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Article

Examination of Multi-Spectral Radiance of the Landsat 8 Satellite Data for Estimating Biomass Carbon Stock at Wetland Ecosystem

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Abstract: The assessment of biomass carbon stocks was conducted at plot scale as a sample to estimate for all vegetation areas by using destructive sampling and or allometric equation method. Remote sensing is one of the techniques can be used to estimate and mapping biomass carbon stock for the entire areas. The objectives of the study are the identification and determine the range of electromagnetic wave of Landsat 8 satellite data that most suitable for assessing and mapping biomass carbon stock distribution. This research analyses exponential regression equation between spectral radiance values ($L\lambda i$) for with biomass measurement results on the field to find the best correlation based on the coefficient of determination value (R2). It also analyses the relationship between field biomass and NDVI value (Normal Differences Vegetation Index) from satellite data. The study area consists of 54.9% bush (Bs), 24.5% scrub (Sc), 16.8% secondary forest (Sf), while the rest (3.8%) is a water body. The with average biomass carbon stock value 4.11 tons.ha-1, 64.43 tons.ha-1, and 85.36 tons.ha-1, for strata Sc, Bs, and Sf respectively. Spectral radiance of SWIR (Shortwave Infra-Red) band 6 is determined as a spectral characteristic that can be used for estimating carbon stock with following the equation Y= 12657(EXP(-0.642($L\lambda_{band6}$)) with r^2 = 0.75. Correlation NDVI and field biomass showed the low r^2 value (0.08), so in this study, NDVI cannot be used to estimate the biomass carbon stock.

Keywords: biomass; carbon stock; wetland; spectral radiance; SWIR

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1. Introduction

The Carbon dioxide (CO2) is one of the greenhouse gasses (GHG) which an important role in climate. According to the IPCC (Eggleston et al., 2006); Hairiah et al., (2007), within a period of 150 years the concentration of CO2 in the atmosphere has increased about 28%. Land use change from forest conversion into open or agriculture area has caused an increasing CO2 concentration in the atmosphere. About half of CO2 emissions from the land use activities and the use of fossil fuels (Lusiana et al., 2010). Therefore, mitigation efforts of climate change in the land-based sector to be a main priority agenda at this time. One of mitigation measures is to consider the avoidance of land with high carbon deposits on the opening of a new development area (RSPO, 2014). The inventory and calculation of any sources of carbon stocks at the landscape level should be done. Carbon stock in the vegetation can be calculated with the tree biomass approaches. Absolute carbon content in the biomass at a given time is known as carbon deposits or carbon stock (Apps et al., 2003).

A common approach for estimating biomass carbon stock of vegetated area is through use destructive sample measurement and or allometric equations for individual trees or ecosystem type respectively (Ketterings et al., 2001; Dharmawan., 2013; Ganeshamurthy et al., 2016). The results were used to determine the carbon stocks at the regional level by extrapolation approach depend on land cover type or forest type (Murdiyarso et al., 2004; Eggleston et al., 2006; Hairiah et al., 2007; Manuri et al., 2011; Krisnawati et al., 2014). The roles of remote sensing data only for land cover

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mapping (Asner et al., 2011). This method assumes that each type of land cover has a single value of biomass carbon stocks. Remote sensing data have not been used optimally to estimate directly.

Landsat 8 has eleven bands with differences of electromagnetic (EM) wavelength range value, consisting of nine bands in the Operational Land Imagery (OLI) sensor and 2 bands in the Thermal Infrared Sensor (TIRS) (USGS, 2016). OLI sensors receive reflectance shortwave EM and TIRS receive outgoing longwave EM radiance from the surface. Spectral radiance value is determined by surface radiation budget, including reflection, absorption, emission and transmission by object's (Coakley and Yang, 2014). Vegetation is one of the surface objects where spectral radiance value was affected by biomass and the water content (Ceccatoa et al, 2010; Borzuchowski & Schulz, 2010).

The study objectives are spectral radiance examinations of the Landsat 8 OLI/TIRS satellite bands respectively to estimate biomass of vegetation. The examination results could be used for biomass carbon stocks mapping at the regional level, without having to undertake land cover mapping and field measurements..

2. Methods

2.1. Site study and material

The site study located at Bongan subdistrict, Kutai Barat district, East Kalimantan-Indonesia, with the astronomical location are 116°13’00” to 116° 24’00” East and 00° 30’00” to 00° 48’15” South. The site consists of four classes of land use, there are water body, building area, agricultural land and forest land. Almost all vegetation cover is wetland ecosystem, including peat swamps, freshwater swamps, flooded area and riparian. The agricultural land founded on the higher and drier land than the surrounding area. On the site, there are four rivers that often cause flooding during the rainy season, that is Bongan river, Bongan Tongkok river, Bongan kiri river and Bongan kanan river.

This study uses primary data and secondary data. The primary data is a measurement of biomass and land cover ground check. Secondary data consist of (i) Landsat 8 OLI/TIRS satellite imagery-path/row: 117/60, acquisition date: October 12, 2014 (https://earthexplorer.usgs.gov), (ii) topographic and base map (http://www.big.go.id), (iii) SRTM DEM 90m (http://www.cgiar-csi.org/data/srtm-90m-digital-elevation-database-v4-1)

2.2. Fieldwork and data analysis

In order to obtain high accuracy, field sampling methods used stratified random sampling. Stratification is effectively used because the effect on the increase of homogeneity within each strata (MacDicken, 1997), also reduces the possibility of a big difference between plots and increase the accuracy even though the number of plots are little. Therefore, the type and density of vegetation become an important criterion in the stratification of the assessment area. The number of observation plots in the field is adjusted to the results of the stratification of vegetation cover. Random sampling is done disproportionately in order to avoid vegetation cover strata with a small area that is not represented. At every strata of vegetation cover, three plots random samples are taken. On each plot sample, three plot lines are made as repetitions (**Figure 1)**. In each plot there are sub-plots that have certain sizes according to the size or the measured vegetation such as diameter at breast height (DBH) (**Table 1**).

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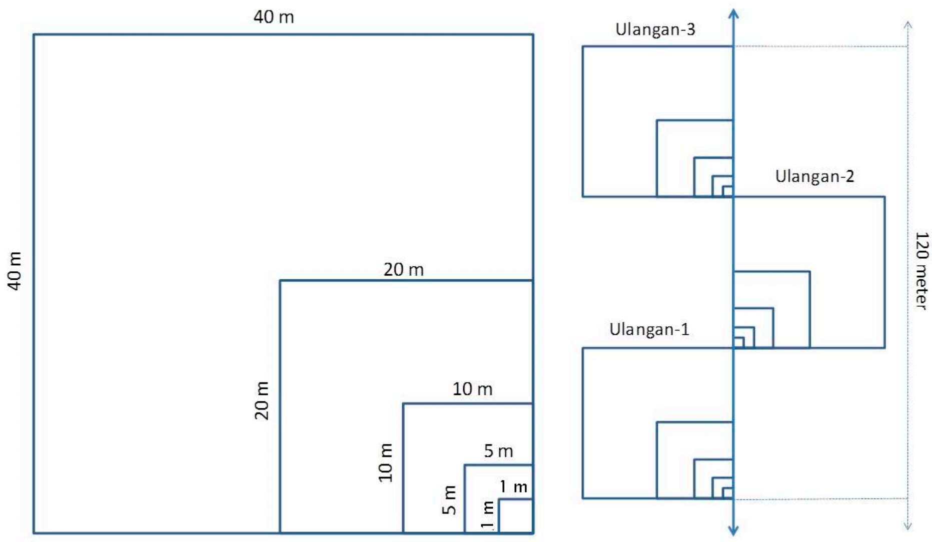

Figure 1. The shape and size of plot and subplot (left) and plot position in the plot lines (right).

Table 1. Size of sub-plot in biomass sampling

Subplot size	Vegetation object/biomass sampling
1 x 1 meter (3x random repetition for each plot)	Herbaceous plants, shrubs, litter, tree seedlings with 2-5 cm diameter.
5 x 5 meters	All liana plants, palms, trees with 5-10 cm DBH, dead trees with 5-10 cm diameter.
10 x 10 meters	All trees with 10-20 cm DBH, dead trees with 10-20 cm diameter, dead wood with 10-30 cm diameter.
20 x 20 meters	All trees with 20-35 cm DBH, dead trees with 20-35 cm diameter, dead wood with > 30 cm diameter.
40 x 40 meters	All trees with > 35 cm DBH.

2.2.1. Above Ground Biomass

The approach to estimate tree above-ground biomass (AGB) at the field is allometric equations of several kinds of research that have been conducted globally and locally. Allometric equations that have developed recently are empirical equations that in their applications can refer to the forest ecosystem as well as on certain tree species. Most of the allometric equations use DBH variable to estimate the value of biomass and the tree volume at particular ecosystem types or at the tree species level. Allometric equations are using the regulation by the Ministry of Forestry of Indonesia (BPPK, 2012), as the main reference. Several other references of allometric equations derived from the results of credible research are also used to supplement and improve the accuracy of the assessment (Brown, 1997; Adinugroho, 2009; Basuki et al, 2009; Anggraeni, 2011; Krisnawati et al, 2012). The allometric equations diversity should be a concern in the choice of equations that will be used in the assessment. Another reason must be considered is that not all species of trees have an allometric equation, so in this case, the ecosystem type approach is used (Krisnawati et al, 2014). In addition to the trees, AGB also comprises biomass derived from herbaceous plants, shrubs, and seedling stage trees. Biomass estimation at this stage is done by destructive sampling on 1x1 meters plot.

2.2.2. Below Ground Biomass

Measurement of root biomass or below-ground biomass (BGB) on the field can only be done by destructive sample, which means cutting and digging every tree species found in the plot, and then

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take the roots and weigh the wet weight. Due to this condition, roots sampling is not conducted because it is difficult to do on the field and also has a negative impact for the ecosystem in the assessment area. Therefore, to estimate the root biomass, use root to shoot ratio (RSR) method or the ratio of BGB with AGB is used. As references of RSR, the values collected as presented in **Table 2**.

Table 2. Ratio of below-ground biomass and above-ground biomass or r*oot shoot ratio*

Ecology Zone	**Above-Ground Biomass (AGB)**	***Root of Shoot Ratio* (RSR)**	**Reference**
Tropical rain forest		0.37	Fittkau and Klinge, 1973
Tropical moist deciduous forest	AGB < 125 ton/ha	0.20 (0.09 – 0.25)	Mokany *et al., 2006*
	AGB > 125 ton/ha	0.24 (0.22 – 0.33)	Mokany *et al., 2006*
Tropical dry forest	AGB < 20 ton/ha	0.56 (0.28 – 0.68)	Mokany *et al., 2006*
	AGB > 20 ton/ha	0.28 (0.27 – 0.28)	Mokany *et al., 2006*
Tropical shrubland		0.40	Poupon, 1980
Tropical mountain systems		0.27 (0.27 – 0.28)	Singh *et al.*, 1994

2.3. Remote Sensing data analysis

Land cover analysis is carried out as the first step to determine the stratification of the vegetation cover in the assessment area. The stratification results are then used to determine the number of samples in the field. Stratification of vegetation cover refers to National Indonesia Standard (NIS) 7645 on Land Cover Classification (BSN, 2010), and the method used unsupervised classification (Wilson and Sader, 2002; Romero et al, 2015). Landsat 8 OLI band combination used was 654 bands, it's the best combination of vegetation analysis (Acharya and Yang, 2015).

Digital number (DN) all bands of Landsat 8 OLI/TIRS converted to spectral radiance values as follows:

$$L_{\lambda}=\left[\frac{Lmax_{\lambda}-Lmin_{\lambda}}{QCAL_{max}-QCAL_{min}}\right]\times(QCAL-QCAL_{min})+Lmin_{\lambda} \quad (1)$$

Where, Lλ = Spectral radiance band-i ($Wm^{-2}str^{-1}\mu m^{-1}$); QCAL = DN band-i; Lmin = Minimum spectral radiance value of band-i; Lmax= Maximum spectral radiance value of band-i QCALmin = Minimum pixel value (metadata); QCALmax = Maximum pixel value (metadata)

The results of the conversion are then filtered to obtain spectral radiance values each band representing field plot. To get the average value of spectral radiance band-1 for each plot, then used compass base approach (Risdiyanto, 2007), which are the average value of nine pixels located around the coordinate of plot sample. These values are independent variables in the regression equation with biomass field measurements as the dependent variable. Coefficient of determination (r^2) of each regression equation showing the representation of biomass by spectral radiance values of band-i. In addition, the Normalized Difference Vegetation Index (NDVI) approach was also used to indicate the relationship with biomass in the same way. As a reference for each regression analysis outcome between biomass and spectral radiance value of band-i use a graph the relationship between the reflectance and the wavelength (Hoffer, 1978) (**Figure 2**).

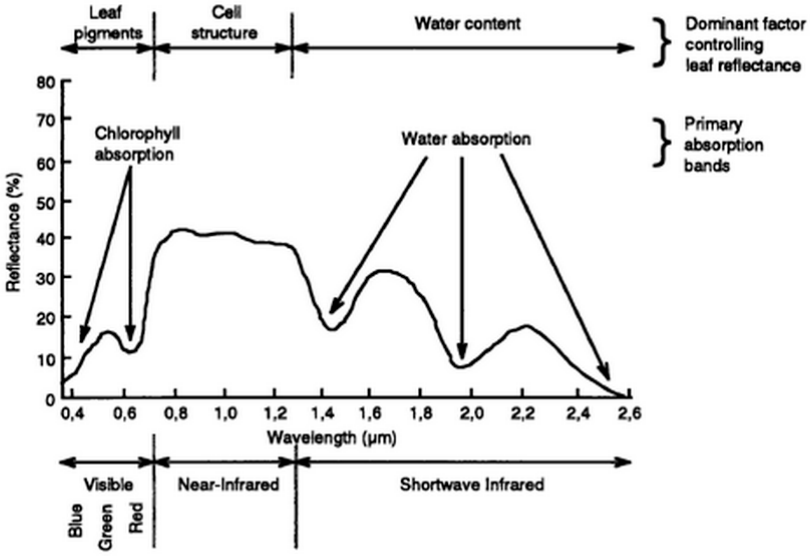

Figure 2. General chart on reflectance at each wavelength of the light spectrum range (Source: Hoffer, 1978)

Table 1. Band characteristic of Landsat 8 OLI/TIRS satellite imagery

Bands	Wavelength range (µm)	Spatial resolution (m)
Band 1 – VIS-coastal aerosol	0.43 - 0.45	30
Band 2 – VIS-Blue	0.45 - 0.51	30
Band 3 – VIS-Green	0.53 - 0.59	30
Band 4 – VIS-Red	0.64 - 0.67	30
Band 5 – Near Infrared (NIR)	0.85 - 0.88	30
Band 6 – Shortwave Infrared (SWIR) 1	1.57 - 1.65	30
Band 7 – Shortwave Infrared (SWIR) 2	2.11 - 2.29	30
Band 8 – VIS-Panchromatic	0.50 - 0.68	15
Band 9 – Cirrus	1.36 - 1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6 - 11.19	100
Band 11 – Thermal Infrared (TIRS) 2	11.5 - 12.51	100

Source: USGS (2013)

2.4. Biomass carbon stocks mapping

The allometric equation and destructive method produce the estimation of vegetation dry weight or biomass level and not in the carbon unit. A common value on the global level uses the estimated value of carbon sourced from biomass, which is 0.47-0.50 of the biomass (Eggleston et al, 2006). It is also in accordance with NIS 7724: 2011 on "Measurement and Calculation of Carbon Stock: Field Measurements for Forest Carbon Stock Assessment (Ground Based Forest Carbon Accounting)". So that the general equation of the total carbon stock value of land or forests are:

$$CS = 0.47\ (AGB+BGB) \tag{2}$$

Where, CS=Carbon Stock (tons.Ha^{-1}), AGB=Above Ground Biomass (tons.Ha^{-1}), and BGB=Below Ground Biomass (tons.Ha^{-1}),

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In order to know the total number of carbon stock in the assessment area, extrapolation of the carbon value resulted from the calculation in each plot is necessary. Extrapolation can be done by one of these two approaches: (i) based on each land covers an area or ecosystem type and (ii) use the regression equation with highest r^2 of band-i. In this assessment, second approach will be used because it will provide higher accuracy than the first approach, although it requires a longer process.

3. Results and Discussion

3.1. Field measurement of carbon stock biomass

The vegetated land cover is classified into three strata, namely the secondary forest (Sf), scrub (Sc) and bush (Bs). The area of each vegetation cover as the result of satellite data interpretation results is 54.9% for Bs, 24.5% for Sc and 16.8% for Sf, while the rest (3.8%) is a water body. The total number of plots sampling for biomass measuring are 49 plots, which consisted of 13 plots for Bs, 22 for Sc and 14 for Sf. The plot number is set purposefully in accordance with the hectare areas and type of vegetation cover.

The average biomass for each stratum of vegetation Bs, Sc and Sf are 9.4 tons. Ha^{-1}, 94.5 tons. Ha^{-1} and 177.8 tons. Ha^{-1} sequentially. These results differ from Astiani et al (2017) who present the value of low degraded peat forest and swamp forest is is 273.8 tons. Ha^{-1}, and scrub is 61.1 tons. Ha^{-1}. Biomasses on Sf close to the result Seo et al (2014). They present the results of AGB field measurements in the tropical forest of the Tangkulap Forest Reserve, Sabah, Sarawak, an average of 255.1±91.8 ton. Ha^{-1}, and diversity coefficient is 36%. Similar results were obtained by Manuri et al (2011) in MRPP SouthSumatera.

Distribution of biomass data for each of the vegetation cover is normal according to the value of the Anderson-Darling (AD) is relatively low and P-value> 0.05). Each vegetation cover type has a biomass measurement deviation. Biomass measurement deviation on Bs is 43.1% of the average value, it is greater than Sc (32.8%) and Sf (24.1%). Standard deviation is lower than the Gonçalves et al (2017), perform measurements at the secondary and primary forest that reaches 77%. Presences of any diameter tree stand 2-10 cm at some BS plot has been generated a higher biomass than the plot contains herbaceous plants and grasses only. At Sc and Sf plot, biomass deviation was caused by differences in allometric equations and species dominance to each wetland ecosystem type, such as between riparian and peat swamp (**Figure 3 and 4**).

The different vegetation species, according to the wetland ecosystem types are not further analyzed. The only difference is determined by the stratum of vegetation which divided into three, namely Bs, Sc and Sf, represent the vegetation and or canopy density. Landsat 8 can only represent spectral radiance band-i accumulate as a response to the surface characteristics which determined by a canopy density. So that, variation in biomass measurements be accepted as a result of the diversity of each vegetation cover or canopy. The biomass data distribution and deviation can be considered to determine the spectral radiance conjunction with band-i.

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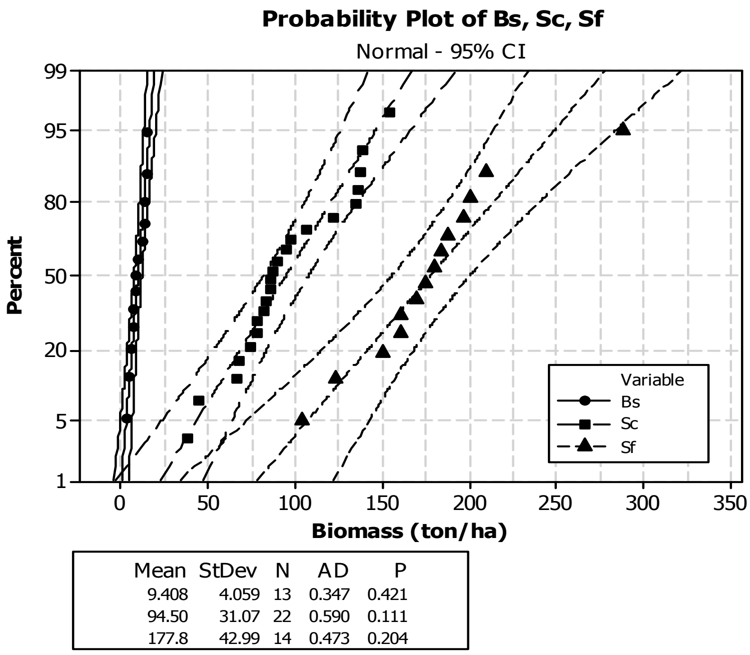

Figure 3. Probability plot biomass field measurements for each vegetation land cover

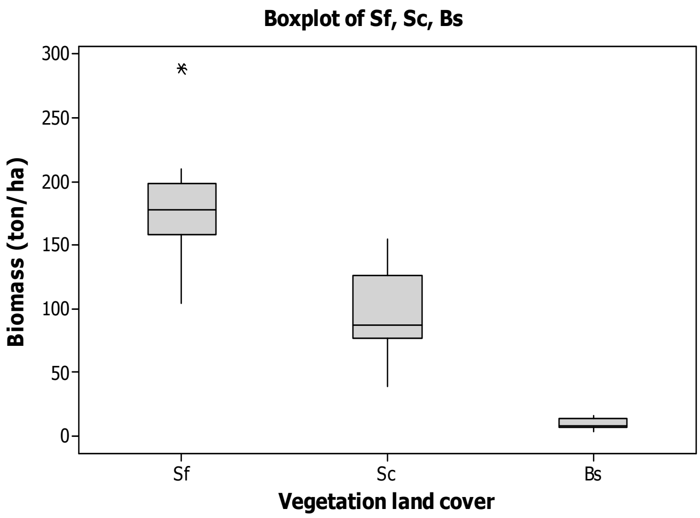

Figure 4. Boxplot of biomass field measurements for each vegetation land cover

3.2. Regression analysis with spectral radiance band-i

The regression equation is required to be able to explain the relationship between the spectral radiance as an independent variable with biomass as the dependent variable. To determine the regression function to be used, then conduct empirical cumulative data fitting (ecdf) analysis to determine the data distribution for all stratum Bs, Sc and Sf. Results ecdf analysis of data showed a fit distribution is exponential (**Figure 5**). Therefore, the regression equation used in this study is a non-linear regression, that is the exponential function. As predictor is a spectral radiance band-i and as the response is a biomass.

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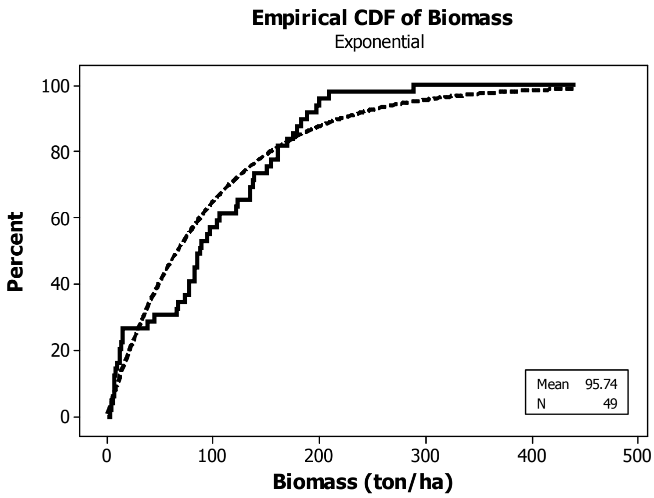

Figure 5. The empirical cumulative distribution function of fit biomass data of each vegetation cover

Spectral radiance of band visible light (VIS) with the range of wavelength is 400-750 did not have a strong correlation with the biomass on the surface, although the VIS may show natural colour, including the green colour of the leaves (**Figure 6 and 7**). VIS can only show the momentary condition of short-wave radiation is absorbed and reflected by the surface. In general, the vegetation canopy reflecting the green spectrum and absorb the red spectrum. The larger the leaf area index value would provide the value of the reflectance green spectrum and absorption red spectrum increases. Although red absorption spectrum by the leaf canopy can provide an indication of photosynthesis, but it cannot explain the accumulation of the assimilate that into biomass. For the assessment of biomass, VIS and infrared spectrum were formulated together to estimate leaf area index first, then biomass (Heiskanen, 2005; Risdiyanto and Setiawan, 2007; Wang and Qi, 2008)

Red and NIR spectrum has been commonly used to identify the growth and development of plants. Both are often formulated as NDVI. If the red spectrum does not have a strong correlation with biomass, as well as NIR (Figure 8), including if they were formulated into NDVI (Figure 9). Aparicio et al. (2002); Alvaro et al. (2007) obtain NDVI correlated with LAI and biomass in monoculture, sensitive to chlorophyll (Zavaleta et al. 2003) and sensitive to changes in tropical forest shadow faction, but not sensitive in the savanna (Asner and Warner, 2003). Almost biophysical factors at monoculture vegetation measured by spectral radiance were associated with canopy greenness level and it was not found in the study area. Forest vegetation with a high diversity indicates that NDVI was not correlated with biomass (Lu et al., 2002).

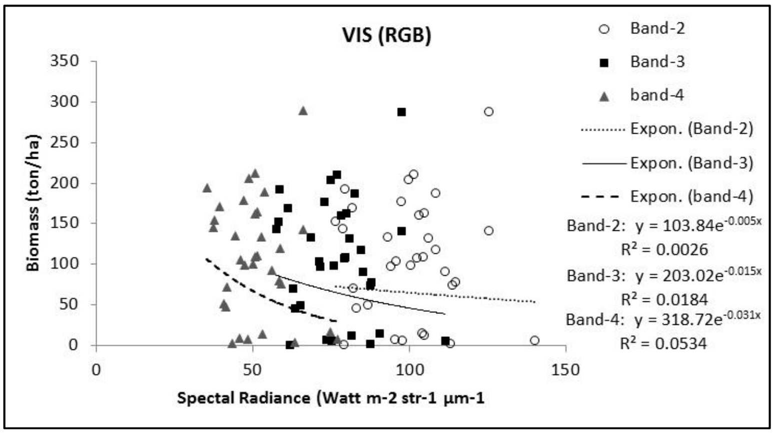

Figure 6. Non-linear regression between VIS (RGB) and biomass

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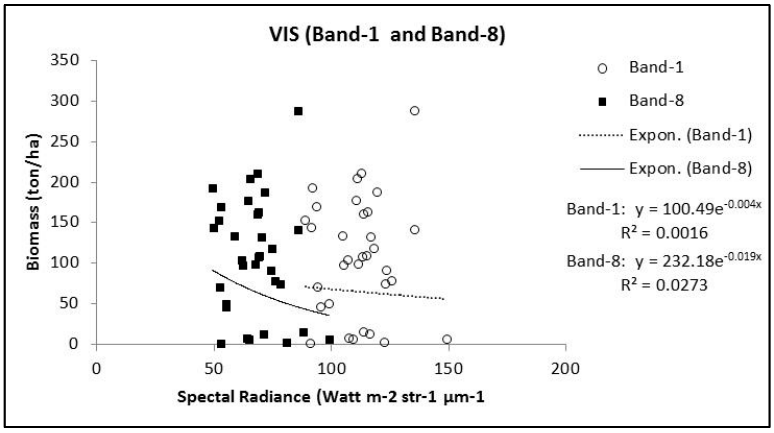

Figure 7. Non-linear regression between VIS (Band-1 and Band-8) and biomass

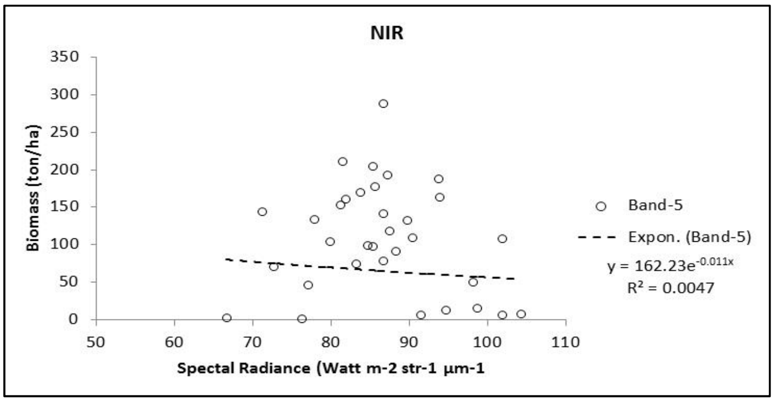

Figure 8. Non-linear regression between NIR and biomass

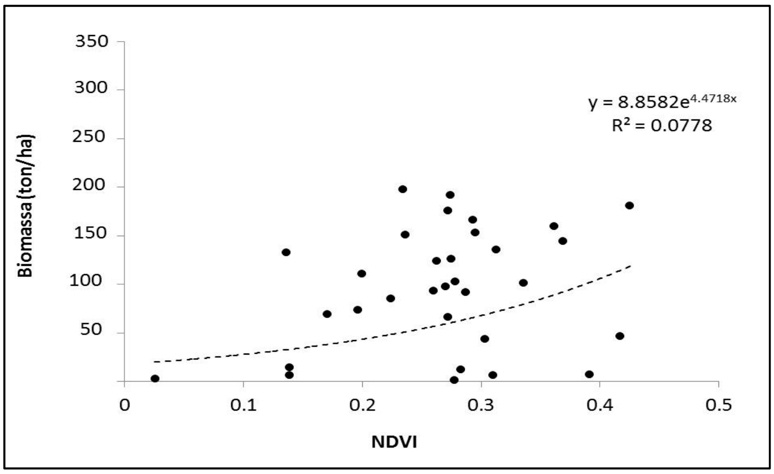

Figure 9. Non-linear regression between NDVI and biomass

The exponential regression function between biomass and SWIR generate a strong correlation (r^2=0.75), especially in the wavelength range from 1:57 - 1.65 µm (Band 6) (Figure 10). The strongest correlation is also generated by Muukkonen and Heiskanen (2005) which estimating biomass for boreal forests using satellite ASTER standwise of data combined with forest inventory data. Avitabile et al (2012) and Baccini et al (2012) also shows the SWIR capability to estimate AGB. Lin and Tsogt (2013) get a strong correlation between the value of AGB with band-6 (SWIR 1), a fairly strong correlation shown by band-3 with LAI while the band 7 (SWIR 2) correlated with stem and AGB.

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Variations in the density of vegetation or canopy in the study area correlate strongly with the SWIR so that this capability can be used to model the biomass in areas with heterogeneous types of vegetation cover. SWIR spectral reflectance is affected by moisture-sensitive objects and water equivalent thickness (EWT) at leaf level (Ceccato, 2001). However, this biomass estimation model should note the physical condition of the study area is a wetland. So that the effect of the water content in the soil should also be considered to improve predictive accuracy. Tian and Philpot (2015) showed the relationship between surface soil water content, evaporation rate, and water absorption band in SWIR spectral reflectance depths

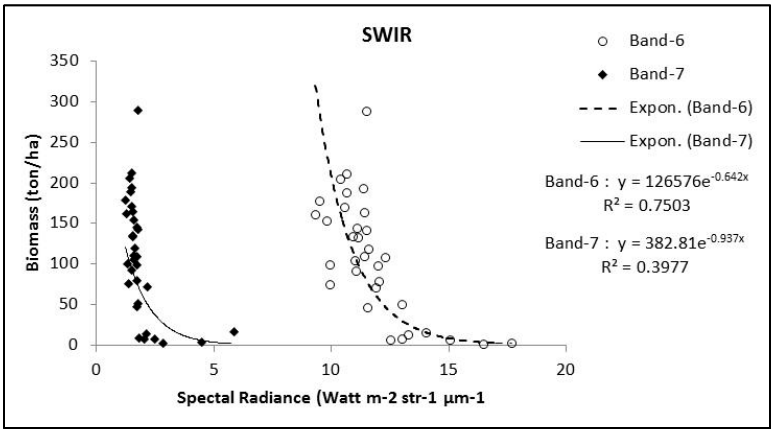

Figure 10. Non-linear regression between SWIR and biomass

TIRS receive the emitted thermal spectral surface whose value is determined by the emissivity of the object. The canopy of trees and or leaves of each plant species has a different emissivity (Rahkonen et al., 2003; Lopez et al., 2012; Chen, 2015), this led to differences in the proportion of long-wave emission (8-14 m) as research generated Salisbury and D'Aria (1992). The emissivity is also a function of the specific heat (Jones and Rotenberg, 2002), so associated with biomass (Gu et al., 2007; Dupont et al., 2014). However, non-linear regression between biomass TIRS this study did not show a strong relationship (**Figure 11**). It can be affected by wetland properties so that water content factor in the soil more dominant than vegetation to determine the amount of heat capacity.

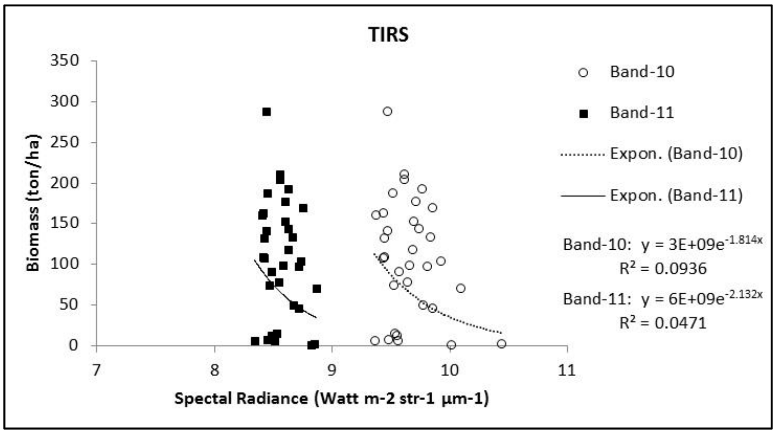

Figure 11. Non-linear regression between TIRS and biomass

3.3. Biomass carbon stock mapping

Commonly, the mapping of biomass by using multispectral satellite data use the NDVI and its variants. NDVI describes the condition of tree canopy, especially the leaves organ. So that in its use, the value of NDVI is often correlated with leaf area index (LAI). Carlson and Ripley (1997) also revealed a high correlation between LAI and NDVI. Pontailler *et al.* (2003) resulted 0.95 relationships between LAI with NDVI. Similarly, the results of other studies, such as one carried out by Nagler *et al.* (2004) and Potithepa *et al.* (*2010*) which showed strong positive correlation. In this

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study, a direct correlation between NDVI and biomass does not produce a strong relationship. Several studies on the relationship of NDVI with biomass does not always generate a high correlation. Seo *et al*. (2014) obtained 77% accuracy in biomass estimation by using the NDVI data in Sabah tropical forests. While Wahyuningrum (2006) produced low R^2, which is below 50%, although theoretically will have a high correlation value. Factors that lead to a low correlation value is the atmosphere, soil moisture, and rectification process of the satellite data. Therefore, to conduct carbon stocks mapping would use the exponential equation between SWIR (band 6) and biomass.

The non-linear regression between SWIR spectral radiance and biomass has strongest correlation, resulted in an exponential equation ($Y=a.\ e^{b.\ x}$) with value of R^2 = 0.75, as follows $Y= 12657\ (EXP\ (-0.642\ (L\lambda_{band6}))$, where Y is biomass. This equation can be used to map the biomass carbon stocks in the study area (**Figure 12**). According to the mapping, the average carbon stock of biomass in the study area for vegetation strata Sf is 208.3 ± 28.3 tons.ha^{-1}, Sc is 130.4 ± 47.8 tons.ha^{-1}and Bs is 20.3 ± 6.7 tons.ha^{-1}.

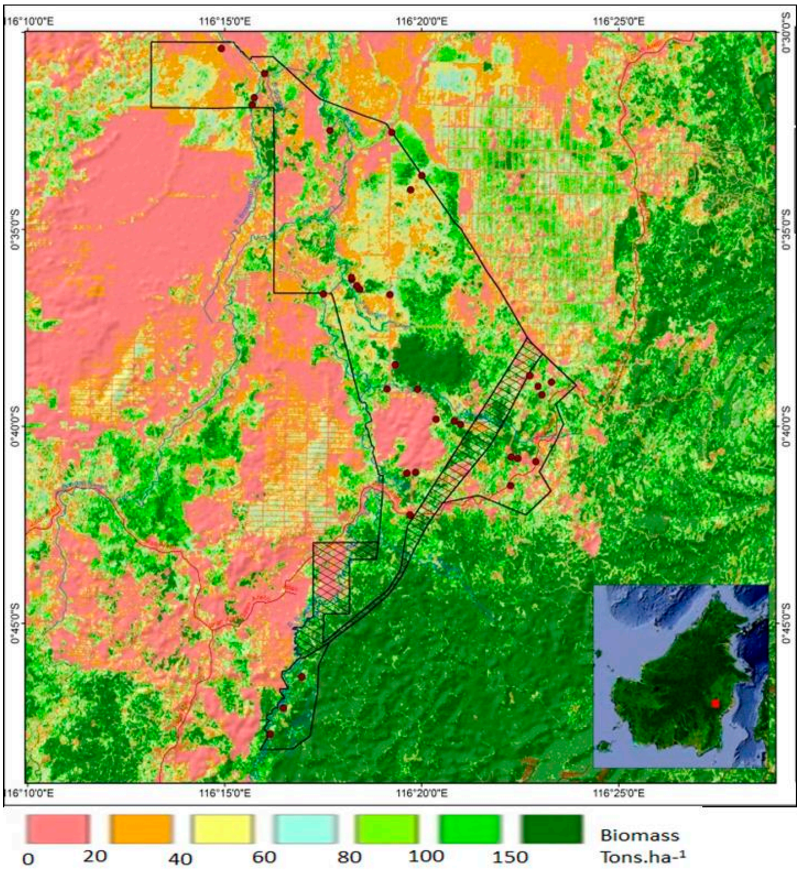

Figure 12. Carbon stock map as a result of estimation by SWIR spectral radiance Landsat 8 (band-6)

4. Conclusions

This study has shown that information on spectral radiance value from surface reflectance and emission by any vegetation strata. It has also established a basis for a more detailed study about remote sensing and biomass. Remote sensing using the visible, NIR, SWIR and TIR wavelength ranges alone or in establishing vegetation indices was demonstrated unsuitable for retrieving biomass at wetland area. The analysis demonstrated that SWIR wavelength range alone is sufficient in retrieving biomass. These studies assume that biomass estimation by SWIR did not consider differences of tree species and various ecosystem types at the wetland. Further research is required to understand how to remove the water content factor in land or under tree canopy for each vegetation strata.

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Conflicts of Interest: The authors declare no conflict of interest.The founding sponsors had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, and in the decision to publish the results

References

1. Adinugroho, W.C. Persamaan alometrik biomassa dan faktor ekspansi biomassa vegetasi hutan sekunder bekas kebakaran di PT Inhutani I Batu Ampar, Kalimantan Timur. *Info Hutan* **2009**, Vol 6 (2), pp:125-132
2. Acharya, T.D and Yang, I. Exploring Landsat 8. *International Journal of IT, Engineering and Applied Sciences Research (IJIEASR)* **2015**, Vol.4, No. 4, pp: 4-10.
3. Alvaro, F.; Garci´a Del Moral, L. F. and Royo, C. Usefulness of remote sensing for the assessment of growth traits in individual cereal plants grown in the field. *International Journal of Remote Sensing* **2007,** Vol. 28, No. 11, pp: 2497–2512
4. Aparicio, N., Villegas, D., Araus, J.L., Casadesu´ S, J. And Royo, C. Relationship between growth traits and spectral vegetation indices in durum wheat. *Crop Science* **2002**, Vol. 42, pp: 1547–1555
5. Apps et al. *Science Statement on Current Scientific Understanding of the Processes Affecting Terrestrial Carbon Stocks and Human Influences*, (eds). IPCC, Geneva, 2003.
6. Asner, G.P.; Hughes, R.F.; Mascoro J.; Uowolo, A.L.; Knap, D.E.; Jacobson, J.; Bowdoin, T.K. and Clark, J. High-resolution carbon mapping on the million-hectare Island of Hawaii. *Front Ecol. Environ* **2003**; doi:10.1890/100179
7. Asner, G.P. and Warner, A.S. (2003). Canopy shadow in IKONOS satellite observations of tropical forests and savannas. *Remote Sensing of Environment* **2003**. Vol 87, pp: 521-533.
8. Astiani, D.; Mujiman and Rafiastanto, A. Forest type diversity on carbon stocks: Cases of recent land cover conditions of tropical lowland, swamp, and peatland forests in West Kalimantan, Indonesia. *Biodiversitas* **2017**, Vol. 18, Number 1, Pages: 137-144 DOI: 10.13057/Biodiv/D180120
9. Avitabile, V., Baccini, A. Friedl, M.A. and Schmullius, C. Capabilities and limitations of Landsat and land cover data for aboveground woody biomass estimation of Uganda. *Remote Sens. Environ* **2012**, 117, 366–380.
10. Baccini, A., Goetz, S.J., Walker, W.S,. Laporte, N.T. ,Sun, M., Sulla-Menashe, D,. Hackler, J., Beck, P.A., Dubayah, R. And Friedl, M.A. Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nat. Clim. Chang*. **2012**, 2, 182–185.
11. Basuki, T.M., van Laake, P.E., Skidmore, A.K., and Hussin, Y.A. Allometric equations for estimating the above ground biomass in tropical lowland Dipterocarp forests. *Forest Ecology and Management* 2009, 257, pp:1684-1694
12. Brown, S. (1997). Estimating biomass and biomass change of tropical forest, a premier. *FAO Forestry Paper 134*.
13. BSN. SNI 7645: Klasifikasi penutupan lahan. *Badan Standarisasi Nasional*, Jakarta. Indonesia, 2010.
14. Borzuchowski , J. & Schulz, K. Retrieval of Leaf Area Index (LAI) and Soil Water Content (WC) Using Hyperspectral Remote Sensing under Controlled Glass House Conditions for Spring Barley and Sugar Beet. *Remote Sensing* **2010**, 2, 1702-1721; doi:10.3390/rs2071702
15. BPPK. Guidelines for the Use of Allometric Model to Estimate Biomass and Carbon Stock of Indonesian Forest (Regulation of the Head of Research and Development Agency of Forestry No.P.01 / VIII-P3KR / 2012), published by the Center for Research and Development and Rehabilitation Conservation, Forestry Research and Development Agency, Ministry of Forestry of Indonesia, 2012.
16. Carlson, T.N and D.A, Ripley. On the relation between ndvi, fractionalvegetation cover, and leaf area index. Remote Sens. Environ **1997** 61:241-252.
17. Ceccato, P., Flasseb, S., Tarantolac, S., Jacquemoudd, S. and Gre´goirea, J.M. Detecting vegetation leaf water content using reflectance in the optical domain. *Remote Sensing of Environment* **2001**: 77 pp: 22 – 33

 doi:10.20944/preprints201704.0020.v1

18. Chen, C. Determining the Leaf Emissivity of Three Crops by Infrared Thermometry. *Sensors* **2015**, Vol. 15, 11387-11401; doi:10.3390/s150511387
19. Coakley Jr, J.A and Yang, P. *The Earth's Energy Budget and Climate Change. 1-39 pp. In Atmospheric Radiation: A Primer with Illustrative Solution* (1st Eds). Wiley-VCH Verlag GmbH & Co. KGaA, 2014.
20. Dharmawan, I.W.S. Persamaan alometrik dan cadangan karbon vegetasi pada hutan gambut primer dan bekas terbakar (Allometric equation and vegetation carbon stock at primary and burnt peat forest). *Jurnal penelitian hutan dan konservasi alam* **2013**.Vol. 10 No. 2, pp : 175-191
21. Dupont, C., Chiriac, R., Gauthier, G. and Toche, F. Heat capacity measurements of various biomass types and pyrolysis residues. *Fuel* **2014**, Vol 115, pp:644–651
22. Eggleston H.S.; Buendia L.; Miwa K.; Ngara T. and Tanabe, K. *IPCC Guidelines for National Greenhouse Gas Inventories, Prepared by the National Greenhouse Gas Inventories Programme*, (eds). Published: IGES, Japan. 2006.
23. Fittkau, E.J. and Klinge, N.H. On biomass and trophic structure of the central Amazonian rainforest ecosystem. *Biotropica* **1973** Vol (5),pp:2-14.
24. Ganeshamurthy, A.N.; Ravindra V.; Venugopalan, R.; Mathiazhagan, M. and Bhat, R. M. Biomass distribution and development ofaAllometric equations for non-destructive estimation of carbon sequestration in Grafted Mango Trees. *Journal of Agricultural Science* **2016**, Vol. 8, No. 8, pp: 201-211
25. Gonçalves, F.; Treuhaft, R.; Law, B.; Almeida, A.; Walker, W.; Baccini, A.; dos Santos, J.R and Graça, P. Estimating Aboveground Biomass in Tropical Forests: Field Methods and Error Analysis for the Calibration of Remote Sensing Observations. *Remote. Sens*. **2017**, 9, 47, pp: 1-23 ; doi:10.3390/rs9010047
26. Gu,L., Meyers, T., Pallardy, S.G., Hanson, P.J., Yang, B., Heuer, M., Hosman, K.P., Liu, Q., Riggs, J.S., Sluss, D. and Wullschleger, S.D. Influences of biomass heat and biochemical energy storages on the land surface fluxes and radiative temperature. *Journal Of Geophysical Research* **2007**, Vol. 112, D02107, Doi:10.1029/2006JD007425
27. Hairiah K., S Rahayu. *Pengukuran Karbon Tersimpan di Berbagai Macam Penggunaan Lahan.* World Agroforesry Centre-ICRAF, SEA Regional Office, University of Brawijaya, Indonesia 77p. 2007
28. Heiskanen, J. Estimating aboveground tree biomass and leaf area index in a mountain birch forest using ASTER satellite data. *International Journal of Remote Sensing* **2006**, Vol. 27, No. 6, pp 1135–1158
29. Jones, H.G. and Rotenberg, E. *Energy, Radiation and Temperature Regulation in Plants*. Secondary article in Encyclopedia Of Life Sciences, John Wiley & Sons, Ltd. 2001.
30. Ketterings, Q.M., Coe, R., van Noordwijk, M., Ambagau, Y., and Palm, C.A. Reducing uncertainty in the use of allometric equation for predicting above-ground tree biomass in mixed secondary forests. *Forest Ecology and management* **2001, Vol** 146, pp: 199-209.
31. Krisnawati, H., Adinugroho W.C. and R. Imanuddin. *Monograph: Allometric Models for Estimating Tree Biomass at Various Forest Ecosystem Types in Indonesia*. Research and Development Center for Concervation and Rehabilitations, Forest Research and Development Agency, Bogor, Indonesia. 2012.
32. Krisnawati, H., Adinugroho, W.C., Imanuddin, R. and Hutabarat, S. *Estimation of Forest Biomass for Quantifying CO2 Emissions in Central Kalimantan: A comprehensive approach in determining forest carbon emission factors*. Research and Development Center for Conservation and Rehabilitation, Forestry Research and Development Agency, Bogor, Indonesia. 2012.
33. Lin, C. and Tsogt, K. *Modeling Forest Stand Structures and Aboveground Biomass Estimation Using LAndsat TM Imagery in Mongolia*. Ph.D. Program of Agriculture Science [Disertasi] China (CN), 2013 : National Chiayi University
34. Lu, D. P. Mausel, E. Brondizio and E. Moran. *Aboveground Biomass Estimation of Successional and Mature Forest Using TM Image in the Amazon Basin*. In Richardson, D. And P van Oesteron,(eds). Advances in Spatial Data Handling. New York: Springer-Verlag. 2002
35. Lusiana, B., N. Khususiyah, K. Hairiah, M. van Noordwijk, and G. Cadisch. Trade-off analysis of land use change, livelihoods and environmental services in the Upper Konto catchment (Indonesia): prospecting land use options with the FALLOW model. *International Conference on Integrative Landscape Modelling. Montpellier, France* 2012. ISBN 978-2-7592-0859-3.
36. Lopez, A., Molina-Aiz, F.D., Valera, D.L. and Peña, A. Determining the emissivity of the leaves of nine horticultural crops by means of infrared thermography. *Sci. Hortic-Amsterdam* **2012**, 137, pp:49–58.
37. MacDicken, K.G. *A guide to monitoring carbon storage in forestry and argoforestry projects*. Winrock International. 1997.

 doi:10.20944/preprints201704.0020.v1

38. Manuri, S., C.A.S. Putra dan A.D. Saputra. *Tehnik Pendugaan Cadangan Karbon Hutan*. Merang REDD Pilot Project, 2011,German International Cooperation – GIZ. Palembang
39. Mokany K.; Raison R.J. and Prokushkin A.S. Critical analysis of root: shoot ratios in terrestrial biomes. *Global Change Biology* **2006,** Vol. 12, pp: 84-96.
40. Muukkonen, P. and Heiskanen, J. *Estimating biomass for boreal forests using ASTER satellite data combined with standwise forest inventory data. Remote Sensing of Environment* **2005,** Vol. 99, p:434 – 447.
41. Murdiyarso, D., Rosalina, U., Hairiah, K., Muslihat, L., Suryadiputra, I.N.N., dan Jaya, A. *Petunjuk Lapangan: Pendugaan Cadangan Karbon pada Lahan Gambut.* Proyek Climate Change, Forest and Peatlands in Indonesia, Wetlands International – Indonesia Programme and Wildlife Habitat Canada, Bogor-Indonesia. 2004.
42. Nagler, P.L., Glenn, E.P., Thompson, T.L., Huete, A. (2004). Leaf area index and normalized difference vegetation index as predictors of canopy characteristics and light interception by riparian species on the Lower Colorado River. *Agricultural and Forest Meteorology* 2004. Vol. 125, issued 1-2, pp:1-7
43. Pontailler, J.Y.; Hymus, G.J. and Drake, B.G. Estimation of leaf area index using ground-based remote sensed NDVI measurements: validation and comparison with two indirect techniques. *Can. J. Remote Sensing* **2003**, Vol. 29, No. 3, pp:381–387.
44. Potithepa, S.; Nasaharab, N.K.; Muraokac, H.; Nagaia, S and Suzukia, R. What is the actual relationship between LAI and VI in a deciduous broadleaf forest?. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Science*, Volume XXXVIII, Part 8, Kyoto Japan. 2010
45. Poupon, H. *Structure et dynamique de la strate ligneuse d'une steppe Sahélienne au nord du Sénégal*. Office de la Recherche Scientifique et Technique Outre-Mer, 1980, Paris, France.
46. Rahkonen, J. and Jokela, H. Infrared radiometry for measuring plant leaf temperature during thermal weed control treatment. *Biosyst. Eng*. **2003**, Vol. 86,pp: 257–266
47. Risdiyanto, I and Setiawan, R. Energy balance method for determining leaf area index using multi spectral satellite imaginery. *J.Agromet Indonesia* **2007**, Vol : 21 (2)
48. Romero, A.; Gatta, C. and Valls, G.C. Unsupervised Deep Feature Extraction for Remote Sensing Image Classification. *IEEE* **2015**. doi: 10.1109/TGRS.2015.2478379
49. RSPO. *Carbon Assessment Tool for New Oil Palm Plantings*-Version June 2014. RSPO. Kualalumpur, 2014.
50. Salisbury, J.W. and D'Aria, D.M. Emissivity of terresterial materials in the 8-14 μm atmospheric window. *Remote Sens. Environ* **1992**, Vol. 42, pp:53-106
51. Seo, H.S.; Phua, M.H.; Choi, B. and Lee, J.S. *Determining above ground biomass of a forest reserve in Malaysian borneo using k-nearest neighbour method. Journal of Tropical Forest Science* **2014**, Vol 26(1), pp: 58-68.
52. Singh S.P.; Adhikari B.S. and Zobel, D.B. Biomasa, productivity, leaf longevity, and forest structure in the central Himalaya. *Ecol Monogr* 1994, Vol. 64, pp: 401±421.
53. Tian, J. and Philpot, W.D. Relationship between surface soil water content, evaporation rate, and water absorption band depths in SWIR reflectance spectra. *Remote Sensing of Environment* **2015**, Volume 169, pp: 280-289, ISSN 0034-4257, http://dx.doi.org/10.1016/j.rse.2015.08.007.
54. U.S. Geological Survey. *Landsat 8 (L8) Data Users Handbook*. LSDS-1574 Version 2.0. 2016.
55. Wahyuningrum, N. *Foliage biomass estimation in tropical logged over forest East Kalimantan, Indonesia*. Thesis International Institut for Geo-Information Science and Earth Observation, 2006, Enschede, The Netherlands.
56. Wang, C and Qi, J. Biophysical estimation in tropical forests using JERS-1 SAR and VNIR imagery. II. Aboveground woody biomass. *International Journal of Remote Sensing* **2008** Vol. 29, Issue 23, pp:6827-6849. http://dx.doi.org/10.1080/01431160802270123
57. Wilson, H. and Sader, S.A. Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment* **2002**, Vol.80, pp:385 – 396
58. Zavaleta, E.S.; Thomas, B.D.; Chiariello, N.R.; Asner, G.P. and Shaw, M.R. *Plants reverse warming effect on ecosystem water balance*. PNAS **2003**. Vol.100, No 17, pp:1892-1893.