The effect of atmospheric correction on object based image classification using SPOT-7 imagery: a case study in the Harapan and Kelapa Islands

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Abstract. Object-based classification (OBIA) has become a new paradigm in remote sensing data analysis. Errors in interpretation of benthic habitat classification image can be caused by deviation of values in reflectance. The absorption, scattering, and atmospheric reflections caused differences between the reflectance value of satellite images and real objects. The author have tried to compare two different approaches of OBIA classification with FLAASH atmospheric correction and OBIA classification without atmospheric correction. In this research, atmospheric correction with FLAASH method on SPOT-7 imagery conducted to eliminate atmospheric effect on the image. The Support Vector Machines (SVM) algorithm is selected for the classification of benthic habitat in Harapan and Kelapa Island. Atmospheric-corrected image was analyzed visually then compared to ortho image in reflectance pattern, object segmentation and classification result. Results showed an improvement of visualization and reflectance pattern in shallow water objects. This study concluded that the FLAASH method as one of the appropriate methods to be used in atmospheric correction in SPOT-7 images.

1. Introduction

The research of marine ecosystem mapping, with spatial scaling and object feature labels mapped in accordance with the geomorphic structure and benthic communities are still a major challenge in the development of remote sensing applications. Benthic habitat mapping using satellite imagery along with the accuracy assessment has been widely performed [1,2,3,4,5,6,7,8,9]. This research aims to compare the object-based image classification result with corrected and uncorrected image. These studies focused on the differences between accuracy derived from the use of hyperspectral and multispectral images; between high and low resolution images; between uncorrected images and corrected image with water column correction [1,2].

Errors in interpretation of benthic habitat classification results can be caused by deviation values of reflectance values. This is due to absorption, scattering, and atmospheric reflections that cause differences in the reflectance value of satellite images and actual objects [10]. The reflectance value is very important in the process of object classification on the image digitally. The atmospheric correction able to eliminate the influence from the atmosphere and return the reflectance value according to the actual object's reflectance value on the earth's surface.
The method of atmospheric correction consists of three methods: radiative transfer, relative correction based on image characteristics and surface linear regression. Among these methods, radiative transfer models are more widely used in satellite imagery with higher accuracy of reflectivity calculations [11]. Methods with radiative transfer algorithms such as the 6S (Second Simulation of the Satellite Signal in the Solar Spectrum) and MODTRAN (Moderate Spectral Resolution Atmospheric Transmittance Algorithm and Computer Model) methods [12].

The MODTRAN4 method is available on the ENVI software with the FLAASH (Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes) modul. FLAASH is an atmospheric correction tool using the MODTRAN4 method which has been able to extract visible, NIR (Near Infrared) and SWIR (Short-wave Infrared) wavelength. FLAASH can eliminate the effect of atmospheric disturbances by obtaining more accurate parameters of reflectivity, emissivity, surface temperature and physical surface. FLAASH has an aerosol and mean value retrieval method using a dark pixel reflectance ratio based on Kaufman's research [13]. The MODTRAN4 model contained in FLAASH reduces the effect of the atmosphere effectively on SPOT-7 thereby enhancing the image information with better accuracy than the QUAC model [14]. The author will try to compare two different approaches of OBIA classification with FLAASH atmospheric correction and OBIA classification without atmospheric correction.

2. Method

2.1. Survey area
The study area is located in shallow water area of Harapan and Kelapa Island, Kep. Seribu, Jakarta (Fig 1.). Collection of benthic habitat data was done by systematic random sampling method with distance of each sampling point about 20 m.

Figure 1. Field survey location (data source: SPOT 7 acquisition image dated June 12, 2016) (5°32’50.64”S - 5°47’21.48”S and 106°30’59.4”E - 106°37’53.4”E).

2.2. Data acquisition
The data sources used are multispectral images (SPOT-7 Kepulauan Seribu), and benthic habitat data sampling. SPOT-7 multispectral image is acquired on June 12, 2016 with a projection system of UTM coordinate zone 48S WGS84. The SPOT-7 image characteristic consists of 4 multispectral bands (Blue, Green, Red, NIR) with a spatial resolution of 6 meters (multispectral). Field data were collected in April 2017 using photo transect technique (1 x 1 meters) with 343 observation point. Benthic habitat data is integrated (spatial join) with polygon of image segmentation result, integration result then used as region of
interest (ROI) in process of classification. The description of the habitat classes is based on the percent of the benthic component cover of the 1x1 m squared photo field observation. The description of the classification scheme is derived from the percentage value of eight benthic components based on the Brail-Curtis coefficient insignificant value of 40% (AHC). The value of dissimiliarity (40%) indicates that each habitat class constructed has a resemblance to the benthic habitat component of at least 60%. The classification scheme was then developed using the percentage of benthic habitat closure data by eliminating components having presence frequency based on centroid values of less than 4% [14].

2.3. Pre-processing image

Pre-processing image consisted of atmospheric correction process was performed using the FLAASH correction module contained in ENVI 5.1 software [15]. FLAASH is a first-principles atmospheric correction tool that corrects wavelengths in the visible through near-infrared and a shortwave infrared region, up to 3 mm. It incorporates the MODTRAN4 radiation transfer code [16, 17]. The input image for FLAASH must be a radiometrically calibrated radiance image. Other information such as flight date, start time, time in GMT, scene center location, sensor altitude, and ground elevation is also required for this correction. Atmospheric correction aims to eliminate the influence of atmospheric particles such as dust and water vapor. This atmospheric correction stage generates new images that have been corrected from atmospheric disturbances.

\[ L = \left( \frac{A\rho}{1-\rho e S} \right) + \left( \frac{B\rho e}{1-\rho e S} \right) + L_a \]

(1)

Where is: \( L \) = the spectral radiance from sensor; \( P \) = the surface reflectance from pixel; \( S \) = the albedo in the atmosphere; \( A, B \) = the coefficient from atmospheric and geometric condition; \( \rho e \) = the average of surface reflectance; \( L_a \) = the radiance of atmospheric reflectance; \( \left( \frac{B\rho e}{1-\rho e S} \right) \) = the radiance energy from object scatter; \( \left( \frac{A\rho}{1-\rho e S} \right) \) = the radiance energy from object reflectance

\[ L_e = \left( \frac{(A+B)\rho e}{1-\rho e S} \right) + L_a \]

(2)

\( L_e \) = the average of image radiance

The calculation to convert Digital Number to reflectance for Blue, Green, Red and NIR bands in SPOT 7 imagery:

| Reflectance = DN x Gain – Bias |
|-----------------------------|
| Band | Gain | Bias |
| Band-1/Blue | 1.66345 | 0 |
| Band-2/Green | 1.559910 | 0 |
| Band-3/Red | 1.085514 | 0 |
| Band-4 NIR | 10.468422 | 0 |

The image used in the study belongs to latitude (-5.5474, -5.7893), longitude (106.5165, 106.6315), recording date of SPOT-7 (June 12, 2016), recording time (08:42 : 38.81), height of sensor (695 km), ground level (0.1 km), pixel size (6 meters), tropical model, aerosol model (maritime), visibility (40 km), solar azimuth angle (121.38 °) and the sun elevation angle (52.84°). Visual analysis is done by taking the same
area in the image before and after the atmospheric correction, observed the visible color changes of the image. The reflectance pattern analysis is performed by taking the same pixel on shallow water objects, deep water, and terrestrial areas (vegetation) on images before and after atmospheric correction. Then the FLAASH corrected image is used as the input image layer of object-based classification (OBIA) and then compared the resulting classification accuracy. The reflectance pattern image (before and after correction) compared with reference to USGS's reflectance pattern.

2.4. Object based image analysis

Object-based classification consists of two stages: segmentation and classification. Segmentation is the concept of building objects / segments from pixels into segments or objects that have the same properties [18]. The segmentation algorithm used in this research is multiresolution segmentation (MRS). This algorithm starts with a single pixel segment and combines neighboring segments until the threshold of heterogeneity is reached. The image segmentation process depends on three components, shape, compactness, and scale [19]. Segmentation is done using shape and compactness parameters of 0.1 and 0.5, respectively.

2.5. Image classification

The image used as the input layer in the classification process is an image that has been corrected and uncorrected image. The rule set classification was created in tree process component. The classification algorithm used is the support vector machines (SVM) algorithm. SVM is a supervised classification algorithm that can search a vector or line that serves as a two-class separator by maximizing margins between classes [19]. This classification algorithm is based on line factor classifiers classified machine learning classification [20].

2.6. Accuracy assessment

The results of image classification accuracy testing was conducted to determine the accuracy of each thematic maps. Accuracy was obtained by comparing the results of image classification with field observations. The accuracy test is performed using an error matrix (confusion matrix). Testing accuracy produce overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and the value of kappa statistics [14]. Kappa value statistics and the data variance was used to compare the accuracy of the test results of two thematic maps in order to know the significance of changes in thematic map accuracy after sunglint correction (Z statistic).

3. Results and discussion

3.1. Atmospheric correction image

The images show visually different images before and after atmospheric correction (Fig. 2). The results of atmospheric correction produce a new image that has been free from atmospheric disturbances. The atmospheric corrected image is seen more clearly, especially on shallow water areas. The application of atmospheric correction has proven to increase the contrast of the image.

Based on Figure 2, there is a change in the reflectance pattern in the corrected image at the object in the shallow water (on reef flat zone) area. There was a significant increase reflectance pattern in blue band (450-520 nm) and green (530-590 nm), while the red band reflectance pattern (625-695 nm) and near infrared (760-890 nm) did not change. As for the deep water area, the reflectance pattern shown did not change significantly. The lagoon area also significant increases reflectance patterns in blue bands (450-520 nm) and green (530-590 nm). While on the vegetation object visible there is a significant decrease of reflectance pattern on blue band (450-520 nm) and green (530-590 nm), while the red band (625-695 nm) and near infrared (760-890 nm) reflectance pattern are changed (table 1).
Figure 2. Comparison image before correction (a) and after atmospheric correction (b) (composite band 321).

Shallow water areas have almost the same spectral response for each objects included. Here is a picture of the spectral pattern from each object found in the field survey based on direct measurements using a spectrometer. The image shows that the spectral pattern of benthic habitat object has the same pattern as the spectral increase in the blue band and the green band. However, the spectral measurements from survey are highly dependent on the sun, the turbidity of the waters and the weather conditions [11].
Table 1. Comparison of spectral patterns between uncorrected and corrected image.

| Object                   | Spectral pattern (uncorrected image) | Spectral pattern (corrected image) | References image (USGS)                                      |
|--------------------------|-------------------------------------|-----------------------------------|----------------------------------------------------------------|
| Shallow water            | ![Spectral Profile](image1)          | ![Spectral Profile](image2)       | Seawater_Coast_SW1[W1R1Ba AREF]                                  |
| Karang Mati Alga         | ![Spectral Profile](image3)          | ![Spectral Profile](image4)       | Ocean_SW2[W1R1Ba AREF]                                           |
| Pasir Rubble Alga        | ![Spectral Profile](image5)          | ![Spectral Profile](image6)       | Vegetation_Dry Grass [W1R1Ba AREF]                               |

3.2. Object Based Image Classification (OBIA)

3.2.1. Scale optimization
The optimization of object-based classification segmentation refers to the results of previous research [21]. Image segmentation on each applied scale produces a different number of polygons. Scale is the average size of the object generated in the segmentation process [19]. The optimal scale parameter value is 15, and at this value the number of generated classes is quite detailed i.e. 11 classes with the highest OA (76.85%). The image shows the difference of the object segment formed from the image before and after the atmospheric correction with the same segmentation parameter values. The corrected image has a segment shape that more closely resembles with the actual object pattern in the field (Fig. 3). This is can caused by
the atmospheric correction can increase the contrast of objects in the image so that differences between objects are more visible. The uncorrected image show that each segment relatively homogen and the corrected image show that the variability in each segment rather high.

Figure 3. Visual comparison of image of segmentation result before (a) and after (b) atmospheric correction (image composite 321).

3.2.2 Classification of benthic habitat
The classification method used is the SVM classification with scale factor 15 [21]. The object-based classification shows the benthic habitat distributed in shallow waters of Harapan and Kelapa Island (Fig. 4, Fig. 5). The characteristics benthic habitat components were identified as 8 habitats, live coral (C), sponge (SP), softcoral (SC), macroalgae (MA), dead coral algae (DCA), sand (P), rubble (R), and seagrass (L). The description of the classification scheme is further derived from the percentage value from 8 benthic components based on the Bray-Curtis coefficient insignificant value of 40%. There is no provision for using similarity values to define a classification scheme based on clustering analysis. It is caused by different conditions and variations of observation site and is adapted to the satellite imagery platform used. Then the classification scheme was developed using the percentage of benthic habitat cover by eliminating centroid value components less than 4% [14]. The 11 benthic habitat classes were obtained based on cluster analysis results.

Figure 4. Classification of benthic habitat mapping using uncorrected image with SVM algorithm.
Figure 5. Classification of benthic habitat mapping using corrected image with SVM algorithm.

The 11 benthic habitat classes formed are sand + rubble + algae (PRA) dead coral + algae (KMA), live coral + rubble (KRB), seagrass (L), sand (P), sand + seagrass (PL), sand + live coral (PKA), sand + rubble (PR), live coral (KH), rubble R) and rubble + algae (RA). The naming of these classes is based on a dominant benthic closure type entirely constructed by benthic components. The application of the classification scheme is influenced by the complexity of the constituent components of coral reefs and the limitation of remote sensing data [22]. The object of 11 classes that have been identified are further used as input data for the classification process.

The classification result shows the uncorrected, the sand habitat (66 Ha) shown by the yellow and mixed class of sand and seagrass (53 Ha) shown by light green dominates in the north, west and east of the Harapan Island. Meanwhile, in the corrected image, the benthic habitat dominated by seagrass habitat shown by dark green in the north and sand habitat dominates in the west and then mixed rubble and sand class shown by pink color dominates the east area.

3.3. Accuracy assessment
Comparison of image classification before and after atmospheric correction looks different from comparison of its accuracy. The confusion matrix using 237 sampling point to produce the accuracy assessment. Image classification accuracy test results before and after atmospheric correction produce an overall accuracy with about 69.43% and 76.68% (Table 2). While at UA and PA between 18-77%. The overall accuracy of the images after atmospheric correction increased with about 7% compared to the uncorrected image. The spectral similarity between coral reef habitat classes is unavoidable. The result of atmospheric correction is able to increase the accuracy of the mapping when compared with the image without correction, although there are two possibilities on the reflectance value of underestimate and overestimate caused by aerosol parameters that are less suitable with field conditions during image recording [17].
Table 2. Comparison of accuracy assessment (PA, UA, OA) before and after correction.

| Class                      | Before |       |       |       |       |
|----------------------------|--------|-------|-------|-------|-------|
|                            | PA     | UA    | PA    | UA    |       |
| Seagrass                   | 54.84  | 54.84 | 69.70 | 77.19 |       |
| Dead coral with algae      | 37.50  | 28.57 | 58.82 | 47.62 |       |
| Sands                      | 70.59  | 73.47 | 69.39 | 69.39 |       |
| Live coral                 | 66.67  | 69.57 | 70.83 | 73.91 |       |
| Coral with rubble          | 58.82  | 58.82 | 72.22 | 76.47 |       |
| Sand with rubble           | 42.86  | 60.00 | 43.48 | 66.67 |       |
| Sand with seagrass         | 64.10  | 71.43 | 62.50 | 57.14 |       |
| Sand-coral-algae           | 45.45  | 50.00 | 50.00 | 30.00 |       |
| Rubbles                    | 40.00  | 37.50 | 47.37 | 56.25 |       |
| Sand-rubble-algae          | 25.00  | 22.22 | 45.45 | 55.56 |       |
| Rubble with algae          | 50.00  | 18.18 | 80.00 | 36.36 |       |
| OA                         | 69.43  |       | 76.68 |       |       |

Significance test of the image accuracy before and after atmospheric correction was about 1.73. The value of the Z statistic between -1.96 to 1.96 mean that the comparison was not significant [15]. It means that the application of atmospheric correction on the images before and after correction of this study did not produce significant differences. The OBIA classification on corrected and uncorrected image was not significantly different based on Z statistic value of 1.73.

4. Conclusion
The atmospheric correction process produce a new image that has been almost free from atmospheric disturbances. The atmospheric correction by FLAASH method can be used to improve the shallow water object reflectance pattern on SPOT-7 images according to reference data. There is a visual difference in OBIA classification results from corrected and uncorrected image with the FLAASH Module. This research shows that the atmospheric correction made in pre-processing image able to the accuracy although the results were not significantly different.

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