Benthic habitat mapping using Object-Based Image Analysis (OBIA) on Tidung Island, Kepulauan Seribu, DKI Jakarta

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Abstract. Tidung Island is one of the islands in Kepulauan Seribu, DKI Jakarta, Indonesia. This island has various benthic that live on the coastal areas, and benthic habitat has various functions both ecologically and economically. Nowadays, remote sensing technology is one way to detect benthic habitats in coastal areas. Mapping benthic habitat is essential for sustainable coastal resource management and to predict the distribution of benthic organisms. This study aims to map the benthic habitats using the object-based image analysis (OBIA) and calculate the accuracy of benthic habitat classification results in Tidung Island, Kepulauan Seribu, DKI Jakarta. The field data were collected on June 2021, and the image data used is satellite Sentinel-2 imagery acquired in June 2021. The result shows that the benthic habitat classification was produced in 4 classes: seagrass, rubble, sand, and live coral. The accuracy test result obtained an overall accuracy (OA) of 74.29% at the optimum value of the MRS segmentation scale 15;0,1;0.7 with the SVM algorithm. The results of benthic habitat classification show that the Seagrass class dominates the shallow water area at the research site with an area of 118.77 ha followed by Life Coral 104.809 ha, Sand 43.352 ha, and the smallest area is the Rubble class of 42.28 Ha.

Keywords: benthic habitat, mapping, OBIA, sentinel-2, Tidung Island

1. Introduction
Tidung Island has potential biodiversity, such as coral reefs, seagrass beds, and mangroves [1]. Benthic habitats in waters have different variations depending on the habitat area and the depth of the waters. Benthic habitats are shallow-water habitats for various organisms like seaweed, seagrass, algae, live coral, dead coral with substrate types such as sand, mud, and coral rubble [2]. Benthic habitat ecosystems benefit environmental goods and services for both ecology and economy in coastal areas or islands [3].

Spatially remote sensing satellite technology has been widely used because it can provide a variety of information. Remote sensing technology data is one of the appropriate methods to determine the existence of benthic habitats in vast shallow marine waters. One method that can be used is the Object-Based Image Analysis (OBIA) method. OBIA is a method that in the classification process also considers the spatial aspects of objects and the spectral aspects to optimize the spatial features in satellite imagery according to the elements of interpretation, like shape or texture. This method has been proven to increase the accuracy of benthic habitat mapping compared to pixel-based image classification in images with medium to high spatial resolution [4-6]. One of the imagery data with good quality is...
Sentinel-2 images with a 10x10 m²/pixel spatial resolution. Thus, applying the OBIA method to Sentinel-2 imagery is expected to qualify benthic habitats, especially at high habitat complexity. This study aims to map object-based benthic habitats on Tidung Island, Kepulauan Seribu DKI Jakarta using Sentinel-2 imagery.

2. Material and methodology

2.1. Location
This research was conducted on Tidung Island, Kepulauan Seribu, in June 2021. Geographically, the research location is located at 05° 47' 48" S and 106° 29' 42" E (Figure 1).

2.2. Data source
This study uses Sentinel-2 multispectral satellite imagery, acquired on April 14, 2021. The image obtained from this satellite has a high temporal resolution and a wide field of view up to 290 km. Sentinel-2 images were obtained free from Sentinels Scientific Data Hub (https://scihub.copernicus.eu/). The downloaded image is a level 1C image with 100 km² subjected to geometric and radiometric corrections. Radiometric correction is used to correct pixel values that do not match the actual spectral values of objects on the earth's surface.

In contrast, a geometric correction is used to correct the location of image pixels caused by systematic sensor errors. The bands used are band 2 (blue), band 3 (green), band 4 (red), and band 8 (NIR). Data on benthic habitats was carried out by direct observation. Then the coordinates are taken using Global Positioning System (GPS) at all locations. Benthic habitat data is taken as many as 155 observation
points with 120 points as a reference for the Region of Interest (RoI) during image classification and 35 points for testing the accuracy of the image classification results.

2.3. Data processing

There are several stages of data processing.

2.3.1. Image preprocessing

The first stage is to perform atmospheric correction using Quick Atmospheric Correction (QUAC) method. QUAC corrects the image by removing the effects of water vapor, oxygen, carbon dioxide, methane, ozone, and molecular scattering [7]. Furthermore, the water column correction was performed using the Depth Invariant Index (DII) algorithm. This technique combines information from several spectral channels to reduce the influence of object reflection disturbances from shallow-water habitats. The band pair used in this study is the sentinel-2 image ray band that is band 2 (blue), band 3 (green), and band 4 (red). This method of water column correction produces the DII of each spectral band pair with the following equations [8].

\[ DII_{ij} = \log(x_i) - \log(x_j) \]  
\[ \frac{k_i}{k_j} = a + \sqrt{a^2 + 1} \]  
\[ a = \frac{\sigma_{ii} - \sigma_{jj}}{\sigma_{ij}} \]

Where \( K_i/K_j \) The coefficient of attenuation, \( \sigma_{ii} \) It is variance band I, \( \sigma_{jj} \) Variance band j and \( \sigma_{ij} \) Covariance pairs band I and j.

2.3.2. Segmentation

This research segmentation is used the multiresolution segmentation (MRS) algorithm. The segmentation process has three essential parameters: shape, compactness, and scale. Moreover, multiscale segmentation is used optimization on several different scale values, namely MRS 1, 1.5, 2, and 2.5. At the segmentation stage, the shape and compactness parameter values use fixed values of 0.1 and 0.5, respectively. There is no standard provision regarding typical parameter values in object-based classifications [9].

2.3.3. Classification

The classification process by the OBIA method uses objects/segments built into the image segmentation process, then classified based on a predefined classification scheme. The concept of multiscale classification built into this study consists of 2 levels of image objects levels, namely levels 1 and 2. In this study, the classification at level 1 uses an assigned class applying certain value limits (threshold) to produce the class of objects following what is desired. Threshold values are obtained through trial and error to find optimum values. Level 2 classification uses a classifier applying the support vector machine (SVM) algorithm with thematic layer input or training area of field data to classify benthic classes. With mathematical equations [10].

\[ f(x) = \sum_{i \in S} \lambda_i y_i K(x_i x) + w_o \]

With, K represents the kernel function, \( x_i \) and \( y_i \) represents the training sample, \( \lambda_i \)Represents the Lagrange multiplier, S is the part of the training sample that corresponds to the non-zero Lagrange multiplier, and AB is the hyperplane parameter.
2.3.4. Accuracy Test
The accuracy test is done using a confusion matrix method; the system works by comparing classification results with data from observations in the field. The accuracy test refers to which consists of overall accuracy, producer accuracy, and user’s accuracy. It can be mathematically written with the following equations:

\[
Producer \ Accuracy \ (PA) = \frac{n_{ij}}{n_{+j}} \times 100\%
\]

\[
User's \ Accuracy \ (UA) = \frac{n_{ij}}{n_{i+}} \times 100\%
\]

\[
Overall \ Accuracy \ (OA) = \frac{\sum_{k} n_{ij}}{n} \times 100\%
\]

Kappa statistics are the accuracy evaluation values generated by the error matrix and can be mathematically written as follows [11].

\[
Kappa = \frac{n \sum_{k} n_{ij} - \sum_{k} (n_{i+} n_{+j})}{n^2 - \sum_{k} (n_{i+} n_{+j})}
\]

Information:
- \( n_{ij} \) = appropriately classified values
- \( n_{+j} \) = number of classified values in the field class column
- \( n_{i+} \) = number of classified grades on the Image class row
- \( n \) = number of observations
- \( \sum_{k} n_{ij} \) = The exact Number of classified values
- \( \sum_{k} (n_{i+} n_{+j}) \) = Number of Multiplication values classified on image class rows with classified values in field class columns

3. Results and discussion

3.1. Classification scheme
In this study, the result shows four classifications of benthic habitats consist of Life Coral (LC), Seagrass (S), Rubble (R), and Sand (Sn). The classification scheme produced in this study consists of two levels of classification scheme. The level 1 classification scheme (reef level) consists of three classes: land, shallow water, and deep sea. Then the level 2 classification scheme (benthic habitat) consists of four classes of shallow water benthic habitat. The classification scheme of shallow water benthic habitat resulting from 155 observation station points will then be divided into two, namely as many as 120 observation stations will be used as RoI data in the image classification process. The remaining 35 observation stations will be used as data for the accuracy test of image classification results.

3.2. Segmentation
The relationship between the scale parameters, the number of objects, and the resulting accuracy is presented in Figure 2. It is seen that the size of the scale significantly affects the number of objects produced. The larger the value of the specified scale, the less the number of objects produced. The shape parameter value and compactness influence the scale parameter value. While the overall accuracy of object-based classification using SVM algorithms is influenced by segmentation parameters. The scale of 10 to 50 results of accuracy increases with the increase in the value of the scale applied. The optimum accuracy of segmentation obtained is 74.29% with a scale value of 15, shape 0.1, and compactness of 0.7.
Figure 2. The effect of the segmentation optimization process produces optimum accuracy Shape: 0.1 and Compactness: 0.7

3.3. Reef level classification (Level 1)
The level 1 classification in this study produced three classes of land, shallow water, and deep water (Figure 3). Shallow water classes became the boundary of benthic habitat study areas and were classified further based on training data (level 2). [4-5] revealed that in the hierarchical classification system, the results of level 1 classification (reef level), i.e., in shallow water classes, become the limits of study areas and are processed into new segments for classification at the next level, in this case, level 2 (benthic habitat).

Figure 3. Level 1 classification.
3.4. Classification of benthic habitats (Level 2)
In classification level 2, the resulting object or segment is further classified with guided classification using several machine learning algorithms such as SVM algorithm by using data classification scheme of shallow water benthic habitat as input thematic layer that has been made before based on direct observations in the field. The input features used in the level 2 classification process are the layer values (mean and standard deviation) of all visible ray bands and the results of the composition of the DII band pair.

![Figure 4. Level 2 classification.](image)

The results of benthic habitat classification showed that the Seagrass (S) class dominated the shallow water area at the study area with an area of 118,772 ha, followed by Life Coral (LC) 104.809 ha, Sand (S) 43.352 ha, and the smallest area is the Rubble (R) class of 42.28 ha (Table 1). The optimum accuracy test result is overall accuracy (OA) of 74.29% (Table 2) and a Kappa value of 0.5909. It is stated that benthic habitat mapping accuracy is suitable or can be used if the benthic habitat classification map produces an overall accuracy (OA) above 60% and a Kappa value that shows statistically significant results [12]. Based on this result, the usage OBIA method with the SVM classification algorithm can determine the differences of shallow-water benthic habitat on Tidung Island.

| Substrat  | Area (ha) |
|-----------|-----------|
| Life Coral| 104.809   |
| Seagrass  | 118.772   |
| Rubble    | 42.28     |
| Sand      | 43.352    |

Table 1. Area of benthic habitat of Tidung Island.
Table 2. Classification accuracy.

| Class       | Producer Accuracy (Percent) | User Accuracy (Percent) | Producer Accuracy (Pixels) | User Accuracy (Pixels) |
|-------------|-----------------------------|-------------------------|---------------------------|------------------------|
| Life Coral  | 37.50                       | 100.00                  | 3/8                       | 3/3                    |
| Seagrass    | 100.00                      | 66.67                   | 16/16                     | 16/24                  |
| Rubble      | 57.14                       | 80.00                   | 4/7                       | 4/5                    |
| Sand        | 75.00                       | 100.00                  | 3/4                       | 3/3                    |

The pixel-based classification method is the general classification method applied that only relies on spectral aspects. The development of the current OBIA method is inseparable from its advantages that can simultaneously connect spectral and spatial aspects in the classification process. In addition, the use of classification algorithms in remote sensing is increasingly developing, such as the utilization of machine learning-based algorithms. In this study, the OBIA method with the SVM classification algorithm has been shown to produce higher mapping accuracy than some other classification algorithms.

4. Conclusion
Shallow-water benthic habitat can be well mapped using object-based classification methods (OBIA) with SVM algorithms on Sentinel-2 imagery at the study site. The accuracy test result has an overall accuracy (OA) of 74.29% at the optimum MRS segmentation scale 15;0.1;0.7. The results of benthic habitat classification show that the Seagrass class (S) dominates the shallow water area on Tidung Island with an area of 118.772 ha followed by Life Coral (LC) 104.809 ha, Sand (S) 43.352 ha, and the smallest area is the Rubble (R) class of 42.28 ha. The optimum accuracy test result is 74.29% overall accuracy (OA).

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