Measuring ocean physical asset account using machine learning approaches

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Abstract

The blue economy concept has been adapted as a strategy in setting development programmes and public policies in managing Indonesia's marine resources. As a supporting instrument, accurate field data is needed when compiling the ocean account. Meanwhile, the support of qualified resources is needed during the field data collection process. Research on mapping water areas using satellite technology and machine learning techniques in producing water maps, especially in coastal areas. The approach is suitable for arranging a physical asset account, which is a component of the ocean account framework. So far, no research has implemented these developments to produce ocean physical asset account. Therefore, this study will cover in arranging the account by utilising Sentinel-2 imagery and implementing Random Forest, Support Vector Machine, and Extreme Gradient Boosting (XGBoost) machine learning methods, which according to previous studies are superior methods for mapping water areas. The modelling results show that there is an extensive change in coral, seagrass, and mixed ecosystem types (a combination of coral, seagrass, and macroalgae ecosystems) between 2020 and 2023.

Keywords: blue economy; ocean account; satellite imagery; machine learning
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1. Introduction

As a country with vast territorial waters, Indonesia also possesses significant marine wealth potential. For instance, in the economic sector, there are at least 11 marine potentials that can be developed from coastal and ocean areas, ranging from capture fisheries and the fish processing industry to energy development and non-conventional natural resources (Arianto, 2020). In this context, natural resources are utilized as the primary capital in economic activities. However, the supply of marine resources is limited, and destructive activities over time can weaken this potential. This pattern subsequently has a feedback effect on the marine and coastal economy. Therefore, to preserve the ecosystem while simultaneously utilizing resources, a system aligned with the concept of the blue economy is needed.

According to Indonesian Law Number 32 of 2014, Article 14, Paragraph 1, the blue economy refers to an approach aimed at enhancing sustainable marine management, as well as the conservation of marine and coastal resources and their ecosystems, to achieve economic growth based on principles such as community involvement, resource efficiency, waste minimization, and multiple revenue generation (Arianto, 2020). The blue economy concept also supports the Sustainable Development Goals (SDGs) set by the United Nations (UN), particularly Goal 14: "Conserve and Sustainably Use the Oceans, Seas, and Marine Resources for Sustainable Development" (Bappenas, 2020). One of the implementations of the blue economy strategy is reflected in the development of marine accounts. Marine accounts serve as a system that enables the measurement of both economic achievements and environmental quality simultaneously (Ministry of Marine Affairs and Fisheries (MMAF), 2022b). Fundamentally, the preparation of environmental accounts follows the System of Environmental Economic Accounting (SEEA) framework, as agreed upon by the UN. The Indonesian government has implemented SEEA guidelines into the Integrated Environmental and Economic Accounting System (Sisnerling). As the central reference for Sisnerling, Statistics Indonesia (BPS) collaborates with relevant ministries and institutions in compiling environmental accounts, which include marine accounts.

There are seven types of accounts within the marine accounting framework: marine asset accounts, marine-to-economy flow accounts, marine-to-environment flow accounts, marine economic accounts, marine governance accounts, combined presentation accounts, and marine wealth accounts (GOAP, 2021). Specifically, marine asset accounts record "environmental assets." The compilation of marine asset accounts enables the measurement of marine ecosystems as wealth assets. Ecosystem measurement is conducted through direct field observations. However, significant support is required for data collection in marine accounting. A pilot study report on the compilation of marine accounts in 2021 highlighted that data availability and financial resources remain major challenges in implementing this activity (Ministry of Marine Affairs and Fisheries (MMAF), 2022a). Therefore, alternative data sources may serve as a solution to these issues.

On the other hand, the rapid advancement of technology enables the utilization of big data as an alternative for field data collection. One type of big data that has gained prominence is satellite imagery spatial data. Satellite imagery provides extensive information, including climate surface temperature, atmospheric conditions, weather, and Earth observations. The ability of satellites to capture Earth's conditions makes it possible to map ecosystems beneath the ocean surface. Several studies utilizing satellite imagery spatial data have successfully classified coastal ecosystem areas. Furthermore, as research progresses, underwater imaging has become a more widely used data source compared to physical sampling (Misiuk & Brown, 2024). Sensors carried by satellites enable highly efficient remote sensing for oceans and seabeds on a global scale. Among low-resolution satellites, the use of Sentinel imagery has increased significantly (Misiuk & Brown, 2024). In addition to being freely available, its spatial resolution remains adequate. This has been demonstrated by previous studies that have successfully classified benthic areas using Sentinel-2 satellite imagery, yielding fairly accurate classification results (Lazuardi et al., 2021b; Wicaksono et al., 2020). These studies classified coastal ecosystems, including benthic areas. Benthic refers to anything located on the seafloor, whether living organisms or non-living elements (NOAA, 2024). Common benthic ecosystems include seagrass forests, seagrass beds, coral reefs, and soft-bottom environments on the continental shelf (Burke et al., 2001).

Machine learning methods are commonly used in these classifications. Misiuk & Brown (2024) state that supervised learning models, a type of machine learning technique, have been widely used and have proven to yield reliable results for benthic classification (Misiuk & Brown, 2024). A review of previous research literature from 2018 to 2020 by Nguyen et al. (2021) on coral reef mapping concluded that Support Vector Classification (SVC) often achieves high accuracy, while Random Forest (RF) is highly efficient for remote sensing classification. The review explains that both algorithms generally perform robustly, although they do not always produce high metric values, with accuracy ranging from 70% to just under 90% when using low- and medium-resolution imagery. Meanwhile, a case study by Nemani et al. (2022) found that among the RF, SVC, and Extreme Gradient Boosting (XGBoost) algorithms, the XGBoost algorithm achieved the highest accuracy.

The advancement of research allows the implementation of these methods in compiling physical asset accounts by mapping changes between two periods. However, no research has specifically compiled physical asset accounts using remote sensing technology for coastal areas. Therefore, based on the aforementioned concept, this study aims to compile physical asset accounts using satellite imagery as an alternative data source, employing supervised learning modeling methods such as the RF, SVC, and XGBoost algorithms, to model and map benthic habitats.

This study is conducted in the research locus of Karimunjawa National Park and the Thousand Islands, both of which contain rich coastal ecosystems. Their geographically favorable conditions make them popular coastal tourism destinations (Ardianto, 2023; Balai Taman Nasional Karimunjawa, 2011). The mapped research locus in the Thousand Islands includes five islands: Pari Island, Tidung Island, Pramuka Island, Kelapa Island, and Harapan Island. These five islands have recorded high numbers of tourists, according to data from the Thousand Islands Tourism and Creative Economy Sub-Department. Moreover, these islands all feature coastal tourism attractions.

2. Methodology

2.1. Benthic Habitat Mapping

Misiuk & Brown (2024) compiled a review of research on benthic habitat mapping conducted over the past years. There has been a shift in approach from manual benthic habitat mapping to empirical approaches, such as supervised modeling. Supervised modeling began to be applied in habitat mapping literature around 2010, starting with Maximum Likelihood classification and k-Means clustering methods. As research progressed, these methods were gradually replaced by more advanced techniques, such as Random Forest (RF), Support Vector Machine (SVM), and boosted regression trees, as these algorithms offered better performance compared to the previous ones. Meanwhile, the use of satellite sensors has been considered an efficient alternative data source for capturing the seafloor on a global scale.

In the literature review by Nguyen et al. (2021) on coral reef mapping using satellite imagery, low-resolution satellites such as Landsat and Sentinel have been widely used. The open access to these satellite images has facilitated many studies on coral reef mapping, although the image quality cannot be compared to medium- and high-resolution satellite imagery. However, it has been observed that the use of Sentinel satellite imagery has increased significantly over the years in benthic habitat mapping research.

Several studies have demonstrated that satellite imagery can produce reasonably accurate habitat maps. According to previous research, the RF algorithm has proven its performance. For example, a case study by Traganos & Reinartz (2018) successfully classified seagrass with very high accuracy, reaching 96.4%, using Sentinel-2 imagery. Meanwhile, another study by Wicaksono et al. (2019) applied RF and achieved accuracy rates of 88.54% and 94.17% in classifying benthic habitats into 14 and 4 classes, respectively, using WorldView-2, a high-resolution satellite imagery. These findings suggest that the RF algorithm is highly capable of balancing the mapping results between low- and high-resolution satellite imagery.

On the other hand, the SVM algorithm has also shown strong performance in classifying coastal ecosystems in previous studies. Wicaksono et al. (2021) demonstrated that an SVM model applied to Sentinel-2 imagery produced better results than the RF model, achieving an accuracy of 73.23%. Similarly, a case study by Lazuardi et al. (2021a) successfully classified coral reefs and seagrass beds using SVM with an accuracy of 73.14%, slightly outperforming the RF model in the same study. Like the previous studies, this research also utilized Sentinel-2 imagery.

Despite the competitive advantages of RF and SVM, a study by Nemani et al. (2022) revealed that XGBoost performed better than both SVM and RF in classifying benthic assemblages, achieving an accuracy of 61.67%. This finding highlights the importance of exploring different model choices in this study.

2.2. Physical Asset Balance

The ocean balance sheet is a structured compilation of consistent and comparable information (maps, data, statistics, and indicators) regarding marine and coastal environments, including social conditions and economic activities (GOAP, 2021; Ministry of Marine Affairs and Fisheries (MMAF), 2022b). Essentially, the ocean balance sheet consists of a set of accounts structured within a conceptual framework. This framework is developed in accordance with internationally agreed-upon standards and frameworks.

In terms of marine governance, governments need to develop policies and programs aimed at enhancing both social and economic development while ensuring the protection of coastal and marine environments. Therefore, a holistic and integrated marine-based development analysis is necessary, based on the evidence provided in the ocean balance sheet. The ocean balance framework offers a means to measure marine wealth, not only in financial terms but also in terms of long-term sustainability, which is represented through the marine asset balance. The Marine Asset Balance allows for recording the physical status and condition, as well as the monetary value of assets ("natural capital") within coastal and marine environments, including energy, minerals, and other biological resources (such as biodiversity).

The approach to ecosystem asset valuation within the marine asset balance is divided into two concepts: ecosystem extent measurement and ecosystem condition assessment (United Nations et al., 2014). The ecosystem extent measurement concept forms the basis for the marine physical asset balance. This assessment focuses on measuring land cover, expressed in terms of area and its changes within each functional ecosystem unit/land cover type. Changes in land cover are categorized into additions to stock and reductions to stock (United Nations et al., 2014).

The potential of benthic habitat mapping in measuring ecosystem extent enables the compilation of the physical asset balance, which is a component of the ocean balance sheet. The physical asset balance essentially measures the ecosystem extent of aquatic habitat land cover, expressed in area, and calculates changes in coverage within each ecosystem class. However, no publications have been found that implement coastal area mapping using satellite imagery with a machine learning approach in the preparation of the physical asset balance.

To achieve the research objectives, a series of research stages were conducted, as described in the study by Jane et al. (2024). These stages include data collection, data pre-processing, modeling using three different algorithms, model validation using stratified cross-validation, and selecting the best model among all generated models. The modeling process was carried out using Random Forest (RF), Support Vector Classification (SVC), and XGBoost algorithms.

Random Forest is a classification method that consists of an ensemble of decision trees, where the majority class is chosen as the final class (Vujović, 2021). The classification tree formula is expressed as follows.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x, T_k) \tag{1}$$

where $\hat{y}_i$ is target of the i-th observation; K is number of trees; f_k is function of the k-th tree; T is training dataset; T_k is bootstrapped training dataset; and x is selected future (input).

The classification tree is grown using the Classification and Regression Tree (CART) method without pruning. When growing the model tree, nodes are split by selecting the partition that reduces impurity.

SVM essentially searches for the most optimal separating hyperplane. The following formula is used (Ng & Ma, 2023):

$$h_{w,b}(x) = g(w^T x + b) \tag{2}$$

where w is the weight vector, defined as $W = \{w_1, w_2, \ldots, w_n\}$ and n is the number of attributes, while b is considered as the bias. XGBoost is a method that combines decision trees while minimizing the additive function and objective function. XGBoost is equipped with an advanced split-searching algorithm, allowing the model to find the best split in tree learning and efficiently process large-scale and sparse input data. This learning method accommodates optimal prefetching algorithms, data compression, and additional techniques to enhance computation beyond the core processing.

Furthermore, to validate the modeling, two accuracy metrics F1-score and Matthew's Correlation Coefficient (MCC) are used. The best model is then selected and applied to map benthic habitats using satellite imagery of the Kepulauan Seribu region for two different periods (2020 and 2023) (Rainio et al., 2024; Vujović, 2021). In general, the research framework is illustrated in the flowchart in Figure 1.

The raster data resulting from the mapping is then analyzed for changes, with the outcomes of this analysis used to construct a physical asset balance sheet, which is one of the components of the balance sheet in the ocean accounting framework, following the guidelines of the *Technical Guidance on Ocean Accounting for Sustainable Development* (GOAP, 2021). According to these guidelines, the physical asset balance sheet is broadly divided into components of additions

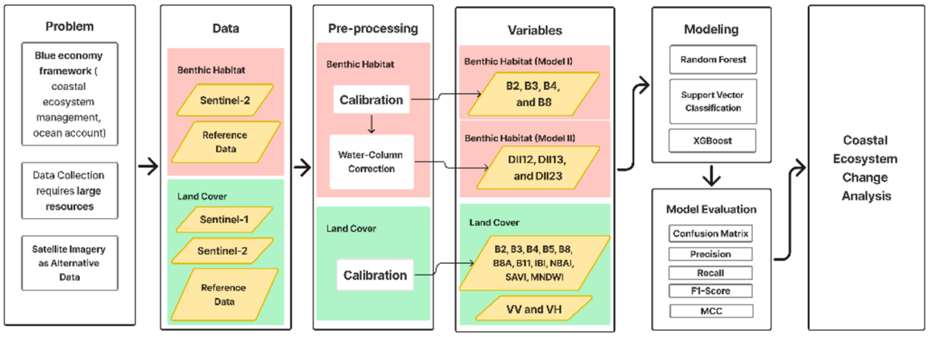

Figure 1: Research Framework for Coastal Ecosystem Change Analysis
Source: Jane et al. (2024)

to stock and reductions in stock. Additions to stock consist of several types, such as managed expansion, natural expansion, reclassifications, discoveries, and upward reappraisals. Meanwhile, stock reductions can be detailed into four categories: managed regression, natural regression, reclassifications, and downward reappraisals.

2.3. Data and Variables

In this study, the predictor variables used include the red (B4), green (B3), blue (B2), and near-infrared (B8) bands from Sentinel-2 Surface Reflectance (SR) imagery (Budhiman et al., 2012; Goodman et al., 2013; Wicaksono et al., 2021). These values were obtained through the Google Earth Engine (GEE) platform, based on a specified time frame and located in the Karimunjawa National Park and the Thousand Islands. The benthic cover classification uses imagery from October 2021 (aligned with the reference data collection period) for training data, as well as imagery from 2020 and 2023 to apply the benthic mapping model. Additionally, these satellite images will be used to implement the trained model for the two periods.

The second dataset used is the official data needed as the basis for labeling. Benthic habitat reference data was obtained from the National Research and Innovation Agency (BRIN). The cover data was gathered from field observations conducted in October 2021 at each available observation station within the research locus. This shapefile data consists of classes such as coral, seagrass, macroalgae, sand, and a mixed class (a combination of coral, seagrass, and macroalgae) in shallow water areas. The official benthic cover data was then used to delimit the benthic habitat areas, with shallow water areas being defined as those close to shore, based on expert assessments who produced this data. This was done to ensure the classification model focuses solely on the changes in benthic patterns of shallow waters, due to the limitations of electromagnetic signal depth (Misiuk

& Brown, 2024). The data and variables are shown in Table 1.

Table 1: Data and variable that are used

Data	Variable	Unit (metric)	Period
Sentinel-2 Level 2A Surface Reflectance (GEE)	Pita B2, B3, B4, B8	Pixels (10 m)	August 2020 and December 2023 (Kepulauan Seribu)
			October 2021 (Taman Nasional Karimunjawa)
Benthos Habitat Shapefile (BRIN)	Benthos Habitat Classes (coral class, seagrass class, macroalgae class, sand class, and mixed class)	-	2021

Source: Processed

3. Result and Analysis

Based on the model built in the reference by Jane et al. (2024), here are the validation results of the best model, the RF model with 100 n_estimators parameter. The RF model in this case outperformed with an overall F1-score metric of 0.773, while XGBoost excelled in the overall MCC metric with a value of 0.784. Both models performed similarly well. However, the RF model demonstrated more stability due to its smaller standard deviation, making it the chosen model for mapping coastal areas. The superior performance of both models aligns with previous studies that highlighted the advantages of RF and XGBoost algorithms over others (Nemani et al., 2022; Traganos & Reinartz, 2018; Wicaksono et al., 2019).

The F1 score is an evaluation metric that combines precision and recall. Precision measures the percentage of observations classified as positive from all observations classified as positive, while recall indicates the percentage of observations classified as positive from all actual positive observations. Meanwhile, the MCC score measures the correlation between predicted class results and the actual class. Both metrics range from -1 to 1. The closer the value is to 1, the better the prediction, and the closer it is to -1, the worse the prediction.

Next, benthic habitat mapping was carried out on five islands in the Thousand Islands across two periods, as shown in Figure 2. The results of this mapping were then analyzed for changes, and a physical asset balance sheet was prepared assuming that all changes occurred naturally.

The mapping results were then analyzed for changes before being compiled into a balance sheet, identifying whether an ecosystem experienced an increase or decrease. These changes are presented in Table 3.

Based on the Table 2, several conclusions can be drawn. In both periods, there was a shift in the dominant class in the coastal areas. The sand ecosystem was the class with the largest area in 2020, while the seagrass ecosystem dominated

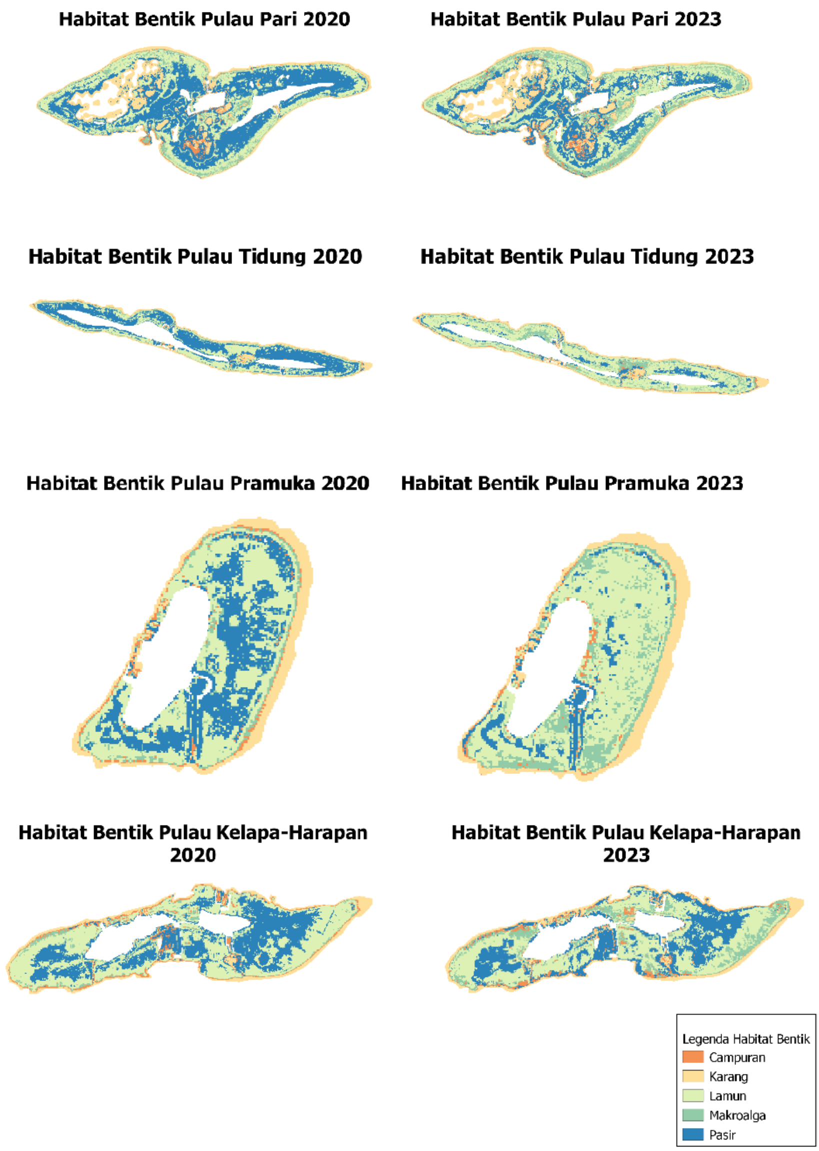

Figure 2: Habitat Classification of Kepulauan Seribu in 2020 and 2023
Source: Processed

Table 2: Changes in the Benthic Habitat Ecosystem of Kepulauan Seribu in 2020 and 2023

	Area 2023 (ha)					TOTAL
Area 2020 (ha)	Mixed	Coral Reef	Seagrass	Macroalgae	Sand	
Mixed	14,84	20,3	4,91	6,99	17,12	64,16
Coral Reef	5,89	240,69	0,23	2,87	6,07	255,75
Seagrass	28,07	2,77	295,94	183,33	46,39	556,5
Macroalgae	18,01	13,55	37,05	45,5	9,45	123,56
Sand	14,52	19,29	329,45	36,01	337,44	736,71
TOTAL	81,33	296,6	667,58	274,7	416,47	1736,66

Source: Processed

the coastal areas in 2023. Meanwhile, the mixed ecosystem remained consistent as the class with the smallest area in both periods. Another observation is that there was an increase in the area of all ecosystem classes except for the sand class. However, field verification is still needed to ensure the accuracy of the model's predictions. After observing the changes, the physical asset balance was prepared with the assumption that all changes occurred naturally. This account was only created for the ecosystem types that are inline with the government's priority, namely coral reefs and seagrass ecosystems. The physical asset balance is shown in Table 3.

Table 3: Physical Asset Balance of Five Islands in Kepulauan Seribu in 2020 and 2023

	Ecosystem Aset		
	Seagrass	Coral	Mixed
Opening Stock	556,5	255,7	64,2
+ Additions to Stock			
Managed expansion Natural expansion Reclassifications Discoveries Reappraisals (+)	371,6	55,9	66,5
TOTAL additions to stock	371,6	55,9	66,5
- Reductions to Stock			
Managed regression Natural regression Reappraisals (-)	260,5	15,1	49,3
TOTAL reductions to stock	260,5	15,1	49,3
= Closing Stock	667,6	296,6	81,3
Units of Measurement	Area (ha)		

Source: Processed

Based on the balance sheet, it can be concluded that each ecosystem type experienced an increase in area. In comparison, the seagrass ecosystem experienced the largest expansion, with an area increase of 111.1 ha, followed by the coral reef ecosystem (40.9 ha) and the mixed ecosystem (17.2 ha). However, when compared by percentage change, the mixed ecosystem had the largest percentage change relative to the initial area, at 26.76%. The second-largest percentage change occurred in the seagrass ecosystem, at 19.96%. These changes align with the findings of Qiu et al. (2017), which state that seagrass areas exhibit seasonal variation due to certain factors throughout the year. Therefore, when compared to the initial area, the mixed and seagrass ecosystems experienced the largest changes among the three ecosystems.

In addition, the Ministry of Maritime Affairs and Fisheries (KKP) implemented marine and fisheries development programs between the two periods, which could support the preservation of these three ecosystems. In 2020, the KKP implemented a marine spatial management program that protected and utilized conservation areas and marine biodiversity, as well as spatial planning and management support programs. The program also included fisheries management to regulate fishing gear and licensing, marine and fisheries resources surveillance, and research programs for marine and fisheries resources that included outreach and research activities (Kementerian Kelautan dan Perikanan, 2020). From 2021 to 2023, the KKP continued its marine and fisheries management program, which included marine resources surveillance and spatial planning activities, environmental quality programs focusing on conservation areas and biodiversity, vocational education and training programs for marine resources surveillance officers, and research and innovation programs in marine and fisheries science and technology (JDIH Marves, 2023; Kementerian Kelautan dan Perikanan, 2022,2023,2024).

4. Conclusion and Implication

Based on the results and discussion, the conclusion that can be drawn is that satellite imagery can be used in the preparation of physical asset accounts. By using machine learning methods, coastal ecosystem type classification allows for the determination of the area of each ecosystem type. The area of these ecosystems can then be analyzed for changes and used to prepare physical asset accounts based on the analysis. According to the results of the asset account, there are differences in the physical assets of coastal ecosystems in the Kepulauan Seribu region between the two periods, 2020 and 2023, particularly in the mixed and seagrass ecosystems.

Meanwhile, there are several recommendations that can be given based on this study. For the government, there are already routine activities for classifying coastal ecosystems using satellite imagery, but no efforts have been made to prepare physical asset accounts from these classifications. Therefore, this idea could serve as a solution in case there are obstacles in the data collection process for preparing physical asset accounts. For future research, there are several suggestions based on the limitations of this study. These limitations include the selection of imagery in benthic habitat classification, which prioritizes image quality over other external factors, such as tidal periods. Additionally, this study did not consider the seasonal variations in seagrass, which should be taken into account in future benthic habitat classification research. Furthermore, this research did not utilize other supporting data, such as depth data, and therefore, it is recommended to include complementary data to improve the accuracy of the modeling.

This research was not accompanied by field verification. Therefore, for future studies, field verification is necessary to validate the classification results.

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