The Use of SPOT 6 and RapidEye Imageries for Mangrove Mapping in the Kembung River, Bengkalis Island, Indonesia

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Abstract. High-resolution satellite imageries believed to map the mangrove area well. Two satellite imageries with almost similar spatial resolution were expected to achieve this objective, including SPOT (Satellite Pour l’Observation de la Terre) 6 and a RapidEye. Two images covered the same area and acquired under the equivalent season at Kembung River, Bengkalis Island, Riau Province. A comparison was tested on several objectives. First, a comparison was conducted band by band through examining their statistical spectral analysis. RapidEye had a higher variance in all visible bands but low at NIR. Second, spectral separability using Jeffrey-Matusita distance was executed with three-band composites (SPOT 6/VNIR, RAPIDEYE/VNIR and RAPIDEYE/VNIR+RedEdge). SPOT 6 had better separability than RapidEye imageries compositions (VNIR+RedEdge and VNIR), with an overall accuracy of 79.9%, 75.3%, and 67.3%, respectively. Third, mangrove land cover classification. Three pixel-based classification rules were used, including a general classifier, maximum likelihood (ML), and two advanced classifiers, i.e., neural network (NN) and support vector machine (SVM). Results indicated that the use of SPOT 6 produced better overall accuracy than the other two image composition for each classifier. SVM was promising in the mangrove mapping algorithm compare to NN and ML.

1. Introduction
Kembung river is one of the mangrove ecosystems found on the island of Bengkalis, Riau Province. It has an extensive area of approximately 3000 hectares [1]. Mangroves are found along the river, with 13 km upstream, creeks, and dealing directly with the Malacca Strait waves. This ecosystem has long been susceptible to interferences and pressures, especially by nature and human activities. Some areas have been degraded by development activities such as bridges, roads, levees, shrimp farms, and settlements. Meanwhile, a small part of the Kembung River is only considered by specific local communities.

Mangrove mapping in Kembung River has not been widely reported and published. Jhonnerie, Siregar conducted several studies [2] to map and detect the mangrove changes using a series of Landsat satellite imageries. Jhonnerie, Siregar, Nababan, Prasetyo and Wouthuyzen [3] mapped the mangrove land cover using satellite images Landsat 5 TM and ALOS PALSAR FBD and spectral transformation.
Currently, high-resolution satellite images are more comfortable to obtain. The platform and satellite sensors developers compete to bring the best of their abilities in data recording. The presence of very-high-resolution satellite sensors provided new opportunities for mapping mangrove land cover than previous sensors [4]. Two high-resolution satellite imagery present since 2009 (RapidEye) and 2012 (SPOT-6) were used. RapidEye has a spatial resolution of 5 meters by five wavelengths (VNIR + RedEdge), while SPOT 6 has a spatial resolution of 6 meters with four wavelengths (VNIR). Both images have been tested mapped mangrove vegetation in tropical regions such as Roslani, Mustapha, Lihan and Wan Juliana [5]. Ibharim, Mustapha, Lihan and Mazlan [6], and Santos, Matos, Schaeffer-Novelli, Cunha-Lignon, Bitencourt, Koedam and Dahdouh-Guebas [7].

Machine learning models have been widely applied in remote sensing data classification. Some common machine learnings are classification and regression tree (CART), support vector machine (SVM), and artificial neural network (ANN) [8]. The use of machine learnings was useful in mangrove mapping applications and was promising compared to other statistical models because they used fewer data assumptions and focused more on the complex processes and unknown [9]. The use of machine learning in mangrove mapping have been reported by Jhonnerie, Siregar, Nababan, Prasetyo and Wouthuyzen [3], and Heumann [10].

This paper aimed to test and compare the use of SPOT 6 and RapidEye satellite imageries and implemented machine learning classification rule, included support vector machine (SVM), neural network (NN) and conventional statistical classifier, maximum likelihood (ML) for mapping mangrove land cover in the part of upstream Kembung River.

2. Research method

This study was conducted within Kembung River, Bengkalis Island, Riau Province, Indonesia (Figure 1) and situated at the upstream Kembung River (1°28′51.9″ N 102°22′16.2″ E – 1°26′10.6″ N 102°24′58.7″ E).

Field data collection was performed in August 2016. Nine classes landcover were observed included: water body (BA), buildings and settlement (BN), roads (JN), rubber trees (KT), coconut trees (KA), bare land (LT), others vegetation (OV), bushes (SB), transition vegetation (VT) and mangrove (ME). Field observation assisted by small and light unmanned aerial vehicles (UAV), DJI Phantom 4. The UAV captured photos and videos. UAV flight height was set to 75 meters above the earth’s surface, so we have clear and detailed objects to be interpreted. The other location where UAV did not capture helped by 0.5-meter WorldView-2, which fused with the panchromatic band. 500 area of interest (AOI) created randomly. Two hundred seventy-five were used as a classification training area and the rest used during classification accuracy analysis. Two tiles of ortho product RapidEye (Level 3A), data acquired on January 19, 2011, and the second one were SPOT-6 (Level 1A), data obtained on January 27, 2013 (Table 1).

| Satellite Data | Blue  | Green | Red   | RedEdge | NIR  |
|----------------|-------|-------|-------|---------|------|
| RapidEye       | 450-510 | 520-590 | 639-685 | 690-730 | 769-850 |
| SPOT-6         | 455-525 | 530-590 | 625-695 |         | 760-890 |
Unfortunately, one of the tile RapidEye data at the downstream part had a poor-quality image. Therefore, the upstream part that can be used only, and SPOT-6 data must be subsetted to fit RapidEye data. The research area covered 500 meters from mangrove edges. Both data were buffered and clipped based on previous mangrove data from the provincial planning and development agency.

Atmospheric correction was implemented for both images and used the FLAASH module [11] to have a similar spectral reflectance value for each AOI. Then, corrected data were segmented, which applied the multiresolution segmentation algorithm. Each segmentation that correlated to the point of interest was extracted and labelled. Each label referred to field observation and visual interpretation classes.

Simple descriptive statistic values, i.e., minimum (Min), maximum (Max), mean and standard deviation (StdDev) performed for each band assessed in both images. StdDev is the most informative and indicates how much spectral detail is present in the whole image [4]. Furthermore, a widely used separability criterion, Jeffries-Matusita (J-M) [12], for optimal data selection and classification results based on the data’s normal distribution assumption.

Since RapidEye had five spectral bands and to have a fair comparison between two data. RapidEye’s image, composed of two data sets. First, image (RE4b) consisted of 4 bands (red, green, blue, and NIR), while the other one (RE5b) consisted of a full band of RapidEye. In comparison, SPOT-6 (S6) was used as is it. These three data sets classified by using three classification pixel-based rules included SVM [13], NN, and ML [14], and compared each other based on overall accuracy [15].

Figure 1. Location and points of interest are used for classification.
was no optimization for each variable or parameter of classification rules performed. Default values were used only in this paper.

3. Result and discussion

Table 2 showed the statistical results of each RapidEye and SPOT-6 imageries spectral bands. Although both the data have the same radiometric dynamic range, 12 bits, the standard deviation value of RapidEye data was consistently higher than the SPOT-6. Including sensitive bands to vegetation, green, and NIR. A high standard deviation value revealed that reflectance image Rapideye able to capture more detail and to object to the same surface, especially mangrove [4].

| Band          | Min  | Max  | Mean    | StdDev   |
|---------------|------|------|---------|----------|
| **RapidEye**  |      |      |         |          |
| Band 1 (Blue) | 0    | 0.2752 | 0.021952 | 0.020189 |
| Band 2 (Green)| 0    | 0.3153 | 0.034707 | 0.031925 |
| Band 3 (Red)  | 0    | 0.3097 | 0.022857 | 0.021859 |
| Band 4 (Red edge) | 0  | 0.3151 | 0.057805 | 0.053656 |
| Band 5 (NIR)  | 0    | 0.5402 | 0.171049 | 0.161815 |
| **SPOT-6**    |      |      |         |          |
| Band 1 (Blue) | 0    | 0.344  | 0.00268  | 0.005356 |
| Band 2 (Green)| 0    | 0.3761 | 0.016155 | 0.016351 |
| Band 3 (Red)  | 0    | 0.3805 | 0.011512 | 0.012929 |
| Band 4 (NIR)  | 0    | 0.5122 | 0.146363 | 0.140430 |

This finding contradictory Wang, Sousa [4], said IKONOS, which had higher standard deviation values, appeared more clearly than QuickBird image. Our finding RapidEye looks darker than the SPOT-6 image (Figure 2). We believed that acquisition time and environment background included tide [15], soil and vegetation affected the image capturing process [16].

![Figure 2. RapidEye (a) and SPOT-6 (b) with true color composite.](image)

No chance for mangrove class can be separated into other land cover classes since the highest values within J-M distance achieved by S6 (1,414.20) are less than 1,900 (the threshold value that can separate between classes) (Table 3). Our previous research demonstrated that the ability of S6 was better due to mangrove separation from other land cover classes [1]. The differences were possibles due to the sample uses and the number of different land cover classes.
Table 3. J-M distance matrix between mangrove and other landcover (values in bold indicated the highest values for each dataset)

| Dataset | BA    | BN    | JN    | KT    | KA    | LT    | OV    | SB    | VT    |
|---------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| S6      | 1,397.76 | 1,379.80 | 1,382.05 | 1,392.32 | 1,256.24 | **1,414.20** | 1,356.74 | 1,400.28 | 1,340.11 |
| RE5b    | 1,381.18 | 1,346.94 | 1,363.64 | 1,278.22 | 1,279.19 | **1,412.84** | 1,361.01 | 1,399.23 | 1,123.48 |
| RE4b    | 1,362.28 | 1,328.74 | 1,356.27 | 1,198.60 | 1,211.29 | **623.13** | 1,398.84 | 623.13 | 1,394.32 | 1,114.44 |

S6’s J-M distance had slightly better than RE5b and RE4b. The average value of the J-M distance S6 for all land cover classes pairwise was 1,338.71, while RE5b and RE4b were 1,252.37 and 1,319.99, respectively. Classification results using the J-M distance’s spectral characteristics stated S6 better than RE5b and RE4b, with 80.0%, 75.3%, and 67.3% overall accuracy.

Each pixel-based rule can classify all land cover classes. However, for sure, we may found some problems such as misclassification (Figure 3). Although this issue can be reduced using the majority filter during post-processing, it still was a problem [3, 17]. Commonly, we found misclassification pixel in transition vegetation associated with mangrove, waters around mangrove, and bare land classes. Pixel-based classification tends to produce the salt and pepper effect, where one pixel is assigned differently from surroundings pixels. The effect of the biophysical environment’s complexity and the spectral similarity between the land cover or classification schemes used [18].

Table 4 showed the results of overall accuracy for each classification rule and dataset used. SVM classification rules (66.9%) were the best mangrove land cover classifier compared to the two rules, NN (65.4%) and ML (64.5%). This finding similar to Wahidin, Siregar [19] that SVM produced the highest accuracy compared to the other machine learning rules such as decision tree, random tree, k-nearest neighbour, and Bayesian.

Although S6 had a smaller spatial resolution and less spectral band, we found S6 promised to map mangrove land cover compared to the RE5b and RE4b dataset. Similarly to Wang, Sousa, Gong and Biging [4], they found that IKONOS multispectral delivered slightly higher classification accuracy than QuickBird multispectral. Lück-Vogel, Mbolambi, Rautenbach, Adams and van Niekerk [15] reported that SPOT-6 produced better classification accuracy than RapidEye for vegetation mapping in the estuary. Finally, We found accuracy increasing in the addition of RedEdge spectral bands for NN and ML classification rules only. Jhonnerie [1] reported the differences in the spectral range of the same spectrum affected mangrove classification while spectral inclusion (SWIR1 and SWIR2) in Landsat 5 TM composite improved 6.8% accuracy mangrove classification.
RE5b_SVM  RE5b_NN  RE5b_ML

RE4b_SVM  RE4b_NN  RE4b_ML

Legend : BA : BN  : JN  : KT : VT : LT : ME : OV : KA : SB

**Figure 3.** Classification results based on classification rules, support vector machine (SVM), neural network (NN), and maximum likelihood (ML). S6 indicated that SPOT-6 imagery and RE indicated RapideEye imagery. 5b and 4b indicated bands used.

**Table 4.** Classification accuracy for each classification rule and image input (values in bold indicated the best result)

| Rule | Image | OA  |
|------|-------|-----|
| SVM  | S6    | 66.9% |
| NN   | S6    | 65.4% |
| ML   | S6    | 64.2% |
| SVM  | RE5b  | 61.5% |
| NN   | RE5b  | 59.5% |
| ML   | RE5b  | 58.0% |
| SVM  | RE4b  | 61.5% |
| NN   | RE4b  | 51.4% |
| ML   | RE4b  | 51.8% |

**4. Conclusion**

This paper examined and compared two high-resolution satellite imagery from RapidEye, and SPOT-6 sensors derived mangrove land cover. Statistically, RapidEye captured more detailed surface objects than SPOT-6 since it had a higher standard deviation for each band. SPOT-6 more promising than RapidEye due to mangrove land cover classification. Support vector machine produced classification more accurately than neural network and maximum likelihood.
5. References

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