The Assessment of Coral Reefs Mapping Methodology: An Integrated Method Approach

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Abstract. Indonesian waters hold the world's mega biodiversity of coral reefs. However, a range of anthropogenic pressures are threatening the coral reefs persistence. Since the early 20th century, remote sensing data has been assessed to map and monitor coral reefs. The reef habitats are monitored at various hierarchical spatial scales using integrated remote sensing and field data, but the level of detail and accuracy at a single point still questionable. Therefore, this study aims to assess the coral reefs methodology based on an integrated digital image processing approach. The method will employ a multi-pair and a single pair or an initial pair of Depth Invariant Index (DII) transformation bands, pixel-based Isodata and K-Means algorithm, and supervised classification method based on maximum likelihood and nearest neighbor algorithms. Object-based classification images, training areas, and data references were supported by previous research. The findings indicate that the maximum likelihood algorithm is better to apply for supervised classification for a single transformation band, while the K-Means algorithm is better for pixel-based classification since better accuracy can be obtained. However, various remote sensing data, band combinations, and clusters may affect the difference in results.

1. Introduction
Located in the world’s coral reefs triangle, Indonesia is the center of the world's finest coral reef biodiversity. According to Greenpeace, the area of coral reefs in Indonesia is about 50,875 km2, which accounts for 18% of the world’s total coral reefs and 65% of the total area coral triangle. Approximately 569 coral species belonging to 82 genera are present in Indonesian coastal waters [1]. Although coral reefs have high economic value, anthropogenic pressures are threatening the coral reefs persistence. Coral reefs degradation is caused by various activities, such as sedimentation and pollution originating from the land industrial and domestic waste disposal, coral reefs mining for building materials, and over-exploitation of marine resources, as well as the use of destructive fishing gears [2]. Naturally, global warming and ocean acidification have already contributed to the degradation of the coral reefs’ ecosystem [2]. With the increasing awareness of threats facing coral reefs’ ecosystems, mapping and monitoring the status of the coral reefs become important to sustain coral reefs in general as well as any endangered endemic coral species.

Since the early 20th century, remote sensing data has been used to map and monitor coral reefs. Reef ecosystems are tracked at different hierarchical spatial scales using integrated remote sensing and
field data, but the level of information and precision at a single point is still uncertain. Some digital image processing method has been developed to identify the conditions of the coral reefs. For example, the Lyzenga algorithm has been commonly applied to identify coral reefs [3]. The unsupervised, supervised, principal component analysis, object-based classification (OBIA) have also been used to determine the coral reef ecosystem conditions [4]. Multi-image resolution has also been used to obtain detailed information of the coral reefs ecosystem by applying some of those methodologies [4]. However, mapping the underwater objects still faces difficulties. For example, Awak et al. [5] used RapidEye image for an unsupervised method to map the coral reefs and obtained an accuracy of 73.42%, while Manessa et al. [3] used WordView-2 for Lyzenga method for mapping the coral reefs ecosystem obtain 78.08 – 89.22% accuracy depending on the selection on the spectral bands. Therefore, this study aims to assess the coral reefs methodology based on an integrated digital image processing approach. For this purpose, a Spot 6 image of Tidung Island -Thousand island, Jakarta-Indonesia, was used for analysis due to its fine multi resolution and panchromatic bands. Tidung Island was selected as a study area because this small island has been developed as one of a tourist destination. On the contrary, this island has a relatively high population density, therefore, the enormous pressure on the surrounding coral reef ecosystems needs to be monitored.

2. Method

This study using the rectified and pan-sharpened Spot 6 image of Tidung island, and the methods are Lyzenga algorithm for water column-correction, pixel-based and supervised classification. Object-based classification derived from previous research will be used as a comparison, while the field data will be employed for accuracy assessment. The image processing is described as follow:

2.1. Pre-processing

The image pre-processing was carried out with several corrections, i.e. atmospheric correction, geometric-correction and water column-correction. Atmospheric correction was used to eliminate atmospheric influences such as dust particles, water vapor, and other particles in the water column, meanwhile water column correction was used to improve image quality by reducing the effects of noise. Based on the Lyzenga theory the radiation received by the bottom sensor from the water is a linear function of the reflection of the bottom waters and the exponential function of the water depth [6]. Energy intensity decreases exponentially with increasing water depth. The technique commonly used for water column correction is based on the algorithm developed by Lyzenga [6], namely the Depth Invariant Index (DII) method and explained in the following equations:

\[ DII = \ln(l_i) - \left( \frac{k_i}{k_j} \ln(l_j) \right) \]  
\[ (1) \]

whereas \( DII = \) Depth Invariant Index; \( l_i \) : digital value at band I; \( l_j \) : digital value at band j; and \( \frac{k_i}{k_j} \) : The ratio of the attenuation coefficient in the pair of band I.

While the value of \( \frac{k_i}{k_j} \) is obtained using the following equation:

\[ \frac{k_i}{k_j} = a + \sqrt{a^2 + 1} \]  
\[ (2) \]

\[ a = \frac{\sigma_{ii} - \sigma_{jj}}{2\sigma_{ij}} \]  
\[ (3) \]

Whereas \( \sigma_{ii,jj} \) : Varian band i or band j and \( \sigma_{ij} \) : Covarian band ij

To improve accuracy, we have developed three (3) transform band pairs applied to the Lyzenga method, which combine the visible band and the near-infrared bands, i.e. band-1 and band-2 (b12), band-
1 and band-4 (b14) and band-2 and band-4 (b24). The band-composite of these three DII pairs was then employed for the further analysis process. Besides that, the initial or single pair of DII bands image was also being used for supervised classification. Then masking is applied to separate features of land and water, in which our research focused on underwater objects.

2.2. Processing

The processing for mapping coral reef ecosystems used pixel-based and supervised classification methods. Two different methods, Isodata and K-means were used as a pixel-based or unsupervised classification method. The method of Isodata depends on the distance threshold for cluster union and the threshold of typical deviation for cluster division [7]. It measures class means continuously circulated in the data space until the continuing pixels are iteratively clustered using less distance approaches [8]. Meanwhile, K-means has a goal to reduce the variability within the cluster, and according to Mengzhao et al. [9] its algorithm can be described in the following equations:

$$J(c, u) = \sum_{i=1}^{k} \sum_{j=1}^{n} \|x_j^i - u_c^i\|^2$$

(4)

where $J$ measures the sum of squared distances between each training example $x_j^i$ and the cluster centroid $u_c^i$ to which it has been assigned.

Meanwhile supervised classification method divides objects into blocks of training area for further study using the multi-resolution segmentation algorithm [10] and can be illustrated in the equations

$$f = \sum_{i=1}^{n} w_i (n_{merge} \cdot n_{obj1} \cdot n_{obj2})$$

(5)

Where $n$ is the number of bands and $w_i$ is the weight for the current band, "merge," "obj1," and "obj2" are respectively the number of pixels within a merged object, initial object-1, and initial object-2. Supervised classification was employed by using maximum likelihood and nearest neighbor algorithm. Both were using the same training data from the previous field observation of Tidung island studied by Narieswari et al.[11]. Figure 1 shows the points of field data observation of Tidung island

![Figure 1 The distribution of points of Field data observation of Tidung island [11]](image)

2.3. Accuracy assessment

The accuracy assessment was employed by using Sutrisno et al. [12] algorithm, which was described in the following equations:

$$Ev = \frac{\sum t_1 + t_0}{\sum (P)_{ref}} \times 100 \%$$

(6)

$$if(x, y)_1 = (x, y)_n \quad then \quad (x, y)_1 \quad is \quad true$$

(7)
\[
if (x, y)_1 \neq (x, y)_n \text{ then } (x, y)_1 \text{ is false}
\]  

(8)

where \(E_v\) is the result of the evaluation (%), based on \(t = \) a true value, \(1 \ldots n\) are the points from the classified image, and \(P_{ref}\) is the field reference data and \((x, y)_n\) is a reference point object within the classified image.

3. Result and Discussion

3.1. Pre-processing image for coral reefs classification

The pre-processing as a stage to provide the basic image used for the classification process plays an essential role in supporting data accuracy besides the resolution and condition of the image itself. The composite bands transformation of DII, there is \(b_{12}, b_{14}, b_{24}\) and namely multi-pair DII band transformation (MPT), showed its ability to distinguish underwater objects compared with the single or initial pair only, namely initial pair of DII band transformation (IPT) (Figure 2). The result of the algorithm transformation represents the distribution of digital values that can distinguish existing objects based on the histogram profile from each spectral channel (see Figure-2). The implementation of Lyzenga algorithm can provide a better image when compared to other methods [13]. Besides that the multi-pair transform bands of DII is better to identify the underwater object compare with single pair one [14]. Since the most critical step of any recognition method is feature extraction, using this composite transformation band, the purpose of feature extraction is to take the important features of the image and classify the overall image, resulting in a greater success rate in the recognition process.

![Figure 2. The images for processing steps (a) MPT image (b) IPT image](image-url)
3.2. Image classification using multi-pair transformation bands

The Indonesian National Standard No 7716:2011 about The mapping of shallow water habitats - Part 1: Mapping of coral reefs and seagrass, classified the shallow water habitat into four classes, there is substrate, coral reefs, seagrass, and macroalgae. Adhering to the standard, the pixel-based method, both Isodata and K-Means could classify the underwater object into four classes. The identified classes consisted of substrate (sand), seagrass, coral and the mix of coral, macroalgae and rubble (Figure 3-a, 3-b). Macroalgae can not be solely classified by these methods because it is scattered in small groups among corals, seagrass and sometimes rubble. Rossiter et al. [15] stated that macroalgae are possible to visually identified and separated if it is covering approximately 8,000 m² of the shallow-water habitats for middle to high-resolution remote sensing imagery. Within a small group, the macroalgae reflectance is mixed with corals, seagrass, sand and rubble, and they are somewhat difficult to distinguish. Meanwhile, the supervised classification shows similar results that the underwater objects were classified into four classes: substrate (sand), seagrass, coral and mix seagrass, macroalgae, and rubble (Figure 3-c). Nearest neighbor algorithm was used for deriving this supervised-MPT image.

However, the comparison of the image-maps derived from these three methods, Isodata-MPT, K-Means-MPT and supervised-MPT, show dissimilarity of the underwater objects area and distribution (see Figure 3 and Figure 4). Comparing both of the pixel-based methods, the findings indicate that K-means algorithm can distinguished coral, seagrass and mix of seagrass, macroalgae and rubble better than the Isodata algorithm. Meanwhile, Isodata-MPT has a higher substrate value compare with K-Means-MPT. The higher class of substrate in Isodata-MPT image indicates that some of the mix objects in K-means-MPT were identified as substrate in Isodata-MPT image. However, when we compare the three methods, it shows that K-means algorithm can classify coral better than Isodata and supervised-maximum likelihood algorithm, while for sand and mix of seagrass, macroalgae and rubble, supervised-maximum algorithm can identify better than others (Figure 4).

Figure 3. Classified coral reefs image based on (a) Isodata, (b) K-Means, and (c) supervised

(a)

(b)

(c)
Calculation of each object's area shows that coral and seagrass features are broader in the K-Means-MPT image compared with Isodata-MPT and supervised-MPT (Figure 5). For pixel-based method, the K-means algorithm gives a better classification result than the Isodata since it has a higher Silhouette Coefficients value than the Isodata algorithm in clustering the objects [16]. Supervised classification usually provides a better classification than the pixel-based ones because the field training area and the analyst's ancillary knowledge were used to identify objects. This is because the object-based algorithm can provide better accuracy in classification compare with the pixel-based algorithm [17]. However, in this study, it cannot be obtained due to the mixed pixel of seagrass, coral and macroalgae within one training area that difficult to separate. On the contrary, the pixel-based classification can classify objects better based on a single-pixel value.

![Figure 4](image1.png)

**Figure 4.** Distribution of the pixel value of the underwater objects based on (a) Isodata, (b) K-Means and (c) supervised

![Figure 5](image2.png)

**Figure 5.** The graphic of the area of underwater classes (in ha) in Isodata-MPT, K-means-MPT and supervised-MPT classified images.
3.3. Classification using the initial transform band.

For comparison of Supervised- MPT image, an IPT image of band-1 and band-4 (b14) were used to further process supervised classification. For this processing, a maximum likelihood algorithm was applied. The result shows that the supervised classification using IPT can classify five classes of interest: coral, seagrass, substrate (sand), a mix of coral and sparse seagrass, and a mix of seagrass, macroalgae and rubble (Figure 6).

Figure 6. Coral map derived from supervised-initial transformed bands

In this classified image, the substrate (sand) class may also be classified into a mix of sand and sparse seagrass, and so did the mix of seagrass, macroalgae and rubble.

Comparing and calculating each object's area shows that coral, seagrass, and sand features are broader in supervised-MPT image classification than supervised-IPT (Figure 7). However, the supervised-IPT can classify the mixed classes better than the supervised-MPT derive image. Since both classified images used the same training data, the maximum likelihood algorithm can classify the more detailed objects than the nearest neighbor algorithm. The maximum likelihood has proven to be a reasonable classification algorithm that can be used to classify coral reef detection and monitoring [18].
3.3. Evaluation of the methods

The object-based classification could classify the underwater habitat better than others, depending on the algorithm's selection[19]. A comparison with the previous study using OBIA [11] was employed for supervised-MPT and supervised-IPT classified images shown in Figure 8.

Although each object has a dissimilar extent, the OBIA has similar coral, substrate (sand), seagrass and mix seagrass, macroalgae & rubble classes with Supervised-MPT. However, for the supervised-IPT the difference was in the class of mix seagrass, macroalgae & rubble in which this class can be classified into mix seagrass, macroalgae & rubble and mix sands and sparse seagrass.

The assessment of the accuracy with the field data as a reference shows that Isodata-MPT has 78% accuracy, K-Means-MPT has 82% accuracy, Supervised-MPT has 71% accuracy dan supervised-IPT has 82% accuracy. The difference in accuracy level is affected by the process and characteristics of each method or algorithm. Coral reefs ecosystem classes by supervised classification method depend on the classifier algorithm, either maximum likelihood or the minimum distance, the training area and the transformation imageries used for classification process. Meanwhile, the pixel-based classification, either Isodata or K-Means is determined by the statistical range value as a reference to classify the underwater objects.

4. Conclusion

Coral reefs ecosystem is vulnerable to the pressure for nature and human activities, making mapping the coral reefs by using remote sensing data is essential. The first step for analysis is the pre-processing of the remote sensing data used for the classification process, there is the band transformation of Lyzenga
algorithm. These bands transformation, either multi-pair or single-pair, is essential to determine. The assessment using the pan-sharpened Spot 6 imageries at 6 meters resolution shows that the coral reefs classification's accuracy depends on the characteristic of the algorithm, the process of the classification and the imageries used. The finding of this assessment states that maximum likelihood is better to apply for supervised classification for a single transformation band, while the K-Means algorithm is better for pixel-based classification. However, different result may occur while using various remote sensing data sets, band combinations, modifying the algorithm, number of clusters etc. So, further study needs to be employed to have the best method and algorithm to map the coral reefs ecosystem.

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