Mapping shallow waters habitats using OBIA by applying several approaches of depth invariant index in North Kepulauan Seribu

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Abstract. The availability of satellite imagery with a variety of spatial resolution, both free access and commercial become as an option in utilizing the remote sensing technology. Variability of the water column is one of the factors affecting the interpretation results when mapping marine shallow waters. This study aimed to evaluate the influence of water column correction (depth-invariant index) on the accuracy of shallow water habitat classification results using OBIA. This study was conducted in North of Kepulauan Seribu, precisely in Harapan Island and its surrounding areas. Habitat class schemes were based on field observations, which were then used to build habitat classes on satellite imagery. The water column correction was applied to the three pairs of SPOT-7 multispectral bands, which were subsequently used in object-based classification. Satellite image classification was performed with four different approaches, namely (i) using DII transformed bands with single pair band input (B1B2), (ii) multi pairs bands (B1B2, B1B3, and B2B3), (iii) combination of multi pairs band and initial bands, and (iv) only using initial bands. The accuracy test results of the four inputs show the values of Overall Accuracy and Kappa Statistics, respectively 55.84 and 0.48; 68.53 and 0.64; 78.68 and 0.76; 77.66 and 0.74. It shows that the best results when using DII and initial band combination for shallow water benthic classification in this study site.

1. Introduction

The benefits of remote sensing technology in providing spatial information is undoubted, given the few advantages it offers. Remote sensing has the ability to record information from a large area with a relatively short time so that can save costs. In coastal and marine areas, remote sensing has been widely-used, for example, to extract information from shallow waters. Shallow waters in the context of remote sensing are the water column where light can penetrate to the bottom, generally at a maximum depth of 25 m [1].

Coral reefs and seagrasses are the main components of shallow water ecosystems. In addition to the two major ecosystems, the complexity of shallow water habitat plays an important role in providing ecological roles in the marine environment. Detailed spatial information on the composition of shallow water habitat covers is certainly required in planning and managing coastal and marine areas. However, the limitations of available information and the uncertainty of the methods and schemes used in mapping shallow water ecosystems are factors that still need attention. The uncertainty of the method and the classification scheme may be caused by several things, including the accuracy resulting from satellite image extraction.

The water column is one of the contributing factors that determine the accuracy of satellite image classification results [1]. The attenuation of energy propagates in the water column thus affecting the information received by the satellite sensor. On the other hand, an area and others have diverse characteristics that have different attenuation coefficients. This is certainly difficult when it will apply a similar model in various waters environment. Correction of the water column is sometimes necessary to improve the accuracy of extraction of shallow shallow water information. One method of water column correction is known and widely applied in shallow water mapping, the Depth Invariant Index (DII) introduced by Lyzenga [2]. The advantage of such method is not necessarily in situ measurement to obtain attenuation coefficient. By using a combination of band pairs, we can estimate the value of the ratio of the attenuation coefficient of the two bands (k_i/k_j).

Generally, the classification approach of remote sensing imagery can be grouped into two, pixel-based and object-based. Pixel-based classification is a technique that has been commonly known, so it can be categorized as a conventional technique. In recent years, object-based classification is quite popular and widely used in remote sensing data processing. Anggoro, et al. [3] for example, using OBIA to map the geomorphological zone of shallow waters in Pari Island. OBIA techniques are also widely used to map shallow water habitats as well as coral reefs [4-6].

The application of remote sensing for mapping shallow water habitats, water column correction such as DII transformation is commonly used in pixel-based classification. The using of water column correction on OBIA is still limited to the literature that discusses the method. Among the studies that applying water column correction on object-based classification was Wahidin, et al. [6] which obtains 56 - 73% classification accuracy from Landsat image for mapping coral reef ecosystem in Morotai Island with 7 classes.

The purpose of this study was to determine the ability of object-based classification on SPOT-7 imagery to map shallow water habitats in the northern of Kepulauan Seribu by using several scenarios. The scenarios are (i) using DII transformed bands with single pair band input, (ii) multi pairs bands, (iii) combination of multi pairs band and initial bands, and (iv) only using initial bands.

2. Method

2.1. Study Site

This research was conducted in North of Kepulauan Seribu, there are five small islands included in research location, that are Harapan Island, Kelapa Island, Kelapa Dua Island, Kaliageh Island, and some areas of Panjang Island. Harapan and Kelapa are two islands that side by side and connected each other. Administratively, the research location is included in the North Kepulauan Seribu sub-district, Kepulauan Seribu Regency - Jakarta. Based on geographical position, the study site extends between 106°33'9.3"E and 5°38'35"S – 106°35'44"E and 5°39'58.39"S. Three of the five islands in this study site are inhabited islands consisting of 2 villages, namely Harapan Island and Kelapa Island. Figure 1 shows the location of the study sites.

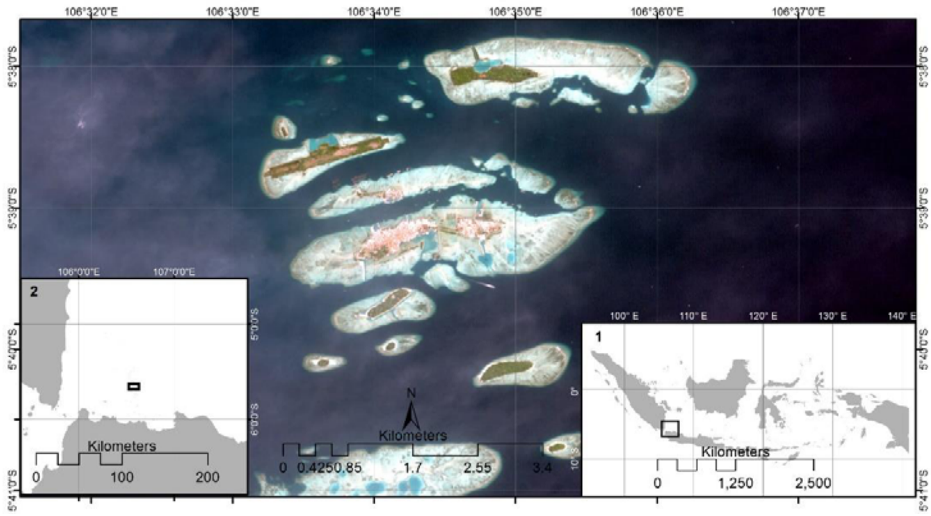

Figure 1. Study site located in the north of Kepulauan Seribu, Indonesia.

2.2. Data Collection

The main data used was a SPOT-7 multispectral image, consisting of four multispectral bands, blue, green, red and NIR bands. The imagery was acquired on 12 of June 2016. The image has spatial resolution on multispectral bands of 6m, and 1.5m on panchromatic bands (Table 1). In addition, field data were used as training and validation of image classification results. Field data were obtained from a field survey conducted in June and November 2016.

Table 1. The characteristics of SPOT-7 imagery

Band	Wavelength	Spatial Resolution
Band 1 (Blue)	485 nm	6 m
Band 2 (Green)	560 nm	6 m
Band 3 (Red)	660 nm	6 m
Band 4 (NIR)	825 nm	6 m
Panchromatic	597,5 nm	1,5 m

Field data were collected using systematic random sampling method, with the distance between sampling points about 20m. The determination of the observation location to represent the study area was undertaken during the designing of the field survey, by visual interpretation of the WorldView-2 imagery. We did not use SPOT-7 for designing field survey because in that time the imagery not available yet. Data collection considers the diversity of shallow water benthic covers and the spatial resolution of satellite imagery used in the classification. Field data collection was assisted by using a square transect and GPS Trimble GeoXT 2008. Each data point was equipped with transect photographs using an underwater camera to facilitate post-processing and categorization of each data set.

2.3. Data Analysis

Digital image processing was done by applying pre-processing and analysis through classification. Digital image processing began by applying some basic corrections, then classifications were performed in two levels, level 1 to separate land, shallow and deep waters, then level 2 to classify shallow waters into several habitat classes. Generally, the processes of satellite image processing performed is presented in Figure 2 below.

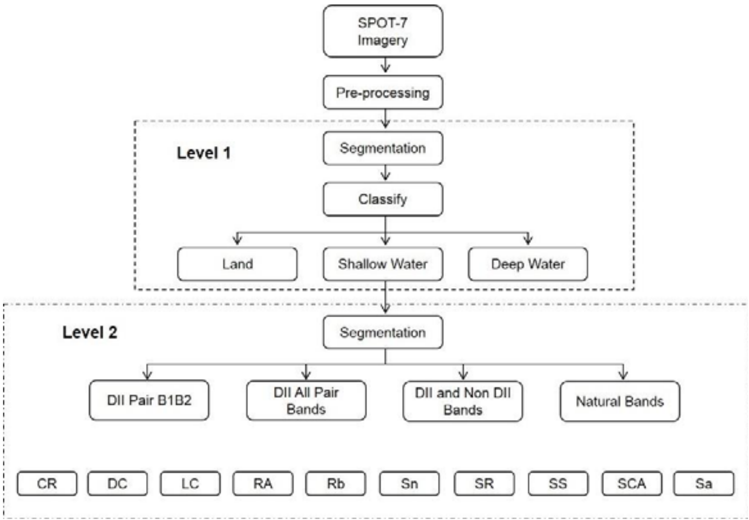

Figure 2. Hierarchy of classification using OBIA in this study

2.3.1. Pre-processing

Pre-processing was done on field data and satellite image data. Field observation data were then grouped into the habitat classes. The field data categorization then obtained the result of habitat class definition as many as 10 class. The habitat classes are used, i.e coral with rubble (CR) live coral (LC), dead coral (DC), rubble with algae (RA), rubble (Rb), sand (Sn), sand with rubble (SR), sand with seagrass (SS), sand coral and algae (SCA), and seagrass (Sa). Initial correction applied on SPOT-7 image was atmospheric correction using FLAASH (Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes) method, geometric correction, then image cropping to focus on the study area.

Water column correction used was the method of Depth Invariant Index (DII) developed by Lyzenga [2]. The method has been widely known and widely used in shallow water mapping. The DII equation is written as:

$$DII = ln(L_i) - \left[\left(\frac{k_i}{k_j}\right)\right].\ln(L_j) \qquad (1)$$

DII = Depth invariant index; Li = the radiance of band i; Lj = radiance of band j; and k_i/k_j = the ratio of the attenuation coefficients of band i and band j. The values of k_i/k_j were obtained from sample extraction of imagery from the substrate i.e. B1B2 0.5837, B1B3 0.2384, and B2B3 0.5029.

2.3.2. Image Classification

As shown in Figure 2, OBIA classification of SPOT image was performed with two levels. Level 1 was for land and deep water masking then takes only shallow waters for classification in level 2. In level 1, the classification was done by applying the threshold values of some transformations for 3 classes. The threshold values used are, land B1/B4<3; shallow waters B1/B3<1.3, and deep water B1/B3>=1.3. Classification at level 2 applied several approaches to obtain the most accurate classification results and to determine the effect of water column correction (DII) on the classification results. The input method used in level 2 i.e (i) using one pair band of DII; (ii), a combination of 3 pairs bands of DII; (iii) combination of 3 pairs bands of DII and initial bands; and (iv) using natural bands without DII transformation.

The method (i), the selection of DII band pairs based on the regression parameters of natural logarithm values of the two bands used, from 3 pairs of DII bands on SPOT-7 image, i.e pairs of B1B2, B1B3, and B2B3, used in the experiment (i) was B1B2. As for the method (ii) used the three pairs of DII band combinations. The relationship between DII band pairs is shown in Figure 3.

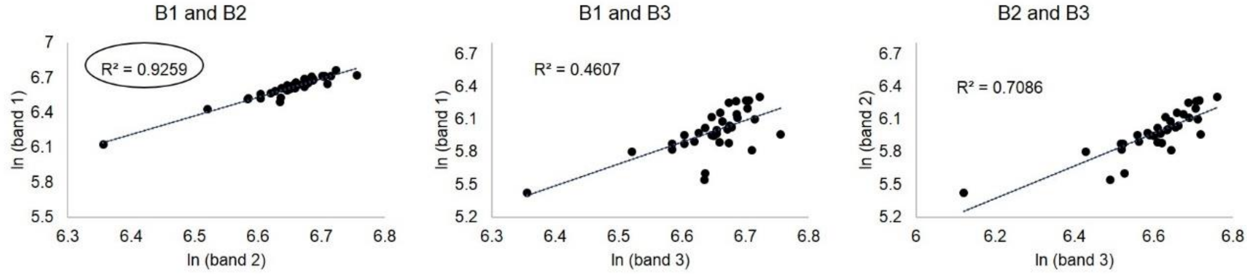

Figure 3. The relation between band pairs of DII from SPOT-7 imagery

Segmenting or grouping pixels into objects is one of the steps in object-based classification. The segmentation was applied multiresolution segmentation algorithm. The size of the object formed from the segmentation result is represented by the scale parameter of the object used in the segmentation process. Determination of parameter scale greatly affects the accuracy of classification [7], so that value is of concern in the classification of satellite imagery. In this study, after experimenting with some value of object scale, finally, we used the value of 40 for level 1 and 10 for level 2. In Table 2 can be seen the number and size of objects formed from the results of segmentation both in 2 levels.

Table 2. Scale parameters, number of objects, and object sizes from 2 levels segmentation

Level	Scale Segmentation	Number of objects	Area (m^2)		
			Min	Max	Mean
L1	40	532	341.14	460,033.86	22,964.39
L2	10	3764	42.64	7,419.66	1,119.00

2.3.3. Accuracy Assessment

The accuracy assessment was done to obtain the accuracy level of thematic map resulting from the four approaches used in classification. This accuracy assessment was done by constructing a confusion matrix, three general parameters obtained from the matrix, i.e overall accuracy (OA), producer's accuracy (PA), and user's accuracy (UA). OA is expressed as the ratio of the amount of data used as a validation sample and is well explained against the number of classes defined. UA is translated as the average probability (%) an object will be correctly classified and on average showing how well each class in the field has been classified. UA is the average probability (%) of an object of a classified image, actually representing the classes in the field [1]. The Kappa statistic value was also calculated from each classification result to compare the approach that gave better classification the benthic habitat.

$$Kappa\ (K) = \frac{N\sum_{j=1}^{r} - \sum_{i=1}^{r}(x_i + .x_{+i})}{N^2 - \sum_{i=1}^{r}(x_j + .x_{+i})} \quad (2)$$

3. Results and Discussion

Spatial distribution of classification results from shallow water habitat shows different pattern and extent of each method applied. The classification using only one pair of DII bands, the coral reef class shows significant differences from the other 3 methods. Figure 5 (c) shows the LC class was found only in some spots with a smaller area than other methods. Similarly, for seagrass class (Ss), both in methods (i) and (ii) indicate patterns of distribution that show significant differences. The seagrass class on the two initial approach classification seems to be spreading to the zone of reef slope.

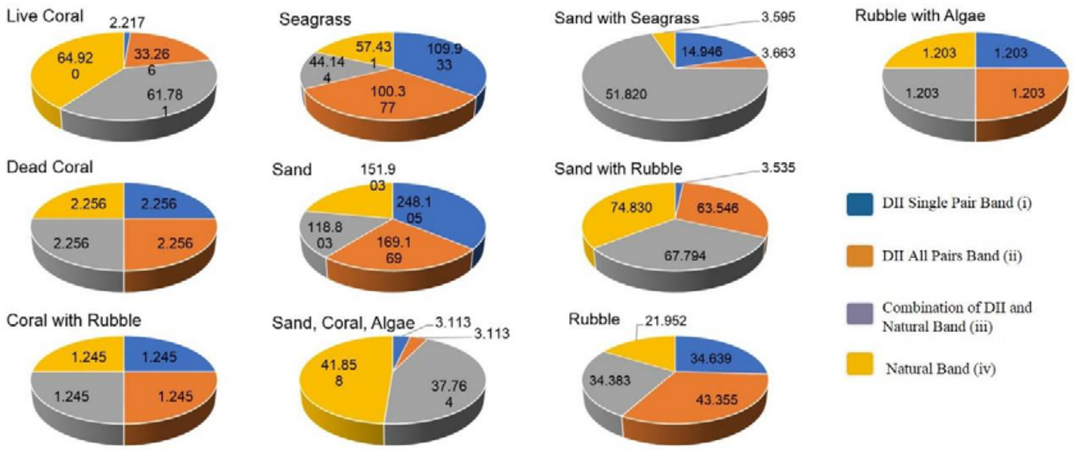

Figure 4. Area (ha) of habitat classes form different method used in classification

The area of classification result from the benthic habitat as shown in Figure 4 appears to vary according to the approach methods used. Habitat classes show significant differences in LC, SCA, SS, and SR. In the use of the first method (i), obtained LC, and SR classes with the smallest than 3 others methods, while SCA and SS obtained the smallest distribution when applying method (ii). From Figure 4 it is also known that the SS class was obtained by the largest area on the use of the method (iii). To determine the most optimal method of mapping the habitat class in this study area, it can be assessed based on the accuracy values presented in table 3 and table 4.

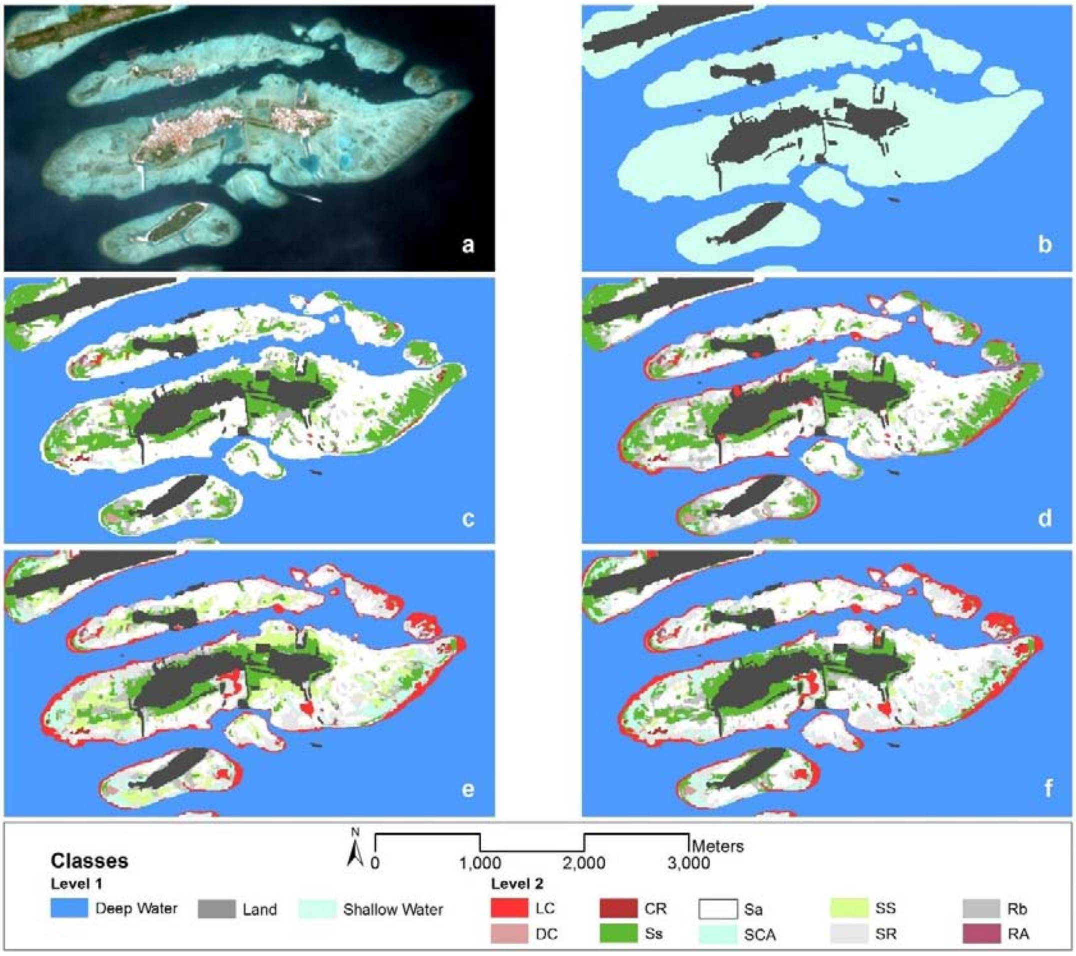

Figure 5. Overview of classification results by applying OBIA, (a) RGB composite of SPOT-7; (b) Classification in level 1; (c) Classification with DII single pair band; (d) Classification of DII all pairs bands (e) Combination of DII all pairs bands and initial bands; and (f) Classification using initial bands

The overall accuracy and Kappa statistics from the four methods applied, obtained the accuracy range 55.84 – 78.68 (%) for OA and 0.48 – 0.74 for Kappa values (Table 3). Table 3 shows the OA and Kappa statistics of each method applied, where the bold value indicates the method with the best accuracy of the four approach methods used. With the number of habitat class schemes of 10 classes, the OA value of 78.68% is considered to be passable to map shallow water habitats at the study site. Previously in the same location, research was done to map habitat with 11 classes and obtained OA value of 76.8% [8]. Another study conducted in the Kepulauan Seribu to map the benthic habitat with 7 classes using WorldView-2 imagery, obtained the accuracy of 72.38 - 84.29% with the use of DII and PCA transformations PCA [9].

Table 3. The overall accuracy (OA) and Kappa Statistic calculated form each classification approach

Method	OA (%)	Kappa
(i) DII Pair B1 and B2	55.84	0.48
(ii) DII All Pair Bands	68.53	0.64
(iii) Combination DII and non DII Band	**78.68**	**0.76**
(iv) Non-DII (Initial bands)	77.66	0.74

The UA and PA values in detail refer to the method used are presented in Table 4. Both UA and PA, the lowest values are found when using the single pair bands, the lowest UA on the Ss class, while the lowest PA found on CR class. The highest PA value on RA class for method (iv), while on the other three methods was highest in class Sa.

Table 4. User's accuracy (UA) and producer's accuracy (PA) values from each method used

Classes \ Methods	DII B1 and B2 (i)		DII All Pair Bands (ii)		Combination (iii)		Non DII (iv)	
	UA	PA	UA	PA	UA	PA	UA	PA
Live Coral (LC)	80.00	22.22	91.67	61.11	83.33	83.33	83.33	83.33
Dead Coral (DC)	100.00	33.33	100.00	47.62	100.00	61.90	100.00	66.67
Coral with Rubble (CR)	100.00	21.43	90.00	64.29	84.62	78.57	100.00	78.57
Seagrass (Ss)	34.69	77.27	44.74	77.27	81.82	81.82	73.91	77.27
Sand (Sa)	53.62	**84.09**	72.55	**84.09**	84.44	**86.36**	80.85	86.36
Sand, Coral and Algae (SCA)	100.00	30.00	100.00	50.00	60.00	60.00	58.33	70.00
Sand with Seagrass (SS)	56.00	58.33	69.57	66.67	71.43	83.33	70.83	70.83
Sand with Rubble (SR)	72.73	44.44	50.00	61.11	60.87	77.78	56.52	72.22
Rubble (Rb)	61.90	72.22	73.68	77.78	73.68	77.78	82.35	77.78
Rubble with Algae (RA)	100.00	50.00	71.43	62.50	100.00	75.00	87.50	**87.50**

The application of DII in classification by using only one pair of bands (i) obtained the classification results with low PA values for the class of LC, DC, CR, and SCA which only ranged from 21 - 30%. While 3 other methods gave better value, especially on method (iii) and (iv).

Based on PA values in Table 4, it shows that methods (iii) and (iv) consistently provide better classification results for the four methods used. The differences methods (iii) and (iv) are found in the SS and RA classes, where (iii) gave better results for the SS class, while in the RA class the method (iv) gave the better result in recognizing the class. Another situation was found that, using the combination DII bands and initial bands (iii) able to explain seagrass and sand mixed with seagrass (Ss and SS) with better results.

From the experimental results in this study by involving some difference of inputs in OBIA, it was generally known that the use of single pair band of DII was not able to give a better result. Similarly, the combination of some DII bands (ii) does not give better results when compared to DII band combined with initial bands (iii), or by using only initial bands (iv). The use of methods (i) and (ii) reduce the area and distribution of the reef classes, i.e. LC, DC, and RC, those classes are more prevalent on the reef slopes. It was be expected because of the depth factor, the conditions in the field showed the distribution of reef class in the deeper areas than the seagrass class. When applied water column correction and only involve single pair band or multi pairs band of DII in classification, reef class reduced to sand and seagrass. Unlike the case when it initial bands including as part of the classification inputs both in (iii) and (iv) methods, it shows differences in classification results, especially on reef classes. On mapping benthic covers, some researchers that applied water column correction i.e. [10] for reefs mapping, [11] mapping seagrass using Sentinel-2 imagery, and [12] that using geomorphological zonation and water column correction approach.

4. Conclusion

Classification with including DII band combine with the initial band (iii) gives classification result with higher accuracy (OA 78.68% and Kappa 0.76). While the lowest accuracy was obtained when applying method (i) which only reached 55.84% for OA and 0.48 for Kappa Statistic. Based on the results obtained in this study site, the method (iii) was well used when mapping the seagrass, but to map the coral reefs should be obtained better results when applying the method (iv). It seems to be better to use water column correction when mapping seagrass, but sometimes it does not be needed when mapping reefs.

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