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

**Gathot Winarso[1], Yenni Vetrita[1],**
**Anang D Purwanto[1], Nanin Anggraini[1], Soni Darmawan[2] and Doddy M. Yuwono[3]**

[1]Remote Sensing Application Center, National Institute of Aeronautics and Space of Indonesia
[2]The Institute of Technology Nasional (ITENAS) Bandung.
[3]Geospatial Information Agency of Indonesia

**E-mail:** gathot_winarso@lapan.go.id

**ABSTRACT**

Mangrove ecosystem is important coastal ecosystem ecologically and economically. Mangrove provides rich-carbon stock, most carbon-rich forest among ecosystems of tropical forest. It will be very important for country has large mangrove area in global community regarding the climate change policy related emission trading on Kyoto Protocol. Estimation of mangrove carbon-stock using remote sensing data play important role on emission trading in the future. Estimation models of mangrove above ground biomass are still rare and based on common forest biomass estimation model that already have been developing. Vegetation indices are most models used for biomass estimation model but have low correlation result according some research. SAR data with volume scattering capability chance to get more good correlation on biomass estimation. In this paper, the new model using combination between optic data and SAR was proposed and studied. Biomass is volume dimension that related with canopy of the tree and also related with height of tree. Vegetation indices provided two dimension information of biomass trough recording the canopy density of vegetation and could be well estimated using optic remote sensing data. One more dimension to be 3 dimensional is height of three and could be provided from SAR data. Vegetation indice which used is NDVI extrated from Landsat 8 data and height of tree calculated from ALOS PALSAR. Field biomass data calcultaed using non-decstructive allometric based biomass estimation at 2 different location that is Segara Anakan Cilacap and Alas Purwo Banyuwangi Indonesia. Vegetation indices and field biomassa and ALOS PALSAR-based biomassa estimationresulted low correlation. 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 heigh. It seems that ALOS PALSAR height was not accurate at relative short tree dominated likes at Segara Anakan Cilacap and pretty good at high tree dominated. Need to validate this method using more data and improve more accuracy of tree heigh estimation.

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

## 1. INTRODUCTION

Mangrove ecosystem is important coastal ecosystem, many functions held by mangroves, which are not limited to ecological but also economical function (Barbier, et al., 2008; Ruitenbeek, 1992). Although early workers regarded mangrove forests as unimportant, transitional communities with a low productivity, most ecologists today view then as highly productive ecologically important system (McKee, 2002). According to McKee (2002), major role of mangrove swamps are mangrove contribute to soil formation and help stabilize coastline, mangrove act as filters for upland runoff, mangrove systems serve as habitat of marine organism, mangrove produce large amount of detritus that may contribute to productivity in offshore waters. In additional to these ecologically important role, mangrove forests serve to human to 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 an important role of aesthetics and tourism (McKee, 2001).

Mangroves are among the most carbon-rich forests in the tropics which containing on average 1,023 Mg C /Ha (Donato et al. 2011).“Blue carbon” has been termed to explain the sequestered carbon in vegetated coastal ecosystems, specifically mangrove forests, seagrass beds, and salt marshes (McLeod, et al, 2011). Estimation of mangrove carbon-stock using remote sensing data play important role on emission trading. The estimated carbon from vegetation which is known as biomass have adequate conducted using remote sensing that extensively employed to measure mangrove biomass (Fatoyinbo and Amstrong, 2010) which can be calculated as 50% of the C stored (IPCC, 2000). By advances in technology which providingnew remote sensing data resources for mapping mangrove forests (Heumann, 2011), exploring the use of these data is also necessary for site specific.

Estimation models of mangrove above ground biomass are still limited and based on common forest biomass estimation model that already have been developing. Remote sensing is often the only practical means of acquiring information on forest biomass but has not always been used successfully (Foody et al. 2001). Mangrove biomass estimated from vegetation indices(Hamdan et al. 2013; Li et al. 2007; Wicaksono et al. 2011)and from Radar data(Hamdan et al, 2014; Li et al. 2007; Dien, et al, 2013). Many of the approaches that have been used were developed for application in other environments and are often inappropriate in the tropics (Foody, et al, 2001). For example, simple vegetation indices such as the normalized difference vegetation index (NDVI) have been used widely to estimate biophysical variables of temperate vegetation but, especially as such indices often lose sensitivity to biophysical properties at high vegetation amounts, they have frequently been applied less successfully to tropical forests (Sader*et al.*, 1989; Foody *et al.*, 1996b, *in* Foody, 2001). Wicaksono et al. (2011) estimated above ground biomass using 13 vegetation indices and resulted maximum $R^2$ 0.34 correlationsfrom GEMI with field biomass.The value of $R^2$ is not enough to see the quality of biomass prediction from remote sensing (Wicaksono et al. 2011). It seems that vegetation indices based only is not enough as biomass prediction. Biomass is volume dimension that related with canopy of the tree and also related with height of tree. Vegetation indices provided two dimension information of biomass trough recording the canopy density of vegetation and could be well estimated using optic remote sensing data. One more dimension to be 3 dimensional is height of three and could be provided from SAR data. Vegetation indices based prediction might work well at area where the tree high is homogenous.

In this paper, the new model using combination between optic data and SAR was proposed and studied. The used of additional parameters of tree height was proposed and studied. The correlation between NDVI times tree height and field biomass measurement was done.

## 2. MATERIAL AND METHOD

### 2.1. Research Location

The amount of mangroves can be found in the Southeast Asia region where its biodiversity is the highest in the world (Polidoro et al., 2010) . About almost 60% Southeast Asia’s total which comprises about 19% of the world’s mangroves is in Indonesia (Giesen, et al., 2007). Algorithm development is done at Indonesia could be more representative to mangrove ecosystem in the world. The research was done atmangrove area of Segara Anakan Cilacap and protected area Alas Purwo National Park located in Banyuwangi East Java Province, Indonesia.

Banyuwangi seawaters are a strategic area because located at hub area of Java Island and Bali Island, the east part is Bali Strait seawater and south part is India Ocean (Latupapua, 2011). Mangrove at Alas Purwo national park has high biodiversity such as fish, vegetation, bird and also nekton where live in mangrove ecosystem. This mangrove area found 14 species that are *Acrosticumaureum, Bruguiera cylindrical, Bruguiera gymnorrhiza, Bruguiera sexangula, Ceriops decandra, Ceriops tagal, Excoecaria agaliocha, Rhizopora apiculata, Rhizopora mucronata, Scyphiphora hydrophyllacea, Sonneratia alba dan Sonneratia caseolaris* and *Ceriopdecandra* and *Scyphiphora hydrophyllacea* were endagered species but commonly found (Satyasari, 2010 *in* Saifullah and Harahap, 2013).

Instead of Alas Purwo area, the other area for comparison reason where area was studied before using same vegetation index, located in Segara Anakan Mangrove Area in Cilacap Central Java Province. Segara Anakan is the largest mangrove area in Central Java Province but already became degraded mangrove area because this area is not protected area and intensively use by coastal community. Segara Anakan is unique and specific, developed from intertidal area that consists of lagoon and sedimentation product delta area and protected from wave and wind from the India Ocean by Nusakambangan Island. This area have high rate of sedimentation process due to the large of water inland input for several big rivers. Intertidal area is the potential mangrove growth area where have high potential of fisheries resources. Segara Anakan have not become protected area yet but has been managed by DinasKelautanPerikanandanPengelolaanSumberdayaKawasanSegaraAnakan (Marine Affair Fisheries and Segara Anakan Area Resources Management) under local government. However, this area also has been managed by Mangrove Forest Management Unit under Ministry of Forestry and also by Law and Human Right Ministry due to be located Nusakambangan Jails.

Mangrove ecosystem in this area 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 is 21.750 Ha and 12.610 area still are affected by tidal 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 is 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 at Landsat-8 sensor is almost similar with Landsat-7 ETM+ that already used for mangrove identification with additional spectrum such as coastal blue band and cirrus band. Standard Level Correction of 1T Level data used that has higher accuracy on radiometric and geometric correction due to DEM from accurate topography map application (USGS, 2013). SAR data was used in this research was ALOS PALSAR K &C Mosaic that provided by JAXA in 50 m ground resolution.

Field data which used in this research was taken on twice field survey for Segara Anakan and once for Alas Purwo area. The first survey at Segara Anakan was done on 27 – 31 May 2013 and the second on 19 – 24 November 2014. For each survey were collected 6 sampling station or have 12 total sampling stations. Field data which used is wood density of mangrove, species for each tree and diameter of breast height (DBH). Densities of mangrove were calculated within 30 x 30 m area and divided into 9 sub-plots that each sub-plot has 10 x 10 m area. The density calculation were not done at all 9 sub-plot but only on randomly 1-5 sub-plot due to the lack of time and area accessibility, then are averaged to representation density of 30 x 30 m of Landsat-8 ground resolution. DBH measurements were done for each tree inside the plot including the species of mangrove tree. Biomass then calculated from DBH measurement using specific allometric algorithm for each species refer to the last and nearest place allometric algorithm development. This biomass measurement is called non-destructive method to measure biomass in the field.

Using almost same method, the field data of Alas Purwo was measured. Alas Purwo field data was provided by Geospatial Information Agency that conducted field measurement on 28 June 2012 until 4 July 2012. The remote sensing data acquisition date, and field measurement in the field were difference, but we assumed that there are significant change between that times.

### 2.3. Method

Mangrove biomass estimation has possibility to calculate from parameters which are extracted from remote sensing data. Several methods already published and used operationally, include method which using simple approach and using more complicated approach. Within forests with a high percentage of tree cover, however, biomass may vary as a function of tree height, tree architecture, wood density, and basal area, none of which is sensed with optical data, and thus variations in biomass at high percentage tree cover may be missed (Houghton, et al. 2001). Vegetation indices are most models used for biomass estimation model but have low correlation result according some research. SAR data with volume scattering capability chance to get more good correlation on biomass estimation. Biomass is volume dimension that related with canopy of the tree and also related with height of tree. Vegetation indices provided two dimension information of biomass trough recording the canopy density of vegetation and could be well estimated using optic remote sensing data. One more dimension to be 3 dimensional is height of three and could be provided from SAR data. Vegetation indice which used is NDVI extrated from Landsat 8 data and height of tree calculated from ALOS PALSAR. Field biomass data calcultaed using non-decstructive allometric based biomass estimation at 2 different location that is Segara Anakan Cilacap and Alas Purwo Banyuwangi Indonesia.

#### 2.3.1. NDVI (*Normalized Difference Vegetation Index*)

Live green plants absorb solar radiation in the photosynthetically active radiation (PAR) spectral region, which they use as a source of energy in the process of photosynthesis. Leaf cells have also evolved to scatter solar radiation in the near-infrared spectral region (which carries approximately half of the total incoming solar energy), because the energy level per photon in that domain (wavelengths longer than about 700 nanometers) is not sufficient to be useful to synthesize organic molecules. A strong absorption at 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). By contrast, 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 pigment in plant leaves, chlorophyll, strongly absorbs visible light (from 0.4 to 0.7 μm) for use in 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, respectively. Since early instruments of Earth Observation, such as NASA's ERTS and NOAA's AVHRR, acquired data in visible and near-infrared, it was natural to exploit the strong differences in plant reflectance to determine their spatial distribution in these satellite images. The NDVI is calculated from these individual measurements as follows:

$$\mathrm{NDVI} = \frac{(\mathrm{NIR} - \mathrm{VIS})}{(\mathrm{NIR} + \mathrm{VIS})}$$

where VIS and NIR stand for the spectral reflectance measurements acquired in the visible (red) and near-infrared regions, respectively (http://earthobservatory.nasa.gov/Features/MeasuringVegetation/measuring_vegetation_2.php). These spectral reflectances are themselves ratios of the reflected over the incoming radiation in each spectral band individually, hence they take on values between 0.0 and 1.0. By design, the NDVI itself thus varies between -1.0 and +1.0. It should be noted that NDVI is functionally, 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 with vegetation properties (e.g. biomass). The simple ratio (unlike NDVI) is 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. Also in this regard, note that 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). But the most important concept in the understanding of the NDVI algebraic 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 pixel is likely to be dense and may contain some type of forest. Subsequent work has shown that the 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) applied in this research. The field survey revealed that the area is covered by mainlyfour 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 (σ0) of HH and HV in mangrove was established. Results show that there was a positive relation between σ0 and tree height with the larger sensitivity to tree height found at HV. Moreover, strong differences were observed between polarizationsat HH and HV. A regression analysis was carriedout between tree height and σ0 at HH and HV polarizationsand it was characterized by equation 1 and 2 withroot mean square errors of 2.2 and 2.0 (db) respectively.

$$HH = 3.6 * \ln(\text{tree height}) - 23.7$$
$$HV = 4.4 * \ln(\text{tree height}) - 24.9$$

Allometric equations among tree height, DBH andabove ground biomass(MAFF, 2010 *in* Takeuchi et al, 2011) reported that the relationship between tree height in meters and diameter at breast height (DBH) incentimeters at *Bruguiera gymnorhiza* mangrove as shownin equation with root mean square errors of 0.85 meters.

$$\text{Tree height} = 2.8 * \ln(DBH) + 0.4$$

Komiyama et al., (2008) reported that the relationship betweenabove ground tree weight (AGW) in kilogram andDBH in centimeters as shown bellow. This equationis commonly used among

*Avicennia germinans, Laguncularia racemosa, Rhizophora apiculata, Rhizophora mangle, Bruguiera gymnorrhiza, Bruguiera parviflora, Ceriops australis*and *Xylocarpus granatum*.

$$AGW = 0.25 * DBH2.46$$

Canopy height and biomass have been shown in field studies to be strongly related for many mangrove species (Fromard et al., 1998; Smith andWhelan, 2006). Biomass can be estimated directly using PolSAR or indirectly using VHR image texture to dectect canopy structure or SAR Interferometry (InSAR), stereo imagery, or LiDAR to estimate canopy height.

## 3. RESULT AND DISCUSSION

### 3.1. Result

Development of method can be done with trial processes by compared some publish method then be evaluated which one is the best. Some time we could not find the best but only found the better one. Then we tried evaluating each processed and tried to find the part where we can improve the method. Before we found the good correlation result, we applied Takeuchi et al (2011) method using K&C ALOS PALSAR dataset with 50 m ground resolution at two different research locations that are at Alas Purwo area and Segara Anakan area. The application of Takeuchi et al. (2011) method in both area resulted not good correlation between satellite bases biomass estimation with field measurement. However, we got tree height estimation from this processing result. The other method we tried were application of some vegetation indices but only 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. This correlation was not good enough to establish the empiric-based algorithm for estimating above ground biomass. At Alas Purwo area, the correlation analysis was only done for NDVI with field biomass resulted correlation with $R^2$ 0.432. EVI-1 and EVI-2 was not used for Alas Purwo area.

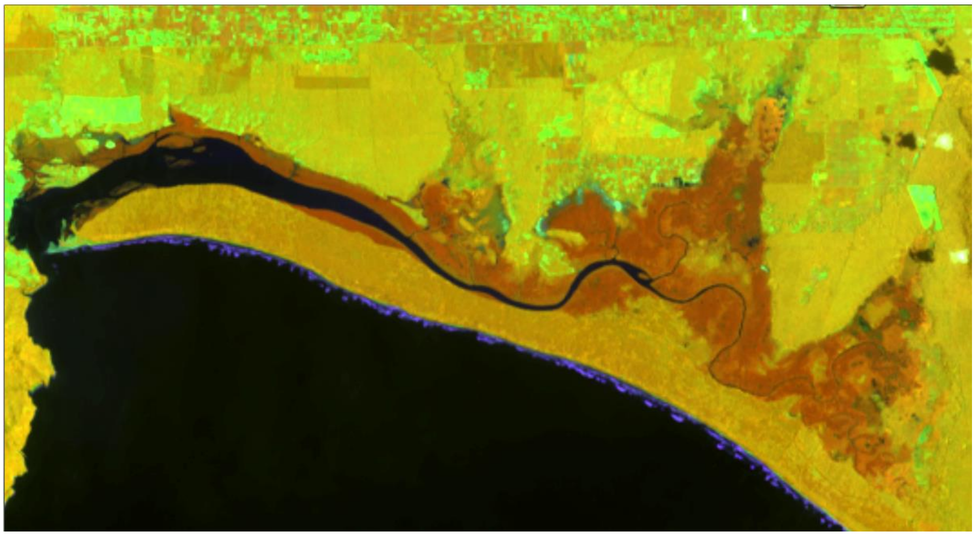

Figure 1. Landsat RGB 564 Composite Image that Shown the Mangrove Area at Alas Purwo

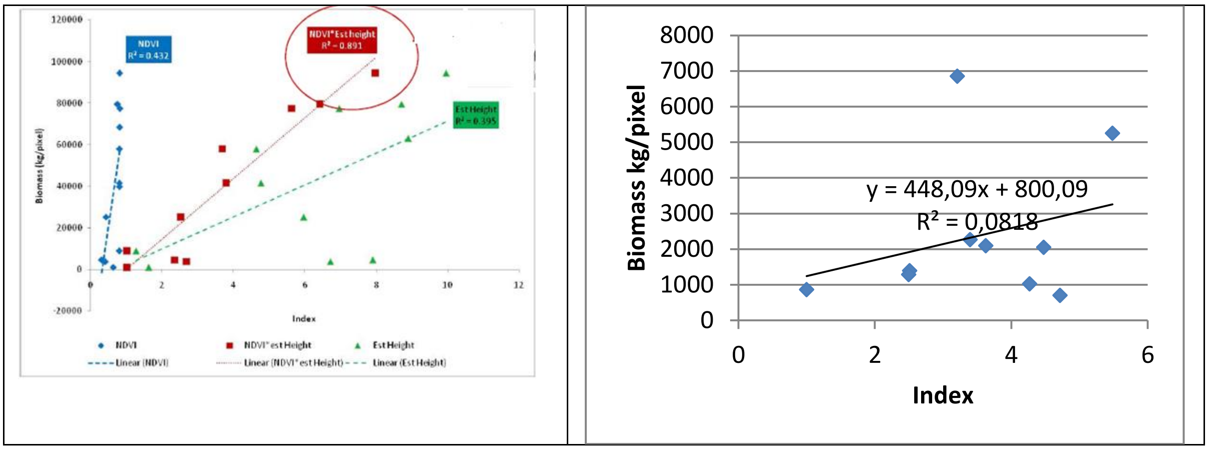

Figure 2. Correlation result of NDVI and Estimated-height with Field Biomass for Alas Purwo Data (left) and NDVI and Estimated Biomass for Segara Anakan Data (right)

Correlation analysis between biomass and NDVI tree height multiplication resulted good correlation with $R^2$ = 0.89 from field data that collected from Alas Purwo Banyuwangi (See Fig. 2 right). However this good correlation could not be found from Segara Anakan Cilacap data (See Fig 2 left). This idea to multiply between NDVI and tree heights come from fact that biomass is function of density or volume. Density or volume is 3-dimensional that NDVI represented of 2-dimensional only, and then one dimension took from height estimation from SAR data. Combining two sensors for getting some information resulted more advantages for more detail information.

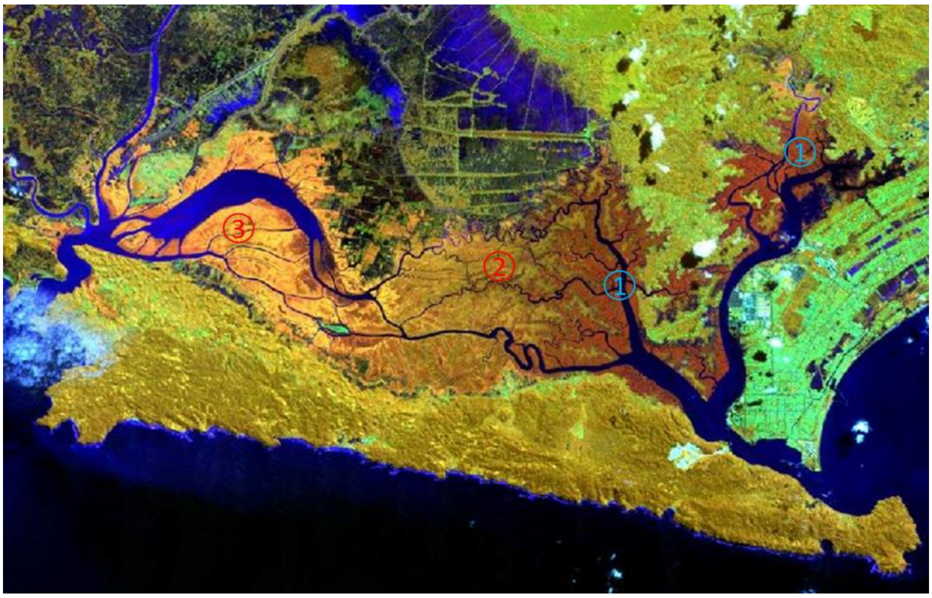

Figure 3. Landsat RGB 564 Composite Image that Shown the Mangrove Area at Segara Anakan

### 3.2. Discussion

Optic data approach commonly used vegetation indices for mangrove biomass estimation (Hamdan et al. 2013; Li et al. 2007; Wicaksono et al. 2011) and for common forest (Foody et al. 2001; Potter et al 1999 *in* Houghton et al. 2001; Mabowe 2006; Anaya et al. 2009). Studies indicate that the index is effective for the monitoring of biophysical variables of temperate vegetation (Foody et al. 2001*in* Li et al. 2007). Vegetation indices is highly related to net primary productivity (Goward et al. 1985*in* Li et al. 2007).

However in this research was resulted low correlation between NDVI (and other vegetation indices) with field biomass. This result is opposite with Hamdan et al. (2013)and Li et al. (2007) that generated good correlation between vegetation indices with field biomass. Our result agreed with Wicaksono et al. (2011) that NDVI have low correlation with field biomass. Both in this research and Wicaksono et al. (2011) were done at same area where is in Indonesia. Empiric based algorithm usually is site specific that even in Indonesia area might not applicable at different part of Indonesia.

Hamdan et al. (2013) did research at Matang Mangrove area that Matang Mangroves is a large tract of managed forest that covers an area extent of 40,710 ha. It is an exemplary managed mangrove forest that has been sustainably and successfully managed to balance between the production of charcoal and poles and the preservation of mangrove ecosystem (Kamaruzaman & Dahlan 2009 *in* Hamdan et al 2013). Managed mangroves commonly have homogenous tree height. This phenomenon leads high correlation between NDVI and biomass, because the third parameter was homogenous. We expected that characteristic of Matang Mangrove area with both Alas Purwo and Segara Anakan Mangrove area is different. Alas Purwo Mangrove area is protected area by government with dense of mangrove and relative high mangrove tree. Segara Anakan mangrove area is not protected area and traditionally used by local people. In those 2 mangrove area expected have not homogenous tree height.

Tree height becomes an important predictor to biomass as SAR scattered with volume scattering. Li, et al. (2007) found that volume scattering from RADARSAT fine mode images have 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. Not only for mangrove forest, affected also for prediction of common forest biomass. Learn from published papers about biomass for common forest such as tropical forest, 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, aboveground biomass, and associate carbon stock for the forests and woodlands of the conterminous United States referred to Walker, et al. (2007). The most important predictor was canopy height variable that's maximum height, average height and basal-area weighted average height from Forest Inventory and Analysis. Canopy height predictor as complementary other predictor such as canopy density that is provided by National Land Cover Database (NLDC), FIA forest type. Canopy height was calculated using Walker et al. (2007) canopy height modeling that need SRTM and Elevation data as 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 development this simple approach. Although the spatial or ground resolution difference between Landsat-8 LDCM and ALOS PALSAR could influence and resulted an uncertainty in estimating biomass.

Low correlation at Segara anakan was due to failed estimation of tree heigh. Investigation of tree height estimation resulted inappropriate tree height estimation. ALOS PALSAR tree height estimation model (Takeuchi, et al., 2011) resulted tree height mostly more than 4 meter and only one station resulted 1.8 m that seem be agreed with tree height in the field. Tree height estimation was related with backscatter value (in dB) that according Darmawan et al. (2015) affected by tidal process. The backscatter was decrease when the tidal was high tide.

## 4. Conclusion

Multiplication of NDVI and tree height with field biomass correlation resulted $R^2$ 0.815 at Alas Purwo. The good correlation between multiplication of NDVI and tree height with field biomass indicated the prospect of development this simple approach. Additional one more parameter to become 3 dimensional of tree height significantly increase the accuracy of estimation. However, empiric approach usually site specific. Accuracy of tree height estimation was low in tree height range 1-3 meter. Need to validate this method using more data and improve more accuracy of tree heigh estimation. Although the spatial or ground resolution difference between Landsat-8 LDCM and ALOS PALSAR could influence and resulted an uncertainty in estimating biomass. Some uncertainties related to geometry or ground resolution of the images could be minimalized by selecting appropriate sample location, for example sample located in the middle of large homogenous mangrove groups.

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