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ACCURACY ASSESSMENTS OF PAN-SHARPENED IMAGE FOR BENTHIC HABITATS MAPPING

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Abstract: *Image-sharpening process integrates lower spatial resolution multispectral bands with higher spatial resolution panchromatic band to produce multispectral bands with finer spatial detail called pan-sharpened image. Although the pan-sharpened image can greatly assist the process of information extraction using visual interpretation, the benefit and setback of using pan-sharpened image on the accuracy of digital classification for mapping remain unclear. This research aimed at 1) highlighting the issue of using pan-sharpened image to perform benthic habitats mapping and 2) comparing the accuracy of benthic habitats mapping using original and pan-sharpened bands. In this study, Quickbird image was used and Kemujan Island was selected as the study area. Two levels of hierarchical classification scheme of benthic habitats were constructed based on the composition of in situ benthic habitats. PC Spectral sharpening method was applied on Quickbird image. Image radiometric corrections, PCA transformation, and image classifications were performed on both original and pan-sharpened image. The results showed that the accuracy of benthic habitats classification of pan-sharpened image (maximum overall accuracy 64.28% and 73.30% for per-pixel and OBIA, respectively) was lower than the original image (73.46% and 73.10%, respectively). The main setback of using pan-sharpened image is the inability to correct the sunglint, hence adversely affects the process of water column correction, PCA transformation and image classification. This is mainly because sunglint do not only affect object's spectral response but also the texture of the object. Nevertheless, the pan-sharpened image can still be used to map benthic habitats using visual interpretation and digital image processing. Pan-sharpened image will deliver better classification accuracy and visual appearance especially when the sunglint is low.*

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1. INTRODUCTION

Multispectral sensors such as Landsat series, SPOT series, EO ALI, IKONOS, Quickbird, Geoeye-1 and Worldview series have panchromatic band on their spectral resolution. Generally, panchromatic band is used to improve the spatial resolution of the multispectral bands using the process called pan-sharpening. The purpose of pan-sharpening is to obtain multispectral image with more detailed spatial information, which is called pan-sharpened image. Visually, pan–sharpened color composite image produces more detail and sharper image compared to the original composite image of multispectral bands. This will greatly assist user to identify more detailed objects using visual interpretation. In addition, with enhanced spatial resolution, the pan-sharpened image can be used to produce map with bigger scale than the original image.

Due to these reasons, several government institutions and non-government organizations (NGOs) working with remote sensing images in Indonesia purchased pan-sharpened image product for their activities. This is mainly due to the lack of understanding about the importance of having image's original spectral bands. While the pan-sharpened bands are beneficial for visual interpretation, using remote sensing data only for visual interpretation will not be effective but also time consuming. It is difficult to perform quantitative measurement and obtain quantitative information of earth surface using merely visual analysis. In order to do so, image classification or modeling using image reflectance values is required. Thus, it is important to perform quantitative assessment about the performance of pan-sharpened image in mapping application using digital image processing.

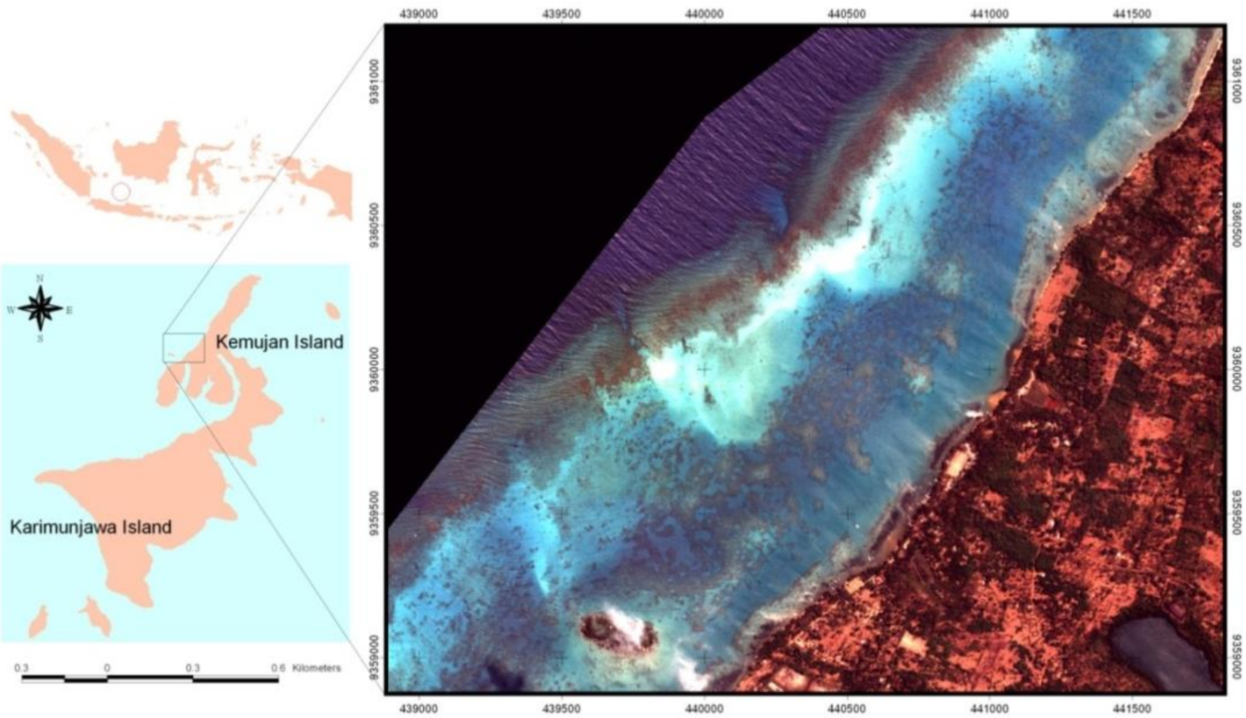
Benthic habitats of the optically shallow water of tropical areas consist of coral reefs, seagrass, and macro algae. These habitats are ecologically and economically important since they provide various supports such as nursery and feeding ground for marine biota, center for biodiversity, supports fish production. They act equally as a carbon sink especially seagrass, and protect the shore from storm and waves (Green et al., 2005). Their beautiful underwater landscape correspondingly triggers tourism activities in many small islands, which support the economics of local people. Indonesia, as the center of coral reefs biodiversity in the world, requires information regarding the spatial distribution or map of these benthic habitats as a basis for managing these habitats sustainably. These benthic habitats map can be produced from remote sensing data (Phinn, Roelfsema, & Mumby, 2012; Wicaksono, Akhyar, & Hidayat, 2015). However, maps of benthic habitats are currently lacking in most parts of Indonesia.

One of the high spatial resolution images frequently purchased is Quickbird image from DigitalGlobe, Inc. Quickbird has been able to map benthic habitats (for four classes benthic habitat classification scheme) with accuracy higher than 60% (Goodman, Purkis, & Phinn, 2013; Wicaksono, 2010). The benthic habitats mapping using high spatial resolution image cannot be highly accurate due to the environmental complexity of benthic habitats and the complex interaction of energy within column as well as the limitation of downwelling irradiance in penetrating water body (Hedley et al., 2012). Quickbird was selected because it is a good representative for high spatial resolution remote sensing data commonly available to date. The performance of the four bands high spatial resolution image of Quickbird can represent the performance of Geoeye-1, or IKONOS, and can be used as a baseline for the performance of the four bands Worldview-2 and Worldview-3. If Worldview-2 and Worldview-3 were used, the result might be better, but the conclusion of this research might not become a good baseline performance for Quickbird, Geoeye-1, or IKONOS, since they have lower spectral resolution compared to Worldview-2 and Worldview-3.

The pan-sharpened Quickbird image is usually delivered on three pan-sharpened visible bands. Frequently, the original (11-bit) radiometric resolution of Quickbird image is compressed into 8-bit after image-sharpening process. This loss of data precision will not significantly affect image's visual appearance. However, when using the image for pixel-based or spectral-based image processing, the data loss may significantly limit the capability of the image to perform digital image processing such as the inability to perform sunglint correction (Kay, Hedley, & Lavender, 2009). This inability is due to the absent of near infrared (NIR) band in the pan-sharpened image and the failure to correctly differentiate object with almost similar spectral response such as seagrass of different abundance (Wicaksono, 2015). Despite the limitations, it is necessary to see how effective the pan-sharpened image for benthic habitats mapping using digital image processing technique. The aims of this study was to (1) conduct benthic habitats mapping using pan-sharpened Quickbird bands and (2) compare the accuracy with the classification result from original Quickbird multispectral bands.

The study area is located on Kemujan Island, one of the islands in Karimunjawa Islands (Figure 1). Karimunjawa Islands are administratively registered as one of Kecamatan in Jepara District Central Java and correspondingly under the authority of Marine National Park of Karimunjawa. Kemujan water area has a very good variation of benthic habitats and water depths. Benthic habitats found on Kemujan are coral reef, macro algae, bare substratum and also seagrass (Nababan, Munasik, & Kartawijaya, 2010; Wicaksono, 2010).

Figure 1. The location of the study area shown in true color composite of Quickbird image.
Note: The scale-bar is for Quickbird image.



2. DATA AND METHODS

2.1. Image and Field Data

Quickbird image used in this study was recorded on 23rd August 2004. The basic specification of Quickbird image is shown Table 1. Quickbird image was pan-sharpened using Principle Component (PC) spectral sharpening method (Welch & Ehlers, 1987). Based on our experiment on different image sharpening algorithms, such as HSV transform, Brovey color normalization, and Gram-schimdt spectral sharpening, visually, PC spectral sharpening algorithm produced better color contrast and sharpness. However, the actual impact of different image sharpening algorithms in the classification accuracy has not been evaluated, and this becomes the agenda for the next research.

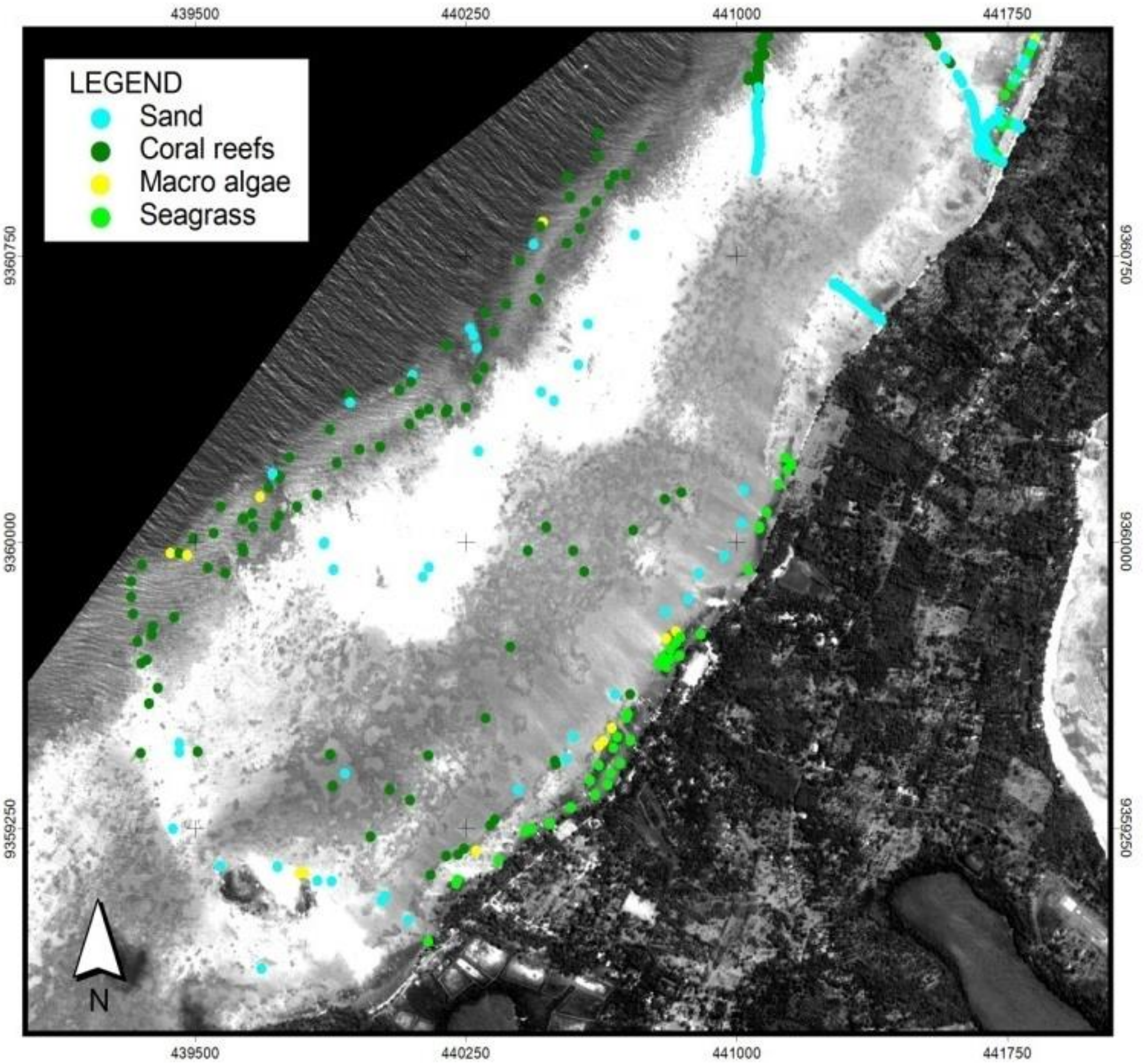
The pan-sharpened bands have their radiometric resolution reduced to 8-bit. There were two procedures that were used to treat the image, 1) using full atmospheric, sunglint and water column corrections on the original Quickbird image and 2) simulating the condition of pan-sharpened images received by users by not applying radiometric calibration and atmospheric correction, which was due to the missing header and band limitation of pan-sharpened image.

Field survey activities were conducted several times from 2009 to 2013. Field benthic habitats data were collected using photo-transect technique (Roelfsema & Phinn, 2009). The determination of transect locations was based on the benthic habitats variation and relative bathymetry obtained from visual interpretation on true color composite Quickbird image. The relative bathymetry map was created based on the concept of light attenuation when traveling within water column (Jupp, 1988). In this study, the classification scheme used (consisting of two levels: the major and detailed schemes) was based on ecological perspective. The field data was used as training areas for maximum likelihood classification and accuracy assessment in both maximum likelihood and OBIA result. For assessing the accuracy of OBIA result, the field benthic point sample was extrapolated to area sample according to the extent of the corresponding segment. The segment was created for each input data, both the original and pan-sharpened images. We preferred the approach using area-based sample for OBIA because it will not be fair to use point sample to test the accuracy of OBIA result that has spatial dimension (Roelfsema et al., 2013).

The spatial dimension of the OBIA result cannot be fairly assessed using point samples (MacLean & Congalton, 2012), especially since some classes have limited number of samples. Generally, the use of point samples will overestimate the classification accuracy assessment and biased conclusion on actual accuracy of the classification result.

Based on the field survey, coral reef class can be further divided into branching, table, massive and encrusting corals. Macro algae can be divided into brown alga i.e. Sargassum sp. and Padina sp., and green alga i.e. Caulerpa sp., and Halimeda sp. The observed bare substratum is mainly carbonate sand and sand with benthic micro benthos. There are 11 seagrass species found in Karimunjawa Islands, however, the scheme used in this research was based on the seagrass abundance i.e. dense, medium density and sparse seagrass mixed with mud and sand. The benthic covers mentioned above are commonly found. There are correspondingly other minor benthic covers such as foliose-type coral reefs, soft corals and red alga i.e. Eucheuma sp. In this research, only the dominant classes were used in order to avoid misclassification due to the limited number of input training areas of the minor classes. The distribution of field benthic habitats data is shown in Figure 2.

Figure 2. Benthic habitats sample distribution in the study area



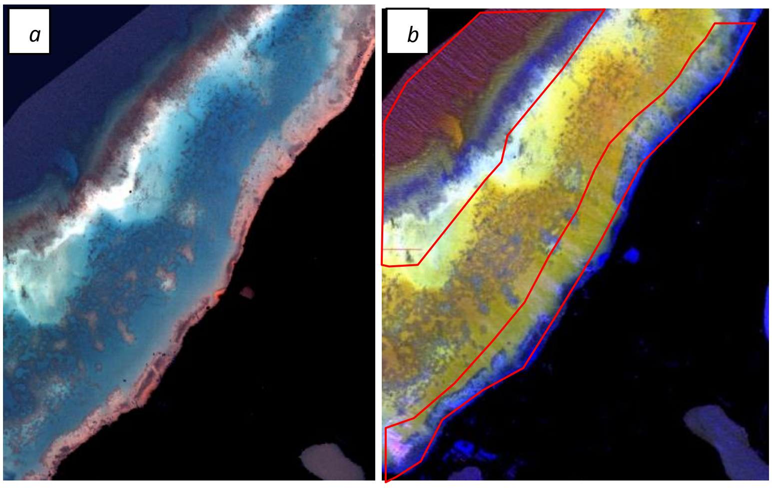
2.2. Image Processing

As mentioned previously, there are two procedures used in this study. The first procedure was for the original multispectral bands. This covers (1) the conversion from digital number (DN) into TOA (Top of Atmosphere) spectral radiance using corrected absolute radiometric calibration factor provided by (Krause, 2003), (2) the conversion into surface reflectance using FLAASH (Fast Line-of-Sight Atmospheric Analysis Spectral Hypercube) (Felde et al., 2003), (3) geometric correction, (4) image masking, (5) sunglint removal (Hedley, Harborne, & Mumby, 2005), (6) depth invariant index generation (DII) (Lyzenga, 1978), (7) integrated model of water column correction (IM) (Wicaksono, 2010), (8) Principle Component Analysis (PCA) (Wicaksono, 2014; 2016). (9) maximum likelihood classification, (10) OBIA and (11) confusion matrix analysis (Congalton & Green, 2008). The second procedure was applied on the 8-bit three visible pan-sharpened Quickbird bands. The methods are similar to the first procedure with additional image sharpening process using PC Spectral Sharpening (Welch & Ehlers, 1987), but without image radiometric calibration and atmospheric correction.

2.3. Sunglint Correction

Land pixels of the radiometrically and geometrically-corrected original Quickbird image were masked. The sunglint in original Quickbird bands was removed using near infrared band, which is strongly absorbed by water body and the minimum reflectance of near infrared band after atmospheric correction, which is assumed to be sunglint-free reflectance. This assumption was adapted to remove sunglint in visible bands using technique developed by Hedley, Harborne and Mumby (2005). The pan-sharpened image, with no near infrared band, used red band to remove sunglint in blue and green band. The sunglint-free image (hereafter deglint) of the original and pan-sharpened image are shown in Figure 3. As seen in Figure 3a, the original Quickbird image produced a much better deglint image. This was due the effectiveness of near infrared band. The pan-sharpened image lack of near infrared band, and the use of red band as band with the longest wavelength and the most sensitive band to water body in visible bands failed to correct the sunglint in blue and green band. Red band is still highly affected by sunglint despite the high water absorption. The sunglint removal did not work for pan-sharpened image because red band that was used to correct blue and green band is still highly affected by sunglint itself. Red boxes show the location where sunglint remain significant as in the uncorrected image (Figure 3).

Figure 3. Subset of the result of sunglint correction of the (*a*) original and (*b*) pan-sharpened Quickbird image.



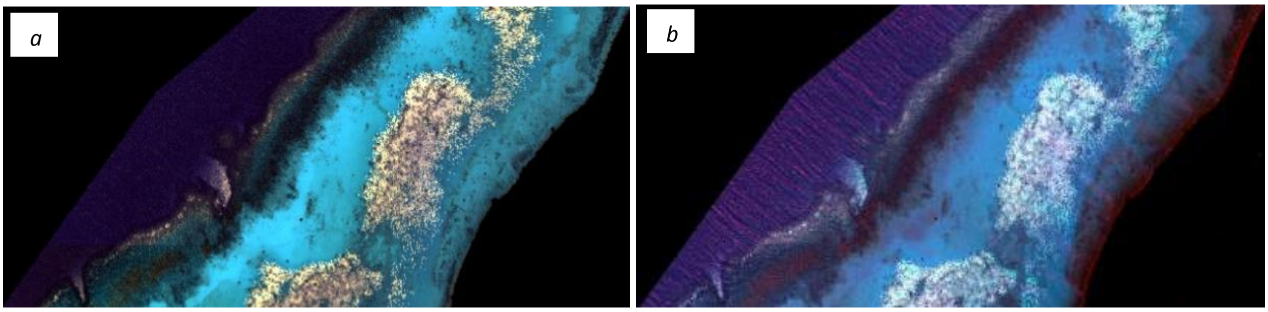
2.4. Water Column Correction

Inputs for IM were water depth at each pixel, clear water reflectance ($R\infty$) and water column attenuation coefficient for each band (k) (Wicaksono, 2010; Wicaksono & Hafizt, 2013). These inputs were calculated using the original multispectral bands, and applied on both original and pan-sharpened image. The purpose was to assume the same input quality for both images, so that the difference in classification accuracy is mainly due to the effect of image sharpening process, and not due to the difference in the input quality. The k values were predicted from the modification of maximum depth of penetration (DOP) model (Jupp 1988), which was initially developed to perform bathymetry mapping. Several approaches of the DOP model were adapted to produce the value of k. The minimum and maximum reflectance of benthic cover in each DOP zone was noted. Since the value of k is mainly the function of wavelength and water quality, the differences in the maximum and minimum reflectance in each DOP zone indirectly represents the rate of light attenuation for the corresponding spectral band. Afterward, k value for each spectral band can be predicted, the value is 0.0184, 0.0717, 0.1781 and 0.6222 m-1 for blue, green, red and near infrared band respectively. Blue band with the weakest light attenuation penetrate deeper than other bands and produce higher reflectance. Near infrared with the strongest light attenuation hardly penetrates at all and produce the lowest reflectance. As expected, bands with longer wavelength have greater attenuation coefficient, which limit the ability to penetrate water body.

Water depth of each pixel was modeled from empirical modeling of band ratio and field bathymetry data and decision tree analysis (Wicaksono, 2010). The benthic habitats in the study area were mostly located on depth shallower than seven meter, and thus, only this depth range was considered on creating the bathymetry map. The best bathymetry model for each depth range was used to transform the pixels into depth data. Decision tree analysis was used to divide depth-transformed pixels into their corresponding effective depth and produce bathymetry data for specific depth range. Final step was to integrate all these unique depth-effective pixels into one complete bathymetry map of the study area. The average Standard Error of Estimate (SE) of the predicted bathymetry for 0 – 7 meter is 0.29 meter. The bathymetry image was only modeled from the original Quickbird image due to the existence of acute sunglint in pan-sharpened image, which adversely affect the quality of the bathymetry empirical modeling.

The mean optically deep water reflectance value for the original Quickbird image is 0.0304, 0.0299 and 0.0212 respectively for blue, green and red band, while for pan-sharpened bands is 35, 77 and 26 for blue, green and red band respectively. These inputs were used to produce IM bands using formula described in Wicaksono (2010). The result of the integrated model is shown in Figure 4. There are not many differences in the IM bands of the original and pan-sharpened image, except the amount of sunglint is greater on pan-sharpened image. In the optically deep water and around the lagoon, the sunglint still exist significantly.

Figure 4. Subset of the result of integrated model for the (*a*) original Quickbird image and (*b*) pan-sharpened image (Own Analysis, 2016)



Depth invariant bottom index (DII) was calculated using the ratio of light attenuation between two bands (ki/kj, where i is band with shorter wavelength and j is band with longer wavelength). These were calculated using the variance and covariance of the log-transformed reflectance value of visible bands. The value of ki/kj for each band pairs of the original image is 0.572, 0.325, and 0.570 for DII12 (blue/green), DII13 (blue/red), and DII23 (green/red) respectively. The values of ki/kj for the pan-sharpened image are 0.554, 0.044, and 0.118 for DII12 (blue/green), DII13 (blue/red), and DII23 (green/red), respectively. The color composite of DII derived is shown in Figure 5. DII of pan-sharpened image has more noises compared to the original bands, mainly due to the present of sunglint that was failed to be corrected using red band. Compared to Figure 2, similar benthic cover appears differently at different depths. In Figure 5, it is clear that similar benthic cover i.e. sand appears visually similar (white) despite the depths.

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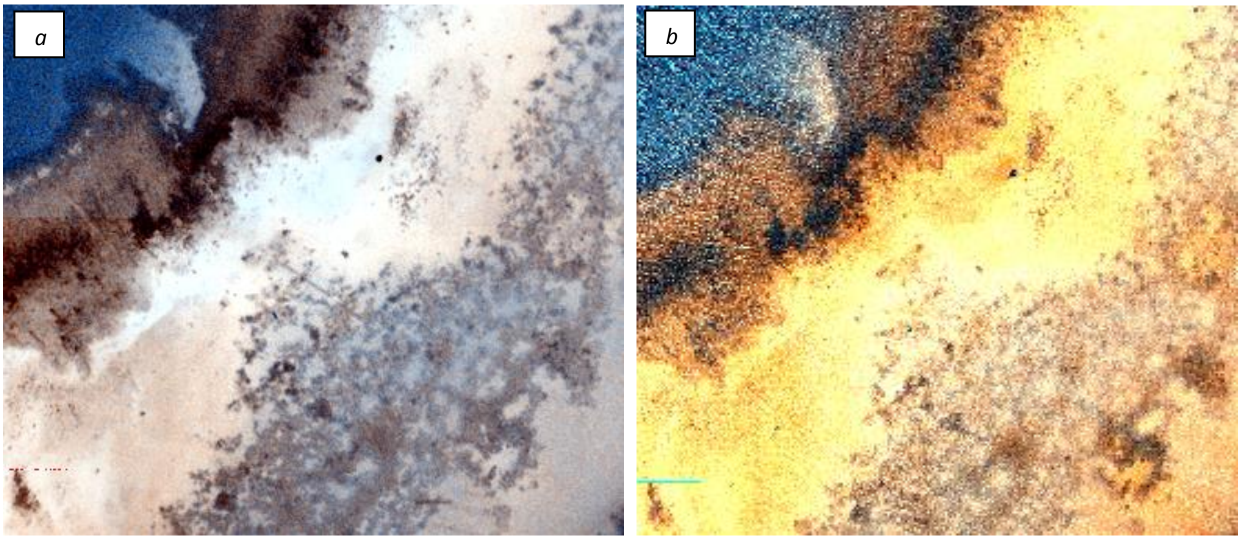
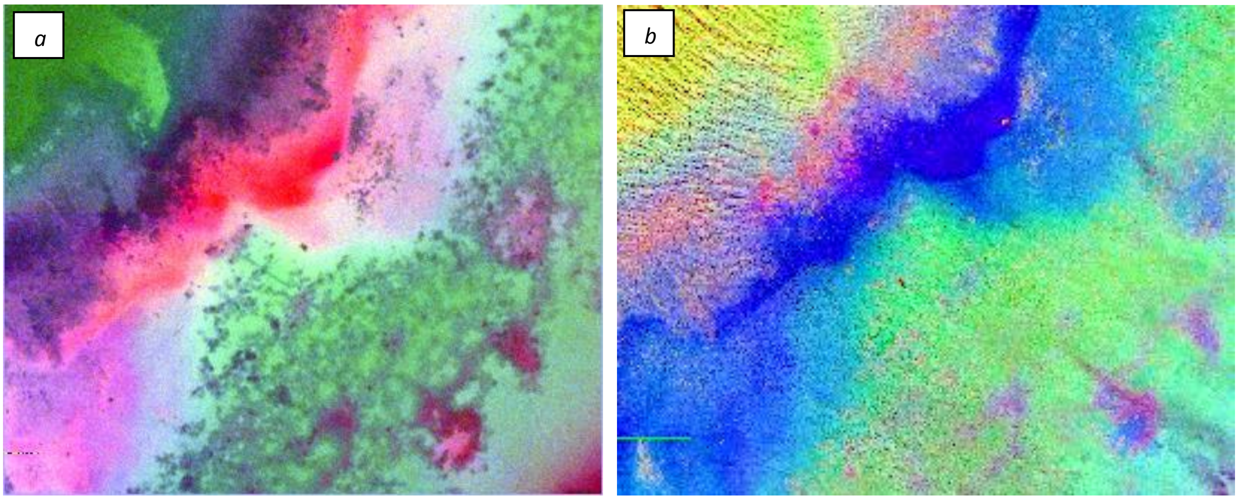
Figure 5. Subset of RGB color composite (R = DII23, G = DII13, B = DII12) of DII from (*a*) original image and (*b*) pan-sharpened image (Own Analysis, 2016)



2.5. PCA Transformation

PCA transformation was conducted based on covariance matrix instead of correlation matrix because there is only one image used in this research, and thus data normalization is not required. PCA was applied on four original bands and three pan-sharpened bands. The use of PC bands managed to improve the effectiveness of benthic habitats mapping activities (Wicaksono, 2016). The PCA results are provided in Figure 6.

Figure 6. Subset of RGB color composite (R = PC1, G = PC2, B = PC3) of PCA result of (*a*) original image and (*b*) pan-sharpened image (Own Analysis, 2016)



2.6. Image Classification

Image classification of benthic habitats was performed using maximum likelihood per-pixel classification algorithm (Mather & Koch, 2011) and Object-Based Image Analysis (OBIA) (Blaschke, 2010; Blaschke, Lang, & Hay, 2008). Maximum likelihood classification was used because the pan-sharpening process directly affects the pixel quality, and thus, per-pixel classification algorithm is a good tool to quantitatively assess the impact of image sharpening in the digital classification. OBIA was also involved because in addition to the pixel value, it incorporates texture, compactness, and variance, which are the spatial dimension of the pixels. Since the process of image pan-sharpening not only changes the spectral feature but also the spatial dimensions of the image, it is necessary to apply OBIA in order to see the effect of these spatial dimension changes to the classification accuracy.

OBIA applied two steps, the segmentations and classification process. In this research, multi resolution segmentation using three parameters namely scale parameter, shape factor and compactness factor was implemented (Benz et al., 2004). Scale parameter determines the size of the segment, where higher value will produce larger segment unit. Shape factor is related to the degree of shape impact to color in the segmentation process, while compactness factor is related to the compactness or smoothness in the segment production. Afterward, the resulting segments were classified to benthic habitats based on the threshold condition of the selected band with clear pattern and differentiation between habitats. Techniques such as Linear Spectral Unmixing (LSU) or Spectral Angle Mapper (SAM) were not used since it requires pure endmember, which is not available to the study area. Although we can find the pure endmember using Pixel Purity Index (PPI) analysis, the uncertainties is too high and it is difficult to justify whether the change in the accuracy is due to the pan-sharpening process or due to the quality of pure endmember.

For image classification, field benthic data was used as the training area. In this research, the hierarchical classification scheme used is based on ecological scheme. The scheme consists of two levels of benthic habitat complexities: the major and detailed schemes. These schemes were created based on the variation of benthic habitats in situ as encountered during field data collection. Separability analysis using Jeffries-Matusita (J-M) technique (Richards, 2013) was conducted to these training areas before classification. The classification schemes used in this study are given in Table 1.

Table 1. Benthic habitats classification schemes used in this study

Major Scheme	Detailed Scheme
Coral reefs	Table coral
	Branching coral
	Mix branching and table coral
	Dense massive and encrusting coral
	Sparse massive and encrusting coral
	Brown algae on coral structure
Macro algae	Mix brown and green algae
Seagrass	Dense seagrass
	Medium density seagrass
	Sparse seagrass
Sand	Sand
	Sand with sparse algae
Optically deep water	optically deep water

3. RESULTS AND DISCUSSION

3.1. Per-pixel Classification

Generally, the accuracy of maximum likelihood classification from pan-sharpened images is lower (Table 2). The decrease of 7 – 10% overall accuracy was noted on DII and PCA results. Taking into account the radiometric uncertainties and data precision loss of the pan-sharpened image, the decrease in accuracy is understandable. By contrast, IM produced better accuracy on pan-sharpened image, with 6.12% accuracy improvement. Nevertheless, for major classification scheme, the pan-sharpened image can still be used to produce good benthic habitat map. As stated by Green et al. (2005), the effective overall accuracy for major classification scheme (4 classes) using multispectral images was between 55 – 75%. However, one must be careful with the misclassification between coral reefs and seagrass in reef crest area as well as the misclassification of sand and coral reefs in the lagoon, especially in IM result (Figure 7 and Figure 8). The decrease in accuracy likewise depends on the amount of sunglint present in scene. When the sunglint is not present or low, pan-sharpened image may yield better classification accuracy and less misclassification.

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The misclassification of seagrass and coral reefs can be addressed to the low separability these classes. J-M separability analysis showed that for DII, PCA and IM the lowest class separability was between coral reefs and seagrass class. For PCA and DII, the separability for coral reefs and seagrass was 1.21 and 1.24, respectively, while for IM it was 0.54, which the lowest of all data. The difficulty of coral reefs and seagrass to be spectrally separated might be due to the similarity of the pigment characteristics in their reflecting tissue (Hochberg & Atkinson, 2000). Similarly for all data, sand and seagrass class had the highest separability since these classes were the brightest and darkest object in the optically shallow water. IM with the lowest class separability produced the lowest classification accuracy.

Table 2. Accuracy comparison of major benthic habitats classification results from original and pan-sharpened image using maximum likelihood classification

Input	Range of class separability	Original bands Accuracy (%)	Pan-sharpened bands Accuracy (%)	Accuracy Differences (%)
DII	1.24 – 1.96	71.42	64.28	-7.14
PCA	1.21 – 1.89	73.46	63.26	-10.2
IM	0.54 – 1.68	52.04	58.16	+6.12

Figure 7. Classification results of the original bands (*a*) IM, (*b*) DII and (*c*) PCA. Red polygons shows area with high misclassification between coral reefs and seagrass (Own Analysis, 2016)

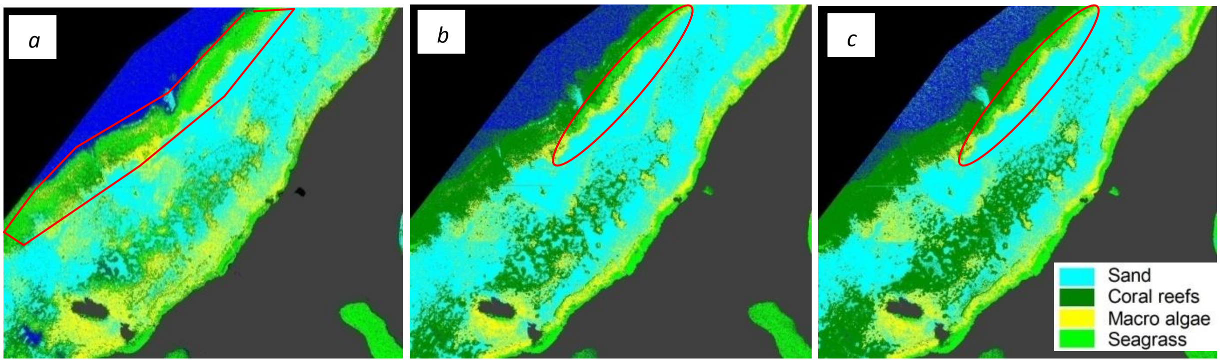
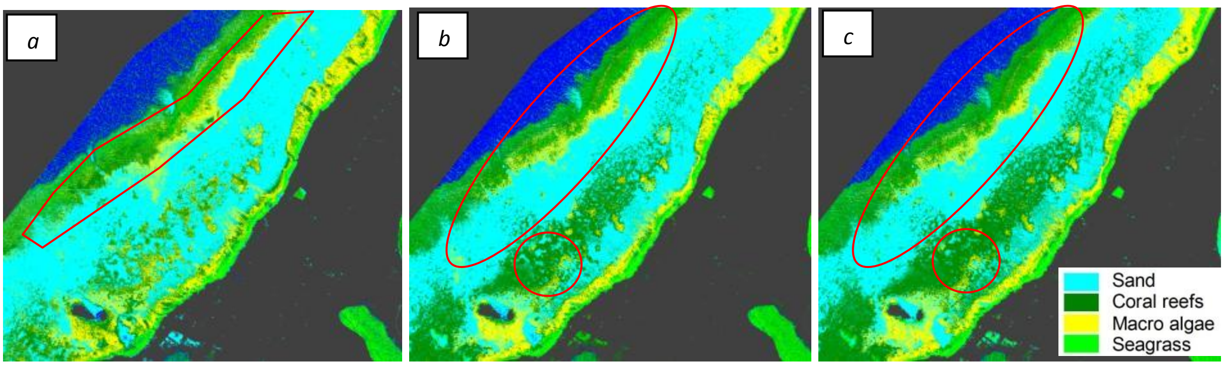


Figure 8. Classification results of pan-sharpened image (*a*) IM, (*b*) DII and (*c*) PCA. (Own Analysis, 2016)



The pan-sharpened results have generally higher misclassification rate, especially in reef crest (between coral reefs and seagrass) and shallow lagoon area (between coral reefs and sand), as highlighted by the red polygons. Accuracy improvement of pan-sharpened IM result is mainly due to the lower misclassification rate between coral reefs and seagrass in reef crest compared to the IM original image. Detailed classification scheme is a complex classification scheme consisting of 13 benthic habitats classes. According to Green et al. (2005), the accuracy of detailed classification scheme (13 classes) was low (21 – 37%). However, recent results have shown that remote sensing could be used to map benthic habitats with complex classes with higher accuracy, mainly using OBIA approach (Phinn, Roelfsema, & Mumby, 2012).

Still, mapping benthic habitats at more than four classes was challenging (Goodman, Purkis & Phinn, 2013). The detailed classification result is given in Figure 9 for original bands and Figure 10 for pan-sharpened bands.

In the detailed scheme classification result, seagrass was correctly distributed along the shoreline, and coral reefs interleaved with macro algae dominated the lagoon area. Sand with benthic micro algae was equally discovered in the lagoon area bordering the coral reefs and macro algae from back reef in the seaward margin and reef flat in the landward margin. However, the misclassification pattern was similar to those of major level scheme. Coral reefs and seagrass were highly confused each other in reef crest area, especially in the north-western part of the scene. Most coral reefs on landward direction were classified as seagrass. In this case, DII result produced the highest accuracy (36.84%) and provided better benthic habitats spatial distribution compared to PCA and IM. PCA result, with slightly lower accuracy (35.78%), overestimated the extent of branching coral in lagoon area while IM results (33.68%) overestimated the extent of brown/green algae class near the shoreline and within the lagoon as well as underestimated the extent of seagrass bed along the shoreline.

Figure 9. Detailed scheme classification results of original bands (*a*) integrated model, (*b*) DII and (*c*) PCA (Own Analysis, 2016)

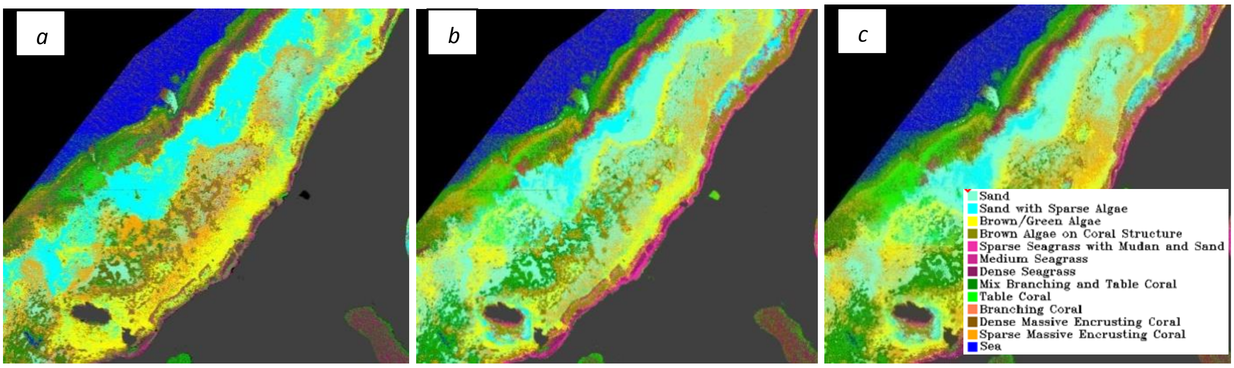
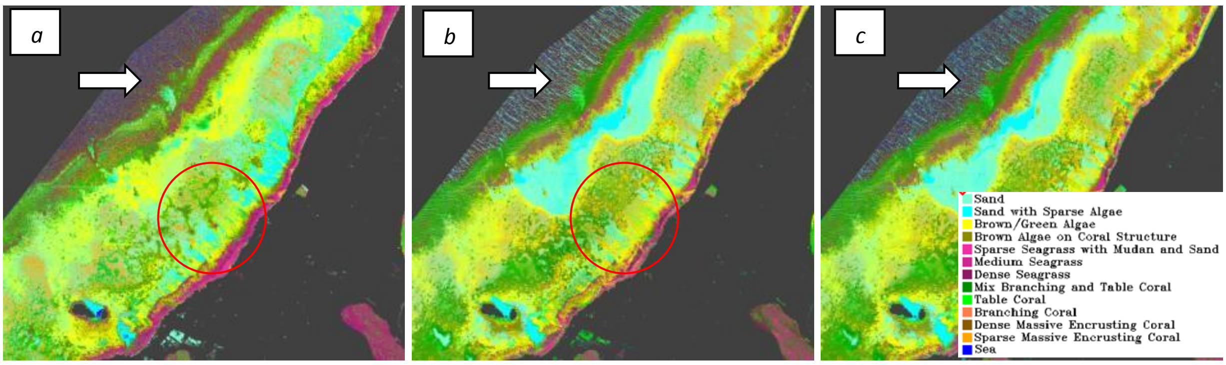


Figure 10. Detail scheme classification results of pan-sharpened bands (*a*) IM, (*b*) DII and (*c*) PCA. (Own Analysis, 2016)



According to Figure 10, the spatial distribution of benthic habitats is obscured. In the lagoon area, uncorrected sunglint pixels were misclassified as brown/algae within sand class (Red polygons in Figure 10). Brown/green algae class was correspondingly highly overestimated in the lagoon area. Optically deep water pixels in the outer reef crest were also partially classified as benthic classes (white arrow in Figure 10), which is also mainly due to sunglint. Reef crest area in the north-western parts of the scene was also misclassified as seagrass. For DII, PCA, and IM, coral reefs classes were also misclassified, which is justified by the very low separability value for all coral reefs classes (<1). In addition, habitats with almost similar characteristics such as sand and sand with sparse algae class and brown algae and brown algae on coral structure were having very low separability as well (<1). Sparse algae and micro benthos lying on bright sand was difficult to be distinguished from pure sand as the reflectance is similar, which is mainly due to the dominant reflectance of carbonate sand. Brown/green algae class was misclassified as brown algae on coral structure because some algae species overgrown the coral reefs are similar. Additionally, seagrass and coral reefs classes were having very low separability (<1) on IM, which made higher misclassification between these two classes compared to PCA and DII.

In general, the spatial distribution of benthic habitats in the sunglint-affected area is incorrect. Although the overall accuracy are still within the acceptable range (Table 3), it is not recommended to perform detailed benthic habitat mapping without additional water penetration bands (i.e. hyperspectral data at high spatial resolution) or other robust classification methods i.e. random forest, classification tree analysis (Eugenio, Marcello, & Martin, 2015; Zhang et al., 2013).

Table 3. Summary of accuracy assessment on detailed classification scheme results using maximum likelihood classification

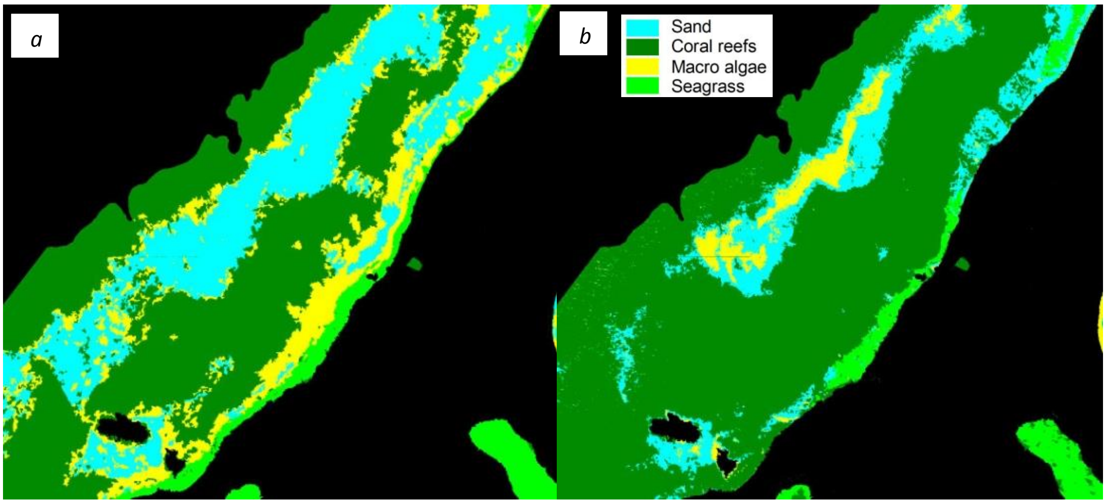
Input	Range of class separability	Original bands Accuracy (%)	Pan-sharpened bands Accuracy (%)	Accuracy Differences (%)
DII	0.39 – 1.99	36.84%	25.26%	-11.58%
PCA	0.40 – 1.99	35.78%	29.47%	-6.31%
IM	0.37 – 1.95	33.68%	28.42%	-5.26%

3.2. Object-Based Image Analysis (OBIA)

In addition to the per-pixel classification, we also applied OBIA to both original and pan-sharpened bands. In addition to the aforementioned reason for using OBIA, another purpose was to observe if OBIA could accommodate the noise and altered texture in the pan-sharpened image due to the failure of sunglint correction. From our experiments, the most effective parameter for the segmentation is explained as follow. The scale parameter was set to 20, the shape factor was set to 0.1 and compactness factor was set to 0.5. The threshold condition for the classification was derived from brightness value and the mean value of red band. These rules were used for both original and pan-sharpened image. Sand, macro algae and coral reefs rules were generated first and were used to classify the segment. Seagrass class was classified using manual classification procedure using brush technique on coral reefs segment. Statistically, the result is promising where the OBIA result of pan-sharpened bands managed to obtain relatively higher accuracy (73.30% from Deglint image) compared to the per-pixel classification results (64.28%) and is comparable to the result of the original image. The OBIA result of the original image (73.10% from DII, 60.83% from PCA) was relatively similar to the per-pixel classification (73.46% at best). The increase in accuracy is mainly because seagrass and coral reefs in reef crest and reef flat are no longer misclassified. Unfortunately, the OBIA result equally generalized the variation of patch reefs in the lagoon, especially on the pan-sharpened image result. Macro algae and sand in between the coral reefs were misclassified as coral reefs. Thus, the extent of coral reefs is highly overestimated.

However, the accuracy between per-pixel and OBIA classification results cannot be directly compared as the unit of analysis is different. OBIA produced map at area basis, while per-pixel classification produced map at pixel basis (Figure 11). Training areas used to perform accuracy assessment were different, where OBIA used area samples to assess the accuracy of classification result instead of point samples used by per-pixel classification. In addition, the level of precision of per-pixel classification result was higher than OBIA result despite the accuracy. Noises due to sunglint yet appeared on the OBIA result, which is also the source for the misclassification. Modifying the scale parameter to remove the noise resulted in the high generalization of the actual benthic habitat classes. We have not performed detailed mapping using OBIA, and it is possible that the OBIA will produce more precise result with higher number of classes.

Figure 11. OBIA result of (*a*) original image and (*b*) pan-sharpened image (Own Analysis, 2016)
Note: how coral reefs is highly overestimated in the lagoon area
while sand and macro algae in between the coral reefs are missing



Finally, the main setback of using pan-sharpened image is the inability to correct the sunglint, hence adversely affects the process of water column correction, image transformation and image classification. This is mainly because sunglint do not only affect object's spectral response but also the texture of the object. Still, pan-sharpened image can be used to map benthic habitats using visual interpretation and digital image processing. Pan-sharpened image will deliver better result especially when the sunglint is low. Visually, when the sunglint is present, the pan-sharpened image gets noisy, while when the sunglint is absent, the pan-sharpened image gets clearer and less noisy. In the context of classification accuracy, areas with high sunglint produced more misclassification compared to areas with less sunglint.

4. CONCLUSION

This study showed that pan-sharpened image is consistently usable to perform benthic habitats mapping even though the accuracy is lower than the original bands. It is recommended to use pan-sharpened bands uniquely at major classification scheme to avoid spatial confusion on benthic habitats spatial distribution. Statistically, the overall accuracy for intermediate and detailed classification scheme were equally acceptable, but the actual spatial distribution of benthic habitats was altered. A decrease in the accuracy of major level mapping up to 10.20% was detected using DII and PCA compared to original bands, while there was 6.12% accuracy improvement for the IM result. For detailed mapping, all pan-sharpened images produced lower accuracy up to 11.58%.

The application of OBIA on pan-sharpened image managed to improve the accuracy significantly (based on statistics). The actual benthic habitats distribution, especially coral reefs, overwhelmed other adjacent classes such as macro algae and sand. Mapping benthic habitats using three visible pan-sharpened bands for benthic habitats mapping has several limitations. These include the absent of infrared band, which forbid the correction of sunglint. When the scene is highly affected by sunglint, the mapping can be really ineffective since sunglint alter both the spectral response and the texture of the pixels. Further processes such as water column correction, PCA transformation and image classification will be highly affected by the existence of the sunglint. Future research will focus on assessing the impact of different pan-sharpening algorithm on the classification accuracy and performing the accuracy comparison at more detailed classification scheme using OBIA.

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