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SEMI-AUTOMATIC CLASSIFICATION MODEL ON BENTHIC HABITAT USING SPOT-7 IMAGERY IN PENERUSAN BAY, BALI

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ABSTRACT

Benthic habitats are one of the interesting marine resources and its existence must be preserved. Provision of up-to-date benthic habitat information requires a relatively large amount of time and money. The use of remote sensing technology is one of the best solution. This study aims to develop a semi-automatic processing model that is fast, accurate, and with broad spatial coverage. The satellite image data used is the SPOT-7 image acquired on April 11th, 2018. The method used is a supervised classification with a decision tree algorithm. The analysis was carried out using a script developed in the open-source R application. The results showed that the model used was able to accelerate the processing of benthic habitat extracted from the initial process to the classification. The model developed is able to classify habitat classes based on the training sample data provided so that it does not affect the user's ability to determine the habitat class. The resulting model accuracy is 93.6%. The validation of the resulting classification showed an overall accuracy of 59% and a kappa accuracy of 0.46. It is necessary to carry out further research by increasing quality and quantity of training samples from each object of benthic habitats and developing scripts in order to produce better mapping accuracy.

Keywords: Benthic habitat, semi-automatic, decision tree, SPOT-7, Penerusan Bay.

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INTRODUCTION

One of coastal ecosystems that has a very important role is benthic habitat. According to SNI 7716:2011 about the classification of shallow-water habitats hereinafter referred to as benthic habitat is part of marine waters used to support marine life which has a depth of between 0 meters to the maximum depth where remote sensing sensors can penetrate the water column in clear water conditions (25 to 35 meters). SNI 7716:2011 classified benthic habitat into seagrass, macroalgae, corals, and substrates.

Remote sensing technology is growing rapidly, especially for the application of resources in coastal and marine areas (Purwanto *et al*, 2019; Wicaksono *et al*, 2019; Effrosynidis *et al*., 2018; Setiawan *et al*, 2021). This is indicated by the increasing use of remote sensing data in line with the increasing need for spatial and up-to-date information. This information must also be supported by a fast and accurate processing system. Information on benthic habitat is one of them because this habitat is experiencing increased disturbance with increased activity on land and sea as well as climate change (Wolff, *et al*. 2015). The reflectance spectral is the key to understanding benthic habitats using remote sensing (Hochberg, *et al*, 2004). Based on research by Brock *et al*. 2006, benthic habitats provide different spectral responses due to the difference in wavelengths of each band used.

Research on the use of remote sensing data to provide information on benthic habitats has been widely carried out. Azhar *et al* (2018) using Landsat 8 data were able to extract four classes of shallow water habitats on Kaledupa Island, namely live coral, dead coral, seagrass and sand using the supervised classification method Mahalanobis, and Maximum Likelihood. The overall accuracy and kappa 71.67% and 0.62 and 73.33% and 0.65, respectively. Selgrath, et.al (2016) used WorldView-2 data with the OBIA method on four classes, namely coral, coral rubble, sand, and seagrass with a confidence level of 76%. The OBIA method can also map well and can even be an alternative method for mapping the geomorphological zone of a coral reef ecosystem in an area (Anggoro *et al*., 2015). Object-based classification methods can also be used to map the health of coral reefs and types of living things with a fairly high degree of accuracy (Ardiyanto *et al*. 2015).

Several previous studies still used conventional methods which still require additional intervention or information from interpreters. This method is deemed ineffective because it requires a long time and the results tend to be subjective because it still depends on the ability of the interpreter, especially in the introduction of shallow marine habitat objects. Therefore, it is necessary to develop a semi-automatic benthic habitat mapping method that can complement the constraints found in the previous method. One of the programming languages that is currently being developed and widely used by many people is R (Ginting & Arjasakusuma, 2021; Belgiu dan Dragut, 2016) . Referring to the main existing sources, it can be explained that the R programming language is an open source application that can be used for statistical and graphic computing (https://www .r-project.org). Analysis of the detection of changes in coral reefs using R was carried out by Gapper *et al*., (2019) which resulted in a fairly good level of accuracy. In addition, R is also used by Gapper *et al*., (2018) to evaluate the spectral characteristics of coral reefs around Pacific waters.

The objective of this study is the use of the R programming language to identify the distribution of benthic habitats using supervised classification methods (decision tree). The aim of this research is to develop a semi-automatic model to extract benthic habitat information with wide spatial coverage. The development of this method is expected to make the interpretation of benthic habitat objects more objective and in accordance with the actual conditions in the field.

METHODOLOGY

The study location in this research is in the Penerusan Bay, Pejarakan Village, Buleleng Regency, Bali Province. In this area, there are many benthic habitat objects, especially seagrass and macroalgae, which are relatively homogeneous with a fairly wide distribution level. Penerusan Bay is one of the locations for marine cultivation development in Bali Province (Radiarta *et al*., 2015) so that the activity that is often found in this area is cultivation using floating net cages media. In addition, the location of Penerusan Bay is close to Pemuteran Beach which is one of the most famous diving spot icons on Bali Island. The location of this research is shown in Figure 1.

Imagery Data

The data used is SPOT-7 high-resolution satellite data which was acquired on April 11, 2018. The SPOT-7 image has four multispectral bands and one panchromatic band with a spatial resolution of 6 m and 1.5 m respectively. SPOT-7 image data was obtained from the Center for Technology and Remote Sensing Data (Pustekdata) LAPAN. Table 1 contains specifications of SPOT-7 satellite imagery.

Field Data

Information of the benthic habitat location (coral, seagrass, macroalgae, and substrate) was obtained through direct measurements in the field which was carried out in June 2018 in Penerusan Bay and

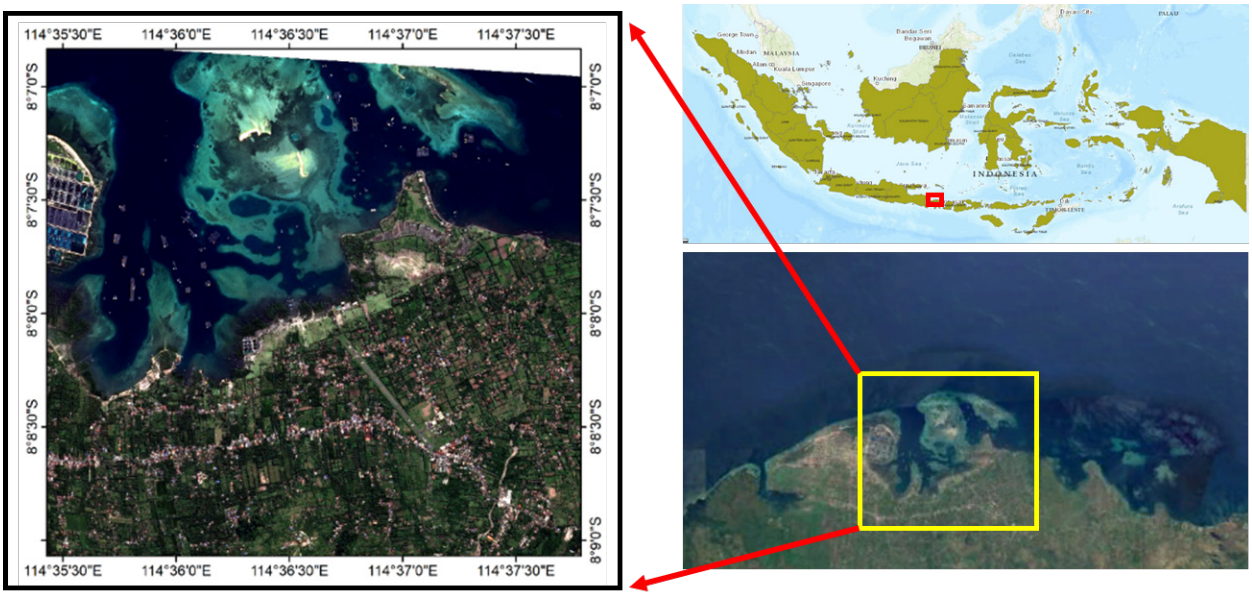

Figure 1. Study Area.

surrounding areas. The sampling method used is purposive and proportional random sampling (Geospatial Information Agency, 2014). Field observation points were recorded using GPS and accompanied by photos of underwater objects. Field measurements were made by making transect 6 x 6 m according to the pixel size in the SPOT-7 image. The distance between transects is 10 m. The selection of measurement points is based on the distribution of shallow water habitat objects in homogeneous areas with a minimum area of 36 m^2. The data collected is the coordinates, type of cover, and percentage of cover. In addition to using transects, field data collection is also assisted by photos from drone. The type of drone used is the DJI Phantom 4 Pro. Based on field data collection and drones, the number of observation points collected was 312 points. The field data is then divided into two with a percentage of 40% for training data to build a model (model data) and 60% as data to test the accuracy of the classification results (validation data). The data model is overlaid with SPOT image. Homogeneous pixels around the model data are used to obtain training sample data in the form of a combination of spectral value in the blue, green, and red bands with the type of cover. This stage is done manually for each type of cover. The training sample data containing the spectral value of SPOT-7 imageand benthic habitat information is used to build a classification model. At this stage, the preparation of the model uses R software with the C5.0 function where the model will be generated automatically. Further explanation regarding the model can be read in the decision tree algorithm sub-chapter. The distribution of field measurement data is shown in Figure 2.

Pre-processing Data

Radiometric correction is performed to convert digital values into reflectant values. The equation used is as follows (Astrium Services, 2013):

$$L_b(p) = \frac{D\quad(p)}{Gain(b)} + BIAS(b) \qquad \text{.............................1)}$$

where,

DC($_p$) = digital value
Gain (b) = gain coeficient
BIAS (b) = bias coeficient
ρ_b (p) = reflectance
L_b (p) = radiation
θ_s = elevation angle

Table 1. Spesification of SPOT-7 Imagery

Band	Resolution			
	Spectral (μm)	Spatial (m)	Radiometric	Temporal
Blue	0.450-0.520	6		
Green	0.530-0.590	6		
Red	0.625-0.695	6	12 bits	1-3 days
NIR 1	0.760-0.890	6		
Pankromatik	0.450-0.745	1.5		

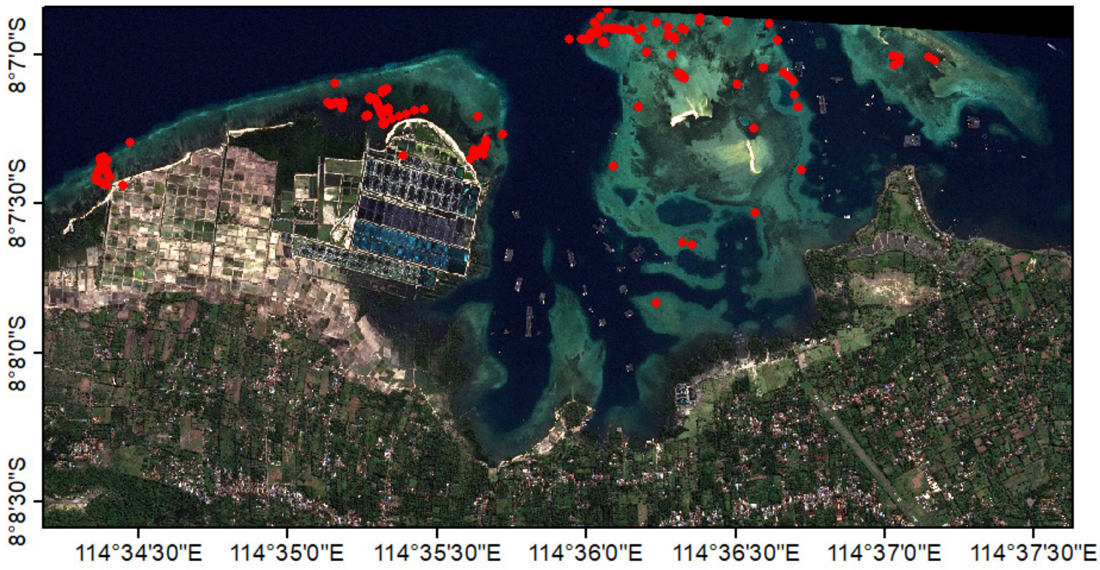

Figure 2. Distribution of observation point.

Image data that has gone through the radiometric correction stage, then the masking process uses the NIR band to separate land and sea. The NIR band is used because the wavelength in this band is well absorbed by water objects so that land objects can be seen more clearly.

Decision Tree Algorithm

The classification model is built based on sampel training data that contain the reflectance values of the blue, green, red bands and benthic information using R software. In this software, there is a C5.0 function that can be used to perform decision tree analysis. According to Suyanto (2011), it is explained that the decision tree algorithm uses a hill-climbing search strategy where this strategy seeks to find a decision tree that will classify data samples accurately and without errors based on existing training data.

Decision tree methodology is a method commonly used in data mining to produce a classification system based on many variables and can be used to develop predictive algorithms on target variables. The algorithm is non-parametric and can compromise high level data and in large quantities without being affected by the parametric structure. When the sample size is large enough, research data can be divided into training and validation data. Use sample data to build a decision tree model and validation data to determine tree size to reach the optimal final model (Song & Lu, 2015).

The C5.0 algorithm used is a refinement of the ID3 and C4.5 algorithms. In the process of forming a decision tree, the highest gain information value will be selected as the root for the next node. This algorithm starts with all the data that is used as the root of the decision tree while the selected attribute will be the divisor for the sample (Han *et al*, 2012). The attribute size formula is

$$Info(D) = -\sum_{i=1}^{m} p_i \log_2(p_i), \quad \text{... 1)}$$

Where Info(D) is the average amount of information needed to classify the class label of a tuple in D. Info(D) is also known as entropy. pi is the nonzero probability of a random tuple in D. The log function uses base 2, because the information is encoded in bits. The resulting entropy value for classifying the tuples of D based on the partition by A is

$$Info_A(D) = \sum_{j=1}^{v} \frac{|D_j|}{|D|} \times Info(D_j). \quad \text{.................................. 2)}$$

To get the value of information gain on attribute A, the formula is

$$Gain(A) = Info(D) - Info_A(D). \quad \text{................................. 3)}$$

Gain (A) states how many branches will be obtained in A. Attribute A with the highest information gain. Gain (A), is selected as the splitting attribute at node N.

The model is used to classify the benthic habitat classes in the image so that spatial benthic habitat information can be generated. In this model, deep water objects are still included in the development of the model to remove deep water information in the image.

Table 2. Confusion matrix

Classification Result	Field Data A	B	C	Total	Producer Accuracy
A	X_{11}	X12	X13	X1+	X11/ X1+
B	X_{21}	X22	X23	X2+	X22/ X2+
C	X31	X32	X33	X3+	X33/ X3+
Total	X+1	X+2	X+3	N	
User Accuracy	X11/ X+1	X22/ X+2	X33/ X+3		

Accuracy Test

In this study, the accuracy tests were carried out by using accuracy assessment and validation. The accuracy assessment is carried out by the system to see the level of separation of the pixels of the training data used. Validation is used to see the level of conformity of the classification results from the resulting model with field data. Confusion matrix is used for accuracy test. The three categories in the confusion matrix are producer accuracy, user accuracy, and overall accuracy (Table 2). The accuracy of producers and users can be use to see misclassification of commissions and omissions. Commission class shows a class misclassification that does not exist in the field while omission errors indicate a class misclassification that actually exists in the field but is eliminated by the algorithm used.

The overall accuracy can be calculated by comparing the number of correctly classified pixels against the observed pixels.

$$\text{Overall accuracy} = \frac{\sum_{i=1}^{n} X_{ii}}{N} \times 100\% \qquad \text{.................. 4)}$$

Based on Jaya's research (2010), the overall accuracy generated in the confusion matrix has a high error. Therefore, for overall accuracy the Kappa accuracy will be used which takes into account all the elements (columns) of the error matrix.

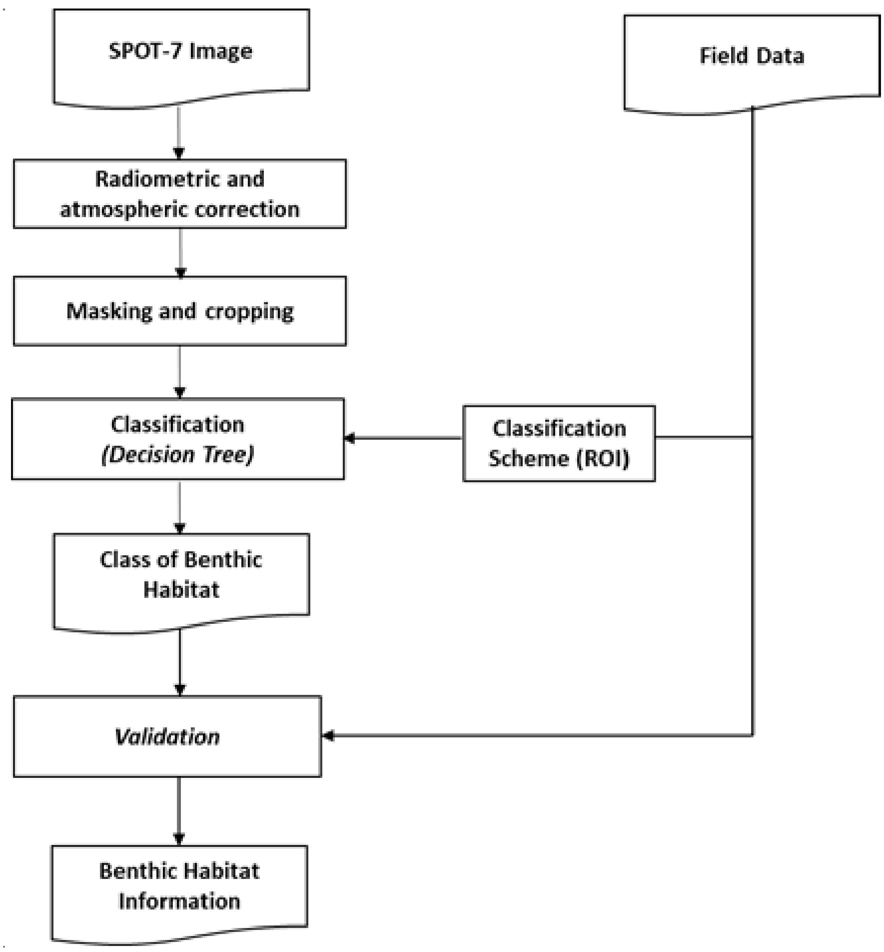

Figure 3. Research Flowchart.

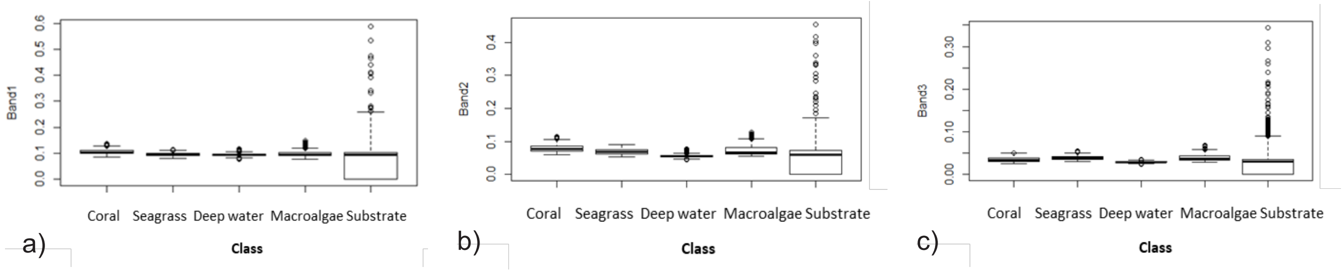

Figure 4. Spectral of SPOT-7 imagery; (a) Band 1; (b) Band 2; (c) Band 3.

$$\text{Kappa}= \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+} + X_{+i}}{N^2 - \sum_{i=1}^{r} X_{i+} X_{+i}} \times 100 \quad \text{.................... 5)}$$

The overall stages of data processing carried out to produce benthic habitat information in this study can be seen in Figure 3.

RESULTS AND DISCUSSION

Field observations

Benthic habitats mapping in Penerusan Bay, Bali was carried out using high-resolution SPOT-7 data. The image data used has a time range that is not much different from the measurement data in the field. The reflectance value of the training sample data on five objects, namely coral, seagrass, deep water, macroalgae, and substrate in the blue (Band 1), green (Band 2) and red (Band 3) bands can be seen in Figure 4.The reflectance values are shown in the form of boxplot to see the reflectance distribution of each object. The boxplot graph shows each object a decrease in its reflectance value as the wavelength increases (blue band - red band). This is due to the propagation ability in the waters of different wavelengths, the closer to the red wavelength, the energy will be completely absorbed.

In the boxplot graph, it explain that the reflectance of the sample data on the substrate object has the most outlier values, which indicates that the training sample data is not good for substrate object which can interfere with the classification process. Based on the conditions found in the field, it can be seen that the substrate object tends to mix with other objects so that this causes many outlier values on the object. The results of the training sample data above are used to build a classification model for the shallow sea bottom habitat. The model is built based on the spectral classification of the three bands on each object. The model used produces an accuracy of 93.6% (Figure 5). This figure indicates that the model is feasible to use to separate benthic habitat objects.

The highest model accuracy sequencely is produced by deep water, substrate, coral, seagrass, and macroalgae (Table 2). The high accuracy obtained for deep water objects and substrate is because the two objects show significantly different spectral patterns compared to other objects. This shows that the model built is able to separate deep water objects, substrate, coral and seagrass very well, but it is relatively difficult to separate macroalgae objects.

Bentic Habitat Classification Results

The distribution of benthic habitats in Penerusan Bay, Bali can be seen in Figure 6. Classification is carried out on 5 (five) object classes, namely coral, seagrass, macroalgae, substrate and deep water. The results of the classification of each object are shown in orange for coral, neon green for seagrass, moss green for macroalgae, and ash for the substrate. Misclassification can easily be seen in aquaculture sites and on land which are considered seagrass.

	TreePredict				
	Deep water	Coral	Seagrass	Macroalgae	Substrate
Deep water	8548	1	0	0	174
Coral	0	369	3	4	36
Seagrass	0	1	398	64	39
Macroalgae	0	5	56	309	100
Substrate	366	15	59	57	4898

1] "Akurasi model rule pada fold ke 5: 0.936782"

Figure 5. Accuracy assessment.

Table 3. Accuracy and error of each object

Producer accuracy (%) Class	Accuracy	Omission Error (%)	User accuracy Class Accuracy	Comission Error (%)	(%)
Deep water	97.99	2.01	Deep water	96.21	3.79
Coral	89.56	10.44	Coral	94.37	5.63
Seagrass	79.28	20.72	Seagrass	77.13	22.87
Macroalgae	65.74	34.26	Macroalgae	71.19	28.81
Substrate	91.29	8.71	Substrate	93.34	6.66

The classification results show that the distribution of benthic habitats in Penerusan Bay is dominated by substrate, then the next largest area is sequentially dominated by corals, macroalgae and seagrass. The distribution of seagrass classes is found on the beach next to the mainland. The distribution of coral objects is found in areas bordering the deep water, while substrate objects tend to be mixed with seagrass and macroalgae objects. Remote sensing technology has the potential to be applied in mapping the composition of seagrass species in more detail (Meyer, 2008). The spectral reflectance characteristics depend on the chlorophyll content and pigment concentration as well as the design characteristics of the leaves (Thorhaug *et al*., 2007).

In Table 4, it can be seen that the extent of benthic habitat in the study area. The classification results show the area of each object from the widest, namely sand (283.05 ha), coral (61.05 ha), macroalgae (8.83), and seagrass (29.97 ha). The results of the area calculation show that the substrate object dominates the distribution of the benthic habitat at Penusan Beach, Bali. The most interesting thing is that macroalgae objects have a fairly wide distribution (around 13.59%). Based on the results of field checks, the types of macroalgae that are often found in the study location include Padina Pavonica, Microdictyon marinum, Ulva sp and others where their lives are separated and not a few are associated with other species yaitu lamun. This causes low accuracy in seagrass and macroalgae objects. An example of the appearance of the types of macroalgae around the study site is shown in Figure 7.

The results of the classification of benthic habitats were evaluated by calculating the accuracy of the classification results with field data (Table 5). The accuracy test shows an overall accuracy of 59.5% and a kappa accuracy of 0.46. This accuracy is close to the minimum accuracy requirement that can be accepted for mapping benthic habitat maps based on SNI 7716:2011 which is 60% (Badan Informasi Geospasial, 2011). The best producer accuracy was shown by coral objects at 82%, followed by seagrass (63%),

Table 4. The Extent of Benthic Habitat

Class	Area (ha)	Percentage (%)
Coral	61.05	14.10
Seagrass	29.97	6.90
Macroalgae	58.83	13.59
Substrate	283.05	65.41

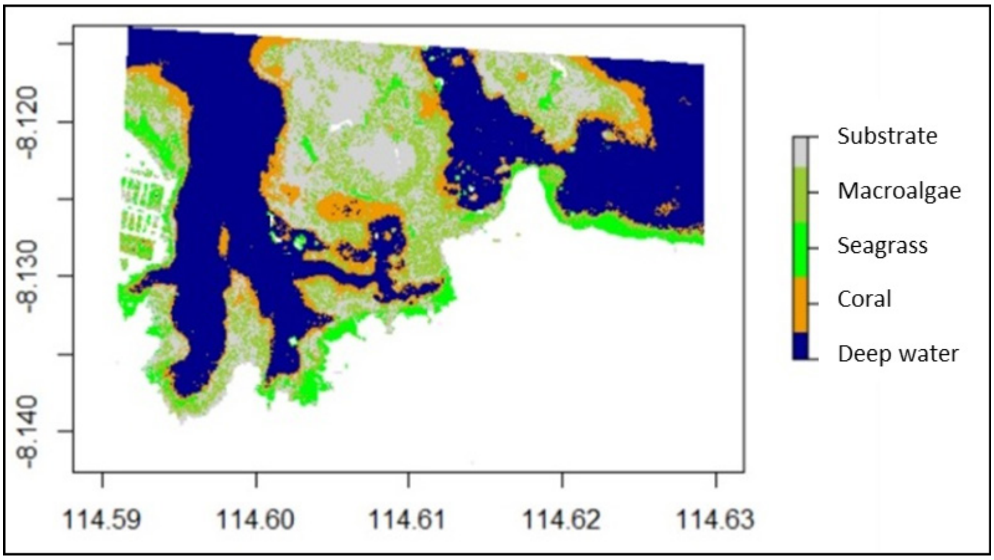

Figure 6. Benthic Habitat Distribution.

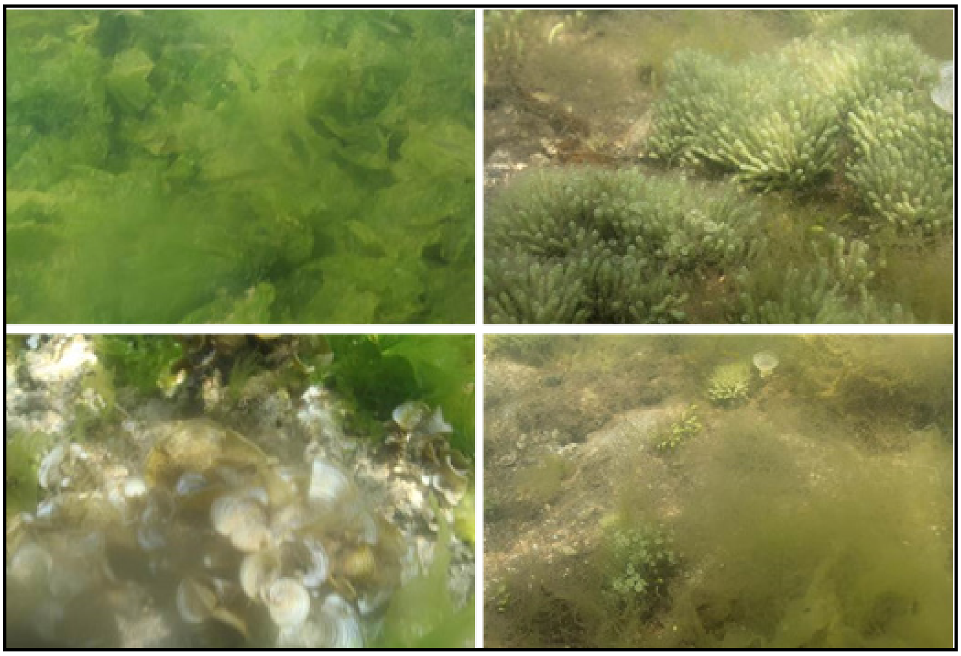

Figure 7. Macroalgae species around the study area (source: Documentation of field survey).

macroalgae (54%), and substrate (37%). User accuracy shows different results from producer accuracy where the best accuracy is shown by the substrate at 71% and the smallest is macroalgae at 45%. The accuracy of this research have a higher level of accuracy than the results of research related to the mapping of the benthic habitat conducted by Purwanto *et al*. (2019) using the pixel-based classification method and the same number of classes (coral, seagrass, macroalgae and substrate) an accuracy rate of 49%. Some of the advantages of the supervised classification method using Decision tree in R software is the approaches used to classifying benthic habitat complexity especially at major classification schemes, reliable with outliers on training data, and can use various dataset as input data (Wicaksono *et al*, 2019). One of the constraints of pixel-based classification often occurs in pixels outside a specific area or between overlapping areas where these pixels will remain classified, which will cause misinterpretation (Ardiansyah *et al*., 2004).

CONCLUSION

Processing benthic habitats using R software can accelerate the process of classifying benthic habitat objects. The classification model that has been developed can minimize the level of interpreter subjectivity in determining habitat classes. The accuracy of the resulting classification model using the decision tree method shows 93.6% so that it can be said that the resulting model is good enough in benthic habitat mapping. The validation of the resulting classification results showed an overall accuracy of 59% and a kappa accuracy of 0.46. This accuracy is sufficient in separating benthic objects semi-automatically.

Furthermore, it is necessary to carry out further research by increasing quality and quantity of training samples from each object of benthic habitats and developing scripts, especially for water column correction in order to produce better mapping accuracy.

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