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MANGROVE ABOVE GROUND BIOMASS ESTIMATION USING COMBINATION OF LANDSAT 8 AND ALOS PALSAR DATA

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Abstract. Mangrove ecosystem is important coastal ecosystem, both ecologically and economically. Mangrove provides rich-carbon stock, most carbon-rich forest among ecosystems of tropical forest. It is very important for the country to have a large mangrove area in the context of global community of climate change policy related to emission trading in the Kyoto Protocol. Estimation of mangrove carbon-stock using remote sensing data plays an important role in emission trading in the future. Estimation models of above ground mangrove biomass are still limited and based on common forest biomass estimation models that already have been developed. Vegetation indices are commonly used in the biomass estimation models, but they have low correlation results according to several studies. Synthetic Aperture Radar (SAR) data with capability in detecting volume scattering has potential applications for biomass estimation with better correlation. This paper describes a new model which was developed using a combination of optical and SAR data. Biomass is volume dimension related to canopy and height of the trees. Vegetation indices could provide two dimensional information on biomass by recording the vegetation canopy density and could be well estimated using optical remote sensing data. One more dimension to be 3 dimensional feature is height of three which could be provided from SAR data. Vegetation Indices used in this research was NDVI extracted from Landsat 8 data and height of tree estimated from ALOS PALSAR data. Calculation of field biomass data was done using non-decstructive allometric based on biomass estimation at 2 different locations that are Segara Anakan Cilacap and Alas Purwo Banyuwangi, Indonesia. Correlation between vegetation indices and field biomass with ALOS PALSAR-based biomass estimation was low. However, multiplication of NDVI and tree height with field biomass correlation resulted R^2 0.815 at Alas Purwo and R^2 0.081 at Segara Anakan. Low correlation at Segara anakan was due to failed estimation of tree height. It seems that ALOS PALSAR height was not accurate for determination of areas dominated by relative short trees as we found at Segara Anakan Cilacap, but the result was quite good for areas dominated by high trees. To improve the accuracy of tree height estimation, this method still needs validation using more data.

Keywords: *mangrove, biomass, Landsat 8, ALOS PALSAR*

1 INTRODUCTION

Mangrove ecosystem is important coastal ecosystem with many functions which are not limited to ecological but also economical functions (Barbier, *et al.*, 2008; Ruitenbeek, 1992). Although previous studies related to mangrove forests were not regarded as important, transitional communities with low productivity, most ecologists today view them as important ecosystem with high ecological productivity (McKee, 2002). According to McKee (2002), the major role of mangrove swamps is contribution to soil formation and stabilize coastline, mangroves act as filters for upland runoff, mangrove systems serve as the habitat of marine organism, mangrove produces large amount of detritus that may contribute to productivity in coastal waters. In addition, mangrove forests also serve as protection for coastal communities against storms, serve as nurseries and refuge for many marine organisms that are commercial or sport value, serve as habitat of threatened species, serve as aesthetics and tourism (McKee, 2001).

Mangroves are among the most carbon-rich forests in the tropics which containing 1,023 MgC/ha in average (Donato *et al.*, 2011). “Blue carbon” is a term to explain the sequestered carbon in vegetated coastal ecosystems, especially mangrove forests, seagrass beds, and salt marshes (McLeod *et al.*, 2011). Estimation of mangrove carbon-stock using remote sensing data plays important role on emission trading. The estimation carbon from vegetation known as biomass has been conducted using remote sensing that is extensively applied to measure mangrove biomass (Fatoyinbo and Amstrong, 2010) and can be calculated as 50% of the C stored (IPCC, 2000).

The mangrove areas can be found in the Southeast Asia region where its biodiversity is the highest in the world (Polidoro *et al.*, 2010). About 60% of Southeast Asia’s total mangroves or comprises about 19% of the world’s mangroves is in Indonesia (Giesen, *et al.*, 2007). The advances in remote sensing technology could provide new data resources for mapping mangrove forests (Heumann, 2011), so the studies on the use of these data is also necessary for specific sites.

The models of above ground mangrove biomass estimation are still limited and based on common forest biomass estimation that have already been developed. Remote sensing is often used for practical means to acquire information on forest biomass but not always successful (Foody *et al.*, 2001). Among of mangrove biomass estimation methods are based on vegetation indices (Hamdan, Khairunnisa, Ammar, Hasmadi, & Aziz, 2013; Li *et al.*, 2007; Wicaksono, Danoedoro, Hartono, Nehren, & Ribbe, 2011) and Radar data (Hamdan *et al.*, 2014; Li *et al.*, 2007; Dien, *et al.*, 2013). Many approaches were used for applications in other environments and are often not appropriate for applications in the tropics (Foody *et al.*, 2001). For example, simple vegetation indices such as the Normalized Difference Vegetation Index (NDVI) have been widely used to estimate biophysical variables of temperate vegetation, but they are often less sensitive to biophysical properties at high vegetation density, so that they are frequently less successful if applied for tropical forests (Saderet *et al.*, 1989; Foodyet *et al.*, 1996b, inFoody, 2001). Wicaksono *et al.* (2011) estimated above ground biomass using 13 vegetation indices and resulted correlations between GEMI and field biomass with maximum R^2 0.34. The R^2 value was not merely suitable to determine the quality of biomass estimation from remote sensing (Wicaksono *et al.*, 2011). It seems that vegetation indices only is not enough as biomass estimation parameters. Biomass is volume dimension related to tree canopy and height. Vegetation indices provide two dimension information of biomass trough recording the vegetation canopy density and could be well estimated using optical remote sensing data. Another additional dimension for being thre-dimension is tree height which could be estimated using SAR data. Biomass estimation based on vegetation indices might work well at the areas where the tree height is homogenous.

This paper describes a new method using a combination between optical and SAR data to analyze additional parameter of tree height. The correlation between NDVI multiplied tree height and field biomass measurement was also analyzed.

2 MATERIALS AND METHODOLOGY

2.1 Time and Research Location

This research was done using satellite images and other ancillary data which were collected in April- June 2014.

Image processing and analysis were done in July-November 2014.

Field data in this research was obtained from twice field survey at Segara Anakan and once at Alas Purwo areas. The first survey at Segara Anakan was done in 27 – 31 May 2013 and the second on 19 – 24 November 2013. Field measurement at Alas Purwo site was conducted on 28 June 2012 until 4 July 2012.

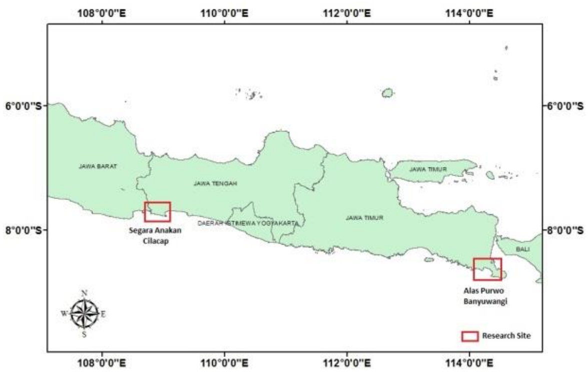

Figure 2-1: Research Location

Algorithm development done for Indonesia could be more representative for most mangrove ecosystems in the world. The research was done at mangrove area of Segara Anakan Cilacap of Central Java Province and protected area at Alas Purwo National Park in Banyuwangi of East Java Province, Indonesia.

Mangrove at Alas Purwo National Park has high biodiversity, such as fish, vegetation, bird and nekton living in mangrove ecosystem. There were 14 species found in this mangrove area which were *Acrosticum aureum, Bruguie-ra cylindrical, Bruguiera gymnorrhiza, Bruguiera sexangula, Ceriops decandra, Ceriops tagal, Excoecaria agaliocha, Rhizopora apiculata, Rhizopora mucronata, Scyphiphora hydrophyllacea, Sonneratia alba* and *Sonneratia caseolaris.* Among them, *Ceriopdecandra* and *Scyphiphora hydrophyllacea* were endangered species but commonly found (Satyasari, 2010 *in* Saifullah and Harahap, 2013).

For comparison with Alas Purwo area, another mangrove area was also selected. This area was previously studied using the same vegetation index, and located in Segara Anakan in Cilacap Central Java Province. Segara Anakan was the largest mangrove area in Central Java Province but has already become degraded mangrove area due to unprotection and intensive utilization by coastal community. Segara Anakan is unique and specific, developed from intertidal area that consists of a lagoon and sedimentation product delta areas. The area is protected from wave and wind from the Indian Ocean by Nusakambangan Island. The area has a high rate sedimentation process due to large of water inland input from several big rivers. Intertidal area is the potential mangrove growth area which has high potential for fisheries resources. Segara Anakan has been managed by *Dinas Kelautan Perikanan dan Pengelolaan Sumberdaya Kawasan Segara Anakan* (Office for Marine, Fisheries and Segara Anakan Area Resources Management) under local government. However, this area has also been managed by Mangrove Forest Management Unit under the Ministry of Forestry and also by the Ministry of Law and Human Rights as there is Nusakambangan prison in this area.

Mangrove ecosystem area in Segara Anakan is 24.000 ha with intertidal wetland area is 14.100 ha (Sunaryo, 1982 in White, *et al.*, 1989). However, Ecology Team (1987) reported that mangrove habitat area was 21.750 ha and 12.610 ha of the area were still affected by tides and dominated by mangrove vegetation (White, *et al.*, 1989).

2.2 Data

Remote sensing data and field measurement were used in this research. Remote sensing data which are used are Landsat 8 LDCM (*Landsat Data Continuity Mission*) path/row 121/65 May, 30, 2013 acquisition date and part/row 117/66 March, 2, 2014, May, 5, 2014 acquisition date. The spectrum used in Landsat 8 sensor is almost similar with Landsat-7 ETM+ that already used for mangrove identification with additional spectrum bands such as coastal blue band and cirrus band. We used Standard Level Correction of 1T Level data with higher accuracy on radiometric and geometric correction due to DEM from accurate topography map application (USGS, 2013). SAR data used in this research was ALOS PALSAR K & C mosaic with 50 m ground resolution provided by JAXA.

We chose 6 sampling stations for each survey site meaning that there were 12 total sampling stations. Field data collection consisted of wood density of mangrove, tree species, and diameter of breast height (DBH). Density of mangrove was calculated within 30 x 30 m area and divided into 9 sub-plots and each sub-plot has 10 x 10 m area. The density was not calculated for all 9 sub-plots, but randomly for 1-5 sub-plots due to the lack of time and area accessibility. The field measurement results were then averaged to represent the density of 30 x 30 m of Landsat 8 ground resolution. DBH measurements were done for each tree inside the plot including the mangrove tree species. Biomass was then calculated from DBH measurement using a specific allometric algorithm for each species referring to the latest allometric algorithm developed for nearest place. This biomass measurement is called non-destructive method to measure biomass in the field.

The field measurements at Alas Purwo were conducted using similiar method. Alas Purwo field data were provided by the Geospatial Information Agency. The acquisition date of remote sensing data, were different from field measurement date, as we assumed that there was no significant change between that time difference.

2.3 Methods

Mangrove biomass estimation is possible to be calculated from parameters extracted from remote sensing data. Several methods are already published and used operationally, including methods using simple approach and more complicated approach. For forests with dense tree cover, biomass may vary as a function of tree height, tree architecture, wood density, and basal area, none of which could be estimated from optical data, and thus biomass variations for dense tree cover could be missing (Houghton, *et al.*, 2001). Vegetation indices are commonly used in biomass estimation models, although some studies showed low correlation results. SAR data with a capability to detect volume distribution could possibly used for biomass estimation with better correlations. Biomass is a volume dimension which is related to the tree canopy and height. Vegetation indices could provide two dimensional information on biomass trough vegetation canopy density recording and could be well estimated using optical remote sensing data. One more dimension to be three dimensional is tree height which could be estimated from SAR data. Vegetation indices used in this research is NDVI extracted from Landsat 8 data and tree height estimated from ALOS PALSAR. Field biomass was measured using non-destructive allometric based biomass estimation at two different locations i.e. Segara Anakan Cilacap and Alas Purwo Banyuwangi, Indonesia.

2.3.1 *Normalized Difference Vegetation Index* (NDVI)

Live green plants absorb solar radiation in the photosynthetically active radiation (PAR) spectral region, which they use as a source of energy in the photosynthesis process. Leaf cells have evolved to scatter solar radiation in the near-infrared spectral region (which carries approximately half of the total incoming solar energy), since the energy level per photon in that domain (wavelengths longer than 700 nanometers) is not sufficient to synthesize organic molecules.

A strong absorption of these wavelengths would only result in overheating the plant and possibly damaging the tissues. Hence, live green plants appear relatively dark in the PAR and relatively bright in the near-infrared (Gates, 1980). In contrary, clouds and snow tend to be rather bright in the red (as well as other visible wavelengths) and quite dark in the near-infrared. The chlorophyll pigment in plant leaves strongly absorbs visible light (from 0.4 to 0.7 μm) for photosynthesis. The cell structure of the leaves, on the other hand, strongly reflects near-infrared light (from 0.7 to 1.1 μm). The more leaves a plant has, the more these wavelengths of light are affected. Since early instruments of Earth Observation, such as NASA's ERTS and NOAA's AVHRR, acquired data in visible and near-infrared, it could naturally detect strong differences in plant reflectance to determine their spatial distribution in these satellite images.

The NDVI is calculated from these individual measurements as follows:

$$NDVI = \frac{(NIR - VIS)}{(NIR + VIS)} \quad (2\text{-}1)$$

Where VIS and NIR stand for the spectral reflectance measurements acquired in the visible (red) and near-infrared regions respectively (NASA, 2013). These spectral reflectances are ratios of reflected over incoming radiation in each spectral band individually, hence the values range between 0.0 and 1.0. By design, the NDVI varies between -1.0 and +1.0. It should be noted that NDVI is functional, but not linearly, equivalent to the simple infrared/ red ratio (NIR/VIS). The advantage of NDVI over a simple infrared/red ratio is therefore generally limited to any possible linearity of its functional relationship to vegetation properties (e.g. biomass). The simple ratio (unlike NDVI) has been always positive, which may have practical advantages, but it also has a mathematically infinite range (0 to infinity), which can be a practical disadvantage as compared to NDVI. In this regard, the VIS term in the numerator of NDVI only scales the result, thereby creating negative values. NDVI is functionally and linearly equivalent to the ratio NIR/(NIR+VIS), which ranges from 0 to 1 and is thus never negative nor limitless in range (Crippen, 1990). The most important concept in the understanding NDVI formula is that, despite its name, it is a transformation of a spectral ratio (NIR/VIS), and it has no functional relationship to a spectral difference (NIR-VIS).

In general, if there is much more reflected radiation in near-infrared wavelengths than in visible wavelengths, then the vegetation in that particular pixel is likely to be dense and may contain some types of forests. Previous works have shown that NDVI is directly related to the photosynthetic capacity and hence energy absorption of plant canopies (Crippen, 1990; Sellers, 1985).

2.3.2 Tree Height Model

Empirical tree height estimation model (Takeuchi *et al.*, 2011) was applied in this research. This algorithm was built from field data in the area mainly covered by four species of mangrove forests with homogeneous spatial distribution, height ranges from 0.6m to 5.0m, DBH from 5cm to 30cm and crown diameter from 0.7 to 1.6m. The relationship between tree height and backscatter coefficients (σ^0) of HH and HV in mangrove was established. The results showed that there was a positive relation between σ^0 and tree height with the larger sensitivity to tree height found at HV. Moreover, strong differences were observed between polarizations HH and HV. A regression analysis was carried out between tree height and σ^0 at HH and HV polarizations and it was characterized by the equation below with root mean square errors of 2.2 and 2.0 (dB) (Takeuchi et al., 2011) respectively.

HH = 3.6 *ln (tree height) − 23.7
HV = 4.4 *ln (tree height) − 24.9

The highest correlation was selected to convert as tree height equation calculated from σ^0. Tree height equation is:

$$\text{Tree Height} = \exp^{(HV+23.7)/3.6} \quad (2\text{-}2)$$

In case there is only single polarization data available, the HH equation could be used.

3 RESULTS AND DISCUSSION

3.1 Results

Development of method can be done by trial processes and comparing several published methods, then be evaluated to choose the best method. Some time we could not find the best method. Then we tried to evaluate each process and tried to find the part where we can improve the method. Before we found the good correlation, we applied Takeuchi *et al.* (2011) method for biomass estimation using K&C ALOS PALSAR dataset with 50 m ground resolution at two different research locations which were Alas Purwo area and Segara Anakan area. The biomass was calculated from tree height estimated from backscatter coefficient of HH or HV SAR data which tree height estimation algorithm was used to derive tree height information for the biomass algorithm in this paper. The application of Takeuchi *et al.* (2011) method in both areas resulted low correlation between satellite bases biomass estimation with field measurement. However, we got tree height estimation from this processing result. The other method we tried was application of several vegetation indices including NDVI, EVI-1 and EVI-2 at Segara Anakan field only, resulted low correlation between vegetation indices with field biomass with R^2 0.312, 0.336, 0.33 for NDVI, EVI-1 and EVI-2 respectively (See Table 3-1). This correlation was too low to establish the empirical algorithm for estimating above ground biomass. At Alas Purwo area, the correlation analysis was only done for NDVI with field biomass which resulted correlation of R^2 0.432. EVI-1 and EVI-2 was not used for Alas Purwo area.

Table 3-1: Compilation of Correlation Result

No	Location	X	Y	R^2
1	Alas Purwo	NDVI	Field Biomass	0.432
2	Alas Purwo	Tree Height	Field Biomass	0.395
3	Alas Purwo	NDVI* Tree Height	Field Biomass	0.891
4	Segara Anakan	NDVI	Field Biomass	0.312
5	Segara Anakan	EVI-1	Field Biomass	0.336
6	Segara Anakan	EVI-2	Field Biomass	0.330
7	Segara Anakan	NDVI* Tree Height	Field Biomass	0.082

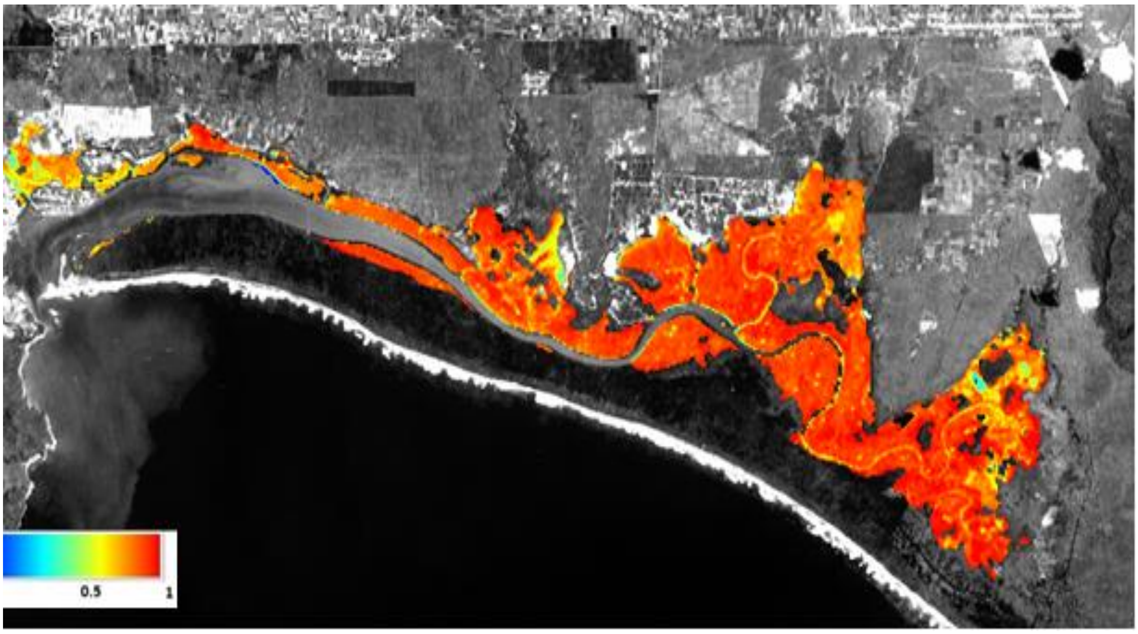

Figure 3-2: Landsat 8 NDVI Image at the Mangrove Area of Alas Purwo

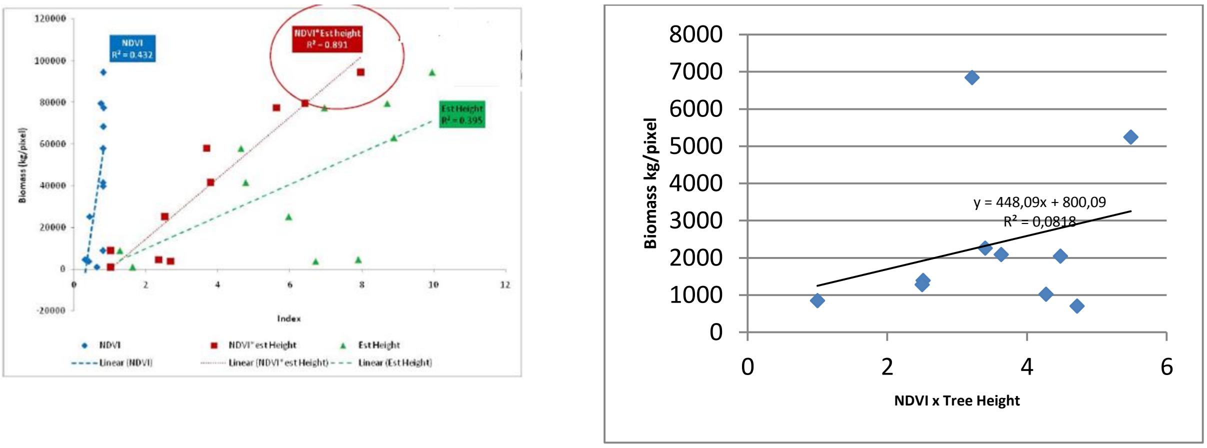

Figure 3-3: Correlation result of NDVI and Estimated-height with Field Biomass for Alas Purwo Data (left) and NDVI and Estimated Biomass for Segara Anakan Data (right)

Correlation analysis between tree biomass with NDVI multiplied height resulted good correlation with R^2 = 0.89 from field data collected at Alas Purwo Banyuwangi (See Table 3-1). However this good correlation could not be found for Segara Anakan Cilacap data (see Table 3-1). The idea to multiply NDVI and tree heights came from fact that biomass is the function of density or volume. Since NDVI only represents 2-dimension, then the third dimension is taken from height estimation using SAR data. Combining two sensors in obtaining object information could be more advantageous for more detailed information.

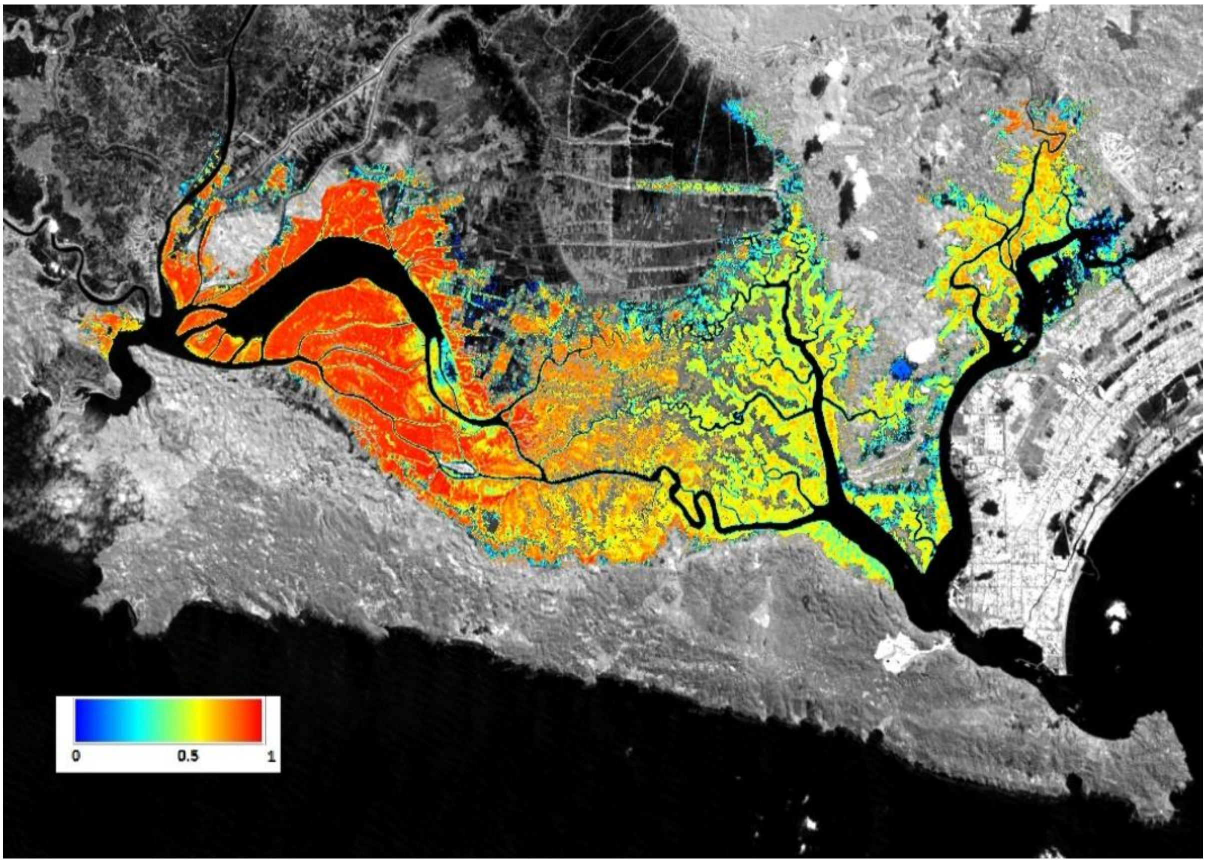

Figure 3-4: Landsat 8 NDVI Image at the Mangrove Area of Segara Anakan

3.2 Discussion

Optical data approach is commonly used to derive vegetation indices for mangrove biomass estimation (Hamdan *et al.*, 2013; Li *et al.*, 2007; Wicaksono *et al.*, 2011) and common forest applications (Foody *et al.*, 2001; Potter *et al.,* 1999 *in* Houghton *et al.*, 2001; Mabowe 2006; Anaya *et al.*, 2009). Studies have indicated that vegetation index is effective for monitoring biophysical variables of temperate vegetation (Foody *et al.*, 2001 *in* Li *et al.*, 2007). Vegetation index is highly related to net primary productivity (Goward *et al.*, 1985 *in* Li *et al.*, 2007). However, this research resulted low correlation between NDVI (and other vegetation indices) and field biomass. This result was in contrary with Hamdan et al. (2013) and Li *et al.* (2007) that generated good correlations between vegetation indices and field biomass. Our result was in line with Wicaksono *et al.* (2011) that NDVI values had low correlation with field biomass. Both this research and Wicaksono *et al.* (2011) were done at the same area in Indonesia. Empirical algorithm is usually site specific that might not be applicable at different part, even in the same country.

Hamdan *et al.* (2013) conducted a research in the Matang Mangrove area which is a large track of managed forest covering an area of 40,710 ha. It is an exemplary of managed mangrove forest that has been sustainable and successfully managed to balance between the production of charcoal and poles and the preservation of mangrove ecosystem (Kamaruzaman and Dahlan 2009 *in* Hamdan *et al.*, 2013).

Managed mangroves commonly have homogenous tree height. This condition leads to high correlation between NDVI and mangrove biomass, since the third parameter or tree height is homogenous. We analyzed that characteristic of the Matang mangrove area is similar with Alas Purwo, but Segara Anakan mangrove area is different. Alas Purwo mangrove area is protected by government with dense mangrove cover and relative high mangrove tree. Meanwhile Segara Anakan mangrove is not a protected area and traditionally utilized by local community. Therefore those two mangrove areas do not have homogenous tree height.

Tree height becomes an important predictor of biomass as SAR signal is scattered according to volume characteristics. Li, *et al.* (2007) found that volume scattering from RADARSAT fine mode images has significant accuracy improvement in terms of Root Mean-Square Error (RMSE) whereas the use of the single Normalized Difference Vegetation Index (NDVI) may produce serious errors in biomass estimation. The errors do not only occur for mangrove forest, but also for prediction of common forest biomass. Learning from previous studies on biomass for common forests such as tropical forests, there are some reasons that tree height is an important predictor. The Woods Hole Research Center published the first hectare-scale maps of canopy height, above ground biomass, and associate carbon stock for the forests and woodlands surrounding United States (Walker *et al.*, 2007). The most important predictors were canopy height variables which were maximum height, average height, and basal-area weighted average height from Forest Inventory and Analysis. Canopy height predictor is a complementary to other predictor such as canopy density provided by National Land Cover Database (NLDC), FIA forest type. Canopy height was calculated using Walker *et al.* (2007) canopy height modeling in which SRTM and elevation data was complementary. So, multiplication of NDVI and tree height with field biomass correlation resulted R^2 0.815 at Alas Purwo and R^2 0.081 at Segara Anakan. The good correlation between multiplication of NDVI and tree height with field biomass indicated the prospect of future development of this simple approach. However, the spatial or ground resolution difference between Landsat 8 LDCM and ALOS PALSAR data could influence and result an uncertainty in biomass estimation.

Low correlation at Segara Anakan (see Table 3-1) was due to the failure of tree height estimation. Research on tree height estimation resulted inappropriate tree height estimation. Tree height estimation model using ALOS PALSAR data (Takeuchi, *et al.*, 2011) resulted over estimation of tree height which was mostly more than 4 meters and only one station resulted 1.8 m that seems to be agreed with tree height in the field. According to Darmawan *et al.* (2015), tree height estimation was related with backscatter value (in dB) that affected by tidal process. The backscatter was decreased when the tidal was high.

4 CONCLUSION

Multiplication of NDVI and tree height with field biomass correlation resulted R^2 0.815 at Alas Purwo area. The good correlation between multiplication of NDVI and tree height with field biomass indicated the prospect of future development of this simple approach. Addition of tree height as the third parameter to become three dimension estimation of mangrove biomass could significantly increase the accuracy. However, empirical approach is usually site specific. The accuracy of tree height estimation was low for tree height range of 1-3 meter. It is necessary to validate this method using more data and improve the accuracy of tree height estimation. However, the spatial or ground resolution difference between Landsat 8 LDCM and ALOS PALSAR data could influence and resulted an uncertainty in the biomass estimation. Some uncertainties related to geometry or ground resolution of the images could be minimized by selecting appropriate sample location, for example by choosing sample area located in the middle of large homogenous mangrove groups.

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