MAPPING BENTHIC HABITAT FROM WORLDVIEW-3 IMAGE USING RANDOM FOREST CASE STUDY: NUSA LEMBONGAN, BALI, INDONESIA

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ABSTRACT:

Benthic habitats are coastal ecosystems that provide many benefits and play an important role in the diversity of nature. The maps are developed using random forest method on the Worldview-3 image. Optically shallow water around Nusa Lembongan was selected as the study area. Sunglint and water column correction were applied to surface reflectance data to produce deglint, depth invariant index, and deglint-depth invariant index band for random forest classification. In addition, tuning parameters, including the number of trees and the function to determine the number of randomly selected, are used in the classification. The benthic habitats classification scheme was constructed based on the variations of in situ data, which consisted of coral reefs, seagrass, macroalgae, and substrate. The confusion matrix was used to analyze the accuracy, and the McNemar test to evaluate the level of statistical significance between different processing scenarios. The best benthic habitats map is determined based on the accuracy and spatial distribution of the object. Meanwhile, the random forest algorithm produced 62.72% – 73.00% overall accuracy and these accuracy variations were not statistically significant. According to the findings, surface reflectance data with the parameter setting comprising 500 trees and square root function yielded the best random forest scenario for mapping benthic ecosystems.

1. INTRODUCTION

Benthic habitats are coastal ecosystems that beneficial in many ways and play a significant role in food security, tourism, and coastal protection (Kritzer et al., 2016; Henseler et al., 2019). Based on SNI 7716:2011 issued by the Geospatial Information Agency, mapping shallow marine bottom habitats, also known as benthic habitats, is classified into four main categories, namely macroalgae, seagrass, substrate, and reefs (BSN, 2011). Remote sensing is one of the mapping techniques that can be applied because it has spectral values which penetrate water and can be used to comprehend benthic habitats (Hochberg et al., 2003). This method's challenge is the accuracy level due to the limitation of remote-sensing sensors and benthic habitats environmental complexities (Hedley et al., 2012; Hedley et al., 2016).

According to Bukata (1995) and Hedley et al. (2016), accuracy is affected by several processes, including atmospheric correction, sunglint, and water column, supported by Tamondong et al. (2013), Anggoro et al. (2016), and Siregar et al. (2018). However, the opposite is shown by Zhang et al. (2013), Wicaksono and Lazuardi, (2018), and Ginting and Arjasakusuma (2021). It is necessary to conduct a comprehensive analysis regarding the effect of correction of input data on the accuracy of the mapping, which is the first objective of this study.

Benthic habitats mapping may benefit from the advancement of computing and remote sensing technology. One of that advancements is the emergence of machine-based processing technology (UNEP, 2020). Random forest algorithm is part of these machine learning techniques. This technique creates multiple decision trees using random vectors with independently taken samples, resulting in the averages of various tree numbers (Salford Systems, 2014; Genuer and Poggi, 2020). Therefore, the random forest can show more complex relationships and process images with a high spatial resolution (Zhang dan Xie, 2012; Zhang et al., 2013; Effrosynidis et al., 2018; UNEP, 2020), and enabling the method to classify remote sensing data effectively (Maxwell, 2018). The application of random forest for benthic mapping has produced successful results (Ariasari et al., 2019; Hartoni et al., 2022) but these research have not been analyze two main random forest parameters. The paramaters are the number of trees and various functions used to determine the randomly selected features (Genuer and Poggi, 2020). Wicaksono and Lazuardi (2019) researched these two parameters and concluded that random forest is a reliable and consistent classification algorithm. This is demonstrated by the insignificant difference in accuracy values between the two parameter settings and the almost similar spatial distribution of benthic habitats. Even though there is no significant difference between the accuracy values in the two input data scenarios, different parameter settings are evident. Therefore, the second goal is to analyze the effect of parameter settings on different input data.

This study focuses on how the input data and tuning parameters affecting the random forest method mapping benthic habitats. They are mapped using the random forest method on WorldView-3 imagery with varying degrees of correction. This study is expected to provide a comprehensive understanding for accurately mapping benthic habitats.

2. METHODOLOGY

The study location is Nusa Lembongan, Klungkung Regency, Bali Province. It is a part of the Nusa Penida Waters Conservation Area, which has a wide variety of seagrasses and is part of the coral triangle known for its richness of reefs (Kabupaten Klungkung, 2012). According to Prasetia et al. (2017), Nusa Lembongan has a distribution of reefs with

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fringing reef formations and seagrass beds covering an area of 250 ha and 108 ha with sand and mud substrate types (Negara et al., 2020). The location is shown in Figure 1.

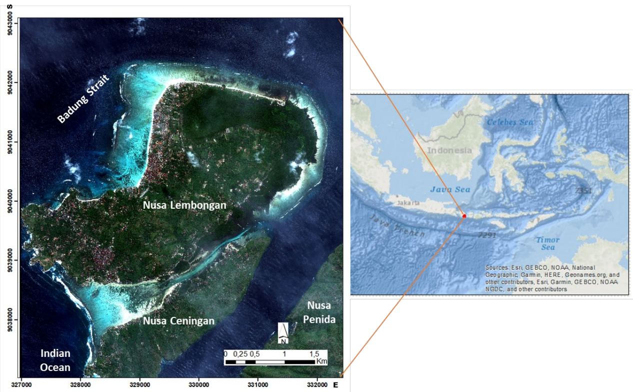

Figure 1. Nusa Lembongan, Bali (WorldView-3)

The field data is secondary data obtained from Kumara (2018). The data was collected in Nusa Lembongan between June 12 until June 19 2017. The data contains information related to object type and location, comprising 760 points (Figure 2). Some samples have been omitted due to the accuracy of GPS, and additional samples are based on expert adjustment with a total data of 861 points. The field data is divided into two, with a percentage of 60% for training data to build a model and 40% for data to test the accuracy of the classification results.

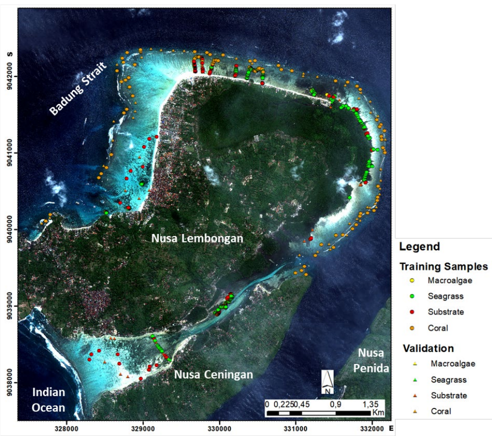

Figure 2. In-situ data

WorldView-3 imagery data was acquired on July 27, 2016. The data have 8 multispectral bands, 1.24 m spatial resolution, and 11-bit radiometric resolution (Table 1). The classification process only uses visible bands, and the data were corrected to produce four data levels, namely surface reflectance, deglint, depth invariant index, and deglint-depth invariant index band. For benthic mapping, these bands are used as the input data.

Band	Wavelength (nm)	Band	Wavelength (nm)
Coastal	400 - 450	Red	630 - 690
Blue	450 - 510	Red edge	705 - 745
Green	510 - 580	Near-IR1	770 - 895
Yellow	585 - 625	Near-IR2	860 - 1040
Spatial resolution	1.24 m		
Radiometric resolution	11-bit		
Temporal resolution	Daily		

Table 1. Specification of WV3 image

2.1 Image masking

Image masking is a technique for removing extraneous components. The NIR band threshold value, which can distinguish between pixels on land and water, is used for this concept. Deep water pixels were masked using the threshold value of the water column corrected image (Wicaksono et al., 2021).

2.2 Radiometric correction

The standard data on the WorldView-3 imagery is the relative radiometric correction value on the sensor (Digital Globe, 2012). Radiometric corrections are used to convert digital values into TOA reflectance.

2.3 Atmospheric correction

The surface reflectance value was obtained after atmospheric correction, and the dark object subtraction (DOS) method was employed (Chavez, 1996). Pixels in deep water are used as dark targets, and this method shows correction results that can be compared with other, more robust algorithms (Wicaksono and Hafizt, 2018). The surface reflectance band is used in sunglint and water column correction

2.4 Sunglint correction

The sunglint correction method is based on Hedley et al. (2005). The linear relationship between the visible and NIR bands in the training area is the foundation for this method. Based on Hochberg et al. (2003), the selected training area is one or more pixels with sunglint but consistent spectral brightness. In this study, Blue, Green, and Red bands correlated with the NIR1, while Coastal, Yellow, and Red Edge bands were correlated with the NIR2.

2.5 Water column correction

The water column significantly impact benthic habitats mapping using satellite imagery (Mumby et al., 1998). Water column corrections are needed to determine the reflection of the bottom of the water. Lyzenga (1978) used two channels in the formulation to perform water column correction. The reflectance of the sand object located at different depths is used to normalize the effect of water column energy.

2.6 Random forest classification

The classification method used is the random forest, and this is a supervised classification machine learning. This study used a scenario based on input data and tuning parameters. The number of trees (ntree) and functions to determine the number of randomly selected features (mtry) are used as tuning parameters. The selected number of the trees are 100 and 500, and the functions to determine the number of randomly selected features are square root (sqrt) of all features and log of all features based on Wicaksono and Lazuardi (2018). The final result is the selection of the best scenario, characterized by the highest accuracy and representative benthic habitats distribution.

2.7 Accuracy assessment

The accuracy of benthic habitats map is determined by calculating the confusion matrix. The overall accuracy is the percentage of validation samples correctly classified relative to all validation samples, regardless of class. Additionally, the McNemar test was processed to determine the degree of significance of the variation in classification accuracy (Foody, 2004). The accuracy is statistically significant when McNemar's z value exceeds 1.96 at the 95% confidence level (Zhang et al., 2013a).

3. RESULTS AND DISCUSSION

3.1 Tuning parameter

The random forest scenario produced 62.72% – 73.00% overall accuracy (Table 2). The difference in accuracy between 100 and 500 trees is less than 0.5% in each of the four input data, which shows an insignificant difference. Based on the number of trees, 500 trees have the highest accuracy among the four input data. This is consistent with Wicaksono and Lazuardi (2018) and Genuer and Poggi (2020), which found that the classification accuracy increased with the number of trees.

Input data	ntree			
	100		500	
Surface reflectance	72.69	72.08	73.00	72.39
Deglint	67.26	67.26	67.26	67.26
Depth invariant index	68.82	68.51	69.13	67.59
Deglint-Depth invariant index	64.49	62.72	65.08	62.72
	Sqrt	Log	Sqrt	Log
	mtry			

Table 2. Summary of RF classification scenario overall accuracy. The values are in %.

According to Table 2, the accuracy of the number of trees between 100 and 500 trees does not differ noticeably. Since there is little variation in the accuracy values, a range of 200–500 trees can be selected to reduce computational time. Figure 3 demonstrates that the error is stable from 200 to 500 trees. The surface reflectance band shows the input data with the highest accuracy based on the number of trees.

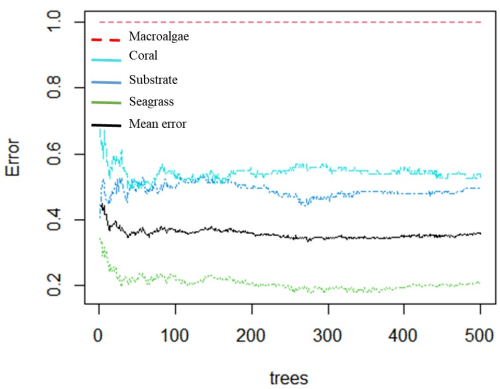

Figure 3. Error with number of tree (Scenario 1 with ntree= 500 and mtry=sqrt)

Based on functions to determine the number of randomly selected features, the difference in the accuracy of the sqrt and log functions is 0 - 2.36%. This study shows that the functions to determine the number of randomly selected features increase the classification accuracy (Genuer and Poggi, 2020). The function with the highest accuracy is shown by the sqrt function in the four input data (Wicaksono et al., 2019). The input data with the highest accuracy based on functions to determine the number of randomly selected features is surface reflectance band. It showed the same result as the number of tree. Based on the accuracy assessment, it can be concluded that the best scenario is a surface reflectance band with tuning parameter, where ntree is 500 and mtry is sqrt. Therefore, the discussion regarding the benthic spatial distribution of the four data inputs focuses on ntree=500 and mtry=sqrt, which show the highest accuracy value in each scenario.

3.2 Benthic spatial distribution and misclassification analysis

Random forests classification with the best tuning parameter for benthic habitats mapping using WorldView-3 image produced overall accuracy of 65.08% - 73.00% (Table 3). Furthermore, Table 3 shows users and producer’s accuracies (UAs and PAs) in each input data of the WorldView-3 image for the benthic habitats map. User’s and producer’s accuracy can be used to analyze the distribution of each object. The overall accuracy for scenario 1 is 73.00%. The UAs are 83.33%, 71.94%, 0%, and 69.84% for coral reef, seagrass, macroalgae, and substrate classes, respectively. The PAs are 56.45%, 87.36%, 0%, and 57.14% for the classes in the same order. This accuracy is statistically high and acceptable based on the Indonesian Nasional Standard for Mapping (BSN, 2011), and the scenario produces an accurate result in the seagrass class. Coral and substrate were misclassified as seagrass, while macroalgae cannot be classified.

Accuracy assessment in scenario 2 shows 67.26%, and the UAs for coral reef, seagrass, macroalgae, and substrate class are 70.17%, 55.55%, 0%, and 79.16%, respectively. Meanwhile, the PAs are 68.96%, 62.50%, 0%, and 71.69% for the classes in the same order. This scenario can classify the substrate and coral class, and the seagrass class is misclassified as coral and substrate. In scenario 3, the overall accuracy is 69.13%, and the UAs are 66.67%, 68.83%, 0%, and 71.67% for coral reef, seagrass, macroalgae, and substrate classes, respectively. The PAs are 35.48%, 87.84%, 0%, and 56.57% for the classes in the same order, and this only shows the same results as scenario 1 with a lower accuracy value. Overall accuracy in scenario 4 is 65.08%, and the UAs for coral reef, seagrass, macroalgae, and substrate class are 65.51%, 54.83%, 0%, and 77.55%, respectively. Meanwhile, the PAs are 65.51%, 60.71%, 0%, and 79.16% for the classes in the same order. This scenario only shows the same results as scenario 2 with a lower accuracy value.

The four scenarios have accuracy above 60%, which has fulfilled the minimum requirement accepted for mapping benthic habitat maps based on SNI 7716:2011 (BSN, 2011). In the four scenarios, the distribution of coral and substrate class is underestimated and misclassified as seagrass, indicating that the spatial distribution of seagrass was overestimated. In contrast, the macroalgae class has not been able to be classified due to the small sample data and the low cover distribution of macroalgae.

Reference	Map Class						
	Scenario 1: Surface Reflectance WV-3						
	Coral	**Seagrass**	**Macroalgae**	**Substrate**	**Total**	**Producer accuracy**	**McNemar test (z-score)**
Coral	35	25	0	2	62	56.45	
Seagrass	7	159	0	16	182	87.36	NA
Macroalgae	0	4	0	1	5	0	
Substrate	0	33	0	44	77	57.14	
Total	42	221	0	63	326		
User accuracy	83.33	71.94	0	69.84	**OA=73.00**		
	Scenario 2: Deglint WV-3						
Coral	40	16	0	2	58	68.96	
Seagrass	13	35	0	8	56	62.50	
Macroalgae	0	1	0	0	1	0	0,17
Substrate	4	11	0	38	53	71.69	
Total	57	63	0	48	168		
User accuracy	70.17	55.55	0	79.16	**OA=67.26**		
	Scenario 3: DII WV-3						
Coral	22	37	0	3	62	35.48	
Seagrass	8	159	0	14	181	87.84	
Macroalgae	0	5	0	0	5	0	0.18
Substrate	3	30	0	43	76	56.57	
Total	33	231	0	60	324		
User accuracy	66.67	68.83	0	71.67	**OA=69.13**		
	Scenario 4: Deglint-DII WV-3						
Coral	38	17	0	3	58	65.51	
Seagrass	14	34	0	8	56	60.71	
Macroalgae	6	1	0	0	7	0	0.013
Substrate	0	10	0	38	48	79.16	
Total	58	62	0	49	169		
User accuracy	65.51	54.83	0	77.55	**OA=65.08**		

Table 3. Confusion matrix of benthic habitat classification using random forests classification

Figure 4a is the classification result with the highest accuracy compared to the other scenarios. Spatially, the distribution of benthic habitats has shown the formation of fringing reefs. It is important to note that there is still a misclassification of seagrass objects marked as coral. A similar distribution is shown in Figures 4b and 4d, specifically in the appearance of the fringing reef. However, the sunglint correction process causes the loss of pixel values, specifically in seagrass/coral objects on the coast. The loss of pixel value is caused by tidal conditions, which affect the class of objects above the water surface. This causes the number of samples to be reduced in scenarios 2 and 4. Different results are shown in Figure 4c, where the fringing reef formation is misclassified as seagrass objects. The classification error is caused by the type of water with insignificant change in depth, and water column correction is unnecessary. Therefore, in mapping benthic habitats, it is necessary to understand the physical conditions of the waters.

Based on the accuracy assessment in Table 2, the surface reflectance and deglint band as a data input show more stable results than the depth invariant index and the depth invariant index. However, the spatial distribution of benthic habitats shows that the deglint band and deglint-depth invariant index eliminate seagrass information due to the sunglint correction process. The depth invariant index performs many misclasses, specifically on fringing reefs. This indicates that surface reflectance is the best input data in benthic mapping compared to the other three input data. This is in accordance with Wicaksono et al. (2019) that the surface reflectance band is the most standard input data with low variability for a random forest.

The accuracy was lower than the previous works using random forest (Zhang et al. 2013b) because of the different spatial and spectral resolutions. It was considered lower than Wicaksono et al. (2019), using a similar image due to in situ data. Wicaksono et al. (2019) used an important step in preparing these data before being used as training/validation data, which is the key to the random forest approach. However, the accuracy is higher than the previous work by Ariasari et al. (2019) and Zhafarina and Wicaksono (2019). This statement shows that there is still room for improvement in producing a more accurate classification, including the representation of field conditions and the balance of the distribution of each object. However, this study strengthens the previous studies by Wicaksono and Lazuardi (2018) and Wicaksono et al. (2019) regarding the best parameter tuning and input data for benthic mapping using the random forest method.

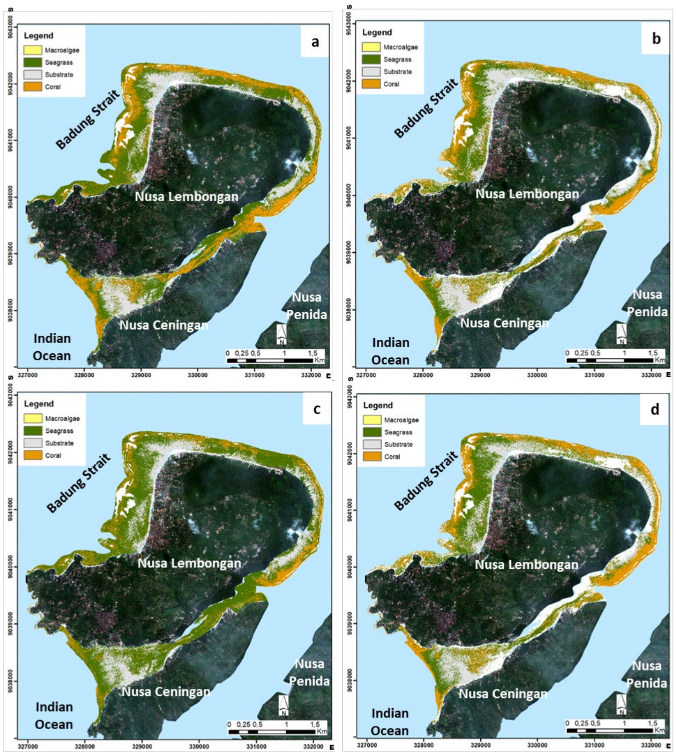

Figure 4. Benthic spatial maps (a) Scenario 1, (b) Scenario 2, (c) Scenario 3, dan (d) Scenario 4

3.3 McNemar Test

To assess the significance level of the accuracy between scenarios, the McNemar test method was used. The McNemar test compares the highest accuracy scenario to others (Table 3). Based on the test result, the z-score has a value of less than 1.96, therefore, it can be concluded that the accuracy is not statistically significant between scenarios (Table 3).

4. CONCLUSIONS

The accuracy of benthic habitats is 62.72 - 73.00%, where 500 trees and the sqrt function indicate the highest in the tuning parameter. The input data in the random forest method is very important in mapping benthic habitats in terms of accuracy and spatial distribution. The surface reflectance band shows the best input data based on the experimental results. The random forest method from the map can show the distribution of benthic habitats well, specifically in coral and seagrass classes.

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