Seagrass Percent Cover Mapping Around Teluk Terima Using Machine Learning for Blue Carbon Stock Estimation

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Abstract *Seagrass ecosystems play a crucial role in blue carbon sequestration and in supporting various coastal ecosystem services. However, spatial information on seagrass distribution and above-ground carbon (AGC) stocks remains limited in Indonesia, particularly in the Teluk Terima area. This study aims to map seagrass cover and estimate AGC using PlanetScope SuperDove imagery combined with a Random Forest (RF) machine learning approach. Field data were collected using a photo-transect method within 1 × 1 m² grids to generate training and validation datasets. Pre-processing included sunglint correction, followed by pixel-based classification using the RF algorithm. The classification achieved an overall accuracy of 59.1% and a user's accuracy of 59.4% for the seagrass class. Seagrass cover was found to be dominant in the Tanjung Kotal and Labuan Lalang areas, with density values ranging from 0% to 82.6%. AGC was estimated using a linear regression model (AGC = 0.4386 × PC + 1.0413), where PC represents the seagrass cover percentage. The estimated AGC values ranged from 1.04 to 37.28 g C m⁻², with an R^2 of 0.4657 and an RMSE of 10.9 g C m⁻², indicating a moderate relationship between modelled and reference AGC. These findings demonstrate that the RF algorithm, supported by representative field data, can effectively map seagrass spatial distribution and predict carbon stocks with acceptable accuracy. The results provide valuable insights for spatially explicit seagrass conservation and climate change mitigation planning in coastal regions.*

Keywords: Blue Carbon, Climate Change Mitigation, Seagrass, Machine Learning

Introduction

Coastal ecosystems are recognized as important providers of various ecosystem services such as carbon sequestration, increased fish productivity, and wave energy reduction (Jacob et al., 2021). Specifically, coastal ecosystems with vegetation, including mangrove forests, seagrass beds, and tidal marshes, can provide a variety of benefits such as food provision, protection against coastal hazards, and support for various cultural benefits (Quevedo et al., 2025). Seagrass beds are a very important marine ecosystem. This ecosystem is defined as underwater grasslands in shallow waters with a growing medium of sediment, widely distributed in tropical, subtropical, and temperate coastal waters, particularly in the intertidal and shallow subtidal zones. This ecosystem is considered a multifunctional and highly productive ecosystem (Amone-Mabuto et al., 2023; Twomey et al., 2022).

Seagrass beds are recognized as crucial blue carbon ecosystems and play a dual role in mitigating climate disasters through global carbon storage and physical coastal protection. This ecosystem contributes to mitigating climate change through the sequestration and storage of large amounts of organic carbon, which is largely accumulated within the sediments (Nava-Félix et al., 2025). Carbon stored in sediments can remain trapped for centuries and millennia. Although they cover less than 0.1% of the total ocean floor, seagrass meadows contribute 10–18% of the total marine carbon burial. In fact, if this ecosystem were included in national mitigation measures, seagrass meadows have the potential to contribute up to 7.03% of a country's carbon emission reduction target by 2030. In addition to carbon mitigation, seagrass beds also provide important functions for climate change adaptation and coastal protection, including protecting the coastline from storm waves and preventing coastal erosion. This protective function is achieved through sediment accretion and increased seabed elevation. Due to this multifunctional capability, seagrass meadows are highlighted as a practical nature-based solution for climate change mitigation (Stankovic et al., 2021).

One of the areas in Indonesia with potential seagrass beds is Bali Island. Mitigation efforts have been carried out with the support of surveys and monitoring to determine the diversity of seagrass species and ecological conditions in the West Bali National Park area, which includes Karang Sewu, Prapat Agung, Labuhan Lalang, and Menjangan Island. However, the study was limited to species composition and did not include carbon stock calculations (Purnomo et al., 2017). Carbon stock research conducted at Putri Menjangan Beach in Buleleng Regency showed a potential carbon sequestration rate of 5.29 tonsC/ha/year, and the total seagrass meadows in Bali are estimated to have a carbon stock of 481.36 tons. These results highlight the important role of seagrass in mitigating climate change in Bali (Angrelina et al., 2019). The availability of spatial data is often a problem for planning related to the management of seagrass ecosystems. The fundamental issue with the unavailability of seagrass spatial data is the hindrance to efforts in sustainable coastal ecosystem management, conservation, and monitoring, considering the important role of seagrass as an indicator of ecosystem health. One of the reasons why seagrass spatial data is difficult to obtain is because traditional survey methods, such as snorkeling or diving, which can be time-consuming and expensive. Traditional methods can also cause physical damage to seagrass during field sampling. This method is also inefficient for monitoring ecosystem conditions on a regional scale (Ambarwulan et al., 2022).

Mapping seagrass beds using remote sensing methods is necessary because this technique offers an efficient and accurate solution and overcomes the limitations of traditional survey methods. Remote sensing has the ability to monitor the condition of seagrass ecosystems on a regional scale, observe large areas, and generate more comprehensive spatial representations than point-based surveys. The development of sensor technology and data processing algorithms continues, driving the development of remote sensing to map seagrass more quickly, accurately, and affordably. The use of high spatial resolution imagery can result in higher accuracy in mapping, especially in complex shallow waters (Sugara et al., 2023).

This study aims to analyze the spatial distribution of estimated aboveground carbon stocks in seagrass meadows derived from machine learning classification in Teluk Terima. Seagrass habitats in this area play a crucial role in maintaining coastal ecosystem balance and contributing to blue carbon sequestration. However, spatially explicit information on seagrass distribution and their associated carbon stock potential remains limited. Therefore, this study seeks to assess the current distribution of seagrass habitats and quantify their aboveground carbon stock potential in Teluk Terima.

Literature Review

Remote Sensing for Seagrass Mapping

Seagrass meadows are among the most effective and efficient natural carbon sinks, playing a crucial role in climate change adaptation and mitigation. To assess their capacity for carbon sequestration, it is essential to obtain accurate information on their spatial extent and carbon assimilation rates (Wicaksono & Harahap, 2023). However, many seagrass habitats are difficult to access using conventional field-based survey methods. Therefore, auxiliary technologies are needed to support data collection over large and often remote coastal areas.

Remote sensing has long been recognized as a valuable tool for natural resource inventory and environmental monitoring. It offers a cost-effective and time-efficient alternative to traditional field surveys (Jensen, 2014). The fundamental principle of remote sensing lies in recording the interaction between electromagnetic radiation and surface features on Earth. Data acquisition can be conducted using various sensor platforms, including satellites, crewed aircraft, and unmanned aerial vehicles (UAVs) (Jensen, 2015).

Nevertheless, mapping submerged targets such as seagrass meadows in shallow waters requires specialized approaches. Unlike terrestrial applications, where atmospheric effects are the main source of signal distortion, underwater remote sensing is influenced by additional factors, including water column attenuation, scattering, and absorption. These interactions alter the original reflectance signal from benthic features, making the retrieval of seagrass information more challenging (Jensen, 2014).

Remote sensing of underwater objects such as seagrass meadows follows the same theoretical principles as terrestrial remote sensing; however, it differs significantly in practice due to the greater number of factors influencing the observed reflectance. In clear water, most sunlight entering the surface is typically absorbed within the first two meters, while some energy may remain detectable until it is fully absorbed at depths of around 20 meters. Beyond this point, light is scattered or attenuated through interaction with water molecules and suspended particles (Lillesand et al., 2015). Therefore, the ability of sensors to detect reflected sunlight from benthic targets is strongly influenced by both the depth-dependent light penetration and the water column properties, which collectively determine the detectability of underwater features.

Remote sensing offers substantial advantages for mapping seagrass ecosystems in terms of efficiency, coverage, and cost-effectiveness. As noted by McCarthy et al. (2017), these advantages include its synoptic view, which allows for large-area observation—including regions that are logistically challenging to access—as well as its increasingly frequent data acquisition and improved data accessibility. However, this does not imply that remote sensing alone is sufficient for accurate seagrass mapping. Integration with field-based observations remains essential, particularly for model calibration, validation, and accuracy assessment (Wicaksono & Harahap, 2023). Field data provide the necessary ground truth for training and evaluating remote sensing models. Consequently, combining in situ measurements with remote sensing analysis enhances the accuracy, reliability, and representativeness of seagrass mapping outcomes.

Random Forest Classification

Random Forest (RF) is a widely used machine learning algorithm for seagrass mapping. It is one of the ensemble classification methods designed to improve the accuracy and robustness of predictive models. In this approach, multiple decision trees are generated during the training phase, and their outputs are combined—either through averaging in regression tasks or majority voting in classification tasks (Van Essen et al., 2012). RF employs a bootstrap aggregating (bagging) technique, whereby multiple random subsets of the training data are created with replacement to build each individual tree. As a result, each tree is trained on a slightly different dataset, reducing the likelihood of overfitting and improving the model's generalization performance (Gislason et al., 2006).

Another key feature of RF is that it uses only a random subset of input variables when splitting nodes within each tree. This random feature selection reduces correlation among the trees and increases the overall robustness of the ensemble model, making it less sensitive to data variability (Prasetiyowati et al., 2020). Due to its high classification accuracy, non-parametric nature, and ability to handle large and complex datasets, RF has been extensively applied in remote sensing for land cover and habitat classification (Rodriguez-Galiano et al., 2012).

In practice, RF has demonstrated superior performance in mapping complex benthic environments. For example, Ginting et al. (2023) reported that RF achieved overall accuracies ranging from 62.72% to 73% when classifying benthic habitats such as coral reefs, seagrass, macroalgae, and various substrates. Their study also showed that optimizing model parameters—such as using 500 trees and applying the square root rule for feature selection—can significantly enhance classification performance. Similarly, Ariasari and Wicaksono (2019) successfully applied RF to map seagrass composition and percentage cover, obtaining high classification accuracies ranging from 83.52% to 85.71%. These findings underscore RF's effectiveness and reliability for detailed seagrass and benthic habitat mapping using remote sensing data.

Blue Carbon

Blue carbon refers to the carbon captured and stored in coastal and marine ecosystems such as mangrove forests, salt marshes, and seagrass meadows (Soares et al., 2022). The study of blue carbon is essential because these ecosystems play a vital role in mitigating climate change by absorbing substantial amounts of atmospheric CO_2 and reducing greenhouse gas emissions. The blue carbon concept encompasses not only the organic carbon fixed by marine vegetation through photosynthesis but also the sustainable management of these ecosystems to enhance their carbon sequestration capacity and prevent further emissions. Owing to their ecological functions, coastal ecosystems serve as long-term carbon sinks, storing carbon in both plant biomass and sediments, thereby contributing significantly to the global carbon balance (Lovelock & Duarte, 2019).

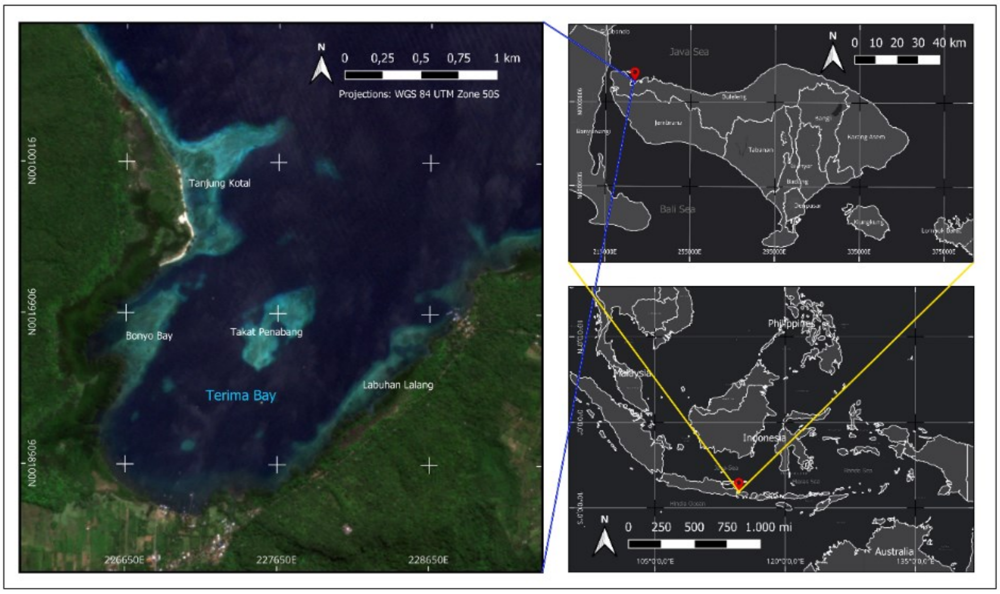
Globally, the blue carbon concept gained prominence with the establishment of the Blue Carbon Initiative in 2011, launched by UNESCO's Intergovernmental Oceanographic Commission (IOC), Conservation International, and the International Union for Conservation of Nature (IUCN) (Howard et al., 2014). Since then, several countries have incorporated blue carbon ecosystems into their Nationally Determined Contributions (NDCs) under the Paris Agreement framework. In Indonesia, blue carbon policies have progressively evolved in recent years. The government recognizes the critical role of blue carbon within the Long-Term Strategy for Low Carbon and Climate Resilience (LTS-LCCR) and the Second NDC (2021). These strategies identify mangrove and seagrass ecosystems as key components for reducing greenhouse gas emissions, aligned with Indonesia's commitment to achieving net-zero emissions by 2060 (Fitria & Dwiyanoto, 2021).

The Ministry of Marine Affairs and Fisheries (KKP) has also launched the Blue Economy Initiative, which incorporates blue carbon conservation as one of its core elements. Furthermore, Indonesia is actively involved in developing Measurement, Reporting, and Verification (MRV) methodologies for coastal carbon through collaborations with international organizations such as UNDP and Blue Forests Indonesia. This policy framework is further reinforced by Presidential Regulation No. 98 of 2021 on the Economic Value of Carbon, which enables the integration of ecosystem-based carbon trading within marine and coastal environments.

Methodology

Research Location

The study area is situated within the West Bali National Park, specifically along Teluk Terima Beach in Buleleng Regency, Bali Province (Figure 1). Buleleng Regency possesses considerable marine resources due to its location along the northern coast of Bali (Negara et al., 2020).



Source: Author, 2025

Figure 1: The location of the study area.

The selection of this site was based on the high likelihood of seagrass dominance within the area. Previous studies conducted in Labuhan Lalang and Teluk Terima have documented the composition of seagrass species, providing valuable information for estimating carbon stocks (Purnomo et al., 2017). Furthermore, this coastal region is recognized for its tourism potential. However, increasing visitor activity poses a growing threat to the integrity of seagrass habitats and associated ecosystems (Mujahid et al., 2022).

Data Collection

A total of 3,237 field samples and PlanetScope SuperDove imagery were used as inputs in this study. The PlanetScope SuperDove imagery, which consists of eight spectral bands and a spatial resolution of 3 meters, was acquired on April 7, 2025. No additional geometric correction was required, as the imagery had already been geometrically rectified and projected to the local coordinate system. To minimize potential noise introduced by sunglint and water-column effects, it is generally recommended to use remote sensing data acquired under conditions with minimal influence from these factors, particularly for bathymetric and benthic habitat mapping (Wicaksono et al., 2022). However, sunglint correction was applied because slight sunglint effects were observed at the study site on the acquisition date. The imagery showed minimal depth variation, indicating that most of the underwater topography in the study area comprises reef-flat features. Given the negligible depth variation, water-column correction was not applied, as the sand reference data required for such correction did not meet the necessary criteria (Zhang et al., 2013).

Input Data Processing

Preparing PlanetScope imagery was the first step in the pre-field operations. Next, unsupervised ISODATA categorization was used to create item class polygons, which were then used as a guide to create sampling transect lines. All the image's variations will be covered by the transect lines that are drawn. A field survey map will be acquired at this point. Training and validation samples are obtained through field survey activities. The photo-transect method is the field survey technique that is employed. The photo-transect approach has been shown to be one of the most successful and efficient survey techniques for gathering field data for mapping benthic habitats. According to Roelfsema et al. (2006), the mapping findings derived from this survey method are likewise acceptable and have the potential to yield high mapping accuracy.

Field data were collected in the form of benthic photographs. These photographs were subsequently processed through a series of steps, beginning with analysis using Coral Point

Count with Excel extensions (CPCe) and georeferencing based on photo locations. This procedure generated georeferenced sample photos accompanied by information on the percentage cover of benthic habitat types. The resulting percentage cover data were then integrated with polygons derived from the Iterative Self-Organizing Data Analysis Technique Algorithm (ISODATA) classification of the satellite imagery. By combining the spatially referenced field observations with the ISODATA classification outputs, a dataset suitable for habitat mapping was produced.

Conversion from Seagrass Percent Cover to AGC

The percentage of seagrass cover is closely related to the AGC of seagrass, where a higher percentage of cover results in a larger aboveground carbon stock (Wahyudi et al., 2020). The calculation of blue carbon stocks, specifically in seagrass, is done by converting the obtained field data on the percentage of seagrass cover into AGC values. The equation used during this conversion process is based on the equation developed by Wicaksono et al. (2025). The mathematically developed prediction model can be written as: AGC = (0.4386 PCv) + 1.041. The range of AGC values that can be predicted by applying this model is between 1.0 and 44.9 g C/m². The minimum value describes the condition without seagrass cover, while the maximum value describes the condition with full seagrass cover (Wicaksono et al., 2025).

Random Forest Classification and Regression

The Random Forest (RF) classification algorithm was employed to develop the mapping model for benthic habitat composition, while RF regression was used to model seagrass percent cover and above-ground carbon (AGC) estimates. The RF algorithm requires several parameters, including the number of trees (n_{tree}), the feature selection function, and the impurity measure used for either regression or classification tasks. In this study, the parameter settings included $n_{tree} = 300$, the square-root function for random feature selection, and the Gini index as the impurity measure. These configurations were adopted based on the findings of experiments conducted by Wicaksono and Lazuardi (2019).

Accuracy Assessment

The accuracy of the generated maps was subsequently evaluated. A confusion matrix was applied to assess the classification accuracy of benthic habitat composition maps, whereas the root mean square error (RMSE), R^2, and plot 1:1 were used to evaluate the accuracy of the continuous predictions for seagrass percent cover and seagrass AGC. The described procedures resulted in the generation of seagrass percent cover, seagrass AGC, and benthic habitat composition maps. The overall methodological framework is illustrated systematically in Figure 2.

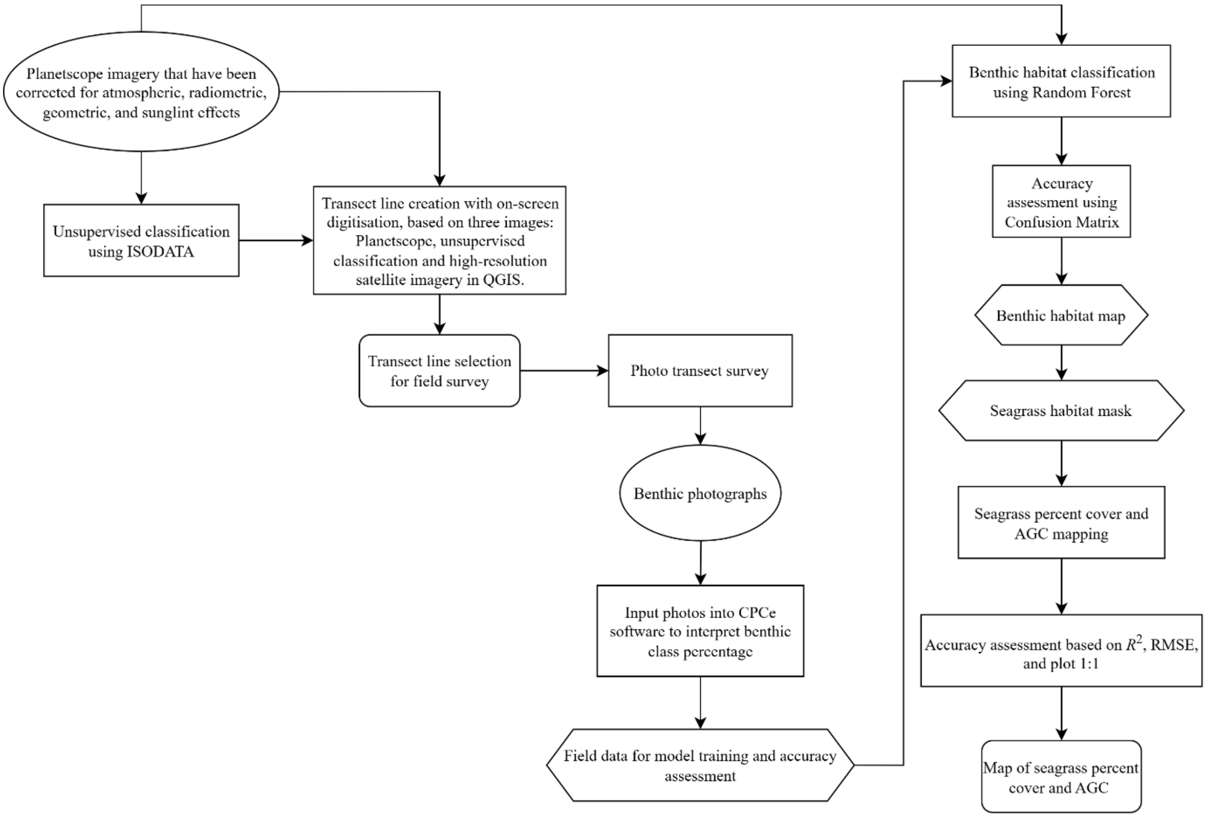


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Figure 2: The research flowchart.

Results and Discussion

Mapping of Benthic Habitat Composition of Teluk Terima

The RF algorithm was trained using in-situ field samples combined with PlanetScope SuperDove imagery acquired on April 7, 2025. The resulting classification map delineates four benthic habitat types and their spatial distribution across Teluk Terima. Figure 3 presents the classified benthic habitat map. The green color on the map indicates the distribution of seagrass meadows, which are predominantly found along the shoreline within the study area. Based on the classification results, the Takat Penabang site, located in the central waters of Teluk Terima, shows no presence of seagrass. While the substrate classes are primarily distributed across the central reef flat, seagrass meadows are concentrated near the coastal zone. In contrast, coral assemblages are abundant in areas adjacent to the deeper reef slope.

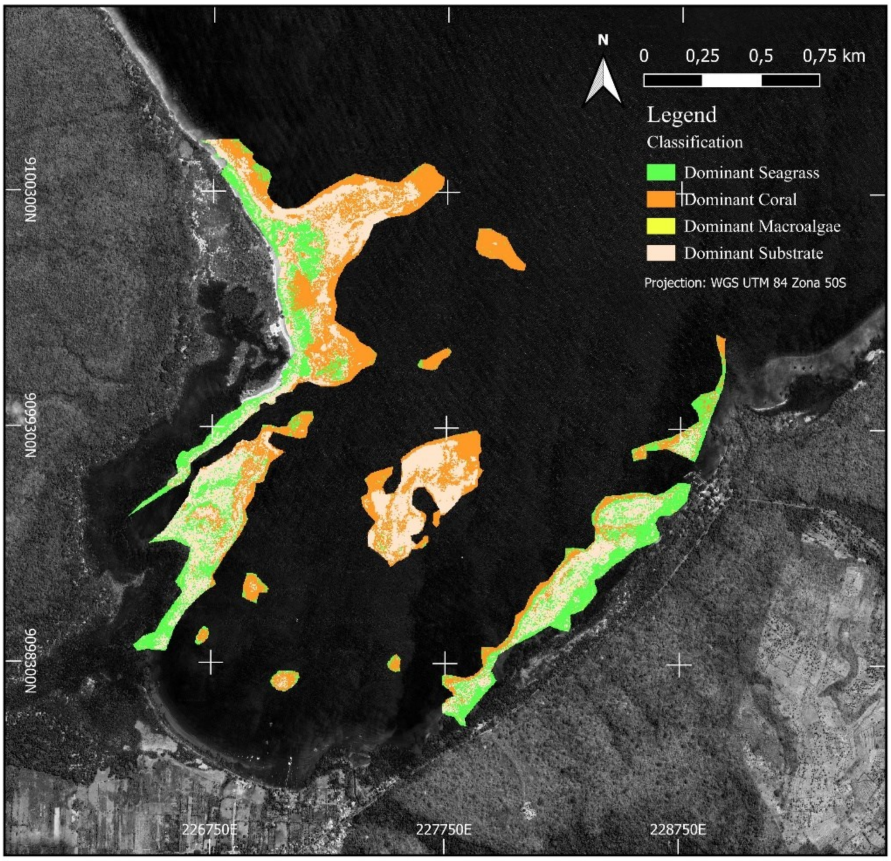

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Figure 3. Benthic habitat map of Teluk Terima using RF algorithm.

The accuracy of the classification was evaluated using a confusion matrix derived from 433 independent validation samples, which had been withheld during the model training stage. The assessment revealed that the RF algorithm achieved an overall accuracy of 59.1% for benthic habitat classification. This indicates that the current model performance remains moderate to low, suggesting a need for improvement in input data quality or feature selection. Details of the accuracy assessment are presented in Table 1.

Only approximately 59% of the pixels classified as seagrass in the map actually corresponded to seagrass in the field, as indicated by the User's Accuracy (UA) of 59.4% for the Dominant Seagrass class. Meanwhile, about 33% of the actual seagrass cover observed in the field was misclassified into other categories, as reflected by the Producer's Accuracy (PA) of 66.6%. Although misclassification was evident, the Dominant Coral class also showed moderate accuracy, with UA and PA values of 62.8% and 58.9%, respectively, indicating that some coral pixels were correctly identified. Such errors may arise from the spectral similarity between coral and other benthic features such as sand or macroalgae that partially cover coral surfaces.

Table 1: Accuracy Assessment Results.

Benthic Habitat 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 Substrate	56.8	57.7	

Source: Author, 2025

The Dominant Substrate class exhibited UA and PA values of 56.8% and 57.7%, respectively, suggesting that more than 40% of substrate pixels were misclassified. The Macroalgae class, however, showed the poorest performance, with both UA and PA values of 0%, indicating that no macroalgae pixels were correctly classified. This complete misclassification may be attributed to limitations in training data, spectral confusion with seagrass, or the small spatial extent of macroalgae patches that fall below the detection threshold of the imagery used. These findings highlight that mapping macroalgae require special consideration, as the current classification approach remains ineffective for distinguishing them from other benthic classes.

The classification results, as shown in Figure 4, indicate that the Dominant Substrate class occupies the largest area, covering approximately 40.2 hectares. This is followed by the Dominant Coral class with 35.9 hectares, and the Dominant Seagrass class with 27.3 hectares. Meanwhile, the Dominant Macroalgae class occupies a relatively small area of only 0.5 hectares. The large extent of coral and substrate suggests that these benthic components are the predominant features within the study area. In contrast, the considerable seagrass coverage indicates the presence of a well-established seagrass ecosystem.

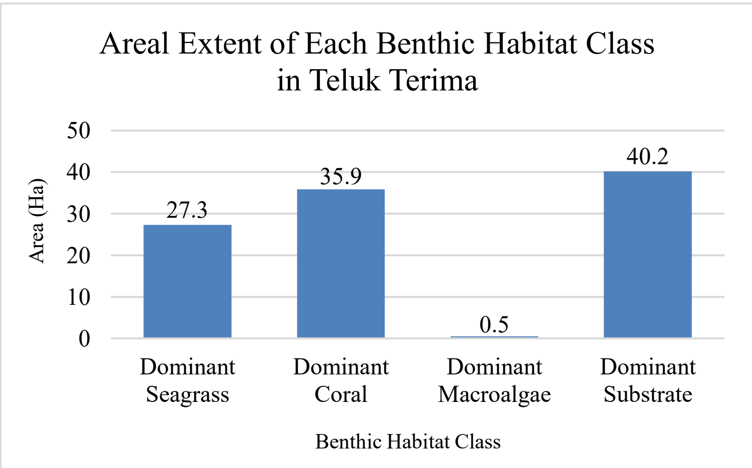

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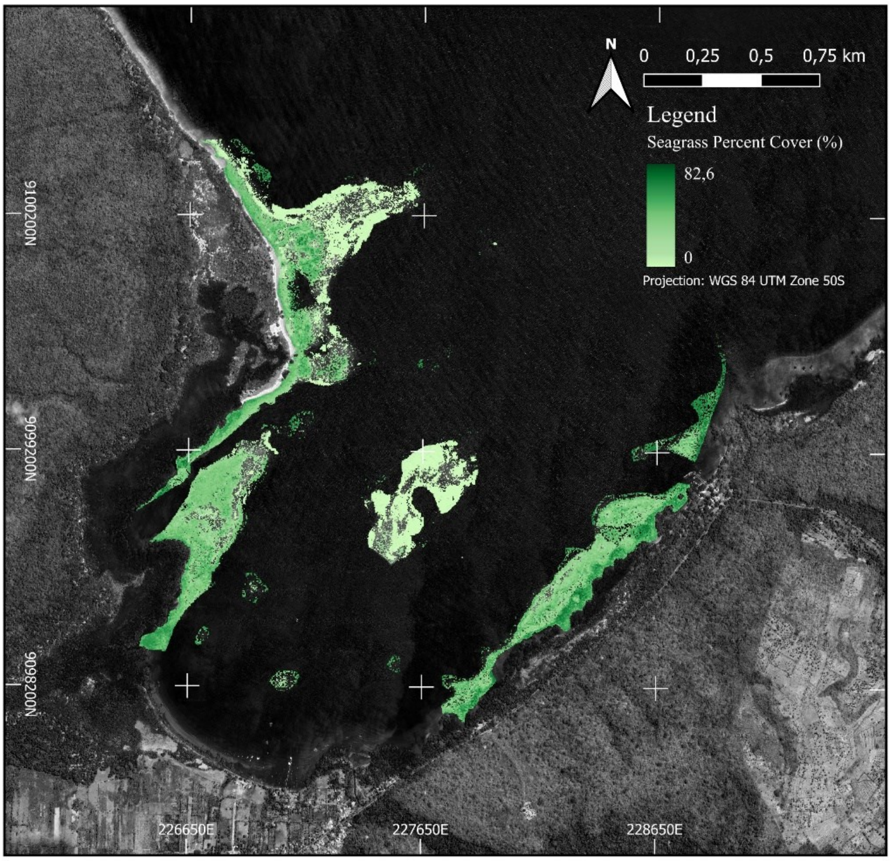
Figure 4. Areal extent of each benthic habitat class from the resulting classification.

Mapping of Seagrass Percent Cover of Teluk Terima

Mapping the percentage of seagrass cover in the Teluk Terima area was performed by extracting information from seagrass and substrate classes obtained from benthic habitat classification results. The RF regression model was then used to estimate the percentage of seagrass cover using field data and PlanetScope SuperDove imagery. The mapping result is visualized with a gradient of light green to dark green colors, representing seagrass percent cover ranging from 0% to 82.6% (Figure 5).



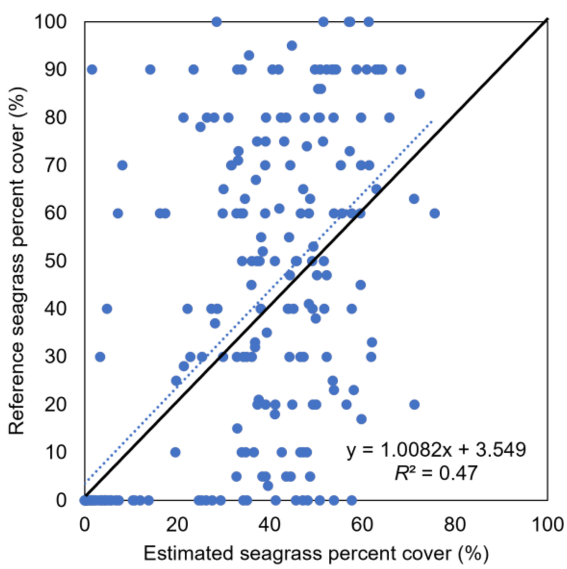
Source: Author, 2025

Figure 5. Map of seagrass percent cover in Teluk Terima.

The seagrass percent cover map (Figure 5) illustrates that areas with high seagrass cover are primarily concentrated in shallow coastal waters and around reef or sandbar formations located further offshore. Among the observed sites, Labuan Lalang exhibits the highest seagrass cover, reaching 44.2%. This indicates a moderately dense seagrass meadow and favorable environmental conditions that support seagrass growth. Teluk Bonyo follows with an average cover of 36.4%, reflecting a relatively well-developed seagrass community, though less extensive than that of Labuan Lalang. Tanjung Kotal ranks next with a cover value of 25.1%, representing a moderate level of seagrass development compared to the previous sites. In contrast, Takat Penabang shows the lowest cover, at only 6.2%, suggesting limited seagrass presence likely influenced by environmental stressors or higher levels of anthropogenic disturbance. The substantial spatial variation in seagrass cover across these locations highlights distinct ecological conditions and management priorities. Labuan Lalang and Tanjung Kotal, with their relatively higher cover, could serve as priority areas for conservation, whereas Takat Penabang may require targeted restoration efforts or mitigation of environmental pressures.

The model performance for predicting seagrass cover percentage was evaluated using the accuracy metrics RMSE and R^2. Based on the PlanetScope SuperDove imagery, with n_{Training} = 1,010 and $n_{\text{Validation}}$ = 433, the model achieved an R^2 value of 0.47 and an RMSE of 24.8%. The 1:1 scatter plot (Figure 6) illustrates a moderate relationship between the predicted and observed values, indicating that approximately 46.6% of the variance in the reference data is explained by the model. Although the regression line shows a positive trend, the relatively wide dispersion of points suggests discrepancies between predicted and observed seagrass cover at several validation sites. An RMSE of 24.8% indicates that the model's average prediction error is relatively high, suggesting potential limitations in capturing fine-scale variability in seagrass cover.

Based on the point distribution shown in Figure 6, the model tends to underestimate seagrass coverage at higher values. This is evident from the concentration of data points with reference values above 60–100% that fall below the identity line (x = y), indicating that the model predicts lower coverage than the observed field data. In contrast, at lower reference values (0–20%), the model tends to overestimate, as reflected by the clustering of points above the identity line.



Source: Author, 2025

Figure 6. Plot 1:1 between estimated and reference seagrass percent cover.

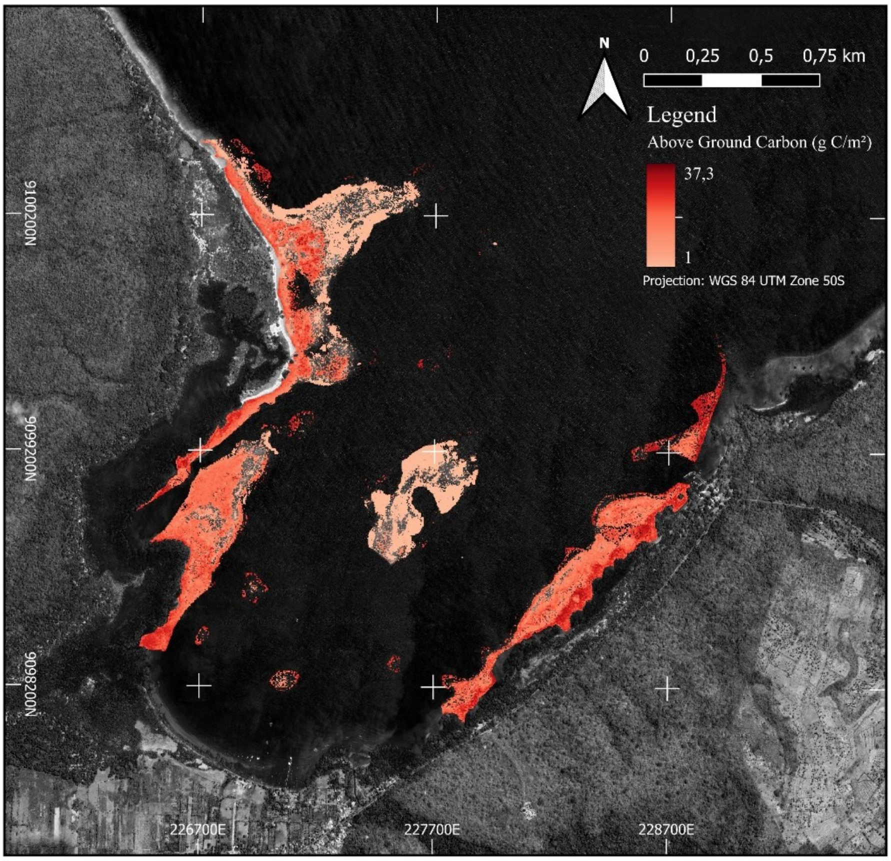
Mapping of Seagrass AGC of Teluk Terima

Mapping of seagrass AGC in the Teluk Terima region was carried out using previously derived seagrass percent cover maps. The seagrass cover data were then applied to an empirical equation developed in a prior study (Wicaksono et al., 2025). The resulting AGC distribution is visualized using a color gradient ranging from bright red to dark red, representing estimated AGC values from 1.04 g C/m² to 37.28 g C/m².

As shown in Figure 7, the AGC estimation map reveals substantial spatial variation among observation sites. Labuan Lalang exhibits the highest total estimated AGC, reaching 419,932.3 g C, with an average of 20 g C/m². This indicates that Labuan Lalang has the greatest carbon sequestration potential among the surveyed areas. The high AGC value is likely associated with denser seagrass cover and more favorable environmental conditions for organic carbon accumulation.

Tanjung Kotal ranks second with an estimated total AGC of 316,986.5 g C and an average of 12 g C/m². Although the total carbon stock remains relatively high, the lower mean AGC value suggests that vegetation density or seagrass coverage is less extensive than in Labuan Lalang. Bonyo Bay occupies the third position, with an estimated total AGC of 265,197.4 g C and an average of 17 g C/m². The relatively high mean AGC compared to Tanjung Kotal suggests denser seagrass cover, though the smaller overall extent of seagrass likely results in a lower total carbon stock. Conversely, Takat Penabang records the lowest estimated AGC, with a total of 38,216 g C and an average of 3.9 g C/m². This low value reflects the limited and sparse seagrass distribution in the area, leading to a reduced carbon storage capacity.

The differences in estimated AGC values among these locations may be attributed to several factors, including variations in seagrass percent cover, substrate characteristics, vegetation productivity, and environmental disturbances such as anthropogenic pressures or sedimentation. However, further studies are required to confirm these relationships. From an ecological perspective, the findings suggest that sites such as Labuan Lalang and Tanjung Kotal hold substantial potential as blue carbon sinks, highlighting their importance for conservation prioritization. In contrast, areas with relatively low AGC values, such as Takat Penabang, may be suitable targets for seagrass restoration initiatives aimed at enhancing their carbon sequestration capacity.

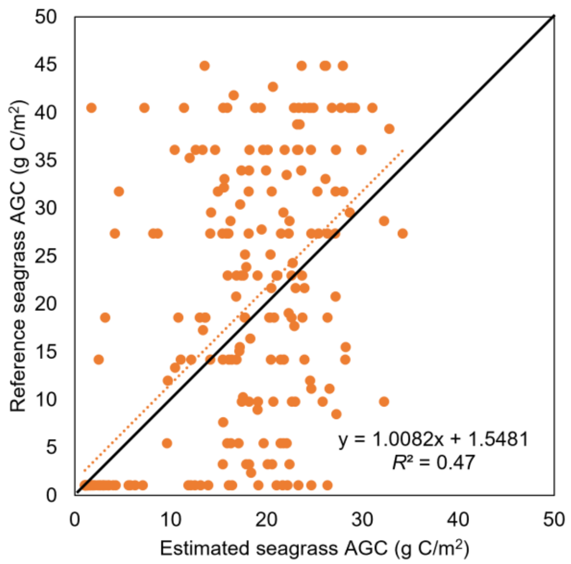


Source: Author, 2025

Figure 7. Map of seagrass AGC in the Teluk Terima.

Based on the validation of 433 samples, the model achieved an R^2 value of 0.47 and an RMSE of 10.9 g C/m². The 1:1 scatter plot (Figure 8) illustrates a moderate correlation between the estimated and reference AGC values. The R^2 value indicates that approximately 46.6% of the variability in the reference AGC can be explained by the variability in the estimated AGC. Although this reflects a reasonable level of model performance, it also suggests that about 53% of the variation remains unexplained, implying room for improvement.

The RMSE value of 10.9 g C/m² represents the average magnitude of prediction error. Because RMSE is sensitive to large deviations, this value is relatively high compared to the observed range of reference AGC values (1.04–37.28 g C/m²). This suggests that the model's predictions exhibit not only systematic bias but also substantial deviation from the observed data. The 1:1 plot further reveals a systematic trend in the residuals: at lower AGC values, the model tends to overestimate, whereas at higher AGC values, it tends to underestimate. This pattern indicates that the model struggles to accurately capture the variability at the extreme ends of the distribution, particularly for very low and very high AGC values.



Source: Author, 2025

Figure 8. The 1:1 plot between estimated and reference AGC values.

Conclusion and Recommendation

This study demonstrates the effectiveness of integrating PlanetScope SuperDove imagery with the RF algorithm for mapping benthic habitat composition, seagrass percent cover, and AGC in the Teluk Terima area. The results revealed that coral and substrate are the dominant habitat types, while seagrass meadows are mainly distributed in shallow coastal zones. Among the sites, Labuan Lalang and Tanjung Kotal exhibited the highest carbon sequestration potential, identifying them as priority areas for conservation. In contrast, Takat Penabang showed the lowest seagrass cover and AGC values, indicating the need for targeted restoration and rehabilitation efforts. Despite these achievements, the overall classification accuracy (59.1%) and AGC model performance (R^2 = 0.47) indicate that further improvements are needed, particularly in distinguishing macroalgae from seagrass due to spectral overlap and limited training data. Future studies should emphasize methodological improvements, such as incorporating higher-quality input data, refining algorithms, and coupling remote sensing analysis with long-term field monitoring, to enhance mapping accuracy and provide more reliable information for sustainable coastal ecosystem management.

Acknowledgments

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