous, leading to spectral mixing among classes such as seagrass, bare substrate, macroalgae, and coral (Koedsin et al., 2016). This spectral overlap can significantly influence reflectance values, contributing to misclassification (Wicaksono et al., 2021a).

Conclusion and Recommendation

This study shows that integrating RF and SVM in a hybrid classification framework within GEE can improve the accuracy and reliability of benthic habitat mapping. The hybrid RF-SVM method effectively addresses key limitations found in single-algorithm classifications, such as the inability of SVM to map coral/macroalgae, and the "salt and pepper" effect commonly observed in RF. In four scenarios, the hybrid approach consistently produced classification results that better reflected field conditions, achieving overall accuracy values that surpassed the national standard threshold of 60%. Scenarios 1 and 2 reached the highest accuracy levels, with an overall accuracy of 82.24% and Kappa values of 0.70, confirming the hybrid method's potential to enhance spatial coherence and delineate classes in complex benthic environments.

Future research should investigate more advanced fusion rules beyond simple class agreement and neighborhood filtering to optimize the hybrid classification approach further. Incorporating methods such as confidence-based selection, weighted voting, or probabilistic decision-making could improve the adaptability of the hybrid model. Additionally, expanding the number of scenarios and integrating other classification algorithms may provide deeper insights into model performance across various habitat conditions. Given benthic features' spectral complexity and heterogeneity, improving pre-processing techniques and refining hyperparameter tuning—particularly for SVM—will be essential for achieving robust and ecologically meaningful mapping outcomes.

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References

Alifatri, L. O, Prayudha, B., & Anggraini, K. (2022). Klasifikasi Habitat Bentik Berdasarkan Citra Sentinel-2 di Kepulauan Kei, Maluku Tenggara. *Jurnal Ilmu Pertanian Indonesia*, *27*(3), 372-384.

Campbell, J. B., & Wyne, R. H. (2011). Introduction to Remote Sensing (5th ed.). New York: The Guilford Press.

Chang, N.-B., & Bai, K. (2018). Multisensor Data Fusion and Machine Learning for Environmental Remote Sensing. CRC Press.

Fakhrurrozi, F., Idris, I., Ardiansyah, M. B. R., Muttaqin, A. D., & Mauludiyah, M. (2025). Assessing benthic habitat distribution in Tunda Island, Banten, Indonesia using Sentinel-2A imagery. In *BIO Web of Conferences* (Vol. 168, p. 05014). EDP Sciences.

Fauzan, M. A., Wicaksono, P., & Hartono. (2021). Characterizing Derawan seagrass cover change with time-series Sentinel-2 images. *Regional Studies in Marine Science*, *48*. https://doi.org/10.1016/j.rsma.2021.102048

Ginting Br, N., Wicaksono, P., & Farda, N. M. (2023). Mapping Benthic Habitat from Worldview-3 Image using Random Forest Case Study: Nusa Lembongan, Bali, Indonesia. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XLVIII(November 2022), 123–129.

Hafizt, M., Yuwono, D. M., Janwar, Z., & Wouthuyzen, S. (2024). Benthic habitat mapping for estimating seagrass carbon stock across Takabonerate Islands, Indonesia. *Regional Studies in Marine Science*, *77*, 103703.

Hamidah, M., Pasaribu, R. A., & Aditama, F. A. (2021, December). Benthic habitat mapping using object-based image analysis (OBIA) on Tidung Island, Kepulauan Seribu, DKI Jakarta. In *IOP conference series: earth and environmental science* (Vol. 944, No. 1, p. 012035). IOP Publishing.

Hamuna, B., Pujiyati, S., Gaol, J. L., & Hestirianoto, T. (2023). Spatial distribution of benthic habitats in Kapota Atoll (Wakatobi National Park, Indonesia) using remote sensing imagery. *Biodiversitas: Journal of Biological Diversity*, *24*(7).

Hartoni, Siregar, V. P., Wouthuyzen, S., & Agus, S. B. (2022). Object based classification of benthic habitat using Sentinel 2 imagery by applying with support vector machine and random forest algorithms in shallow waters of Kepulauan Seribu, Indonesia. *Biodiversitas: Journal of Biological Diversity*, *23*(1).

Hedley, J., Roelfsema, C., Chollett, I., Harborne, A., Heron, S., Weeks, S., Skirving, W., et al. (2016). Remote Sensing of Coral Reefs for Monitoring and Management: A Review. *Remote Sensing,* 8(2).

Hidayah, Z., Budi Wiyanto, D., & Romadhon, A. (2021). The assessment of benthic ecosystems and substrate profile of Bawean Island East Java Province. *IOP Conference Series: Earth and Environmental Science*, *860*(1). https://doi.org/10.1088/1755-1315/860/1/012003

Irawan, A., Supriharyono, Hutabarat, J., & Ambariyanto. (2019). Threat of small scale capture fisheries on the fish biodiversity in seagrass beds of Bontang, East Kalimantan, Indonesia. AACL Bioflux, 12(6), 2286–2297.

Joyce, K. E., Phinn, S. R., & Roelfsema, C. M. (2013). Live coral cover index testing and application with hyperspectral airborne image data. *Remote Sensing*, *5*(11), 6116-6137.

Koedsin, W., Intararuang, W., Ritchie, R. J., & Huete, A. (2016). An integrated field and remote sensing method for mapping seagrass species, cover, and biomass in Southern Thailand. Remote Sensing, 8(4). https://doi.org/10.3390/rs8040292

Kohler, K.E. & Gill, S.M. (2006) Coral Point Count with Excel Extensions (CPCe): A Visual Basic Program for the Determination of Coral and Substrate Coverage Using Random Point Count Methodology. Computers and Geosciences, 32, 1259-1269. https://doi.org/10.1016/j.cageo.2005.11.009

Landis, J. R., & Koch, G. G. (1977). The Measurement of Observer Agreement for Categorical Data. *Biom.*, *33*(1), 159. https://doi.org/10.2307/2529310

Lazuardi, W., Wicaksono, P., & Marfai, M. A. (2021, March). Remote sensing for coral reef and seagrass cover mapping to support coastal management of small islands. In *IOP conference series: earth and environmental science* (Vol. 686, No. 1, p. 012031). IOP Publishing.

Lee, C. B., Martin, L., Traganos, D., Antat, S., Baez, S. K., Cupidon, A., Faure, A., Harlay, J., Morgan, M., Mortimer, J. A., Reinartz, P., & Rowlands, G. (2023). Mapping the National Seagrass Extent in Seychelles Using PlanetScope NICFI Data. *Remote Sensing*, *15*(18). https://doi.org/10.3390/rs15184500

Lesmana, A. R., Abdusysyahid, S., & Fahrizal, W. (2023). Seaweed (Eucheuma cottonii) Cultivation Business Development Strategy in Tihi-Tihi Village, Bontang Lestari Village, Bontang Selatan District, Bontang City. *Jurnal Ilmu Perikanan Tropis Nusantara (Nusantara Tropical Fisheries Science Journal)*, *2*(2), 161-168.

Li, J., Knapp, D. E., Lyons, M., Roelfsema, C., Phinn, S., Schill, S. R., & Asner, G. P. (2021). Automated global shallowwater bathymetry mapping using google earth engine. *Remote Sensing*, *13*(8). https://doi.org/10.3390/rs13081469

Lyons, M., Phinn, S., & Roelfsema, C. (2011). Integrating Quickbird multi-spectral satellite and field data: Mapping bathymetry, seagrass cover, seagrass species and change in Moreton Bay, Australia in 2004 and 2007. *Remote Sensing*, *3*(1), 42-64.

Lyons, M. B., Roelfsema, C. M., Kennedy, E. V., Kovacs, E. M., Borrego-Acevedo, R., Markey, K., Roe, M., Yuwono, D. M., Harris, D. L., Phinn, S. R., Asner, G. P., Li, J., Knapp, D. E., Fabina, N. S., Larsen, K., Traganos, D., & Murray, N. J. (2020). Mapping the world's coral reefs using a global multiscale earth observation framework. *Remote Sensing in Ecology and Conservation*, *6*(4), 557–568. https://doi.org/10.1002/rse2.157

Mountrakis, G., Im, J., & Ogole, C. (2011). Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, *66*(3), 247–259. https://doi.org/10.1016/j.isprsjprs.2010.11.001

Oktawati, N. O., Sulistianto, E., Fahrizal, W., & Maryanto, F. (2018). Nilai Ekonomi Ekosistem Lamun di Kota Bontang. EnviroScienteae, 14(3), 228–236.

Roelfsema, C. M., & Phinn, S. R. (2009). *A Manual for Conducting Georeferenced Photo Transects Surveys to Assess the Benthos of Coral Reef and Seagrass Habitats*.

Roelfsema, C., & Phinn, S. (2010). Integrating field data with high spatial resolution multispectral satellite imagery for calibration and validation of coral reef benthic community maps. *Journal of Applied Remote Sensing*, *4*. https://doi.org/10.1117/1.3430107

Sheykhmousa, M., Mahdianpari, M., Ghanbari, H., Mohammadimanesh, F., Ghamisi, P., & Homayouni, S. (2020). Support vector machine versus random forest for remote sensing image classification: A meta-analysis and systematic review. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *13*, 6308-6325.

Tamondong, A. M., Cruz, C. A., Guihawan, J., Garcia, M., Quides, R. R., Cruz, J. A., & Blanco, A. C. (2018). Remote sensing-based estimation of seagrass percent cover and LAI for above ground carbon sequestration mapping. *Remote Sens. Open Coast. Ocean Inland Waters*, *October*, 10. https://doi.org/10.1117/12.2324695

Traganos, D., & Reinartz, P. (2018). Mapping Mediterranean seagrasses with Sentinel-2 imagery. *Marine pollution bulletin*, *134*, 197-209.

Traganos, D., Pertiwi, A. P., Lee, C. B., Blume, A., Poursanidis, D., & Shapiro, A. (2022a). Earth observation for ecosystem accounting: spatially explicit national seagrass extent and carbon stock in Kenya, Tanzania, Mozambique and Madagascar. *Remote Sensing in Ecology and Conservation*, *8*(6), 778–792. https://doi.org/10.1002/rse2.287

Traganos, D., Lee, C. B., Blume, A., Poursanidis, D., Čižmek, H., Deter, J., Mačić, V., Montefalcone, M., Pergent, G., Pergent-Martini, C., Ricart, A. M., & Reinartz, P. (2022b). Spatially Explicit Seagrass Extent Mapping Across the 176 Entire Mediterranean. *Frontiers in Marine Science*, *9*. https://doi.org/10.3389/fmars.2022.871799

Wicaksono, P., & Hafizt, M. (2013). Mapping seagrass from space: Addressing the complexity of seagrass LAI mapping. *European Journal of Remote Sensing*, *46*(1), 18–39. https://doi.org/10.5721/EuJRS20134602

Wicaksono, P. (2015). Mapping Seagrass Leaf Area Index, Standing Crop, and Above Ground Carbon Stock Using Compressed Remote Sensing Image. *The 1st International Conference of Indonesian Society for Remote Sensing 2015*, *October*, 257–264. https://doi.org/10.13140/RG.2.1.1943.3205

Wicaksono, P., Fauzan, M. A., Kumara, I. S. W., Yogyantoro, R. N., Lazuardi, W., & Zhafarina, Z. (2019a). Analysis of reflectance spectra of tropical seagrass species and their value for mapping using multispectral satellite images. *Int. J. Remote Sens.*, *40*(23), 8955–8978. https://doi.org/10.1080/01431161.2019.1624866

Wicaksono, P., Aryaguna, P. A., & Lazuardi, W. (2019b). Benthic habitat mapping model and cross validation using machine-learning classification algorithms. *Remote Sensing*, *11*(11), 1–24. https://doi.org/10.3390/rs11111279

Wicaksono, P., & Lazuardi, W. (2019c). Random Forest Classification Scenarios for Benthic Habitat Mapping using Planetscope Image. *International Geoscience and Remote Sensing Symposium (IGARSS)*, *346*, 8245–8248. https://doi.org/10.1109/IGARSS.2019.8899825

Wicaksono, P., & Aryaguna, P. A. (2020). Analyses of inter-class spectral separability and classification accuracy of benthic habitat mapping using multispectral image. *Remote Sensing Applications: Society and Environment*, *19*(May), 100335. https://doi.org/10.1016/j.rsase.2020.100335

Wicaksono, P., Danoedoro, P., Nehren, U., Maishella, A., Hafizt, M., Arjasakusuma, S., & Harahap, S. D. (2021a). Analysis of Field Seagrass Percent Cover and Aboveground Carbon Stock Data for Non-Destructive Aboveground Seagrass Carbon Stock Mapping Using Worldview-2 Image. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XLVI-4/W6*-(November), 321–327. https://doi.org/10.5194/isprs-archives-xlvi-4-w6-2021-321-2021

Wicaksono, P., Wulandari, S. A., Lazuardi, W., & Munir, M. (2021b). Sentinel-2 images deliver possibilities for accurate and consistent multi-temporal benthic habitat maps in optically shallow water. *Remote Sensing Applications: Society and Environment*, *23*. https://doi.org/10.1016/j.rsase.2021.100572

Wicaksono, P., Maishella, A., Arjasakusuma, S., Lazuardi, W., & Harahap, S. D. (2022a). Assessment of WorldView-2 images for aboveground seagrass carbon stock mapping in patchy and continuous seagrass meadows. *International Journal of Remote Sensing*, *43*(8), 2915–2941. https://doi.org/10.1080/01431161.2022.2074809

Wicaksono, P., Maishella, A., Wahyudi, A. J., & Hafizt, M. (2022b). Multitemporal seagrass carbon assimilation and aboveground carbon stock mapping using Sentinel-2 in Labuan Bajo 2019–2020. *Remote Sensing Applications: Society and Environment*, *27*. https://doi.org/10.1016/j.rsase.2022.100803

Wicaksono, P., Harahap, S. D., Hafizt, M., Maishella, A., & Yuwono, D. M. (2023). Seagrass ecosystem biodiversity mapping in part of Rote Island using multi-generation PlanetScope imagery. *Carbon Footprints*, *2*(4). https://doi.org/10.20517/cf.2023.9

Wijaya, J., & Wicaksono, P. (2024). Lifeform-based seagrass species composition mapping of Pari Island using WorldView-2 multispectral imagery. In C. M. Roelfsema, A. Besse Rimba, S. Arjasakusuma, & A. Blanco (Eds.), *Eighth Geoinformation Science Symposium 2023: Geoinformation Science for Sustainable Planet* (p. 78). SPIE. https://doi.org/10.1117/12.3009770

Yarmazen, N. & Kurniawati, E. (2024). Benthic Habitat Classification Using Sentinel-2a Image With And Without Water Column Correction In Pengudang Village, Bintan Regency. *AURELIA: Jurnal Penelitian dan Pengabdian Masyarakat Indonesia*, *3*(1), 82-93.