Benthic habitat classification using high resolution satellite imagery in Sebaru Besar Island, Kepulauan Seribu

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Abstract. Remote sensing technology can provide spatial information for mapping shallow water benthic habitat, a case study conducted on Sebaru Besar Island. The purpose of this study was to analyze mapping accuracy of shallow water benthic habitats using WorldView 2 and SPOT 6 (201 imageries). The classification of multispectral images is carried out using the Depth Invariant Index (DII) transformation and by applying the Maximum Likelihood (MLH) algorithm to both satellite images. The number of benthic habitat classes produced are eight habitat classes from each image used. The results of the analysis show that the overall accuracy in Worldview 2 and SPOT 6 images is 61.29% and 51.61%. Results of Z-statistic comparison between Worldview-2 and SPOT-6 imagery was 1.04, means that the results did not differ significantly.

1. Introduction
Remote sensing technology can provide spatial information in studies of shallow water benthic habitat mapping. Remote sensing provides an effective way to detect and monitor the distribution of benthic habitats in shallow water to distinguish coral characteristics and habitat diversity [1]. In the management of coastal areas and small islands, spatial and temporal information about the distribution of benthic habitats is a basic component to consider various management activities.

Various remote sensing satellites have been widely used and are quite familiar for mapping shallow water habitats. At present, very high resolution (VHR) satellite data offers new opportunities [2]. However, better spatial resolution does not necessarily improve classification performance and as a consequence, the development of classification methods has been studied in previous years [2]. There are also difficulties and technical problems in technology implementation, for example the nature of underwater environment with the influence of variable depth and reflectance [3]. In remote sensing applications, determining the level of accuracy and uncertainty is important [4].

The development of remote sensing has increased rapidly from year to year [5]. Research on shallow water habitat mapping has been carried out using various algorithms such as Maximum Likelihood (MLH), Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF) and using Threshold Values to produce good accuracy as presented in Table 1. In addition to the different approaches used,
the classification of benthic habitat mapping results is also influenced by differences in the characteristics of the study area waters and the image resolution used.

Table 1. Several benthic habitat mapping studies using pixel and object approaches.

| Satellite Imagery | Classification approach | Algorithm | No. of benthic habitat class | Study location | Overall accuracy | Source |
|-------------------|-------------------------|-----------|-----------------------------|----------------|-----------------|--------|
| Quickbird         | Pixel-based             | MLH       | 8                           | Karang Congkak and Karang Lebar, Kepulauan Seribu | 88.9% [6] |        |
| Quickbird         | Pixel-based             | Threshold Values | 8                           | Pari Island, Kepulauan Seribu | 87% [7] |        |
| Landsat 8 OLI     | Pixel-based             | SVM       | 5                           | Morotai Island, Maluku | 69% [8] |        |
| Landsat 8 OLI     | Pixel-based             | MLH       | 7                           | Padaido Islands, Papua | 47.57% [9] |        |
| AVIRIS            | OBIA                    | MLH, RF   | 3 - 12                      | Florida Keys | 69-85% [10] |        |
| SPOT              | OBIA                    | SVM, DT   | 11                          | Harapan Island, Kepulauan Seribu | 76-60% [11] |        |
| UAV               | OBIA                    | KNN       | 9                           | Giglio Island | 84% [12] |        |

Note: OBIA= Object Based Image Analysis; MLH= Maximum Likelihood; SVM= Support Vector Machine; RF= Random Forest; DT= Decision Tree; KNN= k-Nearest Neighbor.

MLH algorithm classifies images by taking into account the maximum probability of a number of pixels within the input image. This method aims to minimize overlap classes, but will require more time [13]. The initial stage carried out for the benthic habitat classification using MLH algorithm is to get statistics from potential classes that have been determined. The next step is to read the set of identifiers and compare the related pixels of each identifier with the data of each class statistically (with Bayesian equations) [13].

The purpose of this study was to analyze the accuracy of mapping the shallow water benthic habitats using MLH algorithm on Worldview-2 and SPOT-6 imageries.

2. Methods

2.1. Study site

This research was conducted on 9-10 May 2018 in the shallow waters of Sebaru Besar Island, Kepulauan Seribu Utara which is one island located in the Kepulauan Seribu Marine National Park. Field survey to observe existing benthic habitats was conducted using handheld GPS Garmin 78s and 64s, underwater cameras, quadrant transects, waterproof stationery.

2.2. Data collection

This study was used Worldview-2 and SPOT-6 satellite data. Worldview-2 sensors consisted of 8 bands, one panchromatic and seven multispectral band, which has spatial resolution of 0.46 and 1.85 meters respectively (Table 2). SPOT 6 has 4 multispectral bands (red, green, blue and NIR) which have spatial resolution of 6 meters, and Panchromatic band with spatial resolution of 1.5 (Table 3). Satellite data used were acquired on 7 June 2018, 03:55:11 for Worldview-2 and 15 May 2017, 08:08:50 for SPOT-6.
Table 2. WorldView-2 satellite sensor characteristics.

| Band     | Wavelength Range (nm) | Resolution (m) |
|----------|-----------------------|----------------|
| Blue     | 450 – 510             | 1.85           |
| Green    | 510 – 580             | 1.85           |
| Yellow   | 585 – 625             | 1.85           |
| Red      | 630 – 690             | 1.85           |
| Red edge | 705 – 745             | 1.85           |
| Near IR-1| 770 – 895             | 1.85           |
| Near IR-2| 860 – 1040            | 1.85           |
| Panchromatic | 450-800              | 0.46           |

Table 3. SPOT-6 Satellite sensor characteristics.

| Band     | Wavelength Range (\(\lambda\), nm) | Resolution (m) |
|----------|------------------------------------|----------------|
| Band 1 – Blue | 450 -520                        | 6              |
| Band 2 – Green | 530 – 590                      | 6              |
| Band 3 – Red  | 625 – 695                        | 6              |
| Band 4 – NIR  | 760 – 890                       | 6              |
| Panchromatic  | 450 – 745                        | 1.5            |

Field data were collected using a systematic random sampling method, which is a sampling method that is based on prior knowledge of the study location with observation points chosen randomly under certain intervals distance [4]. Benthic habitat identification was carried out based on existing benthic substrates or dominant benthic community within quadrant transect of 1 m x 1 m or 6 m x 6 m. The distance for each observation point was 40 meters, thus the total number collected was 119 observation points (Figure 1).

Figure 1. Distribution of observation points in Sebaru Besar Island. SBi denotes several lines transects for surveying benthic habitats.

2.3. Data analysis

2.3.1. Pre-processing. Worldview-2 and SPOT-6 image processing was initiated with image cropping, geometric, atmospheric, and water column correction. Geometric correction used the image registration using Ground Control Point (GCP) collected in the field. Atmosphere correction aim is to remove atmospheric constituents such as solid particles and water vapor in the air. The atmospheric correction method applied was the Dark Object Subtraction method. Water column correction is based on an
algorithm developed by [14], namely the Depth Invariant Index (DII) method. Depth Invariant Index is an image transformation using two different images which penetrated in water column:

\[
\text{Depth Invariant Index} = \ln(L_i) - \left[\frac{K_i}{K_j}\right] \ln(L_j)
\] (1)

\(L_i\) is the digital value in band \(i\), \(L_j\) is the digital value in band \(j\) and \(K_i / K_j\) is the attenuation coefficient ratio in band \(i\) and \(j\).

2.3.2. Benthic habitat classification scheme. The classification scheme was obtained by grouping benthic habitat cover based on field survey data. Classification of habitat classes determined by the dominant percentage at each field observation point. The data that has been obtained was analyzed using the Coral Point Count software with Excel extensions commonly called CPCe [15]. CPCe is an application developed through visual basic that can automatically perform random point count and stratified point count analysis. This study uses a stratified random calculation model. The type of specification for the stratified point applied in this study is a uniform grid using 30 points that are overlapped in each quadrant photo (Figure 2).

![Figure 2. Visualization of benthic habitat grouping using CPCe.](image)

Furthermore, the percentage of benthic habitat cover data obtained from CPCe was analyzed using the Agglomerative Hierarchical Clustering (AHC) method. AHC analysis is an analysis based on the value of dissimilarity between objects to be grouped. Similarity is measured using the similarity distance Bray-Curtis coefficient where it can distinguish and explain large amounts of data into uniform data classes. This study uses a Bray-Curtis coefficient object dissimilar value of 40-45%, which shows the classification of benthic habitats identified as having a similarity of 60-65%. There is no stipulation in the choice of scale or dissimilar value to define the classification scheme. This is due to differences in conditions and variations in the location of observation and the image platform used [16].

2.3.3. Maximum likelihood algorithm. Pixel-based classification method was conducted in this study using the Maximum Likelihood (MLH) algorithm, which considers the maximum probability of the number of pixels of the classified image. The decision rule for MLH refers to the following Bayesian equation:

\[
P = \ln(Ac) - 0.5 \ln(|\Sigma c|) - 0.5[(X - \mu c)^T(\Sigma c^{-1})(X - \mu c)]
\] (2)

\(P\) is the likelihood distance weight, \(c\) is the class index, \(X\) is the pixel value of the class candidate, \(\mu c\) is the average of the training for class \(c\), \(Ac\) is the a priori percentage for class \(c\), \(|\Sigma c|\) is Determinant matrix variation for class \(c\), \(\Sigma c^{-1}\) is inverse matrix class \(c\) and \(T\) is Round matrix.

2.4. Accuracy assessment

Accuracy testing is performed on all classification results, using a confusion matrix consisting of overall accuracy (OA), producer accuracy (PA), user accuracy (UA), Kappa statistics, and Z-test [17]. A KHAT-based Z-test or K-statistic is used to assess the classification accuracy of confusion matrix. Kappa coefficient value (KHAT statistics) is within the range of 0-1 and usually smaller than the overall
accuracy value (OA). $Z$ is the standardized distribution of normal Kappa values. Statistical tests to evaluate if there is significantly different matrix errors:

$$Z = \frac{(k1-k2)}{\sqrt{\text{var } k1 + \text{var } k1}}$$  \hspace{1cm} (3)

$Z$ is the standardized value and normal distribution, while the values of $k1$ and $k2$ are the calculation of the statistical kappa of each error matrix.

3. Result and discussion

The result of grouping benthic habitat classes using AHC analysis are displayed in the form of histogram. The classification scheme obtained in this study on Worldview-2 and SPOT-6 images produced 8 habitat classes in Sebaru Besar Island. The labels of benthic habitat classes was decided by determining the dominant class of benthic habitat referring to its percentage cover in the histogram in Figure 3. For example, the first class is called as Alga (AL) class because the algae class is more dominant with a value of 63.33% as well as the classes.

![Figure 3. Scheme of benthic habitat classification of Sebaru Besar Island. AL (algae), RB (rubble), KMKH (dead coral mixed with live coral), KHAL (live coral mixed with algae), KH (live coral), PS (sand), PA (sand mixed with algae) and KMP (dead coral and sand).](image-url)

Based on the assessment, different in accuracy can be seen in each benthic habitat class according to producers and users accuracy. Producer accuracy using Worldview-2 in mapping four benthic habitat classes of KH, KMKH, PA and RB is above 60% which are 100%, 80%, 70% and 75% respectively. While results of SPOT-6 in PA values for AL, PS, and RB classes are 100%, 100% and 71.43% respectively (Table 4).

![Table 4. Confusion matrix of 8 benthic habitat classes in the shallow waters of Sebaru Besar Island based on Worldview 2 imagery. Overall Accuracy = 61.30%](image-url)

| Class | AL | KH | KHAL | KMKH | KMP | PA | PS | RB | Total | UA |
|-------|----|----|------|------|-----|----|----|----|-------|----|
| AL    | 4  | 0  | 0    | 0    | 0   | 0  | 0  | 0  | 4     | 100|
| KH    | 0  | 7  | 3    | 0    | 0   | 0  | 0  | 0  | 10    | 70 |
| KHAL  | 0  | 0  | 7    | 1    | 0   | 0  | 0  | 0  | 8     | 87.5|
| KMKH  | 2  | 0  | 2    | 4    | 1   | 1  | 0  | 0  | 10    | 40 |
| KMP   | 0  | 0  | 0    | 3    | 0   | 0  | 0  | 0  | 3     | 100|
| PA    | 3  | 0  | 1    | 0    | 7   | 1  | 1  | 1  | 13    | 53.85|
| PS    | 0  | 0  | 0    | 1    | 3   | 0  | 0  | 5  | 6     | 60 |
| RB    | 2  | 0  | 0    | 1    | 1   | 1  | 1  | 3  | 9     | 33.33|
| Total | 11 | 7  | 15   | 5    | 10  | 5  | 4  | 4  | 62    | |

Note: AL (algae), RB (rubble), KMKH (dead coral mixed with live coral), KHAL (live coral mixed with algae), KH (live coral), PS (sand), PA (sand mixed with algae) and KMP (dead coral and sand), UA (User Accuracy), PA (Producer Accuracy).
User accuracy using Worldview-2 in mapping four benthic habitat classes of AL, KHAL, and KMP showed value above 60%. UA value for each benthic class respectively are 100%, 87.5%, 100%. While results SPOT-6 in UA values for AL, KHAL, and PS classes are 100%, 100% and 70% respectively (Table 5). The results of the Producer Accuracy for class KMP is 0, means that from 6 accuracy test samples none of it correctly classified and those samples were read or spread in the other benthic habitat classes such as KMKH, PA and RB (Table 5).

Table 5. Confusion matrix of 8 benthic habitat classes in the shallow waters of Sebaru Besar Island based on SPOT 6 imagery.

| Class | AL   | KH   | KHAL  | KMKH | KMP  | PA   | PS   | RB   | Total | UA   |
|-------|------|------|-------|------|------|------|------|------|-------|------|
| AL    | 6    | 0    | 0     | 0    | 0    | 0    | 0    | 0    | 6     | 100  |
| KH    | 0    | 3    | 3     | 0    | 0    | 0    | 0    | 0    | 6     | 50   |
| KHAL  | 0    | 0    | 1     | 0    | 0    | 0    | 0    | 0    | 1     | 100  |
| KMKH  | 0    | 0    | 1     | 3    | 3    | 0    | 0    | 1    | 8     | 37.5 |
| KMP   | 0    | 0    | 1     | 0    | 0    | 0    | 0    | 0    | 1     | 0    |
| PA    | 0    | 0    | 2     | 2    | 7    | 0    | 1    | 12   | 58.33 |
| PS    | 0    | 0    | 0     | 0    | 3    | 7    | 0    | 10   | 70    |
| RB    | 0    | 3    | 6     | 1    | 1    | 2    | 0    | 5    | 18    | 27.78|
| Total | 6    | 6    | 12    | 6    | 6    | 12   | 7    | 7    | 62    |
| PA    | 100  | 50   | 8.33  | 50   | 0    | 58.33| 100  | 71.43 |

Note: AL (algae), RB (rubble), KMKH (dead coral mixed with live coral), KHAL (live coral mixed with algae), KH (live coral), PS (sand), PA (sand mixed with algae) and KMP (dead coral and sand), UA (User Accuracy), PA (Producer Accuracy).

The distribution of shallow water habitats for Sebaru Besar Island with Worldview-2 and SPOT-6 showed substantial difference, especially for KH, KMKH, KMP, and AL classes (Figure 4). The distribution of benthic habitats using Worldview-2 was more detailed in comparison to SPOT-6. This contrasting results was probably due to image spatial resolution as this research was applying pixel-based approach in determining shallow water benthic habitats. Worldview-2 has higher resolution than SPOT-6 with a pixel size of 2 meters. The higher satellite image resolution used will improve the accuracy results in the mapping of shallow water benthic habitats [18].

The effect of image resolution on the classification results was analyzed from the accuracy value calculated using the confusion matrix table. Accuracy calculations are performed on both benthic habitat map classification results (Worldview-2 and SPOT-6). The accuracy of benthic habitat maps produced from Worldview-2 was 61.30% with Kappa coefficient of 0.56. Meanwhile the accuracy of benthic habitat maps produced from SPOT-6 was 51.61% with Kappa coefficient of 0.45 (Table 6).

Table 6. Kappa and Z statistical values on the accuracy of classification test results.

| Image    | Class | Accuracy | Kappa | Variance | Z Statistic | Z statistical Worldview - 2 vs SPOT-6 |
|----------|-------|----------|-------|----------|-------------|---------------------------------------|
| Worldview-2 | 8     | 61.30%   | 0.56  | 0.00133  | 5.24        | 1.04                                  |
| SPOT-6   | 8     | 51.61%   | 0.45  | 0.00953  | 3.74        |                                       |
Figure 4. Map of the benthic habitat classification for Sebaru Besar Island with (A) Worldview-2 and (B) SPOT-6 imagery.

Results of Z-statistic comparison between Worldview-2 and SPOT-6 imagery was 1.04. Z-statistics for benthic habitat maps using Image Worldview 2 and SPOT 6 did not differ significantly. The statistical Z-value is said to be significant if the statistical Z result is greater than 1.96 [17].

4. Conclusion
The result of benthic habitats classification on WorldView-2 and SPOT-6 using MLH algorithm shows that Worldview-2 is better than SPOT-6 but not significantly different.

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