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Spatial distribution of benthic habitats in Kapota Atoll (Wakatobi National Park, Indonesia) using remote sensing imagery

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Abstract. *Hamuna B, Pujiyati S, Gaol JL, Hestirianoto T. 2023. Spatial distribution of benthic habitats in Kapota Atoll (Wakatobi National Park, Indonesia) using remote sensing imagery. Biodiversitas 24: 3700-3707.* This study aims to classify and map benthic habitats in Kapota Atoll, Wakatobi National Park, using Sentinel-2A satellite imagery, that has undergone both atmospheric and geometric corrections. Sentinel-2A satellite imagery was processed using pixel-based classification method. This study used two machine learning algorithms: support vector machine (SVM) and random forest (RF). This study used nine classified benthic habitat classes, namely five homogeneous benthic classes (sand, live coral, dead coral, rubble, and dense seagrass) and four mixed benthic classes (mixed rubble and sand, mixed sand and rare seagrass, mixed medium seagrass and sand, and a mixture of rubble, dead coral, and seagrass). The RF algorithm produced benthic habitat maps with a higher overall accuracy than the SVM algorithm, which was 65.31% and 63.51%, respectively. These accuracy values have met the standards of accuracy for mapping benthic habitats that apply in Indonesia. The SVM algorithm classification results showed that the benthic habitat of the mixed class of medium seagrass and sand was more dominant than other benthic habitat classes. In contrast, the RF algorithm showed the class dense seagrass was more dominant. The selection of the appropriate algorithm for processing satellite imagery was found to be a significant factor in producing an accurate benthic habitat map.

Keywords: Mapping accuracy, pixel-based, random forest, Sentinel-2A, support vector machine

INTRODUCTION

Shallow water benthic habitats are aquatic habitats with very high economic value, both for coral reefs and seagrass beds (Rumahorbo et al. 2020). Benthic habitats are places where various types of shallow-water organisms live. Benthic habitats in shallow waters are highly complex, consisting of live coral, seagrass, algae, and dead coral, with substrate types such as coral rubble, sand, and silt. The diversity of benthic habitats can be essential as spawning grounds, shelter and foraging areas for various types of coastal and shallow marine organisms, especially in coral reef ecosystems (Komyakova et al. 2018; Hamuna et al. 2019a, 2022; Tony et al. 2020). Considering that benthic habitats in shallow waters have a significant role for other organisms, comprehensive and continuous monitoring and studies are necessary. Spatial information about the composition, conditions, and dynamics of shallow water benthic habitats at an appropriate and relevant spatial scale is one of the fundamental prerequisites for understanding and managing ecosystems, especially in shallow waters (Phinn et al. 2012). Additionally, precise mapping of benthic habitats in shallow waters, especially coral reefs with high spatial resolution, is essential for monitoring their health and evolution (Nguyen et al. 2021).

Currently, remote sensing satellite technology is widely used to provide spatial information on natural resources in coastal areas, particularly in tropical waters (Reshitnyk et al. 2014). This technology is employed for assessing natural resources in terrestrial sites, such as mangroves (Valderrama-Landeros et al. 2018; Hamuna et al. 2019b; Ghorbanian et al. 2021; Maurya et al. 2021) as well underwater resources like coral reefs and seagrass beds (Zhou et al. 2018; Wilson et al. 2019; Fauzan et al. 2021; Lizcano-Sandoval et al. 2022; Rosalina et al. 2023; Satya et al. 2023). The advancement of satellite remote sensing technology has been rapid (Nguyen et al. 2021), demonstrated by the development of satellite sensors capable of detecting shallow waters based on specific characteristics (Siregar et al. 2020). The development of multi- and hyper-spectral sensors has improved the spatial detail of satellite images, along with the advancements in satellite image data processing.

Satellite remote sensing offers a practical solution for mapping benthic habitats, overcoming previous limitations in-ground- and aerial-based assessments (Coffer et al. 2020). Several studies have demonstrated that integrating satellite remote sensing data with ground-truth data yields the most accurate results when mapping benthic habitats, particularly through the use of high-resolution satellite imagery (Mohamed et al. 2018; Wilson et al. 2019; Vahtmäe et al. 2021). Furthermore, these maps can effectively describe the characteristics of shallow water benthic habitats across various geomorphological zones

(Roelfsema et al. 2018; Akhlaq and Winarso 2019; Setiawan et al. 2022a). Remote sensing technology is considered more efficient and effective compared to conventional methods when mapping benthic habitats on a large spatial scale.

Kapota Atoll is one of the coral atolls located in the Wakatobi National Park (WNP), Southeast Sulawesi, Indonesia. A recent study by Hafizt et al. (2021) indicates a notable change in the community structure of benthic habitats in the WNP area, including in Kapota Atoll. Previous benthic habitat mapping efforts in Kapota Atoll were conducted by Schuyler et al. (2005), who mapped the entire region, and Hafizt et al. (2021), who focussed on the eastern part of Kapota Atoll. However, both studies used Landsat TM, ETM+, and OLI-TIRS multispectral images with a relatively low spatial resolution of 30 m, providing limited benthic habitat information. To address this limitation and obtain more diverse information, this study aims to employ Sentinel-2A imagery with a higher spatial resolution of 10 m, the production of a comprehensive spatial map of the benthic habitat in Kapota Atoll.

MATERIALS AND METHODS

Study area and field data collection techniques

This study was carried out in Kapota Atoll, which is one of the coral atolls situated within Wakatobi National Park (WNP) in Wakatobi District, Southeast Sulawesi Province, Indonesia (Figure 1). WNP was established as a national park under Minister of Forestry Decree No. 7651/Kpts-II/2002 and is managed by the Wakatobi National Park Office. In 2012, it was officially recognized as a World Biosphere Reserve by the United Nations Convention of the Law of the Sea. WNP is among the national parks in Indonesia, with the majority of its area consisting of sea waters (97%), while the land area only accounts for 3% (Balai Taman Nasional Wakatobi 2020). Kapota Atoll primarily serves as a local use zone, with a small portion in the southern part designated as a tourism zone (Balai Taman Nasional Wakatobi 2020).

Ground-truth data collection was conducted between October 2022 and February 2023. Benthic habitat observations were directly performed within the study area, employing the Stop and Go method (Prayudha 2014; Hafizt et al. 2021; Liang et al. 2022). The distance between observation points was maintained at a minimum of 20 meters. During the stop phase, a 2 × 2 m quadrant transect was utilized to observe benthic habitat types, and photographs of the habitats were captured using an underwater camera (Phinn et al. 2012). The observations of benthic habitat types were conducted while snorkeling or employing scuba diving equipment in relatively deeper waters (>1 meter). To facilitate the processing of satellite imagery, the coordinates of each observation point were determined using a multi-band Garmin 65s handheld GPS (Global Positioning System).

A total of 694 ground-truth data were obtained, which were utilized as training data for the satellite imagery classification process and testing the accuracy of the classification results. The number of data samples employed for training the classification model was greater than those used for accuracy tests (Roelfsema and Phinn 2010; Kovacs et al. 2022).

Satellite image used

The satellite imagery used in this study was Sentinel-2A captured on 30 November 2019. The imagery was acquired from the ESA Copernicus website (https://scihub.copernicus.eu/dhus/#/home). The Sentinel-2A satellite imagery used was level-1C which had undergone atmospheric and geometric correction. The Sentinel-2A satellite offers a temporal resolution of 10 days (for a single satellite) and five days (for the combined constellation) with a radiometric resolution of 12 bits. The Sentinel-2A satellite imagery consists of 13 bands with different spatial resolutions (Table 1). For this study, only the visible bands (B2, B3, and B4) were utilized.

Satellite image classification

Classification is the process of assigning pixels in an image with similar characteristics to specific groups and labeling them to generate an informative map (Green et al. 2000). In this study, a pixel-based classification method was employed to classify shallow water benthic habitats using ArcMap 10.8.1. The Pixel-based classification was conducted using a supervised classification technique, which relies on ground-truth data as training area data. A total of 517 ground-truth data were used as training area data. These training area data represent the pixel spectral value of pixels, serving as references for classifying other pixels. Pixels with spectral values similar to the training area spectral values were assigned to the same benthic habitat class.

The classification algorithms employed in the benthic habitat classification process were Support Vector Machines (SVM) and Random Forest (RF). SVM and RF are considered machine learning algorithms (Wahidin et al. 2015) and are widely used in classification tasks (Nguyen et al. 2021). The SVM algorithm is a guided classification algorithm that searches for a vector or line, maximizing the margin between two classes, which acts as a separator (Wahidin et al. 2015). While the RF algorithm combines multiple non-parametric k-decision trees (classification and regression trees). The RF algorithm integrates the bagging method (bagging aggregation) and random feature selection to construct decision trees with controlled variance (Breiman 2001).

Accuracy assessment

In this study, the confusion matrix developed by Congalton (1991) was used to compare the benthic habitat classification maps derived from satellite imagery with actual field conditions based on ground-truth data. A total of 222 ground-truth data were used to test the accuracy of the resulting benthic habitat maps. The confusion matrix provides three categories of accuracy, namely User Accuracy (UA), Producer Accuracy (PA), and Overall Accuracy (OA) (Congalton 1991). UA represents the accuracy of the classification results for all identifiable objects. It indicates how well the classified objects correspond to their true classes. PA is employed for thematic assessment and reflects the level of correctness of the classification results to the actual field conditions. OA represents the overall agreement between the benthic habitat classification map and the reference data (accuracy test data). The equations of the three categories of accuracy are as follows:

$$UA = (X_{ii} / X_{+1}) \times 100\% \quad [1]$$

$$PA = (X_{ii} / X_{1+}) \times 100\% \quad [2]$$

$$OA = [(\sum_{i=1}^{n} X_{ii}) / N] \times 100\% \quad [3]$$

Where: X_{ii} is the diagonal value of the *i*-th row and *i*-th column confusion matrix, X_{1+} is the number of pixels in the *i*-th row, X_{+1} is the number of pixels in the *i*-th column, and N is the amount of accuracy test data.

In addition to these three accuracy categories, the Kappa Coefficient (KA) was also calculated to account for the errors involved in the classification process. The KA takes into account the overall agreement in the confusion matrix, considering all aspects of accuracy (PA, UA, and OA).

RESULTS AND DISCUSSION

Classification of benthic habitats in Kapota Atoll

The field observations in Kapota Atoll identified a total of 13 types of benthic habitats, including both homogeneous and heterogeneous/mixed habitats. These 13 benthic habitat types include live coral (LC; 104 sites), dead coral (DC; 71 sites), sand (Sd; 107 sites), rubble (Rb; 42 sites), dense seagrass (Sgd; 115 sites), a mixture of rubble and sand (RbSd; 40 sites), a mixture of rare sand and seagrass (SdSgr; 108 sites), a mixture of medium seagrass and sand (SgmSd; 104 sites), a mixture of sand and algae (SA; 16 sites), a mixture of sand and coral dead (SDc; 22 sites), a mixture of rubble, dead coral, and seagrass (RbDcSg; 48 sites), a mixture of seagrass, dead coral, and algae (SgDcA; 11 sites), and a mixture of seagrass, rubble, and algae (SgRbA; 8 sites). Until now, there has not been a standard for determining benthic habitat classification schemes, so the naming of benthic habitat classes in this study was based on the dominance of benthic habitat composition. However, based on Green et al. (2000), which suggests removing benthic habitat classes with a frequency of presence less than 4%, only 9 benthic habitat classes were used in the classification process in this study.

The classification of Sentinel-2A imagery using the SVM and RF algorithms resulted in 9 benthic habitat classes n the shallow waters of Kapota Atoll (Figure 2). These classes consist of 5 homogeneous benthic classes, namely LC, DC, Sd, Rb, and Sgd, as well as four classes of mixed benthic classes, namely RbSd, SdSgr, SgmSd, and RbDcSg. The classification outcomes from both SVM and RF algorithms show relatively similar spatial distribution of benthic habitats. The predominant occurrence of sand was observed in the northern part of Kapota Atoll. Seagrasses, including the mixed class, were predominantly found on the outer side of Kapota Atoll, while corals (LC and DC classes) were dominant on the inner side of Kapota Atoll (with LC classes also found both inside and outside the atoll, particularly in the North). The presence of rubble, including the mixed class, was noted in the southern and northern regions of Kapota Atoll.

Table 1. Characteristics (spatial resolution and wavelength) of Sentinel-2A satellite imagery (Gascon et al. 2017)

Band name		Spatial resolution (m)	Wavelength (µm)
B1	: Coastal aerosol	60	**0.433-0.453**
B2	: Red	10	0.458-0.523
B3	: Green	10	0.543-0.578
B4	: Blue	10	0.650-0.680
B5	: Vegetation Red Edge	20	**0.698-0.713**
B6	: Vegetation Red Edge	20	**0.733-0.748**
B7	: Vegetation Red Edge	20	**0.765-0.785**
B8	: NIR	10	0.785-0.900
B8A	: Vegetation Red Edge	20	**0.855-0.875**
B9	: Water vapour	60	**0.930-0.950**
B10	: SWIR-Cirrus	60	**1.365-1.385**
B11	: SWIR	20	**1.565-1.655**
B12	: SWIR	20	**2.100-2.280**

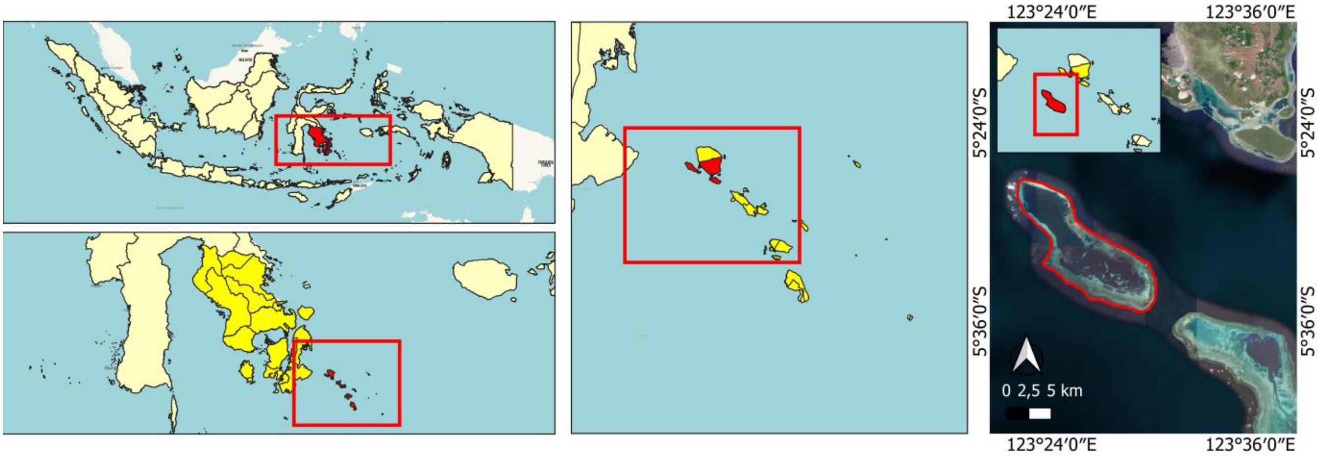

Figure 1. Map of study site in Kapota Atoll, Wakatobi National Park, Wakatobi District, Southeast Sulawesi, Indonesia

According to the spatial analysis results, the total area of benthic habitats in Kapota Atoll using the SVM algorithm was 5,727.99 Ha, while using RF algorithm, it was slightly lower at 5,667.85 Ha. Additionally, the area of each benthic habitat class in Kapota Atoll differs between the two algorithms (Figure 3). These variations in the area of benthic habitats can be attributed to the differences in the classification algorithms used and potential errors in the classification process. Seagrass habitats, represented by the SgmSd and Sgd classes, were found to be more dominant than other benthic habitat classes. The SVM algorithm identified the SgmSd class as the most dominant, accounting for 23.43% of the total benthic habitat area, while using the RF algorithm identified the Sgd class as the most dominant, covering 20.44% of the total benthic habitat area. The area percentage of LC class was nearly the same for both the SVM and RF algorithms, at 17.96% and 17.42%, respectively. The rubble and mixed benthic habitat types (Rb, RbSd, and RbDcSg classes) were found in very small areas using the two algorithms. Overall, the area of each benthic habitat using the SVM algorithm follows the sequence: SgmSd>Sgd>LC>Sd>DC>SdSgr>RbDcSg>RbSd>Rb, while the RF algorithm follows the sequence: Sgd>SgmSd>LC>Sd>DC>SdSgr>RbDcSg > Rb>RbSd.

Benthic habitat map accuracy

The results of the confusion matrix analysis are presented in Tables 2 and 3. The OA value of benthic habitat classification using the RF algorithm (65.31%) was higher than the SVM algorithm (63.51%). The KA values for the two algorithms were 0.60 and 0.58, respectively. The KA values indicate a moderate level of agreement resulting from the classification of benthic habitats in this study (Congalton and Green 2019).

In Table 2, the PA and UA values using the SVM algorithm range from 15.38% to 84.38% and 33.33% to 84.38%, respectively. Based on the results of the classification accuracy estimation, the highest PA value was observed in the Sd class, while the highest UA value was in the Sgd class. The lowest PA and UA values were observed in the Rb class, where many were classified as the RbDcSg class. In addition to the Rb class, mixed habitats such as the SdSgr class showed lower PA values, and the SgmSd class exhibited a low UA value. The low PA and UA values in the Rb, SdSgr, and SgmSd classes indicate that these benthic habitat classes cannot be mapped properly. This may be attributed to the high variability and heterogeneity of benthic objects at each pixel, which can lead to reduced accuracy.

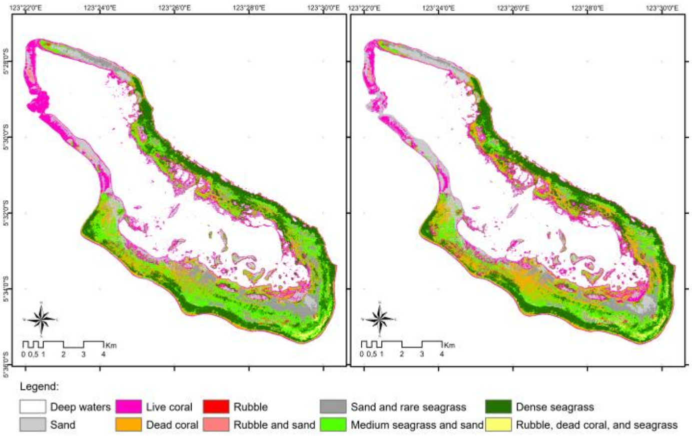

Figure 2. Spatial map of benthic habitat in Kapota Atoll using two different algorithms: SVM (left) and RF (right)

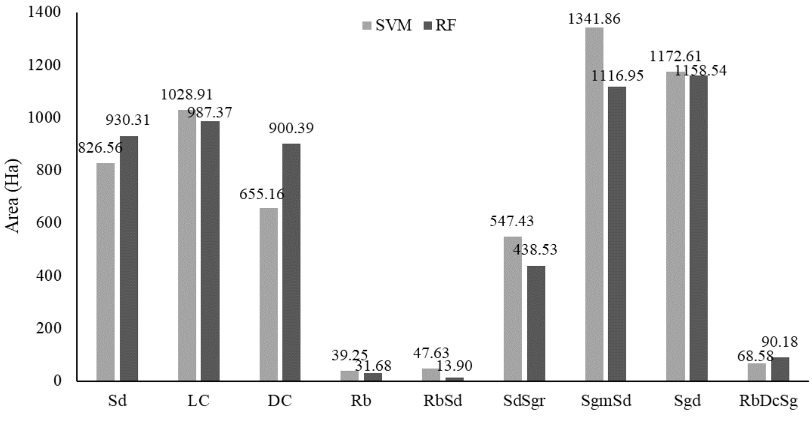

Figure 3. Area of each benthic habitat in Kapota Atoll, Wakatobi National Park, Indonesia

In Table 3, the PA and UA values using the RF algorithm range from 30.77% to 87.50% and 44.44% to 84.38%, respectively. Similar to the results of the SVM algorithm, the highest PA and UA values using the RF algorithm were observed in the Sd and Sgd classes, respectively. Likewise, the lowest PA and UA values were found in the Rb class, which was classified as the RbDcSg class. Mixed habitats such as RbSd and SdSgr classes had low PA values but contrasting high UA values for these two classes.

The SVM algorithm generally produced better UA values for sand, live coral, mixed rubble and dense seagrass habitat types. The RF algorithm demonstrated high UA values for living coral habitat types, mixed rubble and sand, mixed sand and rare seagrass, dense seagrass, and mixed rubble, dead coral, and seagrass.

Discussion

This study has provided valuable information about the spatial distribution of benthic habitats in Kapota Atoll. The resulting map consists of nine benthic habitat classes, which were classified with relatively high accuracy. The number of benthic habitat classes in this study was higher compared to the studies conducted by Schuyler et al. (2005) and Hafizt et al. (2021) in Kapota Atoll. In the study of Schuyler et al. (2005), although the map accuracy was higher at 69.7%, they only identified five benthic habitat classes, including coral, sand (shallow and deep), seagrass, rubble/hardbottom, and edge classes. They did not include mixed benthic habitat classes in this study. Similarly, Hafizt et al. (2021) also identified benthic habitat classes, namely dense seagrass, mixed seagrass, hard coral, mixed hard coral, and sand with a mapping accuracy of 65.35%. According to Green et al. (2000), differences in benthic habitat classification results can be attributed to the variations in satellite imagery used, classification methods, the number of benthic habitat classes identified in the field, and the number of ground-truth points.

The level of accuracy in the process of classification and spatial mapping of benthic habitats remains a fundamental challenge. The accuracy of the maps produced in this study, using both the SVM and the RF algorithm, meets the standards set by Andréfouët et al. (2003). For benthic habitat maps with 4-5 classes, 7-8 classes, 9-11 classes, and more than 13 benthic habitat classes, the accuracy standards were 77%, 71%, 56%, and 53%, respectively. These accuracy standards apply to medium-resolution (Landsat) to high-resolution (IKONOS) satellite images. As Green et al. (2000), suggest, benthic habitat mapping accuracy is considered good and usable if it exceeds an overall accuracy of 60%.

Table 2. Accuracy assessment (confusion matrix) of benthic habitat classification using SVM algorithms

Benthic class	Sd	LC	DC	Rb	RbSd	SdSgr	SgmSd	Sgd	RbDcSg	UA (%)
Sd	27	3	1	0	3	4	0	0	0	71.05
LC	0	21	3	1	2	0	0	0	0	77.78
DC	0	2	13	1	0	2	6	2	1	48.15
Rb	0	0	0	2	0	0	1	0	3	33.33
RbSd	0	0	0	1	7	0	0	0	1	77.78
SdSgr	5	0	0	1	1	13	1	0	1	59.09
SgmSd	0	5	3	3	0	8	21	6	0	45.65
Sgd	0	0	1	1	0	2	1	27	0	84.38
RbDcSg	0	0	0	3	0	2	0	0	10	66.67
PA (%)	84.38	67.74	61.90	15.38	53.85	41.94	70.00	77.14	62.50	
OA (%)						63.51				
KA						0.58				

Table 3. Accuracy assessment (confusion matrix) of benthic habitat classification using RF algorithms

Benthic class	Sd	LC	DC	Rb	RbSd	SdSgr	SgmSd	Sgd	RbDcSg	UA (%)
Sd	28	4	0	0	4	6	0	0	0	66.67
LC	0	21	2	1	2	0	0	1	0	77.78
DC	0	4	16	0	0	2	8	1	1	50.00
Rb	0	0	0	4	1	0	1	0	3	44.44
RbSd	1	0	0	0	5	0	0	0	0	83.33
SdSgr	3	0	0	1	1	14	1	0	0	70.00
SgmSd	0	2	2	3	0	7	18	5	1	47.37
Sgd	0	0	1	1	0	2	1	28	0	84.85
RbDcSg	0	0	0	3	0	0	1	0	11	73.33
PA (%)	87.50	67.74	76.19	30.77	38.46	45.16	60.00	80.00	68.75	
OA (%)						65.31				
KA						0.60				

The benthic habitat maps' accuracy also meets the accuracy standards for mapping benthic habitats in shallow waters in Indonesia, where the Government of the Republic of Indonesia sets a minimum accuracy limit of 60% (Badan Standardisasi Nasional 2011). Based on these accuracy standards for benthic habitat mapping, the two maps resulting from the classification of Sentinel-2A imagery in this study can be used as references for other purposes.

Sentinel-2 satellite images, including Sentinel-2A and Sentinel-2B, show great promise for mapping benthic habitats due to their ideal specifications for remote sensing of coral reefs (Hedley et al. 2018; Wicaksono et al. 2021). Various studies have utilized Sentinel-2 imagery for mapping shallow-water benthic habitats in Indonesia (Table 4). In comparison to these studies, the accuracy of the maps in this study was found to be similar to those that produced benthic habitat maps with 8 to 9 benthic habitat classes. It is worth noting that the accuracy of the resulting map decreases as the number of classified benthic habitat classes increases (Andréfouët et al. 2003; Mastu et al. 2018; Siregar et al. 2020; Wicaksono et al. 2020).

The selection of methods and algorithms for processing satellite imagery is a significant factor in optimizing the ability to produce accurate maps of benthic habitats. The machine learning algorithms (SVM and RF) used in this study have demonstrated excellent performance in mapping benthic habitats in Kapota Atoll. The SVM algorithm is commonly used for mapping benthic habitats and exhibits higher accuracy even with small amounts of data (Wahidin et al. 2015; Nandika et al. 2023). However, in this study, the RF algorithm applied to the pixel-based classification method produced more accurate benthic habitat maps. This finding is supported by Nguyen et al. (2021), who reviewed various articles globally on mapping benthic habitats and concluded that RF algorithm is the most accurate, which can achieve an accuracy of 60% - 85% in the case of mapping benthic habitats with an accuracy ranging from 60 to 85%.

In conclusion, this research provides an overview of the spatial distribution of benthic habitats in Kapota Atoll, Wakatobi National Park. The use of Sentinel-2A imagery allows for a more diverse and detailed classification of benthic habitats compared to previous studies at the same location. The resulting benthic habitat map consists of nine classes, including (1) sand, (2) live coral, (3) dead coral, (4) rubble, (5) dense seagrass, (6) mixed rubble and sand, (7) a mixture of sand and rare seagrass, (8) a mixture of medium seagrass and sand, and (9) a mixture of rubble, dead coral, and seagrass. The Random Forest algorithm outperforms the SVM algorithm in producing benthic habitat maps with accuracies of 65.31% and 63.51%, respectively. Both algorithms meet the accuracy standards for shallow water benthic habitat mapping in Indonesia. The choice of the algorithm also impacts the total area of benthic habitat identified, with the RF algorithm producing an area of 5,667.85 Ha, while the SVM algorithm yields a higher benthic habitat area of 5,727.99 Ha. Therefore, selecting the appropriate algorithm for processing satellite images is a crucial factor in creating an accurate benthic habitat map.

Table 4. Summary of several research results on benthic habitat mapping using Sentinel-2 imagery in Indonesia

Location	Algorithm	Number of classes	Accuracy (%)	Reference
Kapota Atoll, Wakatobi	RF	9	65.31	*This study*
	SVM		63.51	
Pramuka, Panggang, and Karya Islands, Seribu Islands	RF	8	67	Hartoni et al. (2022)
	SVM		65	
Kaledupa Atoll, Wakatobi	SVM	6 (pixel)	61.8	Setiawan et al. (2022b)
		6 (object)	78.1	
Nusa Lembongan, Bali	MLC	6	68.0	Karang et al. (2022)
Parang Island, Karimunjawa Islands	SVM	4	57.14	Lazuardi and Wicaksono (2021)
	CTA		57.26	
Pari Island, Seribu Islands	ISODATA	4	47.98	Munawaroh et al. (2021)
	K-Means		55.64	
Kemujan Island, Karimunjawa Islands	CTA	3	88.97-92.27	Wicaksono et al. (2020)
		4	91.55-90.34	
Kapota and Kompoone Islands, Wakatobi	SVM	5	72.72	Siregar et al. (2020)
		6	70.28	
		8	66.66	
Belanda, Bira Besar, and Pramuka Islands, Seribu Islands	Lyzenga and Unsupervised	4	73.33	Rahman et al. (2020)
Wangi-Wangi Island, Wakatobi	SVM	9	64.1	Mastu et al. (2018)
		12	60.4	
	DT	9	32.8	
		12	29.0	
Lintea Island, Wakatobi	ISODATA	7	83.93	Hafizt et al. (2017)

Note: RF: Random Forest; SVM: Support Vector Machine; MLC: Maximum Likelihood Classification; CTA: Classification Tree Analysis; DT: Decision Tree

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