Improving the accuracy of Multispectral-based benthic habitats mapping using image rotations: the application of Principle Component Analysis and Independent Component Analysis

Pramaditya Wicaksono*

Cartography and Remote Sensing, Department of Geographic Information Science, Faculty of Geography, Universitas Gadjah Mada, Sekip Utara 55281 Yogyakarta, Indonesia
*Corresponding author, e-mail address: prama.wicaksono@geo.ugm.ac.id

Abstract

The low number of water penetration bands in multispectral images limits the maximum descriptive resolution and the accuracy of the resulting benthic habitats maps, especially at higher levels of benthic habitats scheme complexities. This research aimed at improving the accuracy of benthic habitats mapping by exploiting the spectral performance of multispectral images using image rotation techniques, which is very beneficial for fast, accurate, and repeatable mapping. Kemujan Island as part of the Karimunjawa archipelago in Indonesia is selected as the study area. Principle Component Analysis (PCA) and Independent Component Analysis (ICA) were applied on Worldview-2 prior to image classification. The inputs for PCA and ICA are deglint bands and water column-corrected bands. Field benthic data collected from photo-transect technique were used to train the rotated datasets in the classification process and to assess the accuracy of the resulting benthic habitat maps. Three levels of benthic habitats classification schemes were constructed based on the variation of benthic habitats insitu, which covers the variations of coral reefs, seagrass, macro algae, and bare substratum. The results show that the application of image rotations on Worldview-2 improves the overall accuracy of benthic habitats mapping and become more effective as the classification scheme complexities increase. In the absence of water column correction, PCA and ICA become the best option to assist benthic habitats mapping.

Keywords: Benthic habitats, PCA, ICA, Worldview-2, image rotations, Karimunjawa archipelago.

Introduction

Multispectral data have been successfully used to produce a relatively accurate benthic habitats map in optically shallow water area at various classification scheme complexities [Andrefouet et al., 2003; Fonseca et al., 2010; Phinn et al., 2012; Roelfsema et al., 2013]. In addition to the existing benthic habitats mapping of medium spatial resolution data such as Landsat series, SPOT series, and ASTER [Capolsini et al., 2003; El-Askary et al.,
2014], high spatial resolution multispectral data such as Quickbird, IKONOS, Geoeye-1 and Worldview-2 have added the depth of remote sensing application on benthic habitats mapping [Mishra et al., 2006; Vahtmae et al., 2011; Cerdeira-Estrada et al., 2012; Phinn et al., 2012]. The variations of sensor spatial resolution have covered wide range of user needs and management scopes. In Indonesia, benthic habitats mapping is not widely performed and most benthic habitats maps produced by government institution did not report accuracy assessments. In addition, only several areas of interest such as Karimunjawa Islands were mapped intensively [Wicaksono, 2014; Murti and Wicaksono, 2014]. However, only several main islands in Karimunjawa Islands were mapped. Benthic habitats with rich biodiversity in east parts of Indonesia are yet to be mapped, which open the gap for more researches in these areas.

The developments of benthic habitats mapping techniques are strongly correlated to the improvement of sensors spectral resolution due to the high dependency of the methods to the sensor spectral configuration and the complexity of benthic environments [Hedley et al., 2012]. Some researchers try to improve the accuracy of benthic habitats mapping by incorporating hyperspectral data [Velloth et al., 2014], utilizing robust classification techniques [Phinn et al., 2012; Roelfsema et al., 2013], integrating various datasets such as MODIS and Landsat [Hu et al., 2014], integrating airborne LIDAR, hyperspectral and swath sonar [Pe’eri et al., 2013], and using active remote sensing systems such as multibeam echo sounder [Costa and Battista, 2013]. All these researchers attempt to improve the accuracy of benthic habitats mapping for various reasons. The most common issues are the low overall accuracy for mapping at high thematic resolutions, user-friendliness, repeatability, time and cost effectiveness, and the high demand of resources required to do more accurate mapping.

Beside due to the complexities of the benthic habitats environment, multispectral bands have limited capability to map benthic habitats due to the inadequacy of water penetration bands. In addition, water penetration bands are located at shorter wavelengths; hence the noises are higher and the signal-to-noise ratio is lower [Eugenio et al., 2015]. Consequently, multispectral bands are not effective for mapping benthic habitats more than seven classes [Benfield et al., 2007]. Multispectral images are generally only able to confidently map benthic habitats at the most general level i.e. coral reefs, seagrass, macro algae, and sand [Green et al., 2000; Capolsini et al., 2003; Goodman et al., 2013]. Even high spatial resolution data is facing difficulties to map benthic habitats with more than ten classes [Mumby and Edwards, 2002]. Hyperspectral images can be used to perform accurate benthic habitats mapping at detailed level [Zhang et al., 2013], however, the promising use of hyperspectral data is hindered by the availability and cost-effectiveness of this data. Moreover, the application of hyperspectral data to map benthic habitats at detailed level scheme (>10 classes) is also limited, and thus their full potential is yet to be determined [Lesser and Mobley, 2007; Zhang et al., 2013].

The application of full radiometric corrections to remove atmospheric path radiance, sunglint, and water column effect by incorporating radiation transfer model and inverse model is not practical and time consuming [Joyce et al., 2013]. Despite the robustness of methods and corrections performed to improve the accuracy of benthic habitats mapping, the accuracy of multispectral-based benthic habitats mapping at detailed scheme remain limited, especially at species level complexity [Green et al., 2000; Goodman et al., 2013].
The data required to perform full radiometric corrections are not widely available and easily accessible, hence limiting the replication of the mapping approach. Therefore, it is necessary to improve the approach to map benthic habitats so that it can be more effective. Effective mapping can be achieved when an accurate map can be produced with the minimum resources required [Joyce et al., 2013], so that the process can be replicated over time and space. Accurate benthic habitats map obtained from complex image processing procedure may not be able to be replicated elsewhere. In most cases, it is difficult to obtain supporting data as such to perform complex radiometric correction, and the only available data is the image itself and field benthic data. In this paper, a simple, fast and repeatable approach to improve the accuracy of benthic habitats mapping using Principle Component Analysis (PCA) and Independent Component Analysis (ICA) was proposed.

Image rotation techniques such as PCA [Hedley and Mumby, 2003; Shapiro and Rohmann, 2005; Herkul et al., 2013] can be used to assist benthic habitats mapping. PC (Principle Component) bands can be used directly in the digital classification process instead of the original spectral bands in order to produce accurate benthic habitats maps [Wicaksono and Murti, 2011; Tran et al., 2012]. However, the use of IC (Independent Component) bands for benthic habitats mapping has not been reported. Both PCA and ICA transform the input spectral bands to produce new and uncorrelated set of bands with reduced dimension but more efficient information as well as reducing noises [Kattenborn et al., 2015]. The resulting PC and IC bands are the combination of the input spectral bands.

The main objective of this research is to present the benefit of applying PCA and ICA on improving the accuracy of benthic habitats mapping using Worldview-2 multispectral data. There was no previous publication that specifically addresses the effect of PCA and ICA application on benthic habitats mapping. Furthermore, research on the capability of noise removal algorithm on benthic habitats mapping is still limited [Zhang et al., 2013]. PCA and ICA rotations do not require additional data apart from the statistics of the image and were used to exploit the spectral performance of Worldview-2 pixels. Benthic habitats variations at three different levels of complexities were used to compare the classification accuracy of Worldview-2 original multispectral bands, sunglint-free bands (hereafter deglint bands), water column corrected bands, and rotated bands.

Benthic habitats of Kemujan Island were selected as the study area (Fig. 1). The Karimunjawa archipelago is located in the Java Sea between Java and Kalimantan, Indonesia. Kemujan Island encompasses a complex reef morphology including reef flats, shallow lagoons, patch reefs, back reefs, reef crests, fore reefs, escarpments, and shelf in the western parts, and reef flats, reef crests, and escarpments in the eastern parts. Kemujan Island also shelters great biodiversity of benthic habitats. According to Nababan et al. [2010], there are 9 species of seagrass, 69 genera of coral reefs and unreported numbers of macro algae species found in Karimunjawa Islands. This benthic habitat biodiversity is representative and suitable to test the performance of remote sensing data and techniques to perform benthic habitats mapping.
Improving the accuracy of benthic habitats mapping

Wicaksono

436

Methods

Image Data

The Worldview-2 image used in this research was acquired on 24th May 2012. It has three standard water penetration bands (blue, green, and red) and new additional water penetration bands (cyan, yellow and red-edge). These additional new bands can be very useful in assisting the process of information extraction in the complex environment of benthic habitats. It also has two near infrared bands, which is required to perform sunglint correction and is useful for mapping shallow submerged aquatic vegetation.

The image was obtained at 2 m spatial resolution and 16-bit radiometric resolution (2 byte per pixel). However, the original dynamic range of the Worldview-2 image is 11-bit (0-2048).

Worldview-2 image was selected because it is currently the best multispectral image available. The recently available Worldview-3 image has a better specification than Worldview-2, however, the number of water penetration bands is similar [Digital Globe, 2014]. Worldview-3 is special for its newly introduced short wave infrared bands. Thus, Worldview-2 image is still a good representative for setting the baseline for the accuracy of benthic habitats mapping using multispectral images. Table 1 provides the specification of the Worldview-2 image used in this research.
Table 1 - The specification of the Worldview-2 image of Kemujan Island used in this research. ESUN (Mean solar exoatmospheric irradiance) values and the formula to calculate Earth-sun distance (d) were adapted from Updike and Comp [2010]. Other information was taken from image header.

| Name                  | Worldview-2 | d (AU) | 1.025 AU (Astronomical Unit) |
|-----------------------|-------------|--------|-----------------------------|
| Date of acquisition   | 24th May 2012 |        |                             |
| Sun elevation         |             |        |                             |
| Time of acquisition   | 10:18:25 local time |        |                             |
| Sun zenith            |             |        |                             |
| Spectral bands        |             |        |                             |
| Wavelength (µm)       | Coefficient of calibration (W/m² str count) | ESUN (W/m² µm) |
| Cyan                  | 0.400 – 0.450 | 0.009295654 | 1580.8140 |
| Blue                  | 0.450 – 0.510 | 0.01783568 | 1758.2220 |
| Green                 | 0.510 – 0.580 | 0.01364197 | 1974.2416 |
| Yellow                | 0.585 – 0.625 | 0.005829815 | 1738.4791 |
| Red                   | 0.630 – 0.690 | 0.01103623 | 1559.4555 |
| Red-edge              | 0.705 – 0.745 | 0.005188136 | 1342.0695 |
| NIR1                  | 0.770 – 0.895 | 0.01224380 | 1069.7302 |
| NIR2                  | 0.860 – 1.040 | 0.009042234 | 861.2866 |
| Coordinate system     | UTM Zone 49 M |        |                             |
| Projection system     | UTM         |        |                             |

**Field survey**

Field benthic habitats data were collected using photo-transect method [Roelfsema and Phinn, 2009]. The locations of the transect were determined based on the variation of benthic habitats as visually seen from true colour composite of the Worldview-2 image and local knowledge. Benthic habitat photos were taken directly under the water surface by snorkelling along the transect. Benthic habitat photos were taken every three paddles of the snorkeler (±2 m intervals). Coordinates of the surveyed transects and photos taken were recorded using the Global Positioning System (GPS) Garmin Map 76CSx placed inside waterproof dry bag floating on the water surface. The dry bag was towed to the snorkeler. The process of linking the photo and the coordinates in GPS was done manually by identifying and matching the time in the photo metadata and GPS readings. In total, 7 transects were surveyed and 894 samples were collected (Fig. 2). 447 samples were used to train the image via per-pixel image classification algorithms and the remaining samples were used to perform accuracy assessment. Photo samples were interpreted based on the composition of benthic habitats. Afterwards each sample was labelled according to the corresponding class in each level of the classification scheme. These samples were also used as the basis for the construction of benthic habitats hierarchical classification schemes.
Based on the variation of benthic habitats insitu, two levels of benthic habitat classification schemes were constructed. The first level scheme (hereafter major level) consists of major benthic habitats. These habitats are “Coral Reefs”, “Seagrass”, “Macro Algae”, and “Bare Substratum”. These are the most common benthic habitat classes in the existing benthic habitats classification schemes [Mumby and Harborne, 1999; Phinn et al., 2012]. The class descriptor of these classes is widely agreed, and there was almost no confusion in the process of labelling the field samples based on these classes.

Benthic habitats composition was selected as the class descriptor for the detailed level scheme. It is the most consistent class descriptor possible for the high biodiversity of benthic habitats in the study area. There are many possible descriptors that can be used to further detail the major level scheme such as habitats abundance (density, percent cover), species, life-form, and pigment variations. However, not all habitats can be detailed with similar class descriptors, at least from a satellite-based multispectral remote sensing point of view. For example, seagrass [Phinn et al., 2008; Roelfsema et al., 2014] and macro algae [Kutser et al., 2006; Oppelt et al., 2012; Wicaksono, 2014] could be detailed into species
level, but not possible for coral reefs class as the species variation of coral reefs could not be resolved with the satellite remote sensing image available today [Goodman et al., 2013], unless we used hyperspectral measurement on very high spatial precision [Hochberg and Atkinson, 2000, 2003; Lucas and Goodman, 2015]. On the other hand, it might be possible to use the life-form as a working class descriptor for seagrass [Wicaksono and Hafizt, 2013] and coral reefs [Mumby and Harborne, 1999], but not for macro algae since their life-form such as turf, calcareous and coralline is very difficult to be identified spectrally using multispectral image, especially when different life-forms contain similar characteristics of pigmentation [Wicaksono, 2014].

Ideally, since visible bands as the water penetration bands are sensitive to the variation of pigments composition and concentration [Penuelas et al., 1993], the detailed classification scheme should be constructed based on the variation of pigmentation characteristics of coral reefs, seagrass and macro algae. However, seagrass leaves are mostly dominated by chlorophyll (hence the dominant colour is green) and the variation of species determines the variation of chlorophyll concentration contained in seagrass leaves [Clores and Carandang VI, 2013]. When the class descriptor of seagrass classes is the variation of chlorophyll concentration instead of the variation of major pigments such as fucoxanthin (brown) or phycoerythrin (red) as in macro algae, the classification scheme will be difficult to adapt due to the limitation of multispectral bands and sensor spatial resolution. Therefore, the most feasible and consistent benthic habitats classification scheme for remote sensing data is based on benthic habitats composition. Using benthic habitats composition as the class descriptor is unambiguous, more consistent and widely applicable. Table 2 shows the two levels of benthic habitat classification schemes.

Table 2 (Continued on the next page) - Hierarchical benthic habitats classification scheme constructed based on the variation and composition of benthic habitats in situ. For example, the “Coral Sand” class represents an area with ±70% of coral reefs (alive but mainly living coral reefs) and ±30% of carbonate sand, and vice versa.

| Major          | Detailed          | Class descriptor                                                                 |
|----------------|-------------------|----------------------------------------------------------------------------------|
| Macro Algae    | Algae Coral       | Macro algae (any species, ±70%), Coral reefs (live but mainly dead, sand or rubble may present, ±30%) |
|                | Algae Rubble      | Macro algae (any species, ±70%), Rubble (sand may present, ±30%)                 |
|                | Algae Sand        | Macro algae (any species, ±70%), Sand (rubble may present, ±30%)                |
|                | Algae Seagrass    | Macro algae (any species, ±70%), Seagrass (any species, sand or rubble may present ±30%) |
|                | Macro Algae       | 100% Macro algae (any species, sand or rubble may present)                       |
Table 2 (Continued from preceding page) - Hierarchical benthic habitats classification scheme constructed based on the variation and composition of benthic habitats in situ. For example, the “Coral Sand” class represents an area with ±70% of coral reefs (alive or dead, but mainly living coral reefs) and ±30% of carbonate sand, and vice versa.

| Major            | Detailed            | Class Descriptor                                                                 |
|------------------|---------------------|----------------------------------------------------------------------------------|
| Bare Substratum  | Sand Algae          | Sand (rubble may present, ±70%), Macro algae (any species, ±30%)                |
|                  | Sand Coral          | Sand (rubble may present, ±70%), Coral reefs (live or dead, ±30%)               |
|                  | Sand Rubble         | Sand (thin layer of macro algae may present, ±70%), Rubble (thin layer of macro algae may present, ±30%) |
|                  | Rubble Algae        | Rubble (sand may present, ±70%), Macro algae (any species, ±30%)               |
|                  | Rubble              | 100% Rubble (thin layer of macro algae and sand may present)                    |
|                  | Sand                | 100% Sand (rubble and thin layer of macro algae may present)                    |
|                  | Sand Seagrass       | Sand (rubble may present, ±70%), Seagrass (any species, ±30%)                  |
| Coral Reefs      | Coral Rubble        | Coral reefs (live or dead, mainly live, ±70%), Rubble (sand and thin layer of macro algae may present, ±30%) |
|                  | Coral Sand          | Coral reefs (live or dead, mainly live, ±70%), Sand (rubble and thin layer of macro algae may present, ±30%) |
|                  | Coral Reefs         | 100% Coral reefs (rubble, sand and macro algae may present)                    |
|                  | Coral Algae         | Coral reefs (live or dead, mainly live, ±70%), Macro algae (rubble and sand may present, ±30%) |
| Seagrass         | Seagrass Algae      | Seagrass (any species, ±70%), Macro algae (epiphytes, sand, and rubble may present, ±30%) |
|                  | Seagrass Sand       | Seagrass (any species, ±70%), Sand (epiphytes, macro algae, and rubble may present, ±30%) |

**Image Corrections**

Worldview-2 DN values were converted into the Top-of-Atmospheric (TOA) spectral radiance and reflectance using method described in Updike and Comp [2010]. The TOA reflectance image was atmospherically corrected using the Dark Subtraction method using optically deep water pixels as the dark target [Chavez et al., 1977]. Sunglint in visible bands of Worldview-2 is apparent and significantly alters the reflectance of benthic habitats in most parts of the scene, and thus, it should be minimized (Fig. 3). Sunglint was removed using formula incorporating near infrared bands as described in Hedley et al. [2005] and reviewed by Kay et al. [2009]. Since the Worldview-2 image
has two near infrared bands, the selection of the best near infrared band for correcting sunglint in visible bands was performed. Each visible band was regressed with both near infrared bands. The data for regression analysis are optically deep water reflectance at various sunglint intensities. The regression analysis was conducted to obtain the slope of regression (the gradient of calibration) necessary to remove sunglint in visible bands using near infrared band. The regression analyses show that the NIR1 band produced higher $R^2$ (coefficient of determination) for cyan, blue, green, and red band, while the NIR2 band produced higher $R^2$ for the yellow and red-edge band. The slope of regression is 0.383, 0.590, 0.953, 1.481, 0.902, and 1.416 for the cyan, blue, green, yellow, red, and red-edge band respectively. Another input for sunglint correction is the minimum reflectance of optically deep water in the near infrared band, which is 0.005 and 0.004 for NIR1 and NIR2 band respectively. Using these values and the formula described in Hedley et al. [2005], sunglint in Worldview-2 visible bands were removed (Fig. 3).

![Figure 3 - Comparison of the Worldview-2 image prior and after sunglint correction. Due to the high spatial and radiometric resolution of the Worldview-2 image, sunglint is visible across the scene. After the correction, most sunglint effects were removed from the scene, and the underlying benthic habitats information was greatly revealed.](image)

The water column effect, which leads to the variation of benthic habitats reflectance at various depths, was compensated using the Depth Invariant Bottom Index (DII) [Lyzenga, 1978] and the Inversed Model (IM) [Wicaksono and Hafizt, 2013]. To perform water column correction using DII method, the reflectance of benthic habitat located at different depths is required, for which it is necessary to create a scatter plot between band pairs and to derive the ratio of water column attenuation coefficients for each band pair. In this research, sand reflectance at different depths, which is easier to interpret at different depths compared to coral reefs, seagrass and macro algae, was preferred. True colour composite of deglint bands was used to assist the selection of sand pixels located at different depths.
using visual interpretation. As the depth increases, the appearance of sand pixels gradually change from bright white to dark blue, which made the interpretation easier. In total, 15 DII were derived from six visible bands of Worldview-2 deglint bands.

In order to run the IM algorithm, the water depth of each pixel, the water column attenuation coefficient for each band and the reflectance of clear optically deep water are required. These inputs were derived empirically by integrating field data into the image. Empirical modelling was used to convert Worldview-2 pixel values into water depth information. This was done by performing correlation and regression analysis between band ratios and field bathymetry data. The detail and measurement procedure of the field bathymetry data used in this research is described in Wicaksono [2015]. The optically shallow water area of Kemujan Island was categorized into seven depth ranges: 0-1 m, 1-2 m, 2-3 m, 3-4 m, 4-7 m, and 7-18 m. Most benthic habitats in Kemujan Island are located in water shallower than 7 while 18 m is the maximum depth of penetration of visible bands in Kemujan Island water [Wicaksono and Hafizt, 2013]. In order to minimize error propagation in the water depth estimation, the regression analysis was carried out individually for each depth range instead of the whole depth range. Thus, each specific depth range has its own prediction model where the resultant regression function is only effective for the corresponding depth. As an example, the predicted water depth from the regression model built from 0-1 m depth data is only valid for modelled depth shallower than 1 m. Any depth values beyond 1 m obtained from this model is considered to be invalid and therefore masked out. This rule applies similarly for other depth ranges.

The final and complete bathymetry data (Fig. 4) were obtained by combining the modelled bathymetry of different depth ranges using rules created on the Decision Tree Analysis module on ENVI software. The mean SE (standard error of estimate) of the final modelled bathymetry data is 0.74 m. The lowest SE is 0.17 m from modelled bathymetry at 0-1 m using the ratio of green/red and the highest SE is 3.01 m from modelled bathymetry at 7-18 m from the ratio of blue/green. The SE for other depth ranges is 0.19 m (ratio blue/yellow, 1-2 m), 0.24 m (ratio cyan/red, 2-3 m), 0.32 m (ratio green/red, 3-4 m), and 0.78 m (ratio yellow/red-edge, 4-7 m). Figure 4 shows bathymetry map modelled from the Worldview-2 image.

The water column attenuation coefficient for each band ($k$) was compiled from previous researches. The value for the blue, green, and red band is 0.018, 0.072, and 0.178 m$^{-1}$, respectively [Wicaksono and Hafizt, 2013]. These values were calculated using the modified Jupp [1988] bathymetry model. The value of $k$ for cyan (0.009 m$^{-1}$), yellow (0.075 m$^{-1}$), and red-edge (0.381 m$^{-1}$) was compiled from Bukata et al. [1995]. We did not perform the actual calculation of $k$ for cyan, yellow, and red-edge band because we do not have enough data for these wavelengths.

The reflectance of clear optically deep water was obtained from manual pure pixel analysis via visual interpretation. Clear water pixels were selected visually on true colour composite of the Worldview-2 deglint bands, which is any water pixel free of sunglint, thin layer of haze, clouds, suspended materials, and benthic habitats reflectance. Clear water reflectance for the cyan, blue, green, yellow, red and red-edge band is 0.002, 0.011, 0.015, 0.005, 0.003, and 0.003 respectively. From this information, the effect of water column in each deglint band was corrected using the IM formula as described in Wicaksono and Hafizt [2013].
The issue of benthic habitats mapping using multispectral image is the limitation of water penetration band to detect the variations of coral reefs, seagrass, macro algae and bare substratum. As seen from Figure 5, although the benthic habitats reflectance has been isolated from additional reflectance, the variation of benthic habitats is still difficult to be identified visually and spectrally due to sunglint and water column effects. Therefore, to overcome this limitation, image rotation technique was used.

**Image Rotation**

The issue of benthic habitats mapping using multispectral image is the limitation of water penetration band to detect the variations of coral reefs, seagrass, macro algae and bare substratum. As seen from Figure 5, although the benthic habitats reflectance has been isolated from additional reflectance, the variation of benthic habitats is still difficult to be identified visually and spectrally due to sunglint and water column effects. Therefore, to overcome this limitation, image rotation technique was used.

Image rotation is an image processing technique that transforms original data into new data. This is achieved by rotating the original spectral axes, and projecting the original pixel values into these new axes. These new axes encompass data variability of the original...
data [Richards, 1999]. The main purpose of most rotations is to obtain an image with better information representation and interpretation. In this research, two image rotations techniques namely PCA [Richards, 1999] and ICA [Hyvarinen and Oja, 2000] were utilized. PCA and ICA rotation were applied on both deglint and water column corrected bands of Worldview-2. All visible bands of deglint bands were used as PCA and ICA input. Hereafter, PC and IC bands refer to the result of PCA and ICA on deglint bands, respectively. All 15 bands of DII and six visible bands of IM were used in the PCA and ICA rotations. The results of PCA and ICA on DII are called DII-PC bands and DII-IC bands, while on IM are called IM-PC bands and IM-IC bands. The number of the resulting PC and IC bands is similar to the input bands. Useful components can be identified from the eigenvalues; nevertheless, the first three components usually contain most information. The inputs for PCA and ICA are the statistics of the input bands such as the mean, variance-covariance matrix, correlation matrix, eigenvectors, and eigenvalues [Richards, 1999]. The main difference between PCA and ICA is the method for producing the new dataset, where ICA utilizes more robust processing steps than PCA. By utilizing non-Gaussian assumption of the independent inputs and statistical algorithms at higher order, ICA can be used to reveal intrinsic and minor information of the image [Hyvarinen and Oja, 2000]. PCA is less sensitive to the objects of interest occupying small parts of the image. These rotations operate locally, which means that applying PCA or ICA on different pixels composition will result in significantly different results. Since this research only focussed on benthic habitats of optically shallow water, the land and optically deep water pixels were masked out during PCA and ICA. The masking process was performed by finding the threshold between land, optically shallow water, and optically deep water pixels in PC2 (Principle component band with the second highest variance) histogram. This was done by repeatedly identifying the minimum and maximum limit of various normal curves of the PC2 histogram. Compared to other PC bands, PC2 has the most distinctive threshold for optically shallow water, optically deep water, and land pixels. In other PC bands, the value for these three objects is overlapping, and thus it was impossible to generate a good optically shallow water masking image. From this analysis, the threshold for masking out land pixels and optically deep water was determined to be lower than -0.201 and higher than 0.097, respectively. In PC2, values between -0.201 and 0.097 are optically shallow water pixels. This mask image was also applied to speed up the classification process. The result of PCA and ICA are shown in Figure 5. The variation of benthic habitats types is now more apparent, shown by the variation of colours in the colour composite image of the PC and IC bands. Using these PC and IC bands, preliminary information about benthic habitats variation in the study area can be identified prior to the field survey, and this greatly assists the determination of the sampling location. Although the types of benthic habitats represented by pixels with different colours could not be determined yet, we were confident that the variation of benthic habitats in Kemujan Island is not limited to coral reefs, seagrass, macro algae and sand. Thus, applying image rotations may improve the chance of having a good and representative sample distribution across the study area.
Figure 5 - The comparison of RGB colour composite images of Worldview-2 image of Kemujan Island. It is still difficult to detect the variation of benthic habitats in non-rotated images (deglint bands, DII, IM). In the colour composite image of PC bands and IC bands, the variation of benthic habitat types are well represented by different colours.

**Image Classifications**

Minimum distance, mahalanobis distance and maximum likelihood classifiers were used to classify the Worldview-2 image using field benthic habitats data collected from geo-referenced photo-transect samples. Each of these classification algorithms was run to classify benthic habitats using deglint bands, PC bands, IC bands, DII, DII-PC bands, IM, and IM-PC bands. Since the main objective of this research is to exploit the spectral performance of multispectral data, no Object-Based Image Analysis (OBIA) approach was incorporated. Only per-pixel classification algorithms --which solely utilize spectral band performance--, were applied. The use of per-pixel classification algorithms has several benefits. First of all these per-pixel classification algorithms are provided in most image processing software, hence widely applicable. Moreover, the accuracy assessment procedure for per-pixel classification results is more established [Congalton, 1991; Foody, 2004; Congalton and Green, 2009]. OBIA provides a new perspective in the pixels clustering process by incorporating additional information such as texture, shape, pattern, size, and
external sources such as slope steepness, slope aspects, and bathymetry, to classify the object of interest. However, this approach is less applicable (need more resources including time, cost, skill, software, and hardware) and the procedure for assessing the accuracy of OBIA for benthic habitats mapping is more complicated where it is difficult to obtain ground truth data to match the spectral and spatial aspects of OBIA result [MacLean and Congalton, 2012]. Although it is possible to create a ground truth map for land cover or landuse classification, it is almost impossible to create a benthic habitats ground truth map, especially at higher class complexities. In addition, spectral performance evaluation of remote sensing image can only be done from per-pixel classification results, where the only variable is the spectral band. When OBIA was used, it is difficult to evaluate and determine whether the classification accuracy is the function of image spectral bands or other radiometric and spatial factors.

Benthic habitats samples not incorporated in the classification process were used to assess the accuracy of image classification results using the confusion matrix analysis [Congalton and Green, 2009]. The use of independent samples to assess the accuracy of classification results is very important to avoid a biased conclusion, mainly due to the overestimated classification accuracy. Producer and user accuracy were also reported to identify classes with high misclassification rate. Last, the McNemar test was conducted to compare the accuracy of classification results [de Leeuw et al., 2006]. This test was used to draw the conclusion whether the application of PCA or ICA significantly improves the accuracy of benthic habitats mapping.

**Results and discussion**

**Results**

PCA and ICA rotation produced uncorrelated bands, and intrinsic information is possibly placed on the later components. Therefore, not only the first three components with the highest variance were used. Instead, all six components were included interchangeably as the classification input. In general, Maximum Likelihood application on PC bands produced the most accurate benthic habitat maps at major and detailed benthic habitats classification schemes. The classification accuracy from Mahalanobis Distance and Minimum Distance followed respectively. The results of the mapping are as follow.

At major level, DII-PC and PC bands yielded the best results with 65.9% and 65.5% overall accuracy. DII-IC bands and deglint bands followed with 64.8% and 64.0% overall accuracy (Fig. 6). Based on the McNemar test, these classification results were not significantly different. From Figure 7 we could see that all classes in the Level 1 scheme produced relatively consistent accuracy, shown by the small differences between User and Producer Accuracy of each benthic class.

The “Macro Algae” class has the lowest User (55.8%) and Producer Accuracy (38.4%). This tell us that only 55.8% chance of pixel classified as macro algae is actually macro algae in the field, and only 38.4% macro algae in the field are correctly classified. This class was highly misclassified to “Coral Reefs” and “Seagrass” due to the existence of photosynthesizing pigments within their tissue [Hochberg and Atkinson, 2000, 2003]. Coral Reefs also contained algae of various pigments within their polyp, hence resulting almost similar coloration and spectral response to macro algae [Hochberg and Atkinson, 2000, 2003]. The reflectance of the thin layer of macro algae covering the bare substratum
is also overwhelmed by the higher reflectance of rubble or sand, hence the reflectance of some macro algae pixels resembles strongly carbonate sand. As a result, the extent of the “Macro Algae” class in the classification result is highly underestimated as shown by its low producer accuracy. Most macro algae were classified as “Coral Reefs”, “Seagrass” or “Bare Substratum”. Conversely, the extent of other classes is overestimated. At this level, the use of image rotations may not significantly improve the mapping accuracy because the classification scheme complexity is still low (Fig. 6).

![Figure 6 - Overall accuracy comparison between input bands for mapping benthic habitats at the major level classification scheme. DII-PC bands produced the highest classification accuracy with 65.9% overall accuracy. However, the accuracy differences between input bands were not significant, except for the significantly lower accuracy of IM, IM-PC bands and IM-IC bands. The average classification accuracy for mapping benthic habitats at the Level 1 scheme is 53.9 ± 4.3% CL95% (Confidence Level 95%).](image)

![Figure 7 - Producer and user accuracy of the most accurate benthic habitat map at major level scheme. This was obtained using maximum likelihood classification on DII-PC bands (65.9%).](image)
At detailed level, the classification accuracy decreased significantly for all inputs. Nevertheless, PC bands are the best performer with 36.7% overall accuracy (Fig. 8). DII-PC bands came as the second most accurate with 34.2% overall accuracy. IC bands and deglint bands followed with 29.9% and 28.3% overall accuracy respectively. The accuracy from DII-PC and PC bands was significantly higher than from IC and deglint bands. This is mainly due to the capability of PC bands to better classify the “Sand Coral”, “Coral Sand”, and “Seagrass Sand” classes than IC bands and deglint bands.

Figure 8 - Overall accuracy comparison between input bands for mapping benthic habitats at detailed level classification scheme. The highest classification accuracy was obtained from PC bands using the maximum likelihood classification (36.7%). The average classification accuracy for mapping benthic habitats at the detailed level scheme is 21.0 ±3.1% (CL95%).

Classes composed of particular benthic habitats with different coverage composition became the source of the high misclassification rate, which lead to the low mapping accuracy. For example, “Sand Rubble” was confused with “Rubble” (misclassification rate = 33.3%), “Sand” was misclassified as “Sand Algae” (34.0%), “Algae Sand” was mainly misclassified as “Sand Algae” (36.1%), “Macro Algae” was confused with “Algae Seagrass” (30.0%), “Seagrass Algae” with “Macro Algae” (35.3%), “Algae Coral” with “Rubble” (27.3%), “Coral Reefs” with “Coral Algae” (26.5%), and “Rubble” with “Coral Algae” (18.5 – 20.0%). Other misclassifications are below 20% but distributed evenly across classes. The rate of misclassification in this detailed benthic habitats mapping was higher than at major level, which lead to the low user and producer accuracy for each benthic class (Fig. 9). As expected, as the class complexity increases, the mapping is getting more difficult and the accuracy is getting lower.
Due to the low and inconsistent producer and user accuracy of the detailed level classification results, we reconstructed the scheme by combining several spectrally and ecologically similar benthic classes of the detailed level scheme. This new scheme is called an intermediate level (Tab. 3). The new reconstructed benthic habitat classes are “Algae Sand”, “Coral Sand”, and “Sand Rubble” class. The “Algae Rubble” and “Algae Sand” classes were combined into the “Algae Sand” class. Similarly, “Coral Rubble” and “Coral Sand” were also merged into the “Coral Sand” class. The “Sand Rubble”, “Rubble Algae” (thin layer of macro algae covering the rubble), “Rubble”, and “Sand” classes are spectrally similar, hence combined. The spatial distribution of “Rubble” and “Sand” are not always distinct and they produce almost identical spectral response since they both originated from calcium carbonate. Consequently, most classes associated with “Rubble” and “Sand” have low and inconsistent user and producer accuracy (Figs. 9 and 11). In total, there are 13 benthic habitats classes in the intermediate level scheme.

At this scheme, PC bands also produced the most accurate benthic habitats map (Fig. 10). Maximum Likelihood classification on PC bands managed to obtain 40.0% overall accuracy and is slightly higher than from DII-PC bands with 38.3% overall accuracy. These accuracies are significantly higher than the results from deglint bands or IC bands, which was only 30.9%. These 10% differences mainly came from the capability of PC bands to better differentiate the “Coral Reefs” class and the “Seagrass Sand” class from the surrounding benthic habitats classes.
Table 3 - Intermediate classification scheme constructed from spectrally and ecologically similar detailed benthic habitats classes.

| Detailed                  | Intermediate               |
|---------------------------|----------------------------|
| Algae Coral               | Algae Coral                |
| Algae Rubble              | Algae Sand                 |
| Algae Sand                | Algae Seagrass             |
| Algae Seagrass            | Macro Algae                |
| Macro Algae               | Sand Algae                 |
| Sand Algae                | Sand Coral                 |
| Sand Coral                | Sand Rubble                |
| Sand Rubble               | Sand Algae                 |
| Rubble Algae              | Sand Coral                 |
| Rubble                    | Sand                        |
| Sand                      | Sand Seagrass              |
| Sand Seagrass             | Coral Rubble               |
| Coral Rubble              | Coral Sand                 |
| Coral Sand                | Coral Reefs                |
| Coral Reefs               | Coral Algae                |
| Coral Algae               | Seagrass Algae             |
| Seagrass Algae            | Seagrass Sand              |
| Seagrass Sand             |                             |

Maximum likelihood, which utilizes probability analysis to classify pixels into benthic classes, produces higher accuracy than other classification algorithms. Nevertheless, while the assumption of normal Gaussian distribution of feature class in the spectral space is not always met and correct [Su and Huang, 2009], this classifier still manages to produce higher accuracy. Minimum distance algorithm produces the lowest accuracy, especially at intermediate and detailed level scheme because the clustering of pixels based on the shortest distance is not effective on complex classes where the cluster centroid of benthic habitats classes are close to each other. Misclassification issues due to the variation of benthic habitats coverage composition and the similarity of class descriptor, reflectance, and pigmentation are still the issue but less prominent at this new scheme. Figure 11 shows that the user and producer accuracy show better consistency than those from detailed level scheme. In the classification result, “Algae Coral” was mostly misclassified as “Coral Algae” (20.8%) and “Algae Sand” was highly misclassified as “Sand Algae” (30.6%). Benthic habitats with similar pigmentation were also misclassified due to the limitation of sensor descriptive resolution. The “Coral Reefs” class was confused with “Coral Algae” (23.9-27.3%), The “Algae Seagrass” was misclassified as “Macro Algae” (18.6-25.0%), and “Sand Seagrass” with “Sand Algae” (17.9%). It was also quite difficult to differentiate “Sand Algae” and “Sand Rubble” (32.4%). Despite the class descriptor, the actual reflectance is almost similar. The “Sand Rubble” class is the combination of “Sand Rubble”, “Rubble Algae”, “Rubble” and “Sand” from the detailed
scheme. “Rubble Algae” is almost similar to “Sand Algae”. Therefore, the spectral range of this class is quite wide and this class also includes “Rubble Algae”. Furthermore, rubble in the study area is highly covered by turf and fleshy algae, hence, resembles macro algae reflectance. Consequently, “Sand Rubble” and “Sand Algae” were highly misclassified with each other. “Sand Rubble” was also misclassified as “Sand Coral” due to the similarity of reflectance between macro algae and coral reefs (14.8-18.8%). The resulting benthic habitats maps are shown in Figures 12, 13, and 14.

**Figure 10** - Overall accuracy comparison between input bands for mapping benthic habitats at the intermediate level classification scheme. The highest classification accuracy was obtained from PC bands using the maximum likelihood classification (40.0%). The average classification accuracy for mapping benthic habitats at intermediate level scheme is 25.0±3.3% (CL95%).

**Figure 11** - Producer and user accuracies of the most accurate benthic habitat map at the intermediate level scheme. This was obtained using maximum likelihood classification on PC bands (40.0%).
Figure 12 - The most accurate benthic habitats map at the major level scheme (DII-PC bands, Maximum Likelihood, overall accuracy 65.9%).

Figure 13 - The most accurate benthic habitats map at the intermediate level scheme (PC bands, Maximum Likelihood, overall accuracy 40.0%).
Discussion

In a nutshell, image rotations, PCA or ICA can be used to improve the accuracy of multispectral-based benthic habitats mapping. PC bands and IC bands derived from Worldview-2 visible bands produced higher accuracies with faster image processing and lesser resources requirement compared to water column corrected bands. As a result, benthic habitats mapping efforts can be made more effective and efficient. The mapping can be performed directly without normalizing the effect of water column and resolving the complex interaction between downwelling irradiance, water column, and benthic habitats absorption characteristics. This is a great benefit for user who wants to map benthic habitats with limited mapping resources. The result of this study is also coherent with the result from Zhang et al. [2013] where the application of water column correction did not improve the accuracy of benthic habitats mapping, which is mainly due to the relatively shallow area of the study area despite the bathymetry variation.

Worldview-2 advantages over other multispectral data are its spectral and spatial resolution, and applying image rotation techniques further enhanced these benefits. In this research, several image processing steps including sunglint correction, water column corrections, PCA and ICA were applied to Worldview-2 image. The resulting accuracy of the image from each step is different. The source of error for each data also varies accordingly. For deglint bands, the uncertainties and error sourced from the regression
model between visible and near infrared bands during sunglint correction process. It is possible that the near infrared bands are also slightly affected by sunglint. Therefore, the process of sunglint correction is not perfect and still left some noises in the resulting deglint bands. These deglint bands became the input in the water column correction process. There are two methods used to correct the effect of water column, the DII and IM. Water column corrected bands from these methods also produced significantly different accuracies, mainly due the source of the data used to perform the correction. DII produced image with better accuracy than IM because it does not require additional information other than the statistics of the object at different depths, which can be taken directly from the image. In the contrary, IM bands produced the lowest accuracy at all levels of benthic habitats classification schemes, mainly because the error from bathymetry modelling and water column attenuation coefficients estimation propagated within the algorithm and into the resulting IM bands. The main source of error for the estimation of water column attenuation coefficients and bathymetry is the absent of continuous tidal data in the study area, which is important to correct the depth measured during field survey and the depth at the time of the day of image acquisition. In addition, there is also a difference in the actual water condition and water condition represented by pixel of Worldview-2 image due to the time difference between field survey and satellite overpass. Consequently, this water column correction process adversely impacted the radiometric quality of deglint bands pixels. After the application of image rotations, especially PCA, the accuracy of benthic habitats mapping increased.

Other sources of error that can greatly affect the accuracy of the classification result, despite the methods, are the spatial displacement between GPS reading on the coordinates of field benthic data and the corresponding location in the image due to the differences in geolocational accuracy of Worldview-2 image and GPS (between 5-7 m). This is an issue not only encountered in this research but also in assessing the accuracy of image classification result in general [Congalton and Green, 2009]. In addition, environmental complexities of benthic habitats, the sub-pixel variation, and spectral mixing and heterogeneity of benthic habitats also provide challenge for remote sensing data to obtain better classification accuracy [Hedley et al., 2012; Joyce et al., 2013].

The application of PCA and ICA on Worldview-2 image, and supposedly on other passive remote sensing system images, can improve the accuracy and effectiveness of the mapping because PCA and ICA: 1) reveal the hidden and intrinsic information of the input spectral bands; 2) remove data redundancy, separating information from noises, and produce uncorrelated datasets so that each component provide unique information. This will highly enhance the speed of processing hyperspectral data and reducing the number of the field data required to perform classification using hyperspectral data. The benefit of removing noises from data during benthic habitats mapping was also experienced by Zhang et al. [2013]. The application of Minimum Noise Fraction (MNF) to remove noises from hyperspectral data managed to significantly improve the mapping accuracy and effectiveness [Green et al., 1988; Zhang et al., 2013]; 3) produce better contrast and colour variations, which means more benthic habitats can be identified better, so that we require less local knowledge or insitu data prior to mapping activities to understand the variation of benthic habitats in the study area. In addition, more colour variations mean more variation in the pixel value of PC and IC bands. Consequently, during classification, when
the training areas of each detailed benthic class correspond to the difference of colour, the rest of pixels will be classified accordingly. In contrast, when the colour variation is low, different benthic classes may be classified into the same category due to the inability to statistically separate these classes, which lead to the higher misclassification rate. Image with better colour variation will also improve the quality of field data spatial distribution, hence the obtained field data is more representative and the result of classification and accuracy assessment is more confident; 4) do not incorporate field data so that the chance of having propagated errors from empirical modelling is minimal, for example when compared to water column correction bands, which are very sensitive to the quality of the algorithm inputs.

As shown in Figure 15, as the class complexity increases, the use of rotated bands, especially PC bands, is getting more effective. At major level, where the complexity of the classification scheme is low, PC bands only provided slight accuracy improvement over deglint bands or DII (1.1%). However, at higher complexity schemes, PC bands managed to improve the accuracy of benthic habitats classification up to 8.4%. In the low complexity scheme, deglint bands and water column corrected bands also did well in separating and classifying the four major benthic classes. Therefore, PCA only provides slight accuracy improvement. In contrast, as the scheme become more complex, the non-rotated bands are having difficulties on separating the detailed variation of benthic classes and the accuracy decreased significantly compared to the major level scheme. By applying PCA or ICA solely on optically shallow water pixels, benthic habitats reflectance variation is maximized, and thus, detailed benthic habitats classes can be separated more clearly. As a result, compared to deglint and water column corrected bands, the decrease of accuracy due to the increasing classification scheme complexity is lower for PC and IC bands. Maximum likelihood produced the highest overall accuracy. However, for IM, Mahalanobis distance classification results have better accuracy. Mahalanobis distance algorithm has better stability to data that may have been altered such as water column corrected data, especially IM. Maximum Likelihood classifier performed better on data with better quality, hence, producing lower accuracy when using IM.

Interestingly, Worldview-2 PC bands performed better than the IC bands although IC bands have more advantages over PC bands. ICA should be able to identify minor information or benthic class better than PCA due to the algorithm capability to separate and differentiate minor information from noises. Non-Gaussian assumption used by ICA treats unique and minor pixels as information instead of noise. Thus, at higher complexities schemes, ideally, IC bands should produce higher classification accuracy than PC bands. Despite the benefits, ICA application on the Worldview-2 image was not very effective due to the benthic habitats mask that was put on during PCA and ICA rotation. Since the variations of pixel values have been limited to benthic habitats, PCA worked as powerfully to reveal hidden and minor features as ICA. At relatively homogenous category of pixels, covariance matrix based on Gaussian assumption of PCA produced better data variation and separability, hence producing higher accuracies.
Figure 15 – Accuracy difference in applying PCA and ICA to (a) Deglint bands, (b) DII, and (c) IM. The graphics show that 1) accuracy improvement of PCA and ICA is getting higher as the class complexities increases and 2) PC and IC bands are more effective when applying maximum likelihood classification. The graphics also show how the mapping accuracy decreases as the complexity of the classification scheme increases. The decrease in accuracy with increasing scheme complexity was also identified by Andréfouët et al. [2003] and Pu et al. [2012].
Accordingly, PCA and ICA are recommended to assist benthic habitats mapping activities using multispectral images. Benthic habitats maps with higher accuracy could be produced without understanding the concept of light passage within the water column and to collect additional field data such as bathymetry and water column attenuation coefficients. Furthermore, since PCA and ICA are purely based on statistics, they can be applied to any multispectral and hyperspectral images, not only to improve the accuracy of benthic habitats mapping, but also to map other natural resources such as vegetation biomass [Kattenborn et al., 2015; Wicaksono et al., 2016], to decrease the number of training area required to perform classification on hyperspectral images [Hedley and Mumby, 2003], and to detect changes of land or marine environment [Shapiro and Rohmann, 2005]. PCA and ICA can be applied to other regions, even with significantly different environmental characteristics. Nevertheless, the information contained in the resulting PC and IC bands is highly subjected to the variation of pixel values in the study area.

In this research, three levels of benthic habitats classification schemes were constructed. The most widely used and consistent benthic habitats classification scheme consists of a major benthic cover such as coral reefs, macro algae, seagrass, and bare substratum. Although these classes already provide us with a good overview of coastal area conditions, more detailed benthic habitats classes will provide us with more ecologically meaningful information of the coastal areas, including the health, threats, a shift in composition, and inter and intra-connection between habitats, which is an important information in the sustainable management of coastal areas. For example, having the “Coral Reefs” class (major level) and “Coral Rubble” (detailed level) may tell us different stories. The “Coral Reefs” class provides us with the information that a particular pixel is composed of coral reefs with no additional information if they are healthy, degraded, or dead. On the contrary, the “Coral Rubble” class tells us that there are rubbles in between coral reefs, meaning that a threat had happened to the coral reefs in the past. Rubbles are the evident of destroyed coral reefs, which may be caused by illegal fishing activities i.e. bombs, net, anchoring, boating, tourism, mining, or naturally occurring extreme environmental events. Multi temporal detailed benthic habitats map can also be correlated with the social economic conditions of the local people in order to allow us to identify and understand the process of interaction between human and coastal environment. The development of the intermediate scheme is necessary to bridge the level of detail in the major and detailed level scheme, as well as preserving detailed information in exchange to the classification accuracy. Indeed, the detailed level scheme provides the details required to better understand coastal environments and benthic habitats. However, with the current technology of multispectral data, there are many inconsistencies in the accuracy and spatial distribution of the mapped benthic habitats [Goodman et al., 2013]. Many classes in the detailed level scheme have low user and producer accuracy. The big differences between user and producer accuracy of some benthic habitats classes in the detailed level scheme also reflect that the extent of these classes is either underestimated or overestimated (Fig. 9). Therefore, to seek the balance between class accuracy and consistency and the level of mapping detail, the detailed level scheme was reconstructed to produce the intermediate level scheme. Classification results of the intermediate level scheme provide higher accuracy and lower differences between user and producer accuracy of each class in the scheme (Fig. 11). Finally, the availability of an accurate benthic habitats map is critical for various coastal management activities [Green et al., 2000; Eugenio et al., 2015]. Although the overall
accuracy obtained in this research appears to be low (<65%), other similar recent researches also reported that the accuracy for mapping complex benthic habitats cannot be so high. Eugenio et al. [2015] shows that Worldview-2 only produced 73% overall accuracy for less complex benthic environment. Therefore, the accuracy obtained in this study is good enough given the complexities of the study areas, the number of classes and also the minimum mapping resources compared to other researches. In addition, for Indonesia context, the overall accuracy of benthic habitats map at 4 categories is required to be at least 60% to be accepted and used as a base map for government and coastal management activities. Good benthic habitat maps may improve the ability to accurately and precisely perform change detection analysis of benthic habitats composition, which is very important to quantify coastal management impacts, such as tourism activities [El-Askary et al., 2014]. Accurate benthic habitats maps also mean better baseline data, which is very important for future monitoring, quantifying threats, and evaluation of management impacts of coastal areas [Zapata-Ramirez et al., 2013]. Furthermore, accurate benthic habitat maps can be used to better understand biophysical and biochemical processes and dynamics within benthic habitats, such as modelling carbonate production on reef systems [Hamilton et al., 2013] and seagrass beds productivity [Dierrsen et al., 2010].

Conclusions
The application of image rotation techniques on Worldview-2 multispectral image, especially PCA, managed to significantly improve the accuracy of benthic habitats mapping at different levels of benthic habitats classification schemes. The highest accuracy on each level of classification scheme was obtained from PC bands. PC and IC bands provide more accurate results than water column corrected bands. PC and IC bands also produced more accurate result when applying maximum likelihood classification algorithm. In addition, as the classification scheme complexity increases, the accuracy improvements are getting higher. Therefore, PCA or ICA is getting more effective as the mapping complexity increases, especially when the supporting empirical data for water column correction are not available. In short, PCA or ICA can be applied on multispectral data to increase the accuracy and effectiveness of benthic habitats mapping, especially at higher class complexities with fast, repeatable and less resources requirements.

There are several recommendations for future research, among others 1) the application of PCA and ICA on hyperspectral image for benthic habitats mapping, 2) the application of more robust classification algorithms on PC and IC bands, and 3) the reconstruction of benthic habitats classification scheme so that the accuracy of each individual benthic habitat class is more consistent.

Acknowledgements
The author would like to thank Prof. Stuart Phinn from Biophysical Remote Sensing Group of University of Queensland and Digital Globe, Inc. for providing us with Worldview-2 Image of Karimunjawa Islands, CNRD (Center for Natural Resources and Development) and Faculty of Geography Universitas Gadjah Mada for funding the research (Research Grant No.UGM/GE/1683tt/M/04/14), and Muhammad Hafizt from LIPI (Indonesian Institute of Sciences) and Staffs of Karimunjawa National Park for the assistance during field data collection.
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