Benthic Habitat Mapping using Sentinel 2A: A preliminary Study in Image Classification Approach in An Absence of Training Data

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Abstract. Numerous approaches for deriving benthic habitat mapping from visible spectrums of remotely-sensed imagery have been widely used, but image classification without training data for remote benthic habitat remains a few. In many cases, the collection of the needed ground-truth data is often prohibitively expensive or logistically infeasible. This will prevent us from providing training data for image classification purposes. In this paper, we evaluated the accuracy of the classification of benthic habitat from Sentinel 2A imagery in an absence of training data in the optically shallow water of Pari Island, Kepulauan Seribu, Indonesia. Benthic Habitat map was produced from geometrically, radiometrically, and water column corrected Sentinel 2A images. For water column correction, we performed Depth Invariant Index (DII) transformation. It was followed by the classification of Sentinel 2A imagery by applying unsupervised classification, such as IsoData and K-means algorithm. From the experiment, we produced four habitat classes. The analyses result for each unsupervised classification shows that the overall accuracy of IsoData and K-means was 47.98% and 55.64%. However, the results of the Kappa coefficient show that the IsoData algorithm has slightly better accuracy of benthic habitat mapping (0.39) rather than K-Means (0.30).

1. Introduction

Benthic habitat is a type of environment found at the bottom of the waters where various organisms or biological populations live such as seagrass, coral reefs, and also sand. The spatial information on the distribution of benthic habitats is needed by coastal managers and conservationists to manage the ecosystem sustainably. The mattering faction of the coastal biodiversity stands on 2 sides, in terms of ecological functions and the economic side that holds people's well-being [1], [2]. Since benthic habitat consists of manifold biodiversity, it has functioned as a home for various species of coral, seagrass, algae, fish, and molluscs. Sea life enormously centred on the status of the unity of the three foremost coastal ecosystems, i.e coral reefs, seagrass, and mangroves [3]. Therefore, information on biodiversity is useful for describing the condition of a community in an area to environmental changes so that the updated spatial and temporal information of biodiversity particularly in the coastal areas are important to assess [1].
Benthic habitat has been mapped using various approaches ranging from field surveys [4] to the advantages of remote sensing technology [5]. Over decades, remote sensing technology is increasingly being used for mapping benthic habitat because it has advantages compared to field observations, including being able to cover large and difficult areas, time-effective and cost-effective approaches, and multi-time observations [6]. Many researchers have mapped and monitored benthic habitats using satellite imagery data such as from Landsat [7], SPOT [8], WorldView-2 [9]–[11]; PlanetScope [12], Sentinel 2 [13], Ikonos [14] and QuickBird [15].

Satellite imagery combined with in-situ data is a method commonly used in monitoring benthic habitats including coral reefs and seagrass. The ground-truth datasets become important things in mapping to acquire a certain level of accuracy [16]. Deriving benthic habitat information from satellite imagery is affected by distortions caused by components as air-water interface, atmosphere, and water column. Improving the accuracy of mapping results is necessary to correct the causes of distortion. In mapping benthic habitats using multispectral images, a Lyzenga transformation is generally carried out for feature extraction, [3], to enhance the accuracy [17] since the water column gives various yet significant effects that affect values of reflection of an object received by sensor [18].

Sentinel 2A was used for mapping benthic habitat in Papua Indonesia [19]. In this study, the Lyzenga algorithm for water column correction and the unsupervised classification method has been applied. The results show that by implementing the water column correction, the results have better accuracy (60.78%) than without implementing water column correction (37.25%) [19]. Sentinel-2A can be used to model the biodiversity index of benthic habitats using an empirical approach [1]. Siregar et al. [16] utilized the MLH algorithm on Worldview-2 and SPOT-6 imageries and compared the accuracies derived for shallow-water benthic habitats mapping. Purwanto et al. [18] used Sentinel 2A to identify coral reefs in the northern part of Nias. However, Goodman stated that remote sensing still has limitation to be used for benthic habitat mapping up to the maximum depth of penetration of the wavelengths [1], and for high-resolution satellite imagery usually costly to get and subjected to environmental circumstances of the target features such as cloud cover, sun glint, tidal height, and surface roughness [20].

In remotely sensed image processing, the classification stage commonly has two approaches namely pixel-based and object-based [21]. Numerous image extraction and classification methods applied to obtain more definite and accurate information. The pixel-based classification can be divided into supervised and unsupervised methods, where pixels are put into classes that have similarities between pixels. On supervised method, Various algorithms have been applied for shallow-water habitat mapping to achieve good accuracy, i.e Maximum Likelihood (MLH), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and also applying Threshold Values [21]. The unsupervised method consists of repeated self-organizing data analysis (IsoData) and K-means.

The ground truth datasets are important for benthic habitat mapping from remote sensing imagery [22]. However, the collection of ground-truth data is time-consuming and expensive. The unsupervised classification can be used to overcome this limitation because the unsupervised method does not require any field measurements. The unsupervised classification is capable of finding a natural group or clusters by assigning the imagery; which is bearing the multispectral bands, extracting the information, and separating different classes of benthic habitat with the best number of clusters [23], [24]. This study aims to evaluate the accuracy of the unsupervised classification method for mapping benthic habitat from Sentinel-2A imagery in the absence of training data in the optically shallow water of Pari Island, Kepulauan Seribu, Indonesia.

2. Methodology

2.1. Study Area
This research was conducted in Pari Island, Kepulauan Seribu, Indonesia (figure 1). Pari Island is geomorphologically formed by ocean processes that make it has several shallow-water bottom types, such as algae, coral reefs, rubble seagrass, sponges, sand, sediment, and rocks [25]. Pari Island is one of the marine tourist attractions in the Seribu Islands because of its white sand, the beauty of its underwater ecosystem, and its location in front of Jakarta Bay.
2.2. Data Collection

Sentinel-2A Level 1C images were collected for the Pari Island study site on 22 October 2019 (Figure 1). The Sentinel-2A sensor consists of 13 spectral bands with various spatial resolutions (Table 1). All Sentinel-2A bands were resampled to get the highest resolution possible (10 m). Only visible bands were used in the classification process, while NIR and SWIR bands were only used for masking and sun glint correction processes.

The available benthic Habitat Map was used to validate the Sentinel-2 image interpretation. The map was obtained from the 2019 joining project between Thematic Mapping Division, Geospatial Information Agency, and Oceanography-LIPI. We called this map the reference map (see figure 2).

Figure 1. (a) Indonesia; (b) Kepulauan Seribu; (c) Pari Island in Sentinel-2A Image (composite 432).

Figure 2. The Benthic Habitat Map from Thematic Mapping Division, Geospatial Information Agency.
In the present study, the main benthic habitat classes derived from Sentinel-2A data were compared with the reference map to evaluate the accuracy of the proposed method. The specification of Sentinel-2A parameters as described in Table 1.

Table 1. Specification and parameters of Sentinel-2 image used in this research.

| Name | Sentinel-2A |
|------|-------------|
| Date of Acquisition | 22 October 2019 |
| Correction Level | 1 C (Top of Atmospheric reflectance) |

| Multispectral bands | Band Number | Spatial Resolution (meter) | Central Wavelength (nm) | Band with (nm) | Lref (reference radiance)(W m⁻² sr⁻¹ µm⁻¹) | SNR @Lref |
|---------------------|-------------|---------------------------|-------------------------|----------------|------------------------------------------|-----------|
| 1 (coastal aerosol) | 60          | 443                       | 20                      | 129            | 129                                      |           |
| 2 (blue)            | 10          | 490                       | 65                      | 128            | 154                                      |           |
| 3 (green)           | 10          | 560                       | 35                      | 128            | 168                                      |           |
| 4 (red)             | 10          | 665                       | 30                      | 108            | 142                                      |           |
| 5 (vegetation red edge) | 20         | 705                       | 15                      | 74.5           | 117                                      |           |
| 6 (vegetation red edge) | 20         | 740                       | 15                      | 68             | 89                                       |           |
| 7 (vegetation red edge) | 20        | 783                       | 20                      | 67             | 105                                      |           |
| 8a (NIR)            | 10          | 842                       | 115                     | 103            | 172                                      |           |
| 8b (vegetation red edge) | 20         | 865                       | 20                      | 52.5           | 72                                       |           |
| 9 (water vapor)     | 60          | 945                       | 20                      | 9              | 114                                      |           |
| 10 (SWIR-cirrus)    | 60          | 1375                      | 30                      | 6              | 50                                       |           |
| 11 (SWIR)           | 20          | 1610                      | 90                      | 4              | 100                                      |           |
| 12 (SWIR)           | 20          | 2190                      | 180                     | 1.5            | 100                                      |           |

Source: Sentinel E.S.A (2015)

2.3. Image Pre-processing

The Semi-Automatic Classification Plugin (SCP) on QGIS was implemented for atmospheric correction on Sentinel-2A. This process eliminated atmospheric effects and extracted the surface reflectance values. The SWIR wavelength retrieves information from water bodies with greater accuracy than NIR bands and it is used for terrestrial masking to enhance aquatic features [26]. The images used in this study showed the presence of wavy and mildly clear water, so water column correction and sun glint correction procedures were required [27]. Sun glint correction was needed to remove sun glint reflections on the water surface [13]. In this case, an equation from Hedley et al. [28] as applied for sun glint correction. Then, Lyzenga 81 was applied as the water column correction step. The Depth Invariant Index equation was generated from the variance of each visible band, the covariance between 2 visible bands combination, attenuation coefficient (a), and the attenuation ratio (ki/kj). The results can be seen in Table 2.

Table 2. DII equation was generated from 66 samples of ROI.

| Band Combination | Covariance | Attenuation Coefficient (a) | Attenuation ratio (ki/kj) | DII Equation |
|------------------|------------|-----------------------------|---------------------------|--------------|
| Blue and Green (B2B3) | 0.01405 | -0.50025 | 0.61790 | Ln(B2)–(0.61790*Ln(B3)) |
| Blue and Red (B2B4) | 0.01831 | -0.92019 | 0.43876 | Ln(B2)–(0.43876*Ln(B4)) |
| Green and Red (B3B4) | 0.02991 | -0.32837 | 0.72416 | Ln(B3)–(0.72416*Ln(B4)) |

2.4. Unsupervised Classification

The unsupervised classification method is a procedure that entirely data-driven, objective, and no need for prior knowledge of the study area [29]. Two algorithms categorized as the unsupervised
classification method were used in this study, i.e., K-means and IsoData algorithms. Both methods were applied to distinguish various benthic habitats. The K-means algorithm is a clustering method that calculates the distance between the point and the center (centroid) to assign into a cluster. It can be used to divide the individual measurements of bathymetric depth data into several mutually exclusive clusters [23].

The IsoData algorithm is a modification of the K-Means clustering algorithm. The IsoData is an unsupervised classification method that clusters similar spectral values of the pixel. It has the advantages of reducing the possibility of bias, reducing the time of data interpretation, and ensuring the consistency of the classification results [30]. The utility of the IsoData is that it combines multiple variables into a simplified comprehensive overview of the interested area [31].

In general, the procedure to derive benthic habitat maps in this study was divided into six stages i.e data collection, atmospheric, sun glint, and water column corrections, image classification, and the accuracy assessment (see figure 3). The classified benthic habitat images resulted using IsoData and K-Means were classified into 10 classes. Since our reference map only has four classes (see figure 2), to make it comparable then we need to generalized the classification results into four classes as well.

![Flowchart](image)

**Figure 3.** The flowchart of the study

### 2.5. Accuracy Test

The accuracy assessment was derived from the comparison between the classified images to the reference map at the same location [32]. The confusion matrix was used for analyzing the performance of the proposed method. The overall accuracy and Kappa coefficient values can be used as a measure of accuracy and both methods allow to test whether an individual benthic habitat map derived from remotely sensed imagery is significantly better than the reference map. The test was generated by randomly assigning labels to areas [33]. The overall accuracy and Kappa coefficient values refer to the following equations:

\[
\text{Overall Accuracy} = \frac{\text{Total number of correct classified}}{\text{Total number of pixel}} \times 100
\]  
(1)

\[
\text{Kappa} = \frac{P_{\text{observed}} - P_{\text{chance}}}{1 - P_{\text{chance}}}
\]  
(2)
3. Result and Discussion

3.1. The classification results

In this study, the benthic habitat maps have been derived from Sentinel-2A by using K-Means as well as the IsoData unsupervised classification method. The classification step was done by using the corrected scene of Sentinel-2A after eliminating all errors from atmospheric and water column distortions. The classified benthic habitat images resulted using IsoData (in figure 4a) and K-Means (in figure 5a) were classified into 10 classes. Meanwhile, Figures 4b and 5b show the generalization results of the benthic habitat map with four classes namely hard coral (HC), hard coral-algae (HC-AL), sand (SD), and seagrass (SG).

Figure 4. The 10 classes of benthic habitat as the result of K-Means classification (a) and the combined result into 4 classes, namely hard coral (HC), hard coral-algae (HC-AL), sand (SD), and seagrass (SG).
3.2. Accuracy assessment results

Equations 1 and 2 were applied for calculating the accuracy of benthic habitat map results of this study. The accuracy assessment was conducted between the classified maps derived from Sentinel-2A (with K-Mean and IsoData classifications) and the existing reference map. Figure 6 shows the accuracy assessment results. The results show a different degree of overall accuracies. The overall accuracy results show that K-Means produced higher accuracy (55.64%) than IsoData (47.98%). However, the kappa results show the different performance of both methods. IsoData algorithm obtained better accuracy (0.39) rather than K-Means (0.30). Further investigation is needed in order to know the reason for the differences. Also, both methods obtained a relatively low accuracy. The absence of training data.
could be the reason. The training data is expected to improve accuracy [34]. Another cause of the low level of overall accuracy was due to the absence of field data meaning that it gave limitation for the classification processes. Another reason could be due to the difference in the acquisition time of the images and algorithms used in deriving the benthic habitat maps.

![Figure 6](image_url)

**Figure 6.** Accuracy Assessment results of benthic habitat classifications by using K-Means and IsoData algorithms.

### 3.3. Visual comparison

Figure 7 shows the comparison between the classified and composite images as well as the reference map. From the visualization of the results, it is clear classified image obtained by using IsoData (Figure 7b) was quite similar to the classified image produced by the K-means algorithm (Figure 7c). In both maps, the existence of hard coral-algae (HC-AL) was quite dominant compared to the reference map. However, sand (SD) and seagrass (SG) dominated the whole map.

The number of classes that we chose when performing these unsupervised classifications could also give influence the classification results. In this study, we set the number of classes into 10, in fact, an appropriate number of classes need to be specified based on our prior knowledge. It also can be estimated from images for example by estimating the cluster validity index [35].

![Figure 7](image_url)

**Figure 7.** Composite image of the selected area (a), visual comparisons of benthic habitat classifications by using IsoData (b) and K-Means (c) algorithms, and reference map (d).
4. Conclusion
This research compared two methods in deriving benthic habitat maps by using K-means and IsoData algorithm. Both methods performed well despite the low accuracies obtained. Some challenges in improving the method include a further experiment in setting the number of classes when performing the methods. In the absence of training data, the proposed methods are promising.

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