# MONITORING BENTHIC HABITAT USING SENTINEL-2 MSI IMAGES WITH LYZENGA MODEL FEATURES AND MACHINE LEARNING IN WANGI-WANGI ISLANDS

(*Pemantauan Habitat Bentik Menggunakan Citra Sentinel-2 MSI dengan Fitur Model Lyzenga dan Machine Learning di Kepulauan Wangi-Wangi*)

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**ABSTRACT**

Monitoring benthic habitats becomes more difficult when physical visits to sites are required by diving. This is considered to require greater resources and time. This research adopts Sentinel 2 MSI imagery to monitor benthic habitat in the Wangi-Wangi Islands, Indonesia. This research uses the Lyzenga model to extract depth invariant index features on the Google Earth Engine (GEE) API to classify benthic environments. Three Machine Learning algorithms are applied, such as Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Trees (CART), in classifying supervised benthic habitats based on training classes selected under the guidance of an initial K-means unsupervised classification. RF has better overall accuracy than SVM and CART in 2019 and 2023, namely 94.41% and 97.45%, respectively. This research found significant changes between coral, seagrass, and sand due to high environmental and anthropogenic pressure. The use of MSI's Sentinel 2 imagery and the GEE cloud computing platform is very helpful in monitoring and collecting marine data.

**Keywords**: Benthic, Google Earth Engine, Lyzenga, Random Forest, Sentinel 2 MSI

***ABSTRAK***

*Pemantauan habitat bentik menjadi lebih sulit ketika harus melakukan kunjungan fisik ke lokasi dengan penyelaman. Hal ini dinilai membutuhkan sumber daya dan waktu yang lebih besar. Penelitian ini mengadopsi citra Sentinel 2 MSI untuk memantau habitat bentik di Kepulauan Wangi-Wangi, Indonesia. Penelitian ini menggunakan model Lyzenga dalam mengekstraksi deepth invariant index feature pada Google Earth Engine (GEE) API untuk mengklasifikasi lingkungan bentik. Tiga algoritma Machine Learning diterapkan seperti Support Vectore Machine (SVM), Random Forest (RF) dan Classification and Regression Trees (CART) dalam mengklasifiasi habitat bentik yang diawasi berdasarkan kelas pelatihan yang dipilih di bawah panduan of an initial K-means unsupervised classification. RF memiliki overall accuracy yang lebih baik dibandingkan SVM dan CART pada tahun 2019 dan 2023 yaitu masing-masing 94.41% dan 97.45%. Penelitian ini menemukan adanya perubahan yang signifikan antara coral, seagrass dan sand akibat tekanan lingkungan dan antropogenik yang tinggi. Penggunaan citra Sentinel 2 MSI dan platform cloud computing GEE sangat membantu dalam pemantauan dan pengumpulan data kelautan.*

***Kata Kunci**: Bentik, Google Earth Engine, Lyzenga, Random Forest, Sentinel 2 MSI*

## INTRODUCTION

Benthic refers to low-level ecological areas that occur at the bottom of water (NOAA, 2018). Benthic habitats are underwater ecological areas where animals and plants thrive on the bottom or surface of the water. The main focus of most studies stated that corals, seagrasses, and mangroves are the habitat for marine life. Shallow coral reefs, seagrass beds, and mangrove forests are said to be the main nursery biotopes for fish species (Nagelkerken et al., 2000). A complex structural composition for biotopes supports this situation to hide from predators (Bell & Westoby, 1986), which in turn also plays an important role in influencing the genetic diversity of marine populations, as seen in the influence of lagoons in coastal areas on its diversity (Pérez-Ruzafa et al., 2019). Coral polyps, also known as "marine rainforests," play an important role in building coral reefs. Coral reefs, which are home to various marine species, only occupy 0.1% of the ocean area. This percentage is inversely proportional to the number of marine species that use coral reefs as habitat, which reaches 25%. This shows the importance of the existence of coral reefs. Despite this, benthic environments have been threatened by anthropogenic activities.

Anthropogenic activities contribute to marine degradation quite significantly compared to other activities. About 10% of the world's total population

(600 million people) is known to live in coastal areas with an altitude of <10 meters above sea level. Meanwhile, the other 40% of the world's population (2.4 billion people) live within a radius of 100 km from the coast. Around 37% of the world's global population, especially coastal communities, consider ocean, coastal, and marine resources to be very important (United Nations, 2017). This situation can threaten marine ecosystems if these marine ecosystems are not protected and managed well. In comparison, the rate of degradation of marine exosystems is faster than the rate of degradation of terrestrial ecosystems, while underwater observations have only begun recently (Knowlton & Jackson, 2008). Therefore, monitoring benthic habitats is important to improve conservation efforts.

Benthic habitat monitoring can be carried out using multispectral remote sensing imagery by integrating the Lyzenga model in extracting features. The study conducted by Vanderstraete et al. (2006) used Landsat imagery to map seabed types from 1987 to 2000 near Hurghada, Egypt. Pahlevan et al. (2006) also conducted a study using IKONOS imagery equipped with bathymetric data to extract benthic maps on Kish Island in the Persian Gulf. Nieto's (2013) study in St. Eustatius studied the high-resolution WorldView-2 and Quickbird imagery integrated with bathymetric data to classify benthic habitats in the Dutch Caribbean. In this study, the implementation of the Lyzenga procedure still used conventional software to produce benthic habitat maps.

In Indonesia, the use of satellite imagery in benthic mapping has been widely explored. A study by Wicaksono et al. (2019) on Kemujan Island using machine learning with WorldView-2 imagery showed that benthic habitats can be identified using a more general classification scheme. A study by Hamuna et al. (2023) in Wakatobi National Park showed that remote sensing data can classify benthic habitats quite well. Benthic mapping in the Wangi-Wangi Islands had been identified previously but in a very limited area (Matsu et al., 2018).

This study used a Google Earth Engine (GEE) approach in mapping benthic habitats in the center of coral reef biodiversity or what is known as the Coral Triangle Initiative from 2019 to 2023 based on the Sentinel 2 MultiSpectral Instrument (MSI) archive. This study calculated the Lyzenga depth variance index feature from Sentinel 2 MSI imagery to classify benthic habitats. This research adopted K-means unsupervised classification to help collect training data. Then, supervised mapping was carried out using the Machine Learning Support Vector Machine (SVM), Random Forest (RF), and Classification and Regression Trees (CART) algorithms.

## METHODS

### Study Area

This research was conducted in the Wangi-Wangi Islands, Wakatobi, Southeast Sulawesi (Figure 1). The Wangi-Wangi Islands are located in the Coral Triangle and are known as the second-largest coral reef in the world. The region has 942 fish species and 750 of the world's 850 coral reef species. This research location is located at $5^{o}14'13$ S - $5^{o}33'48"$ S and $123^{o}27'14"$ E - $123^{o}39'7"$ E, with an area of 596.47 $km^2$.

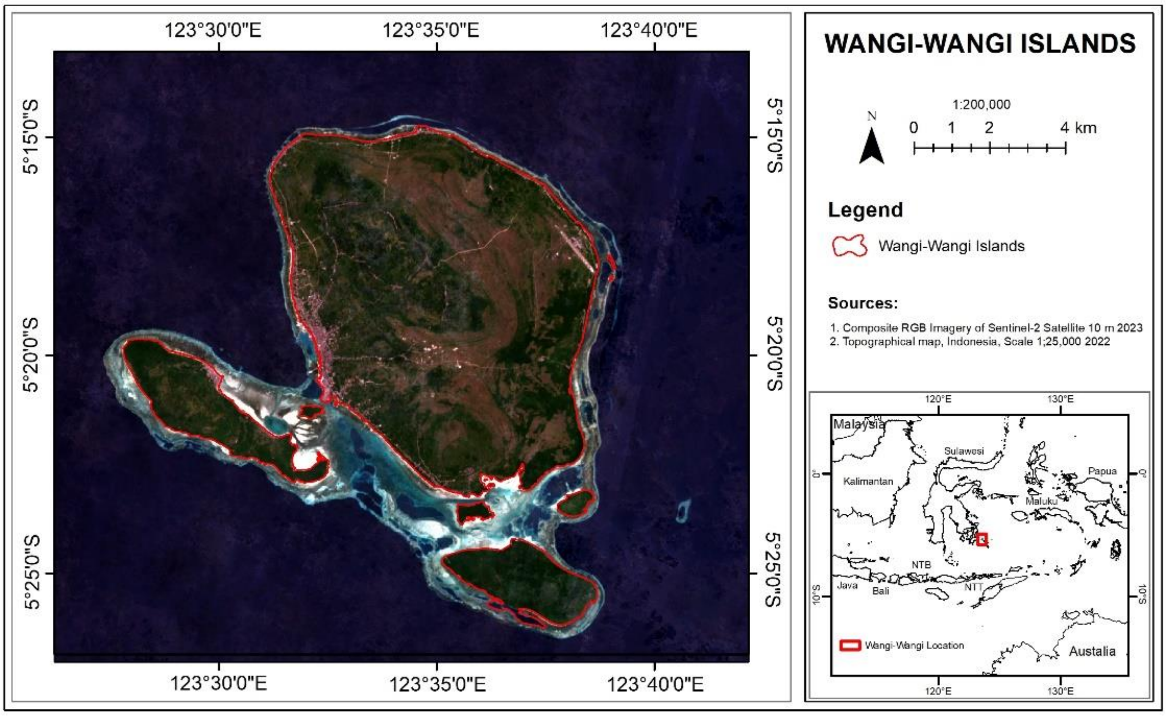



**Figure 1.** The study was located in Wangi-Wangi Islands.

**Data**

Benthic habitat samples were determined from satellite image interpretations that had been adjusted to field survey results and published habitat distribution location documents. Approximately 212 locations were recorded using a Garmin Global Positioning System (GPS) placed in a waterproof dry bag. The collected samples were then recorded as randomly placed points. Each point was labeled based on the benthic habitat class.

This study used the Sentinel 2 MSI image collection from Google Earth Engine (GEE). This image collection had a wide coverage and high resolution, which supported land and water cover studies as well as observations of inland waterways and coastal areas. This image collection had the highest radiometrically and geometrically corrected quality level called Level-1C (L1C). The L1C product contained atmospheric scale ortho-rectification (TOA) reflectance that was more responsive to relative spectra (ESA, 2017). Therefore, this product was suitable for time series analysis. This research used a median composite cloud-free from the image collection (Aldiansyah et al., 2021; Aldiansyah & Saputra, 2023) for each year from 2019-2023. This aimed to obtain good classification results because the presence of clouds and cloud shadows can worsen the separation of pixel values from image data.

**Feature Extraction**

This research used the Lyzenga model (Lyzenga, 1978) to extract features for classification. The Lyzenga model worked by connecting bottom surface reflectance and radiance levels measured by satellite sensors. This feature was obtained from the band pairs of the visible bands (blue, green, and red) of Sentinel 2 MSI.

Pixels at the same bottom type were located at various unknown depths that appeared along the lines in the bi-dimensional histogram of a pair of log-transformed visible bands. The slope of this line was the ratio of diffuse attenuation of the two bands. This step was repeated for different features, and then a series of parallel lines were plotted, with each bottom-type difference and variation in y-intercepts.

Lyzenga's model involved the extraction of the radiance of areas occupied by the same feature regardless of the depth at which they occur. In this study, sand was preferred because of its clear visibility. This occurred because there was a decrease in the attenuation coefficient in various combinations and calculation of the attenuation ratio before the final computation of three single-band Depth Invariant Index (DII) images as **Formula 1**.

$$DII = ln(Li) - \left[\left(\frac{ki}{kj}\right) \times ln(Lj)\right] \qquad (1)$$

where $Li$ is the observed radiance of band $i$ and $Lj$ is the observed radiance of band $j$. The irradiance attenuation coefficient $\left(\frac{ki}{kj}\right)$ of water in bands $i$ and $j$ is computed as **Formula 2** and **Formula 3**.

$$\frac{ki}{kj} = a + \sqrt{(a^2 + 1)} \qquad (2)$$

$$a = \frac{\sigma_{ii} - \sigma_{jj}}{2 \times \sigma_{ij}} \qquad (3)$$

where

$\sigma_{ii}$ is the variance of band $i$, $\sigma_{jj}$ corresponds to the variance of band $j$, and $\sigma_{ij}$ the co-variance of the band pair $i$, $j$.

The procedure used to estimate the attenuation coefficient ratio to determine the average square deviation line. The line was measured perpendicular to the line, where the line value is the minimum (Lyzenga, 1981). The values derived cannot be directly related to the corresponding radiance or reflectance (Watkins, 2015). However, this index was limited in the number of bottom features. This is because some features had close resemblances and hence were defined by the same line, e.g., sand and mud.

**Benthic Habitat Mapping**

This research used 3-band DII features obtained from the Lyzenga model. Benthic mapping was carried out in three classes (coral, seagrass, and sand), which formed the benthic habitat. The 3-band unsupervised classification feature was carried out using K-means by limiting the classes to five classes, namely coral, seagrass, sand, water, and land. K-means aimed to help in the process of partitioning pixels into five classes by assigning each pixel to the cluster with the closest means. In this way, the output of land cover classes at each epoch had five clusters. Next, classes were assigned to their respective clusters to create a land cover map. This land cover was then used as a reference to collect suitable training locations for each class using GEE analysis.

Training data was used to carry out supervised classification using SVM, RF, and CART machine learning classifications. The land cover produced by the supervised classification algorithms was then validated using overall accuracy (OA) and kappa coefficient (K) values, using a comparison ratio of 70 for training and 30 for testing. Overall accuracy (OA) is commonly used to evaluate the accuracy and effectiveness of all classifiers. This accuracy worked by grouping the number of pixels that were correctly classified by the classifier. (Aldiansyah & Saputra, 2023). The OA and K values were calculated as **Formula 4** and **Formula 5**.

$$OA = \left(\frac{Pc}{Pn}\right) \times 100 \qquad (4)$$

Where $Pc$ is the number of pixels classified correctly and $Pn$ is the total number of pixels.

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} x_{+i})} \quad \text{.....(5)}$$

Where $r$ = the number of rows and columns in the error matrix, $x_{ii}$ = the number of observations in row $i$ and column $i$, $x_{i+}$ = the marginal total of row $i$, $x_{+i}$ = the marginal total of column $i$, and $N$ = the total number of observations.

User Accuracy (UA) and Producer Accuracy (PA) were also calculated for each land cover class in the Confusion matrix. Validation with UA was determined by the ratio of the correctly categorized pixels in that class to the total number of pixels classified. Similarly, PA was determined by the ratio of properly categorized pixels to the total number of pixels in the reference data in each class. The classifier that had the best performance was selected for further image classification for Spatiotemporal change analysis. The entire flow of this research is summarized in **Figure 2**.

## RESULT AND DISCUSSION

### Benthic Habitat Change

Based on **Figure 2**, the 2019 SVM is seen incorrectly classifying 64% of coral reef pixels as seagrass. The same thing was also shown by the Water class, where around 88% of water pixels were classified as coral reefs, while 12% were classified as seagrass. This is also shown by RF and CART, but with a significantly smaller error ratio compared to SVM. In **Figure 3**, the same thing is also shown in 2023 in the SVM classifier. However, RF showed an extraordinary performance where only 13% of water pixels were classified as coral reefs, while CART classified 24% of water as coral reefs (**Figure 4**).

The three classifiers show differences. The SVM classifier performed worse than the other classifiers. Meanwhile, RF performed better than the others. Therefore, this study adopted the results of the RF classifier to quantify changes in benthic habitat. Based on the RF classifier, a change in habitat category was visible. There was a significant decrease in seagrass cover from 2019 to 2023 for about 58.21 km$^2$. Sand also decreased that year by 9.26 km$^2$. However, this research revealed an expansion of coral habitat of 76.27 km$^2$. This finding was also similar to that reported by Chairunnisa et al. (2022). The dynamics of changes in this category are depicted in **Figure 5.**

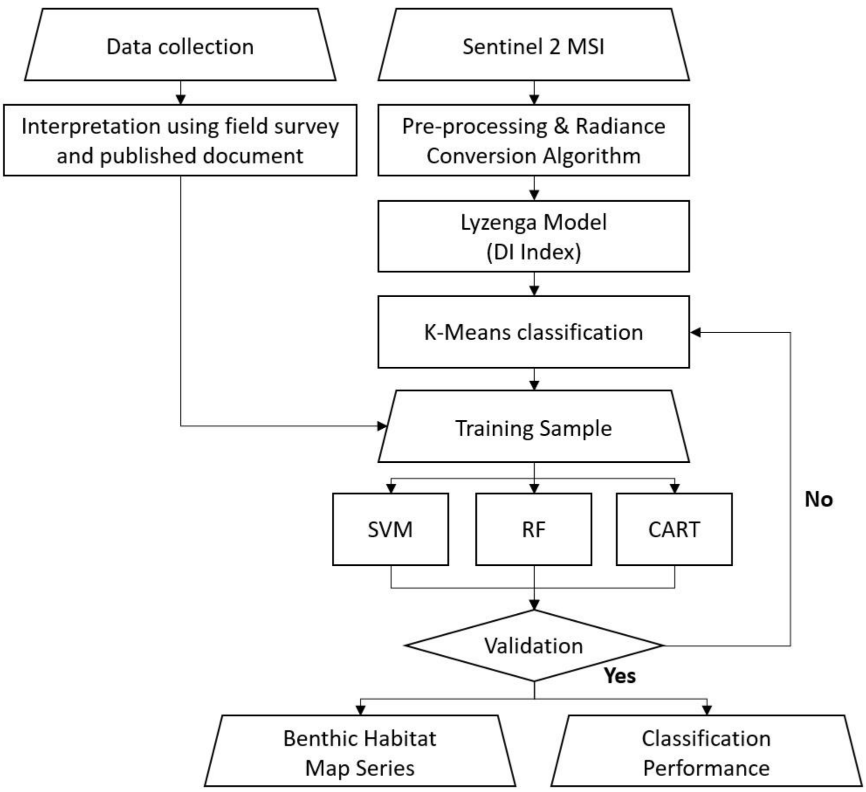



**Figure 2.** Research flow adopted in classifying benthic habitat.

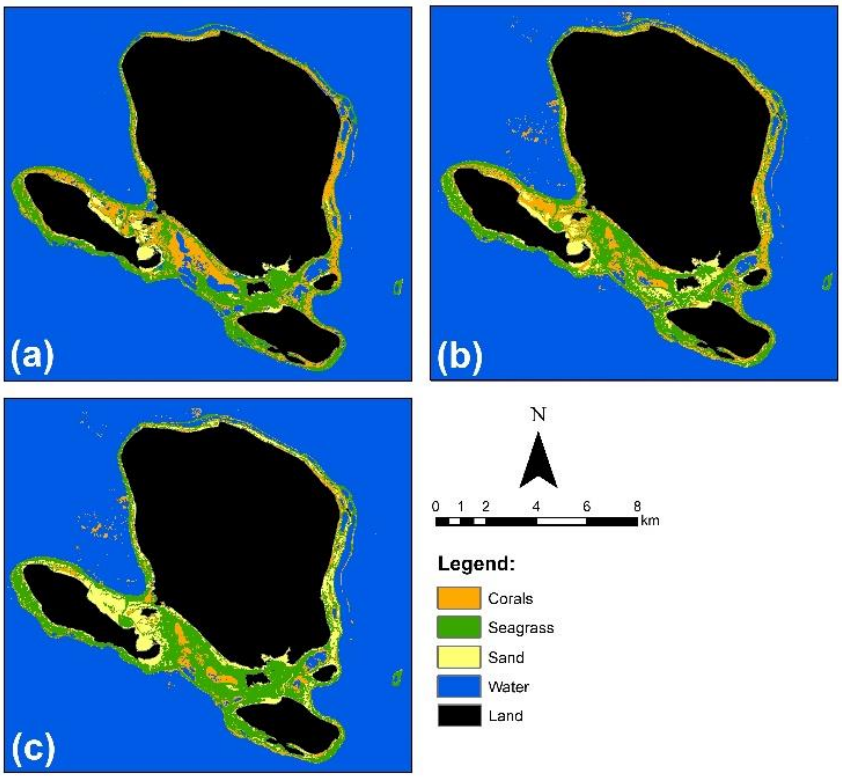



**Figure 3.** Benthic habitat in 2019 based on (a) SVM; (b) RF; and (c) CART.

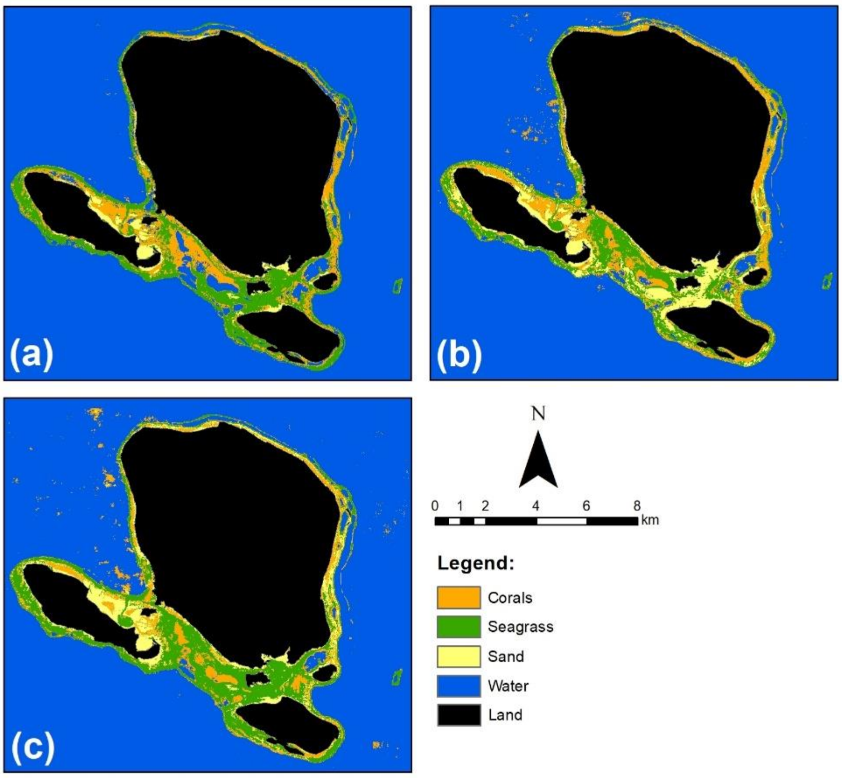
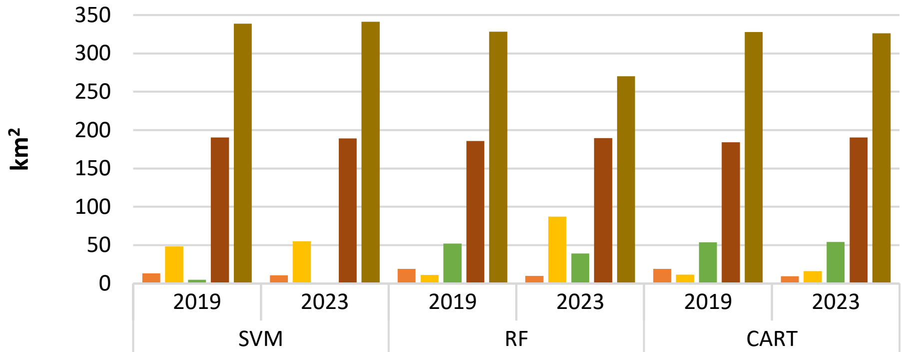



**Figure 4.** Benthic habitat in 2023 based on (a) SVM; (b) RF; and (c) CART.




| | SVM 2019 | SVM 2023 | RF 2019 | RF 2023 | CART 2019 | CART 2023 |
|---|---|---|---|---|---|---|
| Sand | 13,39 | 10,80 | 19,07 | 9,81 | 19,08 | 9,51 |
| Coral | 48,44 | 55,15 | 11,04 | 87,30 | 11,47 | 16,27 |
| Water | 5,01 | - | 52,02 | 39,36 | 53,85 | 54,28 |
| Land | 190,63 | 189,24 | 185,90 | 189,77 | 184,29 | 190,27 |
| Seagrass | 338,99 | 341,28 | 328,44 | 270,23 | 327,78 | 326,14 |

**Figure 5.** Dynamics of benthic habitat changes based on SVM, RF, and CART.

Coral reef and seagrass fluctuations could be triggered by the presence of corals that inhabit non-coral reef areas due to variability in the habitat environment, which was considered less than optimal. Scleractinian corals are known to inhabit seagrass beds despite environmental variability. However, in general, coral diversity and richness in this area were lower than in coral reef areas (Lohr et al., 2017).

The results of this study indicate that there is an increase in coral reefs while sand actually decreases around the habitat. The increase in coral reefs can occur due to ecosystem restoration efforts, changes in environmental conditions, and reduced human activities. In Wangi-Wangi, factors such as stable water temperatures, supportive depths, and good water clarity greatly contribute to the success of healthy coral reef growth. These conditions support photosynthesis by zooxanthellae, which is very important for coral survival. Existing publications and reports, such as those published by the Wakatobi Marine Research Center, WWF Indonesia, and the World Resources Institute (WRI), confirm that the Wangi-Wangi area has ideal conditions for coral reef ecosystems, thanks to good conservation management and supportive environmental conditions (Napitupulu et al., 2022; Leprohon & Nimick, 2023).

Poor water quality can inhibit light penetration, and this situation worsens the condition of seagrass in this habitat. This condition may influence the decline in seagrass areas in this region. Dredging that occurred near coral reef areas and accelerated runoff of eroded soil increased turbidity, which then had an impact on reducing the availability of light for photosynthesis processes (Rogers, 1990).

Another case showed that fishing activities using bombs also influenced benthic distribution in this area. According to Yulius et al. (2015) and Jerosch et al. (2016), the form of the environment indirectly influences the fluctuation of benthic distribution and its environmental conditions, for example, substrate, erosion or sedimentation, currents, and nutrient abundance.

## Comparison of Classification Performance

In addition, the Confusion matrix, UA and PA were adopted in this study to measure the performance of each class of each classifier. The model with the best performance was selected based on the OA and K values. The SVM, RF, and CART classifiers are compared in **Table 1**, while Figure 4 shows the UA and PA in each benthic habitat class.

**Tabel 1.** Overall accuracy and kappa coefficient values for benthic habitat categories based on SVM, RF, and CART.

| Year | SVM | | RF | | CART | |
|---|---|---|---|---|---|---|
| | OA | k | OA | k | OA | k |
| **2019** | 78.77 | 72.30 | 94.41 | 92.94 | 95.53 | 94.35 |
| **2023** | 77.71 | 71.16 | 97.45 | 95.30 | 94.48 | 92.05 |

Based on **Table 1**, the RF classifier outperforms the other two classifiers. The OA values in 2019 and 2023 reached 94.41% and 97.30%, respectively. The UA and PA values for each class are presented in **Figure 6**. The three classifiers were able to extract Land, Seagrass, and Sand very well. It can be seen that SVM had difficulty in identifying water bodies effectively. This can be caused by the number of pixels being quite small, so it was not enough to train the classifier accurately and only produced poor performance when compared to other classes. The accuracy value of CART was close to RF in quantitative terms, but the classification and visual results showed that RF's capabilities were no less superior. However, with limited reference sources, this study found that RF showed good performance in mapping other classes compared to CART and SVM. This finding was also reported by Bennet et al. (2020), Ahmed et al. (2021), Cheng et al. (2022), and Aldiansyah & Wahid (2023) that RF has good

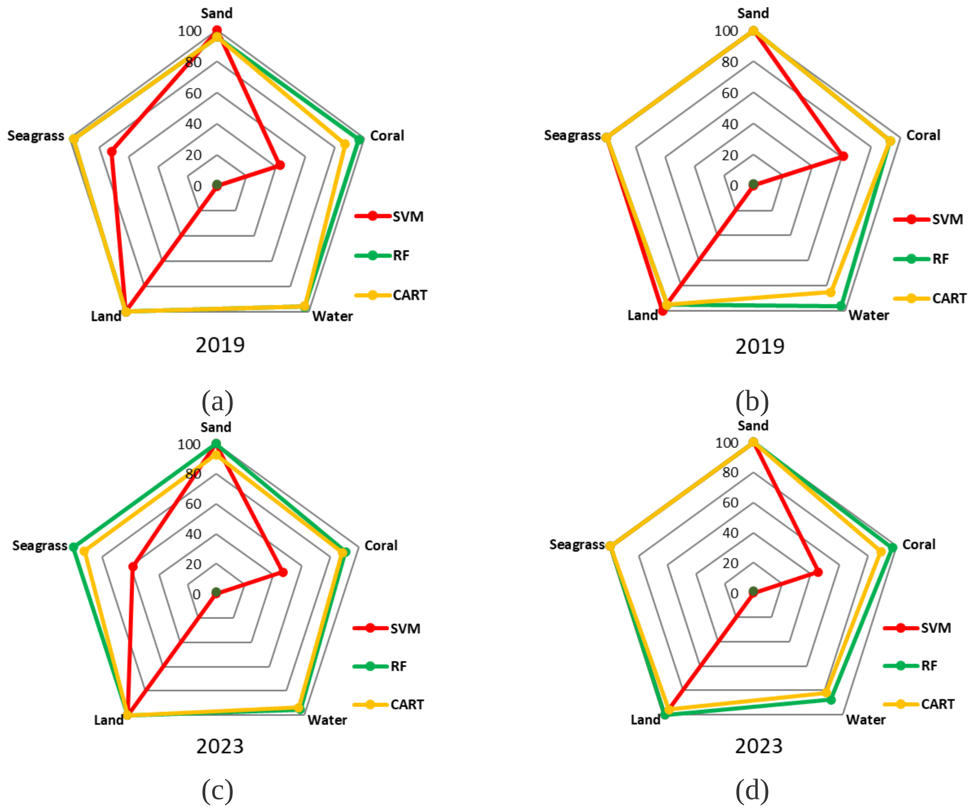



**Figure 6.** Benthic habitat category accuracy values based on SVM, RF, and CART for user accuracy (a and c) and producer accuracy (b and d).

accuracy for mapping habitat distribution. The accuracy of the resulting RF model is quite high in rapid mapping. This accuracy is also within the acceptable limit in benthic habitat mapping with a four to five-class scheme. The tolerable limit is 40-70% (Green et al., 2000) and >60% based on the Indonesian National Mapping Standard (Badan Informasi Geospasial, 2014).

On the other hand, it is quite difficult to compare our results with similar studies, considering that the schemes used tend to be different and unique. The thirteen-class scheme showed 40% accuracy when using the PC band (Wicaksono, 2016). The scheme with hyperspectral data showed >80% accuracy when the number of classes was in the range of three to 12 classes (Zhang et al., 2013). The ten-class scheme with high-resolution imagery showed 73% accuracy (Eugenio et al., 2015). Although our results show high accuracy, the results may be lower or the same when tested with varying scheme complexity.

## CONCLUSION

Benthic distribution mapping was successfully carried out in GEE for the Wangi-Wangi Islands region with acceptable accuracies. This research showed that monitoring changes in benthic habitats can utilize remote sensing technology. Our results show that the RF method has better accuracy than the other two classifiers with a five-class scheme. We suggest exploring different schemes to test the accuracy of the method if the treatment is different.

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