

Above-ground carbon stock estimates of rubber (*hevea brasiliensis*) using Sentinel 2A imagery: a case study in rubber plantation of PTPN IX Kebun Getas and Kebun Ngobo, Semarang Regency

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Abstract. Carbon stock estimates are very important to support carbon policies at the regional level and sustainable environmental management. Rubber plantation is one of the carbon-absorbing ecosystems, due to its long life and large biomass content. The aim of this study was to estimate the above-ground carbon stock based on Sentinel 2A remotely sensed imagery, through vegetation index approaches. In the initial stage, the image was corrected radiometrically to obtain a bottom of atmosphere (BoA) reflectance values, so that all spectral indices that were run could provide reliable results. The vegetation indices used in this study were RVI (Ratio Vegetation Index), NDVI (Normalised Difference Vegetation Index), ARVI (Atmospheric Resistant Vegetation Index), and SARVI (Soil and Atmospherically Resistant Vegetation Index). The values generated from those indices were correlated with field data of carbon stock, which was derived from breast height diameter (BHD)-based biomass measurements and allometric equations. Correlation and regression analyses of carbon stock and vegetation indices were then used to interpolate the samples to the entire study area, using exponential, logarithmic, and quadratic equations. The resultant above ground carbon stock maps were then tested for accuracy assessment using field data collected independently. It was found that the ARVI-based estimation model with BoA reflectance radiometric correction, combined with exponential regression equation, showed the best accuracy values of 84.48% (supported by $r^2 = 0.473$). Based on this model, the above-ground carbon stock estimate in Ngobo and Getas Plantation, PTPN IX were 527,072.39 tons in an area of 2,656,615 hectares, or 198.4 tons/hectares.

1. Introduction

Global warming is a phenomenon closely related to the increase in greenhouse effect intensity. One of the factors accelerating this condition is deforestation which can impair the function of the carbon cycle. Even 20% of greenhouse gases come from deforestation which results in a growing amount of plant biomass released into the atmosphere [1]. In the last 100 years the average temperature has increased by 0,74°C [2]. The concentration of carbon dioxide (CO₂) in the atmosphere is also frequently caused by agriculture and improving global industries [3].

Vegetation in the tropical region has significantly contributed to reduce global warming and associated with climate change, and thus it has provided useful information for the complex coupling of the biosphere and atmosphere [4]. The contribution of agriculture land ecosystems, especially rubber plantations, in the carbon cycle is interesting to researchers and environmental policymakers. Rubber is one of the plantation commodities that provides considerable economic value in Indonesia which areas around 3.4 million hectares spread over the provinces [5]. Rubber plants can replace the function of forest in CO₂ absorption. Naturally, CO₂ gas is processed by plant vegetation including rubber through photosynthesis which produces oxygen and carbon as biomass. One of the companies in the state-owned plantation sector that choose rubber as its main commodity, namely PTP Nusantara IX in the working area of Kebun Getas and Kebun Ngobo, Semarang regency.



Estimation of aboveground biomass may be based either on destructive or non-destructive methods. The first methods are usually not preferred as they are expensive, time-consuming, limited in terms of spatial and temporal samplings, and --although negligible-- cause damage to ecosystem health [6]. Remote sensing has been becoming one method that can be used to estimate plant biomass and carbon stocks [7]. Remote Sensing technology can be used for forest inventory and mapping of other resources including physical conditions of vegetation [8]. Utilization of remote sensing approach is chosen because it is cheap, should be applied to large areas, and requires less time compared to field surveys [9]. The data acquisition process is relatively faster with more affordable costs. Satellite data have got great potential for determination of vegetation carbon stock [2]. Moreover, in inaccessible or remote areas they are the only possibility to find out the carbon stock in vegetation cover. This is the main reason why many research studies have been focused on improved carbon assessment using remote sensing approach [10]. The main parameter in determining remote sensing image data is the quality of the data source. Data quality that isn't in accordance with standards can obscure the truth of the information [11]. This research was conducted to determine the models of rubber aboveground carbon stock estimation using Sentinel 2A through vegetation index algorithms. Type of indices used were RVI (Ratio Vegetation Index), NDVI (Normalized Difference Vegetation Index), ARVI (Atmospheric Resistant Vegetation Index), and (SARVI) Soil and Atmospheric Resistant Vegetation Index.

2. Methods

The research was conducted in rubber plantation of PTPN IX, Kebun Getas and Kebun Ngobo, Semarang regency for collecting field data. Ground check and field data was conducted in April 15-21, 2019.

Tools and materials used in this research include :

1. Primary Data consist of Sentinel 2A imagery date acquired on May 4, 2019 and field survey data.
2. Secondary Data consist of Semarang Regency Landuse map, topographic map (Peta RupaBumi Indonesi) Map, and PTPN IX Work Area Map.

Tools used were a computer set with spatial data processing softwares such as ArcGIS 10.3, ENVI 8.3, QGIS, Ms.Word, MsExcel, a Handheld GPS, Strap, a tape measure, Field Checklist, Camera, Crescent, and other equipments.

Assessment of carbon stock in aboveground biomass has been worked out by methods based on both direct measurement and remote sensing (RS) approaches. A non-destructive method using allometric equation was performed. Information on carbon stock was derived from the results of biomass estimation through field data and various vegetation index transformations. Before the image is processed as a result of biomass estimation, a radiometric and atmospheric correction process had to be done to the level of BoA (Bottom of Atmosphere). Atmospheric correction was arranged to change the value from ToA reflectance (Top of Atmosphere) to BoA reflectance (Bottom of Atmosphere) as a values of at surface reflectance. The method of BoA algorithm correction used in this study was Dark Object Subtraction (DOS) [12]. A reducing parameter is a dark object which is ideally in the form of deep and clear water object. In this case, areas were difficult to identify the ideal object of DOS, so the reduction in digital number was carried out by looking at the minimum value on each band used. As explained by [13] that the minimum value in each band should be used on the condition of dark objects that aren't ideal. The following atmospheric correction equations using the DOS method:

$$\rho_{BoA} = \rho_{ToA} - \rho_{path} \quad 1$$

Where :

ρ_{BoA} = at Surface Reflectance

ρ_{ToA} = at Sensor Reflectance

ρ_{path} = Dark object

Radiometric correction results were used as input for processing the following vegetation indices.

Table 1. Calculation by method based on vegetation index

No	Vegetation Index	Formula
1	NDVI	$\frac{BV\ nir - BVred}{BV\ nir + BVred}$ (2)
2	RVI	$\frac{BVnir}{BV\ red}$ (3)
3	ARVI	$\frac{BV\ nir - rb}{BV\ nir + rb}$ (4) dimana $rb = BVred - \gamma(BVred - BVblue)$
4	SARVI	$\frac{BV\ nir - BVrb}{BV\ nir + BVrb + L}$ (5)

Source : [14, 15]

The samples consisted of 55 plots with 30 of them were used as model samples, while the remaining 25 samples were used as validator ones. Field activities were carried out for above ground biomass and carbon values measuring with an allometric approach at various decided sample points. Measurements were undertaken on 20x20 m² sample plots, by considering the required minimum area size, spatial resolution of Sentinel 2A, and RMSEError. Allometric equations used to estimate biomass are based on the results of the [16] research :

$$W = 3,42 D^{1,15} \quad (6)$$

where :

W = Above ground biomass (kg)

D = Diameter at breast height (cm)

a, b = Constants

The values of various vegetation index (dependent variable) compared through simple linear and non-linear regression equations such as logarithmic, exponential, and quadratic algorithm with the value of biomass field values (dependent variable). A simple linear regression model was chosen based on common research to directly assess the correlation of two variables. While non-linear regression models were based on research [17] that the correlation between vegetation index and vegetation density value was a curve (non-linear). The regression equation obtained was used as input for rubber biomass estimate. Estimated results of biomass are transformed into carbon stock values with assuming 45-50% of plant biomass is part of carbon [18].

$$C = 0,45 \times W \quad (7)$$

where:

C = Aboveground Carbon (kg)

W = Aboveground biomass (kg)

Accuracy assessment of each model was arranged by comparing carbon stock samples with estimation values using various vegetation index. Accuracy results are declared in the standard error of estimate (SEE). Determination the best models considering accuracy values and statistical analysis.

3. Result and Discussion

3.1. Radiometric Correction

Table 2 Statistic Summary after Radiometric Correction

Band	Min	Max
Band 2	0,005	0,904
Band 3	0,002	0,913
Band 4	0,005	1,000
Band 8	0,008	1,000

Table 2 shows the images' statistics values generated after radiometric corrections at BoA levels. The image in this condition will have a minimum value of 0. The minimum value of Band 2 was 0,0005. Band 3 or green band had values between 0.002 to 0.913. Band 4 (red band) after correction contained the minimum value of 0.005. And In the near-infrared (band 8), it had an average of pixel values to 0.164 with a standard deviation of 0.113.

3.2. Vegetation Index Transformation

Vegetation index is a value obtained from specific combination of several bands of optical-multispectral remote sensing imagery. Type of vegetation indices used in this study were RVI,NDVI,ARVI, and SARVI.

Table 3. Statistic Summary of the vegetation index transformation

Vegetation Index	Min	Max
RVI	0.460	10.052
NDVI	-0.371	0.817
ARVI	-0.634	0.809
SARVI	-0.083	0.317

Table 3 shows that each vegetation index has a different range of values. RVI as a basic vegetation index produced values between of 0.460 to 10.052. NDVI model had a smaller range of values *i.e* -0.372 to 0.818. This value was classified in the NDVI value category which is in the range of -1 to 1. NDVI has advantages beyond other types of vegetation index cause of the results are able to reduce multiplicative disturbances including cloud shadow and atmospheric interference [19]. NDVI algorithm is a vegetation index that is suitable to be applied to areas with dense vegetation [20]. Rubber plantations are one of the lands uses that have a tight canopy cover. The results of ARVI index processing in the study area had a minimum value of -0.634 and a maximum value of 0.809. While the SARVI index had a smaller value range than the that of other indices, *i.e* -0.083 - 0.317. SARVI models produced images that reveal a separation between the land area and the water surface. SARVI index also reduced the impact of clouds in the land [21]. The difference results of vegetation indices determined by plant characteristics and also the reflection of the objects received by the sensor due to soil and atmospheric conditions [22].

3.3. Statistical Analysis

Analysis of data normality was carried out using Kolmogorov-Smirnov test. Based on the calculation results it was found that the distribution value of data (D_n) obtained from the maximum component value difference is 0.039. While the standard data value (D_n, α) from the critical table for the number of samples 30 and α that had been determined is 0.05 *i.e* 0.240. Assessment of normality was carried out by analyzing the value of the calculated results with the critical table value on the conditions that had

been determined. The results of the calculation were known that the value of $D_n < D_n, \alpha$, then the data set could be assumed to follow a normal distribution. Based on this analysis, the model samples were used as input to regression analysis, in order to build empirical equations that should be declared to be normally distributed. The results of the correlation analysis of field carbon stock values with all models were found to have varied values. Correlations between the two variables were found to have positive direction. It means that the increasing value of one variable is followed by other variables. The strength of the correlation between field variables and all models is seen from the correlation coefficient values. NDVI, ARVI, and SARVI models corrected by BoA could be categorized as a strong correlation category. Moreover, RVI had a correlation that can be classified as very strong or with a coefficient of >0.801 .

3.4. Spatial Modelling

Sentinel 2A imagery was corrected up to BoA level reflectance, and it was used to develop several types of vegetation index transformation according to Table 4. The results of regression analysis by considering the parameters of the determination coefficient are known that the RVI model has the best R^2 value in the type of linear and quadratic regression. While other vegetation indices such as NDVI and ARVI have the best determination coefficient using quadratic regression. The SARVI model has the best R^2 value using exponential regression. The result of this study showed slight difference as compared to other studies. NDVI index has stronger relationship with aboveground biomass and carbon stock [23]. The low correlation value in some models was indicated due to differences in image recording time with field sampling activities. Sentinel 2A imagery used in this study was recorded on May 4, 2018, while field activities were carried out on April 15-21, 2019. It means that there is a difference of 11 months within the data which can cause significant differences conditions.

Table 4. Result of Regression Analysis

Vegetation Index	Regression Models	Equation	R^2
RVI	Linear	$y = 0.1476x - 0.1474$	$R^2 = 0.671$
	Exponential	$y = 0.1221e^{0.3098x}$	$R^2 = 0.662$
	Logaritmatic	$y = 0.6165\ln(x) - 0.398$	$R^2 = 0.646$
	Quadratic	$y = 0.0031x^2 + 0.1197x - 0.0866$	$R^2 = 0.671$
NDVI	Linear	$y = 1.896x - 0.6697$	$R^2 = 0.615$
	Exponential	$y = 0.0356e^{4.1951x}$	$R^2 = 0.675$
	Logaritmatic	$y = 1.0525\ln(x) + 1.0183$	$R^2 = 0.577$
	Quadratic	$y = 5.0995x^2 - 4.0894x + 1.0545$	$R^2 = 0.667$
ARVI	Linear	$y = 1.651x - 0.1716$	$R^2 = 0.473$
	Exponential	$y = 0.1065e^{3.6654x}$	$R^2 = 0.522$
	Logaritmatic	$y = 0.6389\ln(x) + 1.0849$	$R^2 = 0.467$
	Quadratic	$y = 0.0053x^2 + 1.6467x - 0.1708$	$R^2 = 0.473$
SARVI	Linear	$y = 2.859x + 0.0444$	$R^2 = 0.428$
	Exponential	$y = 0.1734e^{6.3027x}$	$R^2 = 0.466$
	Logaritmatic	$y = 0.4546\ln(x) + 1.3463$	$R^2 = 0.440$
	Quadratic	$y = -8.5322x^2 + 5.7245x - 0.1862$	$R^2 = 0.438$

Table 5 shows that the estimation results for each vegetation index model were entirely varied. RVI model had a maximum estimated value of 2.724 tons/pixel and a minimum value of around 0.104 tons/pixels. The same condition occurred using the NDVI index where the estimated value was greater at 0.861 to 1.451 tons/pixel. The SARVI model at this corrected level had an estimated values of 0.361 - 2.088 tons/pixel. While the estimation model using ARVI at the BoA level was rejected, since it produced a range of estimated values of 0.426 to 2.739 tons/pixel. The assessment of aboveground carbon from remote sensing data especially Sentinel 2A seems to be applicable but we should critically discuss not only the data processing but also the comparative expert-based values. Estimation results at some models were not significant as compared to other studies. Rubber monoculture reserves carbon of 97 tons/ha for plants up to 25 years old, while the carbon calculation method used in this study was categorized as fixed carbon, by determining all carbon components such as aboveground, below ground, and also organic and soil materials [24]. Several models that have similarity results according to this research, were NDVI and SARVI. The estimated values of the results were 99.2 tons/ha and 98.6 tons/ha. The difference margins found were indicated because of the differences in the calculation of carbon components, while the authors only calculated an aboveground carbon in a rubber plant. So that the estimation values were lower than the reference.

Table 5. Carbon stock of aboveground biomass in studies area

Vegetation Index	Regression Models	Carbon (ton/100m ²)			
		Min	Max	Mean	St.dev
RVI	Quadratic	0,104	2,724	1,226	0,319
NDVI	Exponential	0,086	1,461	0,992	0,163
ARVI	Exponential	0,429	2,739	1,984	0,246
SARVI	Exponential	0,361	2,088	0,986	0,245

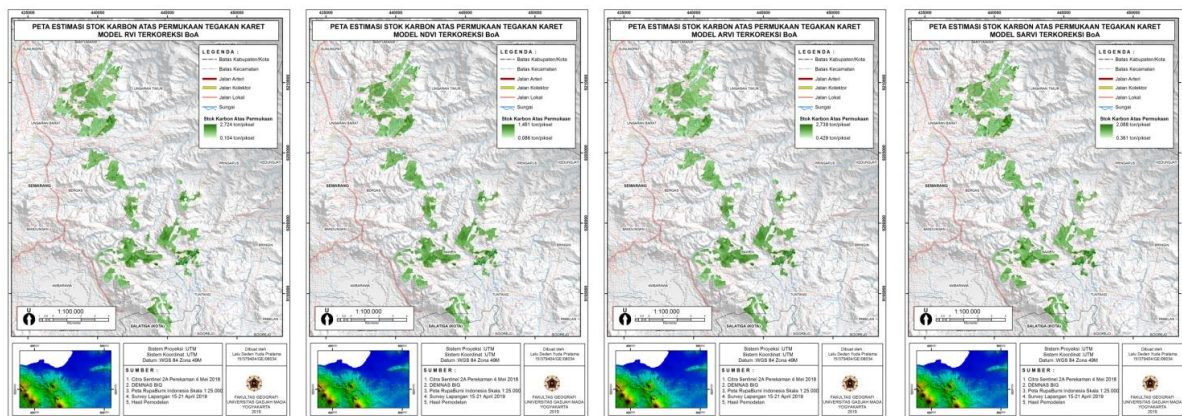


Figure 1. Aboveground Carbon Estimation Map using RVI, NDVI,ARVI, and SARVI models.

3.5. Accuracy Assessment

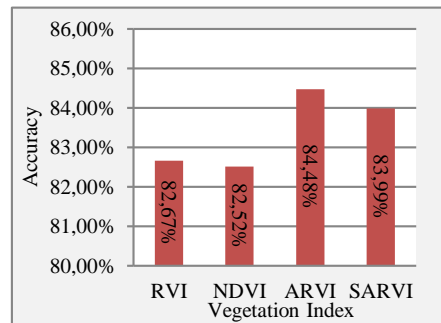


Figure 2. Graph of each models accuracy

Accuracy assessments were carried out on each model of estimating carbon stocks above the surface of rubber plants using RVI, NDVI, ARVI, and SARVI. The evaluation value of the modeling results uses the Standard Error of Estimate (SEE) value with a confidence level of 95%. NDVI and ARVI based models have an accuracy of 82.52% and 82.67%. This value was slightly smaller when compared to models that used the vegetation indices supported by ARVI and SARVI. The SARVI index accuracy value was 83.99% with a correction of 0.664. While modeling using ARVI had the best accuracy value, reaching up to 84.48%. The high value of this arrangement was due to fact taht the ARVI formulation was developed by considering the blue band (band 2) to normalize the atmospheric effects. The research area which is located not far from the south of the equator and image recording which was on May (the end of the rainy season) has an effect on the energy received by the sensor. The high intensity of sunlight due to the sun position on the season provoked evaporation and evapotranspiration process related to the content of water vapor in the atmosphere which allows the process of recording object responses by satellite sensors [25]. The use of band 2 to minimize the impact of water vapor was considered very appropriate in the development of ARVI formulations where the band is sensitive to air vapor. The differences in the accuracy values of the models were determined by the number and the distribution of test samples. Independent test samples also provided value to the valuatorm models so they cannot support the value of the built models.

3.6. Above Ground Carbon Stock Potential

The total aboveground carbon stock of rubber in the study area of 2656,615 ha in each model gave various estimation results. This differences were caused bu the fact that each model had a different estimated average yield per ha. The model that utilized the SARVI and NDVI transformations with exponential non-linear regression equations gave a total estimation result which were smaller than those of other models. Calculated aboveground carbon stock using SARVI method was 261.942,23 tons and 263.536,20 tons respectively using NDVI algoritmn. RVI gave a relatively larger estimate i.e. 325,700.98 tons. While the model used the ARVI transformation had estimated results up to 2 times greater than the other models i.e 527,072.39 ha. Therefore, the estimation results in the ARVI model were chosen as the total aboveground carbon stock of the rubber stand in the study area by considering the results of correlation analysis, regression, ANOVA test, partial test, and accuracy assessment.

Table 6. Above Ground Carbon Totals for each models

Vegetation Index	Regression Models	Carbon Totals (tons)
RVI	Cuafratic	325.700,98
NDVI	Ekspponential	263.536,20
ARVI	Ekspponential	527.072,39
SARVI	Ekspponential	261.942,23

4. Conclusions

The aim of this study was to propose a method based on remote sensing data for assessment of aboveground carbon stock for rubber plantation. Sentinel 2A imagery which was corrected up to BoA reflectance should be used as input data for estimating the aboveground carbon stock of rubber using the RVI, NDVI, ARVI, and SARVI approaches. The results of this research explain that the correlation analyses on the field carbon stock variable and the vegetation index showed a fairly strong correlation that is > 0.5 , which means that there was a significant correlation between the two variables. ARVI model using image with BoA correction and exponential regression analysis showed the best accuracy of 84.48% with a correlation coefficient of 0.688. Calculated aboveground carbon in Kebun Ngobo dan Kebun Getas, PTPN IX is 527.072,39 tons, covering an area of 2.656,615 ha, which means 198,4 tons / ha. In addition, information about aboveground carbon stock in the studies area should be compared in the future with up-to-date values to monitor changes in carbon storage.

5. References

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