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Benthic habitats classification using multi scale parameters of GEOBIA on orthophoto images of Karimunjawa waters

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Abstract

Benthic as a source of food for marine life and an indicator of the quality of the marine environment habitats play an important role in coastal management. Hence, spatial information on benthic habitats is required for coastal management. The nature of benthic habitats requires high spatial resolution image for information extraction. Geographic object-based image analysis (GEOBIA) is an appropriate tool for working with high spatial resolution image. The irregular shape of the benthic habitats and their various dimensions, however, require the application of multi scale parameters for optimal segmentation of benthic habitats. The selection of scale parameter is an important part of image segmentation stage and determine the size of objects and in turn affects the results of classification accuracy. In addition, the selection of image classification algorithm applied to shallow water benthic habitat objects determine the success of the classification. Various combinations of scale parameter and classification algorithms are performed to get the optimal results indicated by classification accuracies. This study used orthophoto images processed from Unmanned Aerial Vehicle (UAV) mission intended to capture benthic habitats in the busiest coastal of Karimunjawa waters, around two Karimunjawa ports. Three classification algorithms, namely Support Vector Machine (SVM), Bayesian statistics, and K-Nearest Neighbors (KNN) are applied with combination of selected scale parameters, namely 100, 200, and 300 resulted from segmentation stage. The classified images are tested their accuracies based on field samples and Training Test Area (TTA) masks. The result showed that combination of SVM algorithm and a scale parameter of 300 produced the best accuracies in terms of overall, producer and user accuracies followed by Bayesian statistic and KNN algorithms.

Keywords: Benthic Habitats; GEOBIA; Multi scale parameters; Karimunjawa waters

1. Introduction

Benthic habitat is a group of species or communities located on the seabed that consistently influence each other and is physically dissimilar [1]. The distribution of benthic habitats need to be known as they provide basic information that can be useds for various applications such as fishery resource management, spatial marine environmental management, marine reserve design, and supporting data for the development of offshore oil and gas infrastructure, port and shipping lane construction, and tourism [1].

Karimunjawa Island is one of the National Parks in Indonesia located in Jepara Regency, Central Java Province. It is one of the oldest National Parks in the world [2], [3] with a marine habitat covering an area of 1101 km^2 [4]. In addition, Karimunjawa is the location of various kinds of tourism. Its natural beauty attracts tourists to visit. However, the tourism activities can cause the decrease of ecological function of benthic habitats.

Benthic habitats in shallow waters in tropical areas are generally dominated by coral reefs, rubbles, sea grass, macroalgae, sand, mud and rocks [5]. Benthic habitats area is a natural environment in which organisms or communities from the physical environment surrounded are influenced and utilized by species or communities [1]. The spatial distribution of benthic habitats is important to know various applications as mentioned earlier.

One of the technologies that can be used to map the spatial distribution of benthic habitats is Unmanned Aerial Vehicle (UAV) that offers flexibility of data acquisition such as the ease of maneuver, setup of flight, speed and landing. UAV provides high spatial resolution of imagery data while orthophoto images can be produced. With its high spatial resolution offered, benthic habitats that have irregular shapes, variations in color and spectral and their spatial distribution, can be monitored.

Such information can be extracted from orthophoto images using image classification techniques. Conventional pixel-based image classification method applied on high spatial resolution image will face problems such as pepper and salt effect caused by isolated pixels. On the other hand, object-based image classification or analysis (OBIA) is an alternative solution to such problems. GIS scientists call it as Geographic Object-Based Image Analysis (GEOBIA) [6]. GEOBIA is superior technique compared to previous one in terms of avoiding pepper and salt effects on high-spatial resolution of classified image [7]. GEOBIA can be used quickly and repeatedly in monitoring shallow water objects such as coral

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reefs [8].

GEOBIA consists of two stages, image segmentation and image classification. Several machine learning algorithms such as SVM (Support Vector Machine), algorithms based on statistical concepts Bayes, and simple classification algorithms KNN (K-Nearest Neighbors) can be applied by means of learning training samples [7].

Application of GEOBIA image segmentation stage of benthic habitats requires information of the scale of benthic habitats. Unfortunately, the exact scale of benthic habitats segment is unknown. Therefore, it is important to find appropriate scale parameter in order to result in good quality of image classification. The selection of scale parameter will affect the segmentation. Use of large scale parameters may cause the objects to be under-segmented, while use of small ones may cause the object to be over-segmented [9].

The use of a particular scale parameter in image segmentation may affect the level of accuracy at the image classification stage. In search of best classification results, machine learning algorithms are required to apply in such a case of mapping of benthic habitats [10]. This study is intended to obtain appropriate scale parameters and machine learning algorithms for monitoring benthic habitats using GEOBIA technique.

Currently, the use of the scale parameter does not specify or lead to a particular spatial image resolution and vice versa. In this study, an orthophoto image with a Ground Spacing Distance (GSD) of 3.5 cm pixel size is explored to find appropriate scale parameter to avoid experiencing under-segmentation or over-segmentation. A combination of the use of different scale parameters and machine learning algorithms to find best classification result is explored in this research.

2. Materials and Methods

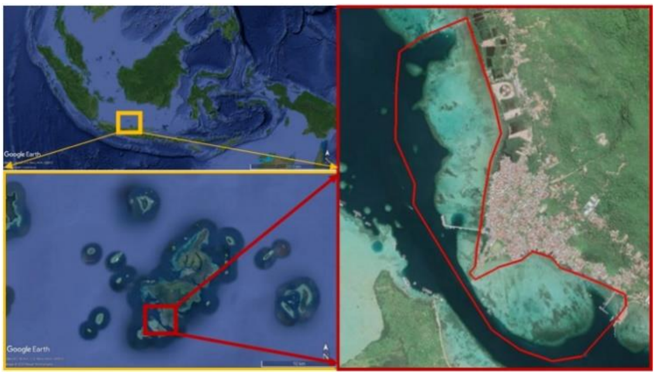


Fig.1. Location of the research study

2.1. Data and location

The research was conducted in Karimunjawa National Park (commonly known as TNKJ), particularly in Karimunjawa Waters of Tanjung Benteng, Jepara Regency of Central Java Province. The location covers Karimunjawa tourism and local fishing ports. The total area of study is about 2.5 km^2 indicated by a closed line in red in figure 1. The main data source is an orthophoto image taken using an UAV type namely DJI Phantom 4 Pro V.2. The UAV flying height was up to 130 m above ground level. Another data used was Ground Truth Habitat (GTH) taken by means of duck diving technique by recording benthic habitat types and their coordinates. All GEOBIA processing stages used Ecognition software version 9.

2.2. Methods

The orthophoto image with GSD of 3.5 cm was processed through two stages, image segmentation and image classification. The segmentation stage was divided into two levels. The first level separated the study area into land, shallow water, and deep water classes. Furthermore, the second level focused on breaking down the shallow water class where benthic habitats are located into six classes namely sand (S), algae (A), and living coral (LC), dead coral (DC), seagrass (L), and rubblesh (R) at segmentation stage.

Segmentation stage applied multi resolution algorithm. This algorithm facilitates a wide range of scale parameters. By trial and error tests, scale parameters that indicated good segmentation are selected based on the variability of the six classes [11]. Scale parameters that avoid either under-segmented or over-segmented were selected for further classification stage.

Classification stage applied three algorithms, 1) KNN, a simple method based on neighbor digital number values, 2) Bayesian statistics, a statistical method, and 3) SVM, a machine learning method. The result of image classification of each algorithm was tested their accuracies using confusion matrix method, i.e., a quantitative method of characterizing image classification accuracy. It produces overall accuracy (OA), producer accuracy (PA), and user Accuracy (UA). OA is a measure that the fraction of the total samples are correctly classified by the classifier. OA was used to evaluate and select the best classification algorithms.

This study applied two accuracy tests, namely 1) accuracy test based on samples collected in the field and manually selected, and 2) accuracy test based on Training and Test Area (TTA) masks, based on GTH. The difference between the two accuracy tests is in the number of test samples. The first test was based on actual field sampling while the second one was based on extended samples gained from visual interpretation of orthophoto image, called as TTA masks. The first accuracy test was to test the classification results based on classified samples, the six classes as mentioned earlier. The second one was the test of the classification result compared to the extended number of samples.

Assessment of the result of accuracy tests was conducted by examining error matrix that is commonly known as confusion matrix. The confusion matrix in the form of a matrix table describes the performance of the classification algorithm from which the classified classes are compared to a series of test data where the actual benthic habitat types are known, either from actual and selected GTH or from extended samples, the TTA masks. The confusion matrix shows the match between the classified samples and the image classification results carried out by the algorithms. Some classified objects might experience omission or inclusion to respective actual classes. OV is a measure how good the accuracy test of the resulted image classification is and therefore it is also a measure of how good the image classification algorithm applied is.

3. Results and Discussion

3.1 Image segmentation

Application of different scale parameters at the image segmentation stage is aimed to properly separate objects according to the actual objects in the field. The initial stage (level 1) of segmentation is aimed to separate land, shallow and deep water based a scale parameter of 5000, a form parameter of 0.1 and a compact parameter of 0.5. The selection of three classes is intended to search and focus on shallow water area. This area is selected for reason as benthic habitat area and for level 2 of image segmentation for six marine classes. The level 1 of image segmentation is shown in figure 2. The land, deep sea and shallow water are marked by colors orange, blue and light blue accordingly. Figure 3 shows level 2 of image segmentation of shallow water class.

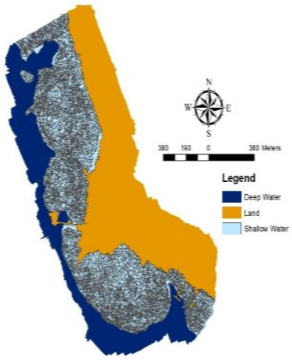


Fig. 2. Level 1 of image classification

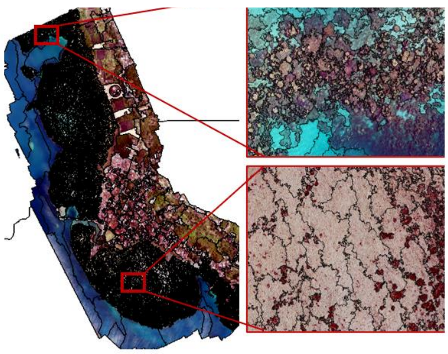
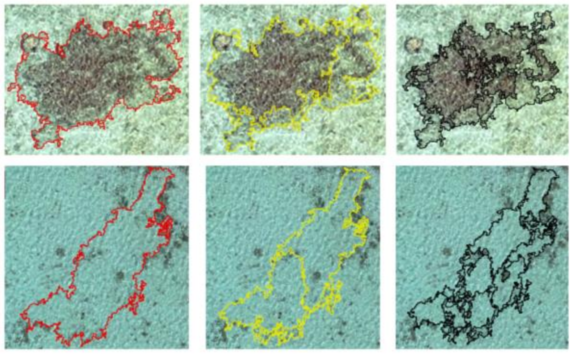


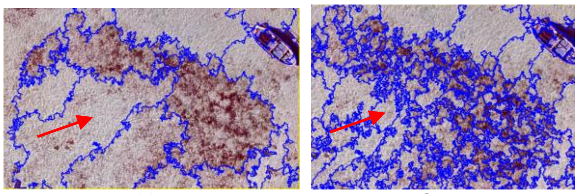
Fig. 3. Level 2 of image segmentation

Based on trial and error tests, it was found that scale parameters that provided a good separation of objects were 100, 200, and 300. Figure 4 shows level 2 of image segmentation using these three scale parameters. Use of scale parameters below 100 causes the object experiencing over-segmentation in which one object is identified as many objects. Meanwhile, the use of the scale parameters above 300 causes the object experience under-segmentation. In other words, several objects are identified as only one object. Figure 5 enhances conditions of normal and over-segmentation. The figure shows that on homogeneous area, which is visually interpreted as sandy area on the left figures indicated by a red arrow, it experience over-segmentation shown on the right figure compared to the left figure that represents normal segmentation.



(a) (b) (c)

Fig. 4. Image segmentation results using multi resolution algorithm by using scale parameters of (a) 300, (b) 200, and (c) 100 on Algae (above) and Sandy coverage (below)



(a) (b)

Fig. 5. Image segmentation results, (a) normal, and (b) over segmentation

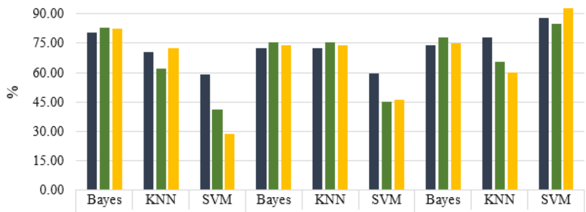
A scale parameter of 100 produced more segmented objects. However, there were some objects that should be considered as one object cut into several pieces, called as over segmentation as on figure 5 (b). Using a scale parameter of 200, it produced segmentation results that were not much different from using that of 100. Parts of a particular object were segmented less well in representing an object. An example of under segmentation condition is shown in figure 4 (a) where a segmented sand-dominated area still contains other objects identified as algae. This used a scale parameter of 300. Both two errors in image segmentation can be prevented by increasing the value of the scale or homogeneity parameter. Based on these results, a scale parameter of 300 shows the best segmentation compared to the remaining.

Using a scale parameter of 300, several objects could be separated properly so as to produce meaningful objects that have some characteristics similar to the actual benthic habitats. However, using this scale parameter, there were still some objects experiencing over-segmentation, although not as many as those of other scale parameters produced. If the scale parameter was enlarged by more than 300, there would be some objects experiencing under-segmentation where difference objects were identified and segmented as one object.

It is shown on the left figure of figure 4 that both algae and sandy area are best segmented using a scale parameter of 300. The effect of over segmentation is considerably small using this scale parameter. Figure 5 emphasize on this effect. The left figure written as normal segmentation is the result of using a scale parameter of 300. Figure 3 also shows level 2 of image segmentation using a scale factor of 300.

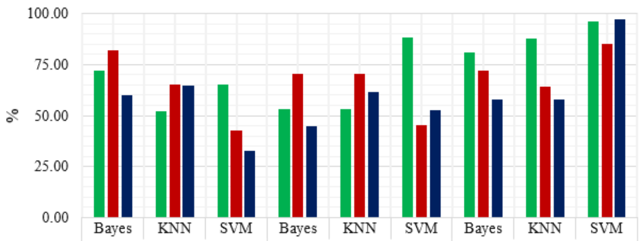
3.2 Image classification

Three classification algorithms, namely KNN, Bayesian statistics and SVM, were applied to each scale parameter. Therefore, a combination of each segmentation scale and three classification algorithms resulted in a total of 9 classified images. The accuracy of the image classifications was then examined using confusion matrix. Figure 6 and figure 7 show the results of accuracy test based on samples collected in the field and TTA masks. In general, SVM algorithm using a scale parameter of 300 produces the best OV according to both figures, namely 80% and 96.17% for both samples accordingly. Overall accuracy is achieved by dividing the total number of correctly classified segments by the total number of reference segments.



	Bayes 100	KNN 100	SVM 100	Bayes 200	KNN 200	SVM 200	Bayes 300	KNN 300	SVM 300
OA	80.39	70.59	58.82	72.22	72.22	59.26	74.00	78.00	88.00
PA	82.66	62.00	41.28	75.24	75.24	45.32	77.72	65.69	84.83
UA	82.48	72.22	28.83	74.12	74.12	46.02	74.99	60.11	92.73

Fig. 6. Comparison of accuracy test based on field samples



	Bayes 100	KNN 100	SVM 100	Bayes 200	KNN 200	SVM 200	Bayes 300	KNN 300	SVM 300
OA	72.20	51.93	65.36	53.34	53.34	88.50	81.08	87.90	96.17
PA	81.90	65.08	42.45	70.27	70.27	45.39	71.93	64.30	85.36
UA	59.85	64.49	32.48	44.86	61.53	52.77	57.75	57.75	97.00

Fig. 7. Comparison of accuracy test based on TTA masks

More detailed about the results of image classification using SVM algorithm, on a scale parameter of 100 it produced a number of classed objects as follows: Algae (58.538 objects), LC (47.267 objects), DC (2675 objects), L (80 objects), S (37.619 objects), and Rubblesh (13 objects). Using a scale parameter of 200 it produced fewer objects than those of 100 as follows: Algae (12.395 objects), LC (5669 objects), L (1237 objects), S (9186 objects), and Rubblesh (498 objects). DC was not identified. Whereas on a scale parameter of 300 it produced as follows: Algae (2974 objects), LC (2771 objects), DC (117 objects), L (3968 objects), S (1442 objects), and Rubblesh (938 objects). The latest result produced the least number of objects. It is more like the condition of the objects in the field. Figure 8, figure 9 and figure 10 represent the image classification results using SVM algorithm with scale parameters of 300, 200, and 100 accordingly. The latest of course suffer the most pepper and salt effects compared to the others.

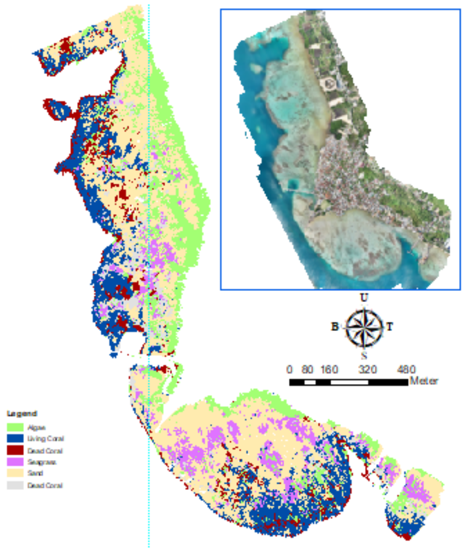


Fig. 8. Classification using SVM algorithm a scale parameter of 300

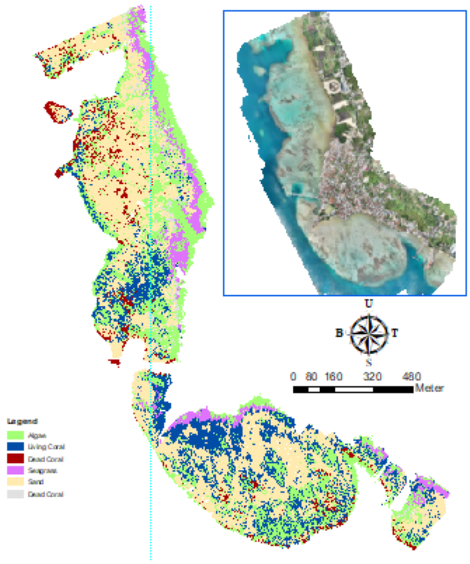


Fig. 9. Classification using SVM algorithm with a scale parameter of 200

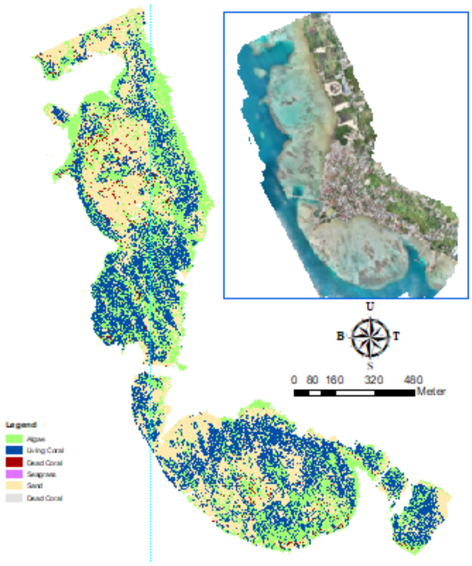


Fig. 10. Classification using SVM algorithm with a scale parameter of 100

Other measures of image classification accuracy are producer and user accuracies. The first represents how well reference segment of field sample types are classified. The second represents the probability that a segment classified into a given class actually represents that category on the field. Both accuracy test are shown in figure 6 and figure 7. It confirms that a combination of SVM algorithm and a scale parameter of 300 produced superior accuracy compared to other combinations. Accuracy test based on samples collected in the field produced PA and UA of 84.83% and 92.73% while accuracy test based on TTA masks produced PA and UA of 85.36% and 97%. This research also shows that accuracies resulted from combination of Bayesian statistics with a scale parameter of 300 produced takes second place after combination of SVM and a scale parameter of 300. While combination of KNN algorithm with that scale parameter produced the lowest accuracies.

4. Conclusion

Based on the results, it is found that using small scale parameters could get more objects and vice versa. Setting the scale parameter is an abstraction value in the software so that it depends on the size of the object to be formed and the classes to be created. Smaller scale parameters can describe smaller and more detailed objects, but the likelihood of objects experiencing potential error of over-segmentation is enormous. This research shows that a scale parameter of 300 best describe the actual objects on the field. In addition, another stage that affected the accuracy of the classification results was the selection of the right algorithm. Combination of a scale parameter of 300 and all algorithms shows that SVM algorithm produced the most superior accuracies compared to the remaining algorithms.

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