PERFORMANCE OF MLH AND SVM ALGORITHMS IN MAPPING MACROALGA HABITATS USING SATELLITE DATA IN PANNIKIANG ISLAND, SOUTH SULAWESI

(Performa Algoritma MLH dan SVM dalam Pemetaan Habitat Makroalga Menggunakan Citra Satelit di Pulau Pannikiang, Sulawesi Selatan)

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ABSTRACT

Efforts to inventory macroalgae are urgently needed, mainly to provide information on its potential to produce sodium alginate. Recently, the availability of various satellite sensors and rapidly developing algorithms for processing satellite imagery can map macroalgae habitats more accurately. This study aims to map the benthic habitat and assess the potential of brown macroalgae by pixel-based classification approach with the maximum likelihood (MLH) and support vector machine (SVM) algorithms. The sampling site of this study was in Pannikiang Island, and the survey conducted in September and October 2020. A total of 400 field collection data was used as a reference to classify the benthic habitats and to test the map accuracies derived from the Pleiades-1A (P-1A) and Sentinel-2A (S-2A) satellite imageries. Results show that at least three species of brown and two species of green macroalgae were detected and dominated at the study sites. Benthic habitat was classified into seven classes. The P-1A image produced overall accuracy for the MLH algorithm (70.4%) and SVM (71.9%), while the S-2A image produced overall accuracy for the MLH algorithm (68.6%) and SVM (67.6%). The assessment of the potential stock of sodium alginate using P-1A and S-2A was 133.8 tons and 116.6 tons, respectively. This mapping technique was effective and efficient in mapping, predicting, monitoring, and managing the potential of brown macroalgae.

Keywords: algorithms, benthic habitat, macroalgae, Pannikiang Island, satellite image

ABSTRAK

Upaya inventarisasi makroalga sangat diperlukan, terutama pemanfaatan potensinya dalam memproduksi Natrium alginat (Na-alginat). Belakangan ini, ketersediaan berbagai sensor satelit dan algoritma berkembang pesat melalui pemrosesan citra satelit dalam memetakan habitat makroalga dengan lebih akurat. Penelitian ini bertujuan untuk memetakan habitat bentik dan potensi makroalga dengan pengujian klasifikasi pemetaan berbasis piksel dengan algoritma maximum likelihood (MLH) dan support vector machine (SVM). Lokasi pengambilan sampel adalah di Pulau Pannikiang pada bulan September dan Oktober 2020. Sebanyak 400 data diperoleh dari pengamatan lapangan digunakan sebagai acuan untuk mengklasifikasikan habitat bentik dan menguji akurasi peta yang diturunkan dari citra satelit Pleiades-1A (P-1A) dan Sentinel-2A (S-2A). Hasil penelitian menunjukkan setidaknya ada tiga spesies makroalga cokelat dan dua spesies makroalga hijau yang mendominasi di lokasi penelitian. Klasifikasi habitat bentik menghasilkan tujuh kelas. Citra P-1A memproduksi akurasi keseluruhan masing-masing untuk algoritma MLH (70,4%) dan SVM (71,9%), sementara citra S-2A menghasilkan akurasi keseluruhan untuk algoritma MLH (68,6%) dan SVM (67,6%). Dugaan potensi stok Na-alginat yang diekstraksi dari citra P-1A dan S-2A masing-masing sebesar 133,8 ton dan 116,6 ton. Teknik pemetaan ini efektif dan efisien untuk memetakan, menduga, memantau, dan mengelola potensi makroalga cokelat.

***Kata kunci**: algoritma, habitat bentik, makroalga, Pulau Pannikiang, citra satelit*

INTRODUCTION

Macroalgae is one of the components in marine ecosystems with high species richness and also contains various bioactive substances, so it plays a significant role in diverse ecological and economic aspects (Satheesh & Wesley, 2012; Ayhuan et al., 2017; Sun et al., 2018). Various substances contained in macroalgae can potentially be raw materials supporting multiple industries. For example, brown macroalgae contain biomass and sodium alginate (Na-alginate) (Calumpong et al., 1999; Zailanie et al., 2001; Jr & Cunha, 2006), which significantly supports the pharmaceutical/medical (cosmetic) industries, food-beverages, as well as non-food industries (paints, textiles, and toothpaste), because of their ability as emulsifiers and thickeners (Parthiban et al., 2013).

Indonesia requires large amounts of Na-alginate stocks for various industries, but data and information on the potential distribution of brown macroalgae are still limited, so it needs to be mapped based on remote sensing technology through various satellites. Recently, the availability of different satellite sensors with better spatial, spectral, and radiometric resolutions has been matched by the development of machine learning classification algorithms, resulting in more accurate mapping and potential estimation. Pramaditya Wicaksono (2014) mapped macroalgae based on their pigmentation (brown, green, red, and mixed macroalgae) on Kemujan Island using the maximum likelihood (MLH), Mahalanobis, and minimum distance algorithms applied to the Worldview-2 (2 m) satellite image. Wouthuyzen et al. (2016) mapped the habitat of brown macroalgae using Landsat-7 ETM+ (30 m) satellite imagery by applying the iso cluster method on the coastal coast of Bitung-Bentena, North Sulawesi. Setyawidati et al. (2018b) used GeoEye-1 (1.65 m) satellite imagery to map the geomorphological structure of macroalgal habitat with MLH classification on Libukang Island, Mallasoro Bay, South Sulawesi. Several previous studies were able to map macroalgal habitats with sufficient accuracy, but misclassification could only partially be avoided. The main factor causing the error is the symbiosis of macroalgae habitats with other benthic habitats such as coral reefs, rubble (coral fractures), seagrass, and other substrates that are difficult to separate. In addition, variations in pigments (green, brown, and red) of macroalgae pose a challenge in identifying and mapping macroalgae (Wicaksono, 2014; Wicaksono et al., 2019). The solution to overcome these problems was to use several algorithms in machine learning algorithms such as support vector machine (SVM), random forest (RF), and classification tree analysis (CTA) (Wicaksono et al., 2019). These algorithms were applied to the Worldview-2 satellite imagery, which produced excellent accuracy for 14 benthic and macroalgal habitat classes on Kemujan Island, Karimunjawa Archipelago.

Mapping macroalgae habitats in Central Indonesia has yet to be widely carried out, especially in South Sulawesi Province. Meanwhile, the area has the potential to produce seaweed (macroalgae) with a production value of 3.4 million tons in 2016, based on a report by the Ministry of Marine Affairs and Fisheries (2018). One of the islands in the Spermonde Cluster, which is quite large, is Pannikiang Island, located in Barru Regency. Unfortunately, there is no spatial information regarding the distribution of benthic and macroalgae habitats and their potential on the island. Until now, there has been no standardization in mapping benthic habitats from macroalgal habitats (Wicaksono, 2016) so a comparative study of classification algorithms is critical to be applied in quite complex areas such as Pannikiang Island. Based on this description, this study aims to test the performance of the pixel-based classification algorithms, namely the MLH and SVM algorithms, to map macroalgae habitats and estimate the potential of Na-alginate on Pannikiang Island, Barru Regency, South Sulawesi. Additionally, to know the diversity of satellite imagery with different spatial resolutions in mapping using high-resolution satellite imagery of Pleiades-1A (2 meters) and medium Sentinel-2A (10 meters).

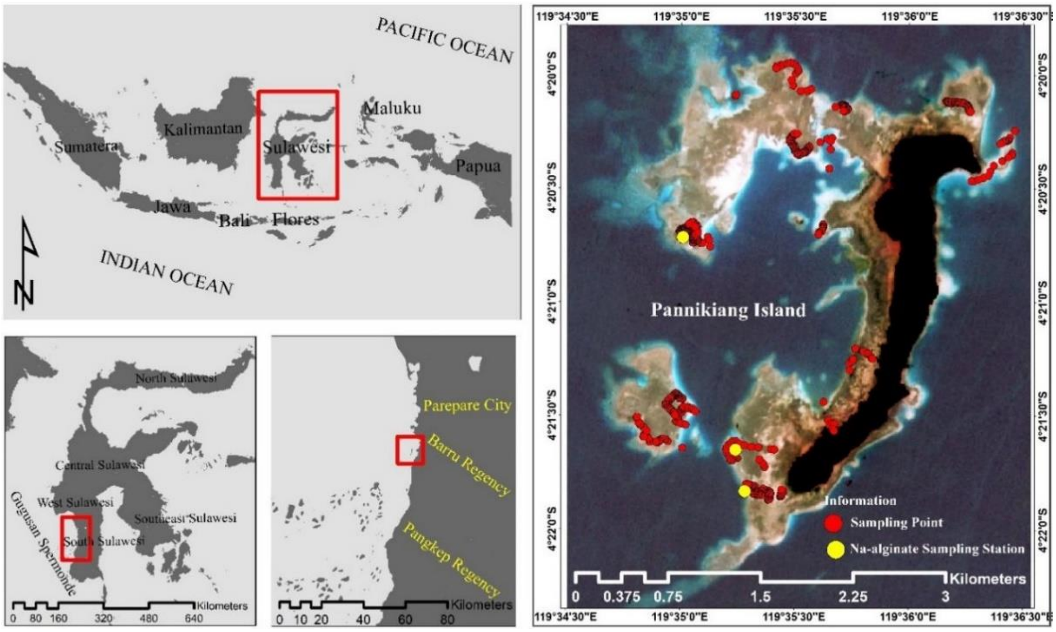

Figure 1. Map of research locations on Pannikiang Island showing sampling points (red dots) and stations for estimating Na-alginate stock(yellow dots).

METHODS

Study Area and Investigate Time

This research was conducted on Pannikiang Island, Barru Regency, South Sulawesi. Geographically, the island is located between 4°20'00" South Latitude; 119°34'30" East Longitude; and 4°22'15" South Latitude and 119°36'30" East Longitude (**Figure 1**). Field observations were accomplished on 4–7 September and 4–26 October 2020. Water quality analysis was carried out at the Chemical Oceanography Laboratory; macroalgae biomass measurements at the Oceanographic Physics and Coastal Geomorphology Laboratory; and extraction and analysis of Na-alginate were carried out at the Water Productivity and Quality Laboratory. The entire sample was analyzed at the Faculty of Marine and Fisheries Sciences, Hasanuddin University.

Tools and materials

The tools and materials used during sampling were the Global Positioning System (GPS) type GPSmap 78s, basic snorkeling equipment, underwater camera, 1x1 meter quadrant transect, identification book, sample bag, sample bottle, and stationery. The satellite data used were P-1A (acquisition May 11, 2020), obtained from Parepare Remote Sensing Earth Station, Indonesia, and S-2A satellite (the date of acquisition was August 22, 2020), downloaded from the USGS website (earthexplorer.usgs.gov). The specifications of the two satellites are presented in **Table 1**.

Field Observation

A sampling of macroalgal habitat was conducted by applying a photo transect method using 1x1 meter frame (Roelfsema & Phinn, 2008). The parameters recorded included a transect of GPS positions, a percentage of benthic habitat cover, and a sampling of brown macroalgae, Sargassum sp, and Turbinaria sp from the transect frame. The sampling of these macroalga was stored in sample bags. In total, 400 points were captured from benthic habitats used to build a classification scheme and test the accuracy of the classification algorithm.

Preprocessing of Satellite Data

Radiometric correction of P-1A and S-2A image data was conducted using the Dark Object Subtraction (DOS) method. If ND is greater than 0 (ND minimum/NDmin), then the difference in value between 0 and Dmin is considered a bias due to the influence of the atmosphere. These disturbances can be minimized by using the **Equation 1** (Prayudha, 2014) as follows:

$$\mathrm{NP'i} = \mathrm{NPi} - \mathrm{NP}_{min}\mathrm{I} \;\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad \textbf{(1)}$$

Where:

NP' i = the pixel value of the correction result
NPi = the pixel value of the image in channel/band i
NPmin i = the minimum pixel value in band i

Tidal Conditions

The sun glint phenomenon as a reflection of the light recorder on the sensor field only occurs on the water surface in high tide conditions. Meanwhile, water column correction is needed to eliminate errors in pixel values due to attenuation of the surface water before reaching the bottom of the object. The tidal conditions at the recording time of two satellite data on Pannikiang Island are required to determine whether sun glint and water column correction are necessary for this study. If the satellite passes over the study site during high tide conditions (all components of the benthic habitat are below the surface water), then correction for the effect of sun glint (Hedley et al., 2005; Anggoro et al., 2016) and water column (Lyzenga, 1981; Siregar, 2010) must be carried out. Otherwise, if there is a receding condition (all components of the benthic habitat appear on the water surface), no correction is necessary. Tide conditions use tide tables from the Geospatial Information Agency (BIG).

Data analysis

Classification Scheme

The classification scheme was designed based on the dominant class of benthic habitats as a result of observations of the quadratic transect visually and transect photos (Siregar, 2010). Field observations showed that 7 components of benthic habitats could be identified, including 1) coral reef, 2) seagrass, 3) rubble, 4) sand, 5) rubble + sand, 6) brown macroalgae, and 7) green macroalgae. In this study, the habitat component consisted of brown macroalgae (dominated by Sargassum spp. and Turbinaria spp.) and green macroalgae (dominated by Halimeda spp. and Caulerpa racemosa).

Table 1. The sensor specifications for the Pleiades-1A (P-1A) and Sentinel-2A (S-2A) satellites.

Band	Wavelength (µm)		Spatial Resolution (meters)		Radiometric Resolution (bit)	
	P-1A	S-2A	P-1A	S-2A	P-1A	S-2A
Blue	0,43-0,55	0,46-0,52				
Green	0,50-0,62	0,54-0,58	2			
Red	0,59-0,71	0.65-0,68		10	12	
***Near Infrared* 4/8**	0,74-0,94	0.76-0,90	0,5			

Classification of Benthic and Macroalgae Habitats

The benthic and macroalgal habitats were classified using a pixel-based classification method with the MLH and SVM classification algorithms. The MLH algorithm is a guided classification method considering the maximum probability of several pixel values, assuming the data is normally distributed. The MLH classification process begins by collecting the values of each class identifier and then calculating the class members from the training data set for each pixel in the satellite image (Bolstad & Lillesand, 1991). Meanwhile, the SVM algorithm is developed for kernel-based classification needs, where several objects are classified into one category or class. This method aims to find the maximum hyperplane (decision boundary) as a separator function between two classes in the input space (Supribadi et al., 2014). The classification process begins with creating a Region of Interest (RoI) for each habitat class as a reference for identifying satellite image pixels.

Test Accuracy

The accuracy test of the image classification results is carried out to determine the accuracy of the classification map by comparing the classification data with the actual data in the field (in situ). Accuracy is calculated using an error matrix (confusion matrix) with the equation to get the Overall Accuracy (OA), Producer Accuracy (PA), and User Accuracy (UA) values (Congalton & Green, 2008). The statistic (kappa) is used to assess the classification accuracy of an error matrix. The value of the kappa coefficient is in the range of 0 to 1 and is generally smaller than the overall accuracy value and can be calculated by **Equation 1**, **Equation 2, Equation 3, Equation 4,** and **Equation 5** (Congalton & Green, 2008):

$$\%\,OA = \frac{\sum_{i=1}^{k} n_{ii}}{n} \quad \textbf{(2)}$$

$$\%PA = \frac{n_{jj}}{n_{+j}} \quad \textbf{(3)}$$

$$\%UA = \frac{n_{ii}}{n_{i+}} \quad \textbf{(4)}$$

$$k = \frac{n\sum_{i=1}^{k} n_{ij} - \sum_{i=1}^{k} n_{i+} n_{+j}}{N^2 - \sum_{i=1}^{k} n_{i+} n_{+j}} \quad \textbf{(5)}$$

Where:

k = the number of rows contained in the matrix
n = the total number of observations
n_{jj} = the number of observations in the j column and j row
n_{ii} = the number of observations in the i column and i row
n_{ij} = the number of observations in row i and column i
n_{i+}, n_{+j} = the total margins of row i and column i

Furthermore, if k_1 and k_2 are estimated kappa statistics from each error matrix, then var (k_1) and var (k_2) are estimates of the variance of the correct calculation results, the statistical test **Equation 6** for a single matrix is:

$$Z = \frac{k_1}{\sqrt{\mathrm{Var}\,(k_1)}} \quad \textbf{(6)}$$

Furthermore, the statistical tests applied to the two independent error matrices were significantly different as calculated by the following **Equation 7**:

$$Z = \frac{k_1 - k_2}{\sqrt{\mathrm{Var}(k_1) + \mathrm{Var}(k_2)}} \quad \textbf{(7)}$$

Z is the standardized value and the normal distribution of kappa, while the values of k_1 and k_2 are kappa calculations of each error matrix with the hypothesis H_0:(k_1-k_2) = 0, alternative H_1:(k_1-k_2) ≠ 0, H_0 is rejected if $Z \geq Z\alpha/2$. If the results of the Z test calculation are greater than 1.96, then the results are significantly different (Congalton & Green, 2008).

Estimation of Macroalgae Biomass Stock and Na-alginate Potential

All types of macroalgae contained in the transect frame were taken, washed thoroughly, and put into sample bags. The samples were then sorted; only brown macroalgae, Sargassum spp., and Turbinaria spp. were taken, weighed for their wet weight, and dried in the sun. After that, the samples were dried again in the laboratory using an oven at 70–80^{o}C temperature to obtain a constant dry weight. The dry weight density of macroalgae (gr/m^2) was then calculated. Furthermore, dry brown macroalgae were ready to be extracted for their Na-alginate content by referring to the method of Zaelanie et al. (2001). Several stages of extraction included soaking, crushing, acidification, and precipitation. The extracted product was dark brown flour. The product was then weighed to obtain the weight of Na-alginate from macroalgae. The potential of brown macroalgae can be calculated using the following **Equation 8**.

$$S = A * D \quad \textbf{(8)}$$

Where:

S = standing stock of brown macroalgae (ton/ha)
A = total area based of satellite data analysis (ha)
D = density of each species (gr/m^2)

RESULTS AND DISCUSSION

Distribution of Macroalgae Habitat

The macroalgae habitats found during field observations were Sargassum spp., Turbinaria spp., Caulerpa racemosa, and Halimeda spp. Turbinaria were more commonly found in the south of the island, but almost all had aged. Meanwhile, sargassum was found to thrive in the northern part of the island. Both types of macrolgae were found at a depth of 100 to 200 cm. On the other hand, Caulerpa racemosa and Halimeda spp. were found growing and spreading close to mangrove areas at a depth of 50 to 100 cm. Differences in conditions and distribution types of macroalgae were influenced by seasonal and enviromental factors (Dwimayasanti & Kurnianto, 2018).

Pannikiang Islands Water Quality

The water quality parameters measured included temperature, salinity, turbidity, and pH on the north, east, south, and west sides of Pannikiang Island. The sea temperature ranged from 30^{o}C to 32^{o}C, where macroalgae were still tolerant to this temperature range. Salinity varied between 33 $_o/_{oo}$ and 34 $_o/_{oo}$. The macroalgae habitat had tolerance for a low to high salinity range (Kadi, 2017). The value of turbidity in almost all measurement locations was 5 NTU. This value still follows the standard value of seawater quality based on the Ministry of Environment (2004), except in the southern part of the island, where the turbidity was 5.83 NTU. The activity of fishermen and fishing boats on the island's south side was relatively high because it is close to the Garongkong Port, so the turbidity was higher than in other areas. The pH value ranges from 7.7 to 8.0, which was still in accordance with the pH quality standard for habitats in seawater of 7.7-8.5 (Kepmen LH, 2004).

Tidal Conditions

Figure 2 shows the tidal conditions on May 11, 2020, and August 22, 2020, when the P-1A and S-2A satellites passed at the study site between 09.00 and 10.00 WITA. Figure 2 shows that when the P-1A satellite passed, the water conditions at the study site were at shallow tide conditions (1-3 cm), while when the S-2A satellite passed, the water conditions were slightly higher (7-18 cm) but can be considered at low tide, so sun glint correction and water column correction were not applied.

Maximum Likelihood Algorithm (MLH) Classification

Figure 3 shows the results of the classification of benthic habitats as a result of image processing P1A and S-2A using the MLH algorithm. The macroalgae habitat appeared to be normally distributed in the reef flat area. This looks like the same as the study results (Wicaksono et al., 2019) on Kemujan Island. The results from the P-1A image clearly show that the distribution of brown macroalgae is more dominant than green macroalgae. In contrast to the S-2A image, green macroalgae have a more dominant distribution. The difference in acquisition time between the two images is the cause of the significant difference in information about the distribution of macroalgae. The season affected the presence of macroalgae; satellite P-1A acquired in May shows maximum growth for macroalgae habitat (predominantly brown macroalgae) at the study site. While in the west monsoon period, most of the macroalgae were cut off from the substrate due to being hit by waves (Wouthuyzen et al., 2015), elsewhere macroalgae experienced a period of aging as described from the results of S-2A satellite analysis.

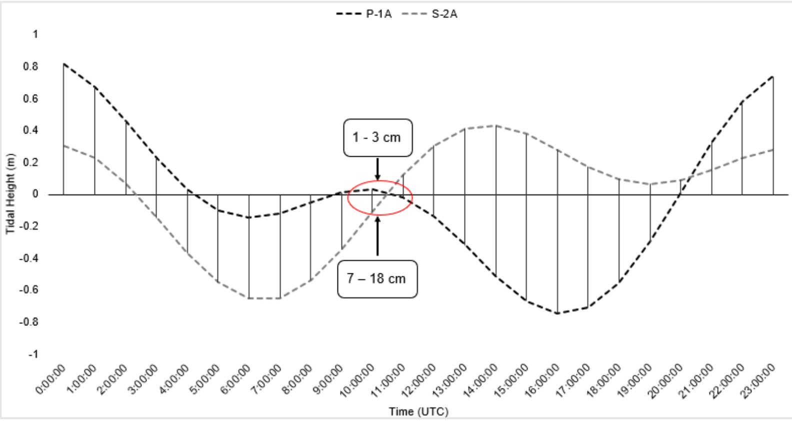

Figure 2. The tidal height of Pannikiang Island on May 11, 2020, and August 22, 2020, when the P-1A satellite and S-2A satellite scanned the study location.

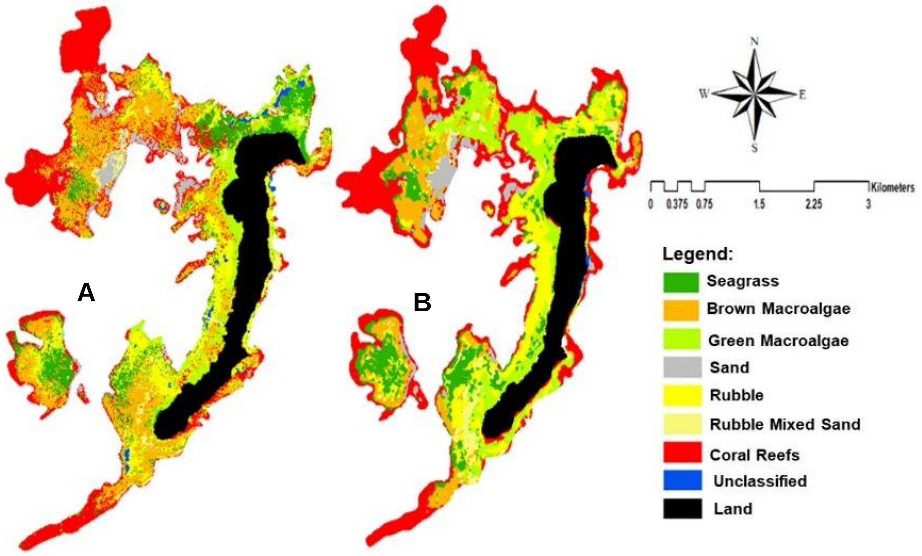

Figure 3. Map of benthic habitats processed on satellite imagery P-1A (A) and S-2A (B) using the MLH classification algorithm.

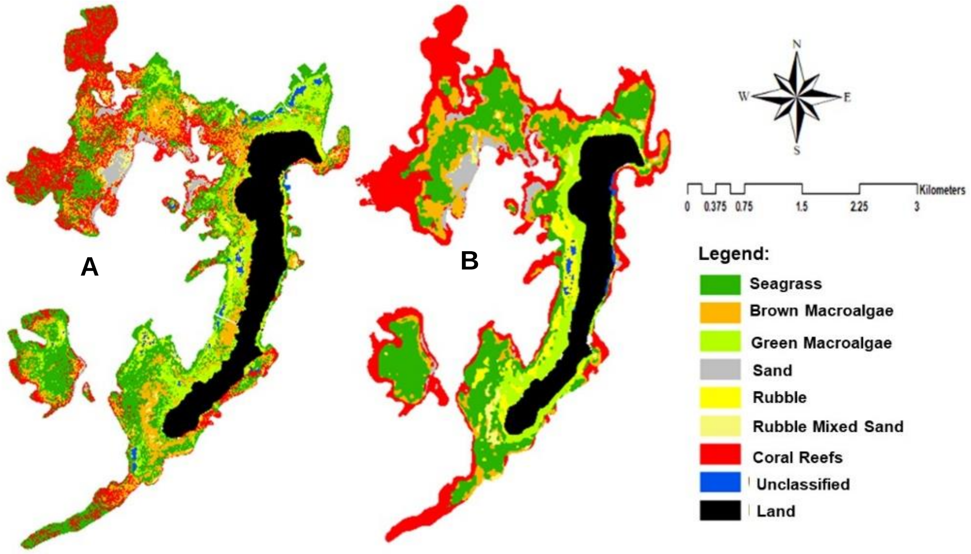

Figure 4. Map of benthic and macroalgal habitats processed on satellite images P-1A (A) and S-2A (B) using the SVM algorithm.

Support Vector Machine (SVM) Algorithm Classification

Figure 4 shows the results of the classification of benthic habitats from image processing P-1A and S-2A using the SVM algorithm. Similar to MLH (Figure 3), the P-1A and S-2A images produced a benthic map with a more dominant distribution of brown macroalgae. Several other high-density benthic habitat components were mapped, namely seagrass, Halimeda spp., and Sargassum spp. On the other hand, there are also unclassified pixels using the MLH and SVM algorithms. This is commonly found in any mapping of benthic habitats, such as seagrass (Hafizt & Danoedoro, 2017). In the classification process, mixed pixels often occur. In the classification process, mixed pixels often occur. In this case, many coral or rubble classes were included in the brown macroalgae habitat class. Therefore, this type of macroalgae was more dominant than green macroalgae, as found by Siregar et al. (2020), where benthic habitats were mapped using two different satellites, WorldView-2 (WV-2) and SPOT 6 on Sebaru Besar Island. WV-2 detected the distribution of rubble in the southern part of the island, while SPOT 6 detected macroalgae habitat in that area.

Test Accuracy

The results of the accuracy test on all components of the benthic habitat using P-1A and S-2A satellite images by applying the respective MLH and SVM classification algorithms are presented in **Table 2**. The P-1A imagery with the MLH classification algorithm shows that almost all benthic habitats are mapped with both with an accuracy range of 50%-100%, except for green macroalgae, with the lowest PA value (36.7%) and coral reefs (46.7%). The SVM classification algorithm showed that all benthic habitats can be mapped accurately except for coral reefs with the lowest PA value (36.7%). The S-2A image shows different things. The accuracy per class is categorized as good by applying the MLH classification algorithm, except for the seagrass class, where the PA value is low (35%). Applying the SVM classification algorithm has the lowest PA value for rubble (31.3%) and rubble mixed with sand (43.8%). The accuracy value for green and brown macroalgae ranges from 50%–100%, meaning that both types of macroalgae have been mapped well according to actual conditions in the field, except for the green macroalgae class in the P-1A image with the application of the MLH algorithm. Some accurate samples are in the rubble class and seagrass with a PA of 50%.

The overall accuracy of the P-1A satellite data using the MLH and SVM classification algorithms is slightly higher at 70.4% and 71.9%, respectively, while the accuracy of the S-2A satellite data is 68.6% and 67.6%. Wicaksono (2016) applied the MLH classification algorithm for high-resolution WorldView-2 images after sun glint correction and obtained the highest accuracy of 52.8% in mapping macroalgal habitat at the pigment level in the Karimunjawa Islands. Without correcting, Wouthuyzen et al. (2016) also mapped 6 benthic habitat classes on coral reef flats at Bitung-Bentena Beach with the iso-cluster classification method. They successfully mapped rock-macroalgae habitats. Chocolate was dominated by Turbinaria spp species, and brown seagrass-macroalgae was dominated by Sargassum sp, Hormophysa sp, and Padina spp, with an accuracy of 73.6%. Setyawidati et al. (2018) mapped five benthic habitats that are brown macroalgae substrates on Libukang Island, South Sulawesi using high-resolution satellite imagery GeoEye-1 with an accuracy of 74.2%. The MLH classification algorithm for both P-1A and S-2A satellite sensors still gave moderate mapping accuracy results because the distribution of samples used as training samples for classification processing and accuracy calculations did not represent all study areas or the sampling distribution is uneven (Hafizt & Danoedoro, 2016). In addition, the MLH classification can provide high accuracy if the spectral reflection of the benthic habitat has a Gaussian distribution (Wicaksono et al., 2019).

The accuracy obtained in this study was > 60%. The accuracy of 60% is a threshold value that is still acceptable in mapping benthic macroalgae habitats (Green et al., 2000). Meanwhile, based on the Indonesian national mapping quality standard from the Geospatial Information Agency (2014), it is stated that the accuracy of benthic habitat maps must be 60% with four benthic classes at a scale of 1:50.000. Based on these two references, the results of mapping benthic and macroalgal habitats using the MLH and SVM classification algorithms on P-1A and S-2A satellite data provide adequate results. The overall accuracy of the P-1A satellite is higher than that of the S-2A due to its higher spatial resolution (2 meters) than the S-2A image (10 m). Other factors causing the low accuracy (75%) of the MLH and SVM classification algorithms on P-1A include S-2A, in addition to the uneven sampling distribution as previously mentioned, and the presence of a mixture of several habitat classes with other classes, such as brown macroalgal habitat with rubble, where the roots of brown macroalgae species, especially Turbinaria spp. species are commonly found firmly attached to the rubble substrate, such as those found in the southern part of Pannikiang Island. Another cause is the preparation of a classification scheme (Siregar et al., 2018), which is not well structured, as well as the influence of turbidity (Siregar et al., 2013), especially in the south of the island, with high turbidity values (NTU>5) compared to the northern part (NTU<5). Furthermore, kernel-based SVM algorithms have limitations in finding hyperplanes between two habitats with relatively similar spectral reflections (Mastu, 2018).

Table 2. The results of the accuracy test for the classification of benthic and macroalgal habitats using the MLH and SVM algorithms on P-1A and S-2A images.

Satellite Image/ Benthic Habitat	MLH			SVM		
	PA	UA	OA	PA	UA	OA
P-1A						
Coral Reefs	46.7%	82.4%		36.7%	61.1%	
Rubble	86.7%	56.5%		65.5%	100%	
Sand	100%	100%		95%	100%	
Rubble Mixed With Sand	100%	75%	70.4%	100%	83.3%	71.9%
Seagrass	54.3%	61.3%		82.9%	48.3%	
Brown Macroalgae	90%	66.7%		67.5%	79.4%	
Green Macroalgae	36.7%	91.7%		76.7%	74.2%	
						S-2A
Coral Reefs	80.6%	78.1%		74.2%	95.8%	
Rubble	59.4%	54.3%		31.3%	83.3%	
Sand	100%	84.6%		100%	73.3%	
Rubble Mixed With Sand	50%	50%	68.6%	43.8%	70%	67.6%
Seagrass	35%	73.7%		90%	48.7%	
Brown Macroalgae	87.8%	65.5%		68.3%	65.1%	
Green Macroalgae	72%	75%		56%	100%	

Table 3. Compares the Kappa value, Z statistic, and significance test of the MLH and SVM algorithms.

Satellite Image	Algorithms	Kappa	Kappa Coefficient (Richards, 2013)	Z	Sig. MLH vs SVM
P-1A	MLH	0.65	<0.4 (low)	12.73	-0.25
	SVM	0.67	0.41 – 0.60 (moderate)	13.97	
S-2A	MLH	0.63	0.61 – 0.75 (good)	11.93	0.21
	SVM	0.61	0.76 – 0.80 (very good)	10.80	

The Kappa value analysis, Z statistic, and significance test were used to assess the performance of the two MLH vs SVM classification algorithms (**Table 3**). This table shows that the results are not statistically significant between the MLH and SVM classification algorithms for both satellite images, with a value range of 0.61-0.67. Referring to the kappa coefficient, Richards (2013) states that the range of values can be categorized as a good classification result (0.61-0.75) (**Table 3**). The kappa value indicated a reduction in misclassification with a range of 0 to 1 (Congalton & Green, 2008). A kappa value of 0.67 means the algorithm can avoid 67% of errors in the random classification process. The statistical Z value shows that using the SVM algorithm on the P-1A image is better than other treatments, with the highest statistical Z value of 13.97. In addition, the significance test results of two different matrices between the MLH and SVM algorithms obtained a value of -0.25 vs 0.21. According to Congalton & Green (2008), the value of Z is said to be significantly different if the value is outside the value range of 1.96–1.96. So, these results indicated that the two error matrices were not significantly different.

Distribution and potential of macroalgae habitat

The results of the calculation of the habitat area of brown macroalgae using the MLH classification algorithm in the P-1A image are wider (128.5 ha) than green macroalgae (51.8 ha). The area obtained from the S-2A image shows a slightly wider green macroalgae (84.1 ha) compared to brown macroalgae (76.8 ha) (**Figure 5**). Meanwhile, the SVM algorithm showed that brown macroalgae were more dominant than green macroalgae in P-1A satellite imagery (88.1 and 59.8 ha) and S-2A satellite imagery (66.7 and 48.1 ha). The difference in acquisition time between the two satellites causes obtaining different areas of macroalgal habitat. The P-1A image acquired in May coincided with the maximum growth month for brown macroalgae (Sargassum spp.) in August, when macroalgae growth decreased (Setywidati, 2018a). The results of this study described the distribution and extent, especially of brown macroalgae, which represent the growing season of brown macroalgae in Pannikiang Island.

Brown macroalgae habitat potential was calculated using benthic habitat maps, with an accuracy of 60% (BIG, 2014; Green et al., 2000). The benthic habitat map is classified by the SVM and MLH algorithms analyzed from satellites P-1A (71.9% accuracy) and S-2A (68.6% accuracy). Furthermore, this study exclusively aims at the potential of alginate produced from brown macroalgae, so green macroalgae are no longer discussed. **Table 4** shows the potential of brown macroalgae at the study site. From 9 sampling stations, the average wet weight was 3498 gr/m^2 for Sargassum and 1839 gr/m^2 for Turbinaria. The conversion of the average biomass of wet macroalgae to dry weight after drying in the sun and then drying in an oven at 70 ^{o}C until the weight becomes constant, the ratio of wet weight to dry weight of Sargassum was 1000: 159 gr, while Turbinaria spp was 1000: 190 gr (**Table 4**). These results indicated that the water content of Sargassum was higher than that of Turbinaria.

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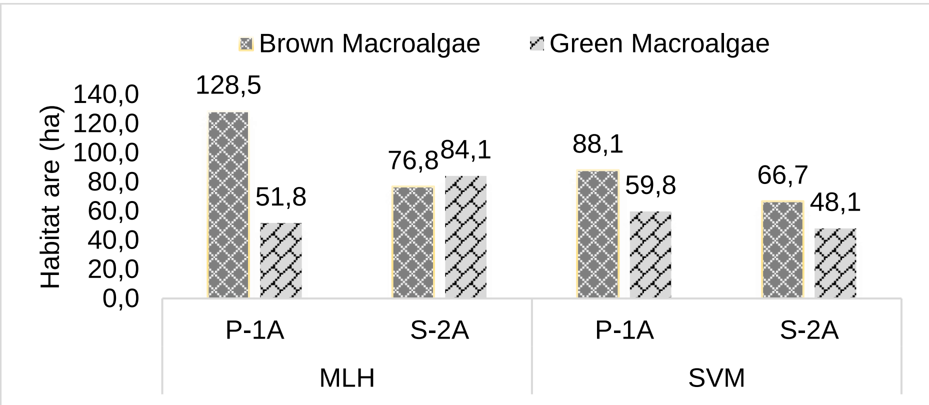

Figure 5. Habitat area of brown macroalgae and green macroalgae from P-1A and S-2A images using MLH and SVM classification algorithms.

Results of the study (Wouthuyzen et al., 2016) the Bitung-Bentena coast showed that the ratio of wet weight to dry weight of brown macroalgae (Sargassum, Turbinaria, Padina) was 1000 g to 140 g or lower than in this study. Based on the laboratory analysis results, brown macroalgae's dry density was 112.2 gr/m2 for Sargassum and 87.4 gr/m2 for Turbinaria. Meanwhile, the habitat area of two macroalgae was based on the analysis of satellite P-1A (88.1 ha) and S-2A (76.8 ha); this area will be the basis for calculating the potential for macroalgae. The potential for dry macroalgae Sargassum and Turbinaria from image analysis P-1A were 98.0 and 77.0 tons for a total of 175 tons. The results of image analysis S-2A were 85.4 and 67.1 tons for 152.5 tons. The results of the extraction of dry brown macroalgae into Na-alginate carried out in the laboratory showed that one (1) gram of dry brown macroalgae (Turbinaria) yielded 0.779 and 0.544 gr of Na-alginate, respectively, with an average value of 0.662 gr (66.2% yield). The dry brown macroalga Sargassum yielded 0.827 and 0.862 gr of Na-alginate, respectively, with an average value of 0.845 (84.5% yield). Based on the respective yield values of Sargassum and Turbinaria, the estimated stock of Na-alginate for each satellite data was 133.8 tons (P-1A) and 116.6 tons (S-2A) on Pannikiang Island. The average yield of brown macroalgae in Pannikiang Island (73.4%) was very high compared to the yield of various brown macroalgae from different Indonesian waters (**Table 5**), which was only around 10.9–42.2% with an average value of 21.9%, meaning that the Na-alginate produced from Pannikiang Island was the highest.

In Pari Island, located in Seribu Islands, the growth season with high density for brown macroalgae (Hormophysa sp, Sargassum spp, and Turbinaria spp) was in September (7.05 gr/m2) rather than in June (4.02 gr/m2). In the western season (December-February), brown macroalgae break off from the substrate (rubble) due to strong waves and later will re-grow in the following season (Wouthuyzen et al., 2015). Furthermore, several studies yielded different potentials of brown macroalgae, such as those carried out by Wouthuyzen et al. (2016), whose estimated alginate stock was 29.9 tons on the Bitung-Bentena Coast. Setyawidati et al. (2018b) study showed an abundance of Sargassum and Padina in May-Juni with a potential biomass of 1189.9 and 166.7 gr/m^2, respectively. While the abundance of Turbinaria in November estimated a biomass of 3245 gr/m^2 on Libukang Island (South Sulawesi). Another study by Setyawidati et al. (2018a) in Ekas Bay (Lombok Island) estimated the dry weight potential of Sargassum and Turbinaria in May-June (669.7 tons) and November (147.7 tons) with Na-alginate potential of 207.6 tons.

Table 4. The estimated dry macroalgae potential of Sargassum spp. and Turbinaria spp. species based on sampling density in the field and the area of satellites P-1A (May 2020) and S-2A (August 2020).

Parameter	*Sargassum* spp	*Turbinaria* spp
Number of transects = 9	5	4
Frame transects	1 m^2	1 m^2
Total wet weight (gr)	3498	1839
Wet weight density (gr/m^2)	699.6	459.8
The ratio of wet: dry weight	1000:159	1000:190
Dry weight density (gr/m^2)	111.2	87.4
Average yield (%)	84.5	66.2
Brown macroalgae area (ha);		
P-1A SVM	88.1	
S-2A MLH	76.8	
Dry weight stock potential (tons)		
P-1A (Mei 2020)	98.0	77.0
S-2A (Agustus 2020)	85.4	67.1
Total potency of Na-alginate		
May 2020 (P-1A)	133.8	
August 2020 (S-2A)	116.6	

Table 5. The Na-alginate yield from various types of brown macroalgae extracted from various Indonesian waters using various methods.

No	Types of brown macroagae	Macroalgae samples (gr)	Natrium-alginate (gr)	Yield (%)	Library resources
1	*Sargassum* sp	25	10.6	42.4	(Prasetyaningrum & Purbasari, 2002)
2	*Sargassum* sp	450	177.3	39.4	(Subagan et al., 2020)
3	*Sargassum* sp	90	20.2	22.4	(Sunar, 2015)
4	*S. fuitans*	100	11.7	11.7	(Maharani et al., 2017)
5	*S. muticum.*	100	14.8	14.8	(Nurkhanifah & Husni, 2020)
6	*Sargassum sp*	1000 500	108.6 68.8	10.9 13.8	(Suryani & Rohaeti, 2008)
7	*Sargassum* sp	40	5.2	12.9	(Jayanudin et al., 2014)
8	*Sargassum* sp	50	8.7	17.4	(Putriyana et al., 2018)
9	*S. cristaefolium*	50	16.1	32.3	(Tambunan et al., 2013)

No	Types of brown macroagae	Macroalgae samples (gr)	Natrium-alginate (gr)	Yield (%)	Library resources
10	*Sargassum* sp	2000	219.0	11.0	(Setyoaji et al., 2019)
11	*Sargassum* sp	25	7.9	31.6	(Wardani et al., 2009)
12	*S. polycystu*m	25	4.9	19.5	(Dharmayanti et al., 2021)
	Sargassum sp	10	2.8	28.1	
13	*Turbinari*a Sp	10	2.2	22.2	(Nastiti, 2016)
	*Padin*a sp	10	1.6	16.2	
14	*Padina* Sp	50	13.4	26.8	(Pasaribu et al., 2020)
15	*Padina* Sp	50	8.9	17.8	(Septiani et al., 2017)
16	*Padina* sp	1000	250.0	25.0	(Hamrun et al., 2018)
17	*Turbinaria ornata*	150	33.7	22.5	(Laksanawati et al., 2017)
18	*Turbinaria* sp	50	14.0	28.0	(Wibowo et al., 2013)
19	*Turbinaria* sp	30	7.1	23.8	
	T. triquetra	100	22.2	22.2	
20	*Hormophysa cuneiformis*	100	13.3	13.3	(Rashedy et al., 2021)
Average yield *Sargassum* spp				22.0	
Average yield *Padina* sp				21.5	
Average yield *Turbinaria* sp				24.1	
Average yield of all macroalgae				21.9	

This study found that brown macroalgae in several locations (Pannikiang Island, Libukang Island, Bitung-Bentena, Ekas Bay, and Pari Island) have a high potential to be extracted into Na-alginate. Therefore, there is no doubt that all coastal areas of Indonesia can also produce high alginate, which can reduce national imports of alginate. Alginate is urgently needed by various industries, such us: non-food, food, pharmaceutical, cosmetic, and medical industries, which various countries have supplied.

CONCLUSION

This study successfully mapped benthic and macroalgal habitats with an overall accuracy of>60%. This accuracy complies with BIG standards in shallow water habitat mapping, classifying habitat classes. The performance of the SVM classification algorithm was better than the MLH classification algorithm based on the calculation of accuracy and kappa value. Differences in acquisition time and pixel size affect the results of classification and accuracy tests. This method can estimate the potential of brown macroalgae and Na-alginate stocks on Pannikiang Island. This is because the yield of brown macroalgae was higher than brown macroalgae in other parts of Indonesia that used various extraction methods.

The combination of accurate mapping and macroalgae biomass obtained from the field was effective and efficient for predicting, monitoring, and managing the potential of brown macroalgae and the Na-alginate they contain. However, this method still needs to be developed and tested in other coastal areas of Indonesia. This is because each water area has different characteristics. Therefore, it can eventually be used as a standard benthic habitat mapping method.

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