Canopy cover of mangrove estimation based on airborne LIDAR & Landsat 8 OLI

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Abstract. Mangroves are very important ecosystems, because of their economic value and environmental services, including as a habitat for various wildlife species, storing carbon, and protecting land from sea abrasion. Indonesia is known to have large mangrove area and diversity. It is estimated that the area of mangroves in Indonesia in 2015 reached about 3 million hectares, with 15 families, 18 genera, 41 true mangrove species and 116 species of mangrove associations. Unfortunately, the area to continue to decline due to degradation and conversion to other land uses, especially ponds and built up areas. Usually, mangrove degradation assessment is carried out by field survey and relying on Normalized Difference Vegetation Index (NDVI) clustering derived from satellite image data. Field surveys require a large amount of time and cost, meanwhile NDVI clustering is either inaccurate or too rough. Therefore, exploration of another methods are needed. Our result showed that pixel value of Band 5, Band 6, NDVI and PC1 can be used to estimate canopy cover. Regression using quadratic equation is better than linear equations. However, we noticed limitations of optical Landsat 8 OLI data for canopy cover mapping, namely pixel saturation on high canopy cover and high pixel value of bush/shrubs/regrowth that was not always representing high canopy cover.

Keyword: airborne, canopy cover, mangrove

1. Introduction

It is estimated that the area of mangroves in Indonesia in 1990 reached about 3.6 million hectares, however, the area decreases to 2.94 million hectares in 2015, in which of about 1.4 million hectares is secondary mangrove forest [1]. The deforestation and degradation mangrove forest is due to anthropological factors such as logging, ponds development, and settlements [2][3]. This will lead to species extinction since mangrove consist of 116 species, 18 genera and 15 families of plant and host of aquatic and terrestrial wildlife [4][5].

The Ministry of Environment and Forestry measured the degradation of mangrove based on stand density in the field, in which stand density below 1000 individual/ha is classified as degraded mangrove.
Meanwhile, [7] proposed another approach based on Normalized Difference Vegetation Index (NDVI) and Canopy cover. NDVI is an index derived from remote sensing data (band red and near infrared) and its value ranging from -1 to +1 [8]. Positive index represents vegetation, while below 0 indicates non vegetation. It is widely used for canopy cover estimation [9], forage [10] and vegetation changes [11]. Based on this method, the mangroves are heavily degraded if the NDVI value is in the range of -1 to 0.32 or canopy density is less than 50%. Meanwhile, mangroves are moderately degraded if NDVI ranges from 0.32 to 0.42 or canopy cover is between 50-70%. Field observation based data is precise for measuring degradation, but it is timely and costly, meanwhile, the NDVI clustering approach is either inaccurate or the classification is too rough. The same conclusion also mentioned [12], that there is limitation to use the NDVI to measure forest degradation. It is an urgent need to explore another approach to measure mangrove degradation.

Light detection and ranging (LIDAR) is widely used and accurate to estimate canopy cover [13][14][15], tree height and forest structure [16] and above ground biomass mapping [17][18]. However, LIDAR is very expensive and only cover limited area. The objective of the research is to look a relation between canopy cover derived from LIDAR and the pixel value of LANDSAT 8 OLI. The algorithm can be used for mapping mangrove degradation in area beyond the LIDAR coverage.

2. Material and Methods

2.1. Study area
Mangrove of the study area is located in Banyuasin District of South Sumatra Provinces (figure 1). Part of the mangrove forest is situated within Berbak-Sembilang National Park. The mangrove condition is very good with very limited disturbance. The common species in the ecosystem are *Rhizpora mucronata*, *R. apiculata*, *Bruguiera gymnorhiza*, *B. sexangula*, *B. paviflora*, *Ceriops tagal*, *Xylocarpus granatum* and nipah.

![Figure 1. Study area](image)

2.2. Landsat 8 OLI & LIDAR data acquisition
Landsat data over the area study with acquisition date on 25th July 2014 (Path/Row: 124/061) was downloaded from the United Stated Geological Survey ([https://earthexplorer.usgs.gov/](https://earthexplorer.usgs.gov/)). Meanwhile, high resolution aerial photo and LIDAR data were taken by fixed wing from 800 m above ground level, with swath width of 851 m in October 2014 (figure 2). There were two Lidar acquisition mode namely full waveform (8-15 points/m²) with 60% overlap and discrete return (6-8 points/m²) with 80% overlap.
In this research discrete returns data were utilized. The raw LIDAR was taken by PT ASI Pudjiastuti Geosurvey and provided by GIZ-Bioclime project.

2.3. Landsat 8 OLI data processing
Prior further analysis, the Digital Number (DN) of Landsat 8 OLI were converted to spectral reflectance based on algorithm of [19], which was also adopted by [20]. An important part of this method is changing the DN value by taking into account the illumination of each pixel, which previously only used illumination values of the center scene of Landsat. NDVI, Principal Component 1 (PC1) and Principal Component 2 (PC2) were calculated by using ERDAS Imagine software.

![Figure 2. (a) Lidar Swath on overlaid with Landsat 8 OLI, (b) 3D of LIDAR Point clouds](image)

2.4. Canopy cover estimation
Canopy cover were calculated by using open source software lidR package of R ([https://github.com/Jean-Romain/lidR](https://github.com/Jean-Romain/lidR)) based on First-Return Cover Index (FRCI) as shown in formula 1. The FRCI was adopted from [13] and it was selected since was more appropriate compare to other algorithm such as All-return cover index (ARCI) and CHM-based method. The FRCI was calculated for every 30 m x 30 m, in accordance to Landsat 8 OLI spatial resolution.

\[
FRCI = \frac{\Sigma \text{First canopy} + \Sigma \text{Single canopy}}{\Sigma \text{First total} + \Sigma \text{Single total}} \tag{1}
\]

Where FRCI: First-Return Cover Index; \(\Sigma\text{First canopy}\): Total point of canopy return; \(\Sigma\text{Single canopy}\): Total point of single canopy return; \(\Sigma\text{First total}\): Total of point clouds; and \(\Sigma\text{Single total}\): Total point of single return.

Prior the FRCI calculation the point clouds of LIDAR data were normalized with Digital Elevation Model/ DEM (30 m x 30 m spatial resolution) derived from LIDAR. To ensure good fit of spatial position between Landsat 8 OLI & LIDAR, the boundary of FRCI calculation was made based on fishnet (.shp) of LANDSAT 8 OLI. The FRCI calculation result were extracted as point attribute data (.shp) of the center point of the pixel (figure 3).

2.5. Data Analysis
Total 2078 data were selected from 4562 original data points to ensure representativeness of data distribution. The selection is done due to the fact that more than 85% data are above 60% canopy cover. To determine the relationship between FRCI values as dependent variable with the NDVI, PC1, PC2
and reflectance values of each bands from Landsat 8 OLI as independent variables, correlation and regression analysis were performed using SPSS version 22. Prior to regression analysis data outliers’ removal, and normality test based on standard residual histogram and P-P plot as well as heteroscedasticity test based on scatter plot of standardized predicted value and standardized residual analysis were conducted. Finally, after the above step 707 points were selected as data sample. The significant independent variables with high correlation (>0.5) were analyzed further.

3. Results & discussion
Correlation analysis result showed that all independent variables (spectral value of Band 1, Band 2, Band 3, Band 4, Band 5, Band 6, Band 7, Band 8, NDVI, PC1 and PC2) have a significant correlation with the percentage of canopy cover (FRCI). However, correlation with NDVI (0.698) was the highest, followed by Band 5 (0.666), PC1 (0.634), PC2 (-0.662) and Band 6 (0.545).

The scatter plot of the data showed that the FRCI increase with the increase of spectral values (B5, B6, NDVI, PC1), but when the FRCI close to 80% the spectral reach to saturation. Unlike the other responses, PC2 have a negative response to the increase of FRCI (figure 4). Therefore, the quadratic function model are more appropriate with the data distribution which is indicated by the highest coefficient of determination (R^2) (table 1).

Observing in more detail of figure 4, it appears that there are several cases where the FRCI value are low but the pixel value of band 5, band 6, PC1 and NDVI bands are high. This may be related to the condition of land cover in the mangrove gap. If the condition of land cover in the gap is water/river, then the pixel of NDVI/Individual bands value is low. Conversely, if the condition of land cover inside the gap is understory vegetation/bush/shrub, then the pixel value will remain high. This is due to a high
rate of photosynthetic activity, in which vegetation absorb red as well as blue bands, but reflects green and near infrared bands. Variation of gap within mangrove is presented in figure 5.

4. Conclusion
Band 5, Band 6, NDVI and PC1 values can be used to estimate canopy cover. Regression using quadratic equations is better than linear equations. We noticed limitations of optical Landsat 8 OLI data for canopy cover mapping in forest mangrove ecosystem, namely pixel saturation on high canopy cover and high pixel value of bush/shrubs/regrowth that is not always representing high canopy cover.

![Figure 4. Fitting curve of regression](image-url)
Table 1. Fitting of the equation

| No | The independent variable | Model      | R    | R Square | Adjusted R Square |
|----|--------------------------|------------|------|----------|-------------------|
| 1  | Band 5                   | Linear     | 0.67 | 0.44     | 0.44              |
|    |                          | Logarithmic| 0.69 | 0.48     | 0.48              |
|    |                          | Quadratic  | 0.72 | 0.51     | 0.51              |
|    |                          | Exponential| 0.68 | 0.46     | 0.46              |
| 2  | Band 6                   | Linear     | 0.55 | 0.30     | 0.30              |
|    |                          | Logarithmic| 0.62 | 0.38     | 0.38              |
|    |                          | Quadratic  | 0.74 | 0.54     | 0.54              |
|    |                          | Exponential| 0.58 | 0.34     | 0.34              |
| 3  | NDVI                     | Linear     | 0.70 | 0.49     | 0.49              |
|    |                          | Logarithmic| 0.70 | 0.49     | 0.49              |
|    |                          | Quadratic  | 0.71 | 0.50     | 0.50              |
|    |                          | Exponential| 0.72 | 0.51     | 0.51              |
| 4  | PC1                      | Linear     | 0.63 | 0.40     | 0.40              |
|    |                          | Logarithmic| 0.66 | 0.43     | 0.43              |
|    |                          | Quadratic  | 0.71 | 0.51     | 0.51              |
|    |                          | Exponential| 0.66 | 0.43     | 0.43              |
| 5  | PC2                      | Linear     | 0.66 | 0.44     | 0.44              |
|    |                          | Logarithmic| -   | -        | -                |
|    |                          | Quadratic  | 0.72 | 0.51     | 0.51              |
|    |                          | Exponential| 0.67 | 0.46     | 0.45              |

Figure 5. FRCI value regarding the gap land cover of mangrove (note: the yellow number in the center of the grids (30 x 30 m) is FRCI value, while the light blue color is NDVI, meanwhile the background image is a very high resolution air borne images)

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Acknowledgement
This research was supported by World Class University Research Program in 2018 (Program Riset Kolaborasi Indonesia-World Class University 2018). The data are supported by the UK Space Agency
(UKSA) International Partnership Program (IPP) under the Forests2020 program coordinated by Ecometrica, Ltd. The Forests 2020 is a collaborative program to advance Earth Observation applications to forests monitoring.