Nitrogen Content and Carbon Stock Prediction in Oil Palm using Satellite Image Analysis

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ABSTRACT— ***Nitrogen content and carbon stock prediction method using satellite image analysis is inexpensive, time-saving, labor-saving and accurate. This research aimed to predict nitrogen content and carbon stock on oil palm using satellite imagery. The research was conducted at IPB-Cargill Teaching Farm of Oil Palm, Jonggol, Bogor Indonesia, starting from August until October 2016. Landsat 8 satellite imagery was used in this research with the digital number classes 17,000 – 22,000. Leaf nitrogen content observed in the field, analysed using Kjeldahl digestion method. Carbon stock was obtained using allometric method (above ground biomass =0.0976*Height+0.0706). Sampling of the leaves frond number 17 and plant height of oil palm plant respectively was 25 samples. Prediction model used weighted least square regression between the actual nitrogen content and the digital number, band reflectance, vegetation index. The same model was used to estimate carbon stocks. The result showed that the best model to estimate nitrogen content using the band reflectance with R^2 = 0.964, and vegetation index with R^2 = 0.987. The best model for estimate carbon stocks using digital number with R^2 = 0.874, band reflectance, with R^2 = 0.856, and vegetation index with R^2 = 0998. There was similarity between actual measurement and model for predicting nitrogen content and carbon stocks.***

Keywords— satellite imagery, vegetation index, nitrogen, carbon stock

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1. INTRODUCTION

Proper fertilization is a critical factor to increase the productivity of oil palm. Nitrogen is one of the major nutrient elements needed by oil palm for the production of chlorophyll, protein, nucleic acid, amino acid, and major regulators for leaf physiological processes such as photosynthesis, respiration, and transpiration. Oil palm plantation contributes to the reduction of greenhouse gas emissions by absorbing CO_2 of photosynthesis process. Oil palm is able to absorb 161 tons CO_2 ha^{-1} year^{-1} [1]. CO_2 absorption is used to produce large quantities of biomass reaching up to 40 ton ha^{-1} year ha^{-1} [2]. Based on the research, oil palm produces 136 tons ha-1 of biomass with a wide range from 62 to 202 tons ha^{-1} [3]. Biomass production is used to estimate the carbon stock, it's because about 50% of plant biomass consist of carbon[4]. In the Introduction section, present clearly and briefly the problem investigated, with relevant references. The main results should be enunciated.

Estimation of nitrogen content is important to know the nitrogen requirement, fertilizer efficiency, plant growth rate, and estimation of carbon stock is to study the correlation with CO_2 absorbtion by plant. The conventional method of measuring the nitrogen content used to estimate the nitrogen content is by conducting the analysis in the laboratory, as the analyzed material is a leaf of frond no 17. The conventional method of measuring the carbon stock is a destructive method. The weakness of the conventional method is time-consuming, expensive cost, and labor intensive. The use of remote sensing technology has been tried and successfully used to estimate the nitrogen content and carbon stocks as reported by some reserchers [5,6,7,8]. Remote sensing technology makes it possible to estimate nutrient status and carbon stock of oil palm plants. The technology can be used for a very large area, non destructive sampling, and low cost applications. The principle of remote sensing is reading the magnitude of reflectance which is the ratio between the reflected energy from an object to an object on it (a remote sensing satellite sensor), in one or more wavelengths.

Plant nitrogen is present in chloroplasts and chlorophyll binding protein as much as 75% [9]. The result of field research on oil palm plants found that nitrogen fertilizer treatment strongly correlated to the increase of chlorophyll content in oil palm plant [10.11,12]. Chlorophyll greatly affects the light reflectance in the leaves. Leaves with high chlorophyll and nitrogen tend to absorb visible light resulting in decreased reflectance in blue, green, and red bands [13]. The high absorption of the visible light causes the reflectance of blue, green, and red lights become low. The light reflectance pattern can be used to assess the condition of plant health which related to the availability of photosynthetic pigments and the nitrogen content of the leaf. The band near infrared reflectance are closely related to nutrient conditions in the leaves such as nitrogen, phosphorus, magnesium and sulfur 2. Nitrogen deficiency can be assessed by the range of visual (eye) lights and spatial patterns of staining in plants. These two patterns suggest a hypothesis that the assessment of nitrogen deficiency could be performed by using the spectral and spatial information [14]. Spectral bands can be used to calculate the differences between the vegetative index which strongly correlated with agronomic parameters and biophysical which associated with photosynthesis and crop productivity [15,16]. So that the reflectance is possible to be used for the estimation of leaf area index, biomass of surface, and nitrogen content. The use of remote sensing in the estimation of nutrient and carbon in oil palm plantation have not been sufficiently quantified. Thus, it is necessary to conduct a research using various vegetation index and multispectral reflectance bands at different age and planting locations. This study aimed to determine the estimation model and measure the results of nitrogen content and carbon stocks in oil palm using satellite image analysis.

2. MATERIAL AND METHOD

The study was conducted from August to October 2016 in the IPB-Cargill Oil Palm Teaching Farm, Bogor, West Java, Indonesia at coordinates of 06^o 28.319 'South, 107^o 01.103' North at altitudes 115 m above sea level. The materials consisted Landsat 8 image which taken on August 2016 and oil palm plants. The tools used was global positioning system (GPS), compass, and tape measure.

The study used seven bands of Landsat 8 images and vegetation index (Table 1). Image processing was done by stages of radiometric correction, compilation of RGB (Red-Green-Blue) composite. The next step was to map the experimental location, classify the reflectance value, specify the sample plot. The sampling units were 5 in each block, so there were 25 sampling units. The sample unit was made with a size of 30m x 30m and placed in line with the predefined coordinates in the image. Furthermore, the trees height on all trees in the plot was measured. Analysis of leaf nitrogen content using Kjeldhal digestion method, leaf samples was leaf of frond number 17 of trees in the plot. The calculation of field biomass used an allometric formula to estimate the biomass of some common crops grown on agroforestry land that is Above Ground Biomass = 0.0976 H + 0.0706 [26]. The biomass calculation results are used to calculate the carbon content of oil palm plant using formula that is C content= W * 0.5 (W = biomass) [4].

Table 1 Band reflectance and vegetation index used in this research

No	Digital Number/ Band Reflectance/ Indeks Vegetation index	Wave lenght/Formula	Reference
1	Near blue	0.43-0.45	17
2	blue	0.45-0.51	17
3	green	0.53-0.59	17
4	red	0.64-0.67	17
5	NIR	0.85-0.88	17
6	SWIR1	1.57-1.65	17
7	SWIR2	2.11-2.29	17
8	DVI	(2.4*NIR)-Red	18
9	NDVI	(NIR-Red)/(NIR+Red)	19
10	RVI	NIR/Red	20
11	TNDVI	SQRT((NIR-Red)/(NIR+Red))+0.5	21
12	PVI	((0.647*NIR)-(0.763*Red))-0.02	22
13	CHLI	(NIR/Green)-1	23
14	TGI	-0.5*((Red-Blue)*(Red-Green))-((Red-Green)*(Red-Blue))	24
15	OSAVI	(NIR-Red)/(NIR+Red+0.16)	25
16	GI	Green/(Red+Blue+Green)	

Preparation of nitrogen content and carbon estimation model used multiple linear regression analysis and weighted multiple linear regression with the dependent variable (Y) is nitrogen content and carbon stock of field measurement, while the independent variable is the digital number, reflectance band, and vegetation index. The model was then selected to be the best model with the criteria of the highest R^2 and correlation coefficient (R). Models with high R^2 are sufficient to predict the dependent variable or Y [27]. The data obtained was analyzed using SPSS, MS Excel and XL Stat applications.

3. RESULT AND DISCUSSION

Naturally, the plants absorb, transmit, and reflect light received by the plant surfaces, especially for leaves. The magnitude of absorption, transmission, and reflectance is highly dependent on the availability of absorbent pigments such as chlorophyll. Leaves with high nitrogen and chlorophyll content absorb more light in visible light and absorb lower in the band near infrared [28]. The visible reflectance patterns of the visible bands (red, green, blue) (400-700 nm) and NIR (700-900 nm) are strongly influenced by chlorophyll and leaf cell structure [29]. The high visible light causes the reflectance of blue, green, and red light become low. The light reflectance pattern can be used to assess the condition of plant health related to the availability of photosynthesis and nitrogen pigments in the leaves. Plants with nitrogen deficiency lead to the reduction of chlorophyll and causes the increase of visible light reflectance [30].

Table 2 shows the regression model of the nitrogen content and carbon stocks estimation in oil palm plants. The model composed by multiple linear regression showed a relatively low relationship between nitrogen content and carbon stock to the digital number, reflectance band, and vegetation index with the highest R^2 value in the carbon stock estimation model using vegetation index. The results of the model test using variance analysis showed that the digital number, reflectance, and vegetation index had no significant effect on nitrogen content and only significant effect on the model of carbon stock estimation. The weighted regression result was related to nitrogen estimation, 4 vegetation index (RVI, TNDVI, TGI, GI) correlated strongly with nitrogen level, followed by 4 digital number bands (near blue, green, swir1, swir2) and 5 reflection bands (Near Blue, Green, NIR, SWIR1). The regression model for the actual carbon estimation is composed of 6 digital number bands (near blue, blue, green, nir, swir1, swir2), six reflectances bands (blue, green, nir, swir1, swir2) and 3 vegetation index (RVI, TNDVI, GI). The actual correlation between nitrogen content and carbon stock to the digital number (DN), reflectance, and vegetation index is very strong with a positive correlation coefficient (R) above 0.9 while the highest correlation for nitrogen content and carbon stock estimation using vegetation index was R of 0.991 and 0.999 respectively

Table 2 Nitrogen (N) and carbon stock (C) prediction model using digital number, band reflectance, and vegetation index

Model	R	R^2	Sig.
Multiple linier regression models			
N = -12.417 + (.007DN1) – (0.008DN2) – (0.001DN3) + (0.005DN4) + (0.000DN5) – (0.00005DN6) – (0.001DN7)	0.700	0.491	0.072ns
N = - 4.817 + (341.307Near blue) – (407.116Blue) – (36.298Green) + (226.734Red) – (7.082NIR) – (3.929SWIR1) – (56.389SWIR2)	0.692	0.480	0.083ns
N = 4.632 + (5.781DVI) + (0.203RVI) + (1.054TNDVI) – (1.216CHLI) + (471.261TGI) – (11.507GI)	0.461	0.213	0.576ns
C = 111.446 – (0.039DN1) + (0.065DN2) – (0.062DN3) + (0.045DN4) + (0.001DN5) + (0.007DN6) – (0.025DN7)	0.757	0.574	0.022*
C = 77.046 – (-2065.796 Near blue) + (3423.314Blue) – (3095.608Green) + (2211.539Red) + (48.943NIR) + (370.698SWIR1) – (1257.081SWIR2)	0.757	0.573	0.022*
C = 545.757 + (170.948DVI) + (33.404RVI) + (42.210TNDVI) – (76.857CHLI) + (24015.520TGI) - (1753.015GI)	0.778	0.605	0.005*
Weighted multiple linier regression models			
N = -959 + (0.001DN1) - (0.001DN3) + (0.000DN6) + (0.0000346DN7)	0.991	0.981	0.000*
N = -2.842 + (97.658Near blue) - (57.868Green) + (8.122NIR) - (35.445SWIR1) + (39.162SWIR2)	0.982	0.964	0.000*
N = -6.494 - (130RVI) + (1.500TNDVI) + (546.538TGI) + (24.627GI)	0.994	0.987	0.000*
C = -50.420 + (0.007DN1) + (0.031DN2) - (0.039DN3) + (0.002DN5) - (0.009DN6) + (0.017DN7)	0.935	0.874	0.000*
C = 11.122 - (402.861Nearblue) + (2241.889Blue) - (1985.404Green) + (85.013NIR) - (308.056SWIR1) + (662.962SWIR2)	0.925	0.856	0.000*
C = 200.357 + (4.599RVI) - (24.995TNDVI) - (455.399GI)	0.999	0.998	0.000*

Notes : F test α = 5% ; ns = non significance ; * = significance ; DN = digital number; near blue = band near blue; blue = band blue; green = band green; NIR = band near infrared; swir1/2 = band short wave infrared; DVI = difference vegetation index ; RVI = ratio vegetation index; TNDVI = transformed normalized difference vegetation index ; CHLI = chlorophyll index ; TGI = triangular greenes index; GI = greenes index.

All of the models composed have a determination coefficient (R^2) above 90%, the best determination for nitrogen content estimation was obtained using vegetation index (RVI, TNDVI, TGI, GI) with a determination coefficient of 98.7%, while the best determination for carbon estimation using vegetation index (RVI, TNDVI, GI) was 99.8%. Assessment of multiple linear regression models using adjusted R^2 was very high above 90%, the highest value obtained by the model of nitrogen estimation using digital number was 97.7% and carbon estimation model using vegetation index was 99%. Very strong correlations between results of measured nitrogen and satellite image components (digital number, reflectance band, vegetation index) are indicated by the high determinants of the compilation model (Table 2). Nitrogen estimation models using digital number and reflectance band were composed by near blue, green, near infrared, swir1, and swir2 bands. The five bands collectively modeled with determinations of 98.1% and 96.4%, this result was in line with the opinion that the use of 2 bands or more was strongly correlated with the chlorophyll and nitrogen content on leaf compared to the use of single band [31]. The Strong determination, in addition, was composed by several bands, it was also supported by a reflectance band that had a function to explain the condition of vegetation and plant canopy conditions. Some spectral bands are very sensitive and are used to predict vegetation conditions, plant vigor, and plant stress conditions especially green, red, NIR, SWIR1, and SWIR2 bands [17]. The nitrogen estimation model using vegetation index composed by RVI, TNDVI, TGI, GI yielded a very high correlation with R^2 value of 98.7%. The vegetation index has been widely used and has a strong correlation with plant nitrogen content such as TGI which is used to estimate the need of plant nitrogen content[24] and RVI that was successfully used to estimate nitrogen status in wheat crop [20].

In order to obtain the best estimation result, the determination coefficient (R^2) and the highest correlation coefficient (R) were selected, it was obtained that the best estimation model of nitrogen concentration and the carbon stock were prepared using weighted double linear regression (Table 3).

Tabel 3 Best models for nitrogen and carbon stock prediction

Model	R	R^2	Sig.
N = -959 + (0.001DN1) - (0.001DN3) + (0.000DN6) + (0.0000346DN7)	0.991	0.981	0.000*
N = -2.842 + (97.658Nearblue) - (57.868Green) + (8.122NIR) - (35.445SWIR1) + (39.16SWIR2)	0.982	0.964	0.000*
N = -6.494 - (130RVI) + (1.500TNDVI) + (546.538TGI) + (24.627GI)	0.994	0.987	0.000*
C = -50.420 + (0.007DN1) + (0.031DN2) - (0.039DN3) + (0.002DN5) - (0.009DN6) + (0.017DN7)	0.935	0.874	0.000*
C = 11.122 - (402.861Nearblue) + (2241.889Blue) - (1985.404Green) + (85.013NIR) - (308.056SWIR1) + (662.962SWIR2)	0.925	0.856	0.000*
C = 200.357 + (4.599 RVI) - (24.995 TNDVI) - (455.399 GI)	0.999	0.998	0.000*

Notes : F test α = 5% ; * = significance ; DN = digital number ; near blue = band near blue; blue = band blue; green = band green; NIR = band near infrared ; swir1/2 = short wave infrared; RVI = ratio vegetation index; TNDVI = transformed normalized difference vegetation index ; TGI = triangular greenes index; GI = greenes index

The variance of nitrogen estimation results using digital number, reflectance, and vegetation index models are very small, it could be seen from the standard deviation of 0.1, as well as carbon estimation results with the standard deviation of 2.39, 2.97. 3.06 (Table 4). The average of the nitrogen content of the whole block was considered optimal with a value of 2.58%. The variance of actual nitrogen content from the analysis of leaves is categorized as deficiencies (block 1, block 3) and optimum (block 2, block 4, block 5). The T-test between the actual and estimated nitrogen content indicated that there are differences in results using the model of digital number, and no significant difference of using the reflectance band and the vegetation index models. Estimated carbon stocks using the digital number, reflectance band, and vegetation index models were not significantly different with the actual measurements, the results showed no significant difference between estimated results and actual measurements. Actual and estimated nitrogen content in the experimental site were categorized as optimal except in Block 1 and Block 3 which were categorized as deficiency categories (Table 4). These categories were consistent with 3 categories of nutrient status based on leaf analysis of 17 plants which less than 6 years into the category of deficiency (<2.5%), optimal (2.60% -2.90%), and excess (> 3.10) [32]. The average result of surface carbon stock measurement on the entire block was 36.27 ton ha^{-1}, this carbon stock was higher 3.45% than the research result of 35.06 ton ha^{-1} [33]. High carbon content is a description of the high activity of photosynthesis and good plant response to the environmental conditions. Well-managed oil palm absorbs more carbon per unit of wide than tropical rainforests, so the palm oil plantations are an important part for carbon management [34]. The increase of carbon stocks in plants are highly dependent on the availability of nitrogen in plants. Nitrogen deficiency indirectly affects the production of biomass by decreasing the photosynthesis rate due to the decrease of the chlorophyll number in the leaves. N accumulation is positively correlated with plant biomass [35]. Reflectance values have a very close relationship with plant characteristics such as biomass [36].

Table 4 Result of nitrogen and carbon stock measurement and prediction using digital number, band reflectance, dan vegetation index models.

Plot	Actual nitrogen (%)	Nitrogen prediction (%)			Actual carbon (ton ha^{-1})	Carbon prediction (ton ha^{-1})		
		DN	Ref	VI		DN	Ref	VI
B1P1	2.35	3.06	3.07	2.41	50.58	43.47	42.69	42.01
B1P2	2.24	2.74	2.68	2.60	38.03	39.53	39.62	37.75
B1P3	2.35	2.35	2.35	2.35	40.41	40.41	40.41	40.41
B1P4	2.39	2.65	2.51	2.57	43.61	42.42	42.98	39.00
B1P5	2.84	2.84	2.78	2.60	32.29	40.55	40.25	37.35
B2P1	2.75	2.65	2.64	2.65	35.48	33.02	33.08	37.26
B2P2	2.72	2.72	2.71	2.53	35.21	36.80	36.75	40.18
B2P3	2.71	2.68	2.70	2.56	36.62	36.67	36.86	39.33
B2P4	2.59	2.69	2.74	2.52	36.13	36.40	36.72	39.87
B2P5	2.71	2.68	2.67	2.59	38.24	33.50	33.80	37.99
B3P1	2.57	2.73	2.83	2.50	33.58	37.51	37.37	40.91
B3P2	2.6	2.67	2.64	2.62	34.72	33.96	33.81	37.63
B3P3	2.58	2.60	2.61	2.65	33.96	34.59	34.80	37.51
B3P4	1.83	2.65	2.63	2.55	32.01	34.73	35.07	37.92
B3P5	2.24	2.67	2.75	2.45	35.86	37.09	37.27	41.30
B4P1	2.83	2.77	2.84	2.62	36.35	38.04	37.52	37.85
B4P2	2.58	2.64	2.64	2.71	39.11	35.08	35.13	35.72
B4P3	2.54	2.69	2.64	2.66	33.47	33.45	33.42	35.72
B4P4	2.36	2.65	2.49	2.74	29.89	30.47	30.75	34.14
B4P5	2.41	2.70	2.62	2.65	31.14	33.15	33.39	36.65
B5P1	2.97	2.78	2.80	2.62	35.80	35.44	35.39	35.41
B5P2	2.83	2.73	2.74	2.75	33.26	35.28	35.02	33.28
B5P3	2.97	2.82	2.87	2.60	36.78	36.21	35.97	36.20
B5P4	2.73	2.89	2.68	2.66	37.49	36.20	35.86	34.69
B5P5	2.8	2.61	2.61	2.80	36.67	36.50	36.58	33.90
Mean±stdev	2.58	2.71±0.12[a]	2.69±0.14	2.6±0.1	36.27	36.42±4.22	36.42±2.97	37.6±2.39
T test		*[b]	ns	ns		ns	ns	ns

Notes : a: mean and standard deviation; b : t-test ; ns : non significant ; * : significant α = 0.05% ; DN = digital number ; Ref = reflectance ; VI = vegetation index

T-test results showed no significant difference between actual and estimated nitrogen content and carbon stock using digital number, reflectance band and vegetation index except on nitrogen estimation model using the digital number. The results with no significant difference indicated no difference between actual and estimated measurement results. This result explained that the nitrogen measurements could be done by using the estimated model composed by reflectance band and vegetation index, while for the estimation of the carbon stock could use the digital number, reflectance band, and vegetation index (Table 3). The estimation of nitrogen content and carbon stock using digital number estimation model, reflectance band, and vegetation index approximate the actual measurement result, this result showed that the model arranged was quite accurately to estimate the nitrogen content and carbon stock in oil palm plant.

4. CONCLUSION

1. The best nitrogen estimation model is composed by the reflectance band of N = -2.842+(97.658Near blue) - (57.868Green) + (8.122NIR) - (35.445SWIR1) + (39.162SWIR2), and vegetation index of N = -6.494-(130RVI) + (1.500TNDVI) + (546.538TGI) + (24.627GI),
2. The carbon stock estimation model using digital number is C = -50.420+ (0.007DN1) + (0.031DN2) - (0.039DN3) + (0.002DN5) - (0.009DN6) + (0.017DN7), reflectance of C = 11.122- (402.861Near blue) + (2241.889Blue) - (1985.404Green) + (85.013NIR) - (308.056SWIR1) + (662.962SWIR2), and vegetation index of C = 200.357+ (4.599RVI) - (24.995TNDVI) - (455.399GI).

3. The result of nitrogen content estimated with reflectance band model and vegetation index are 2.69% and 2.6% respectively. The estimation result of the carbon stock using the selected model found an average of 36.42 tons carbon ha^{-1} (digital number), 36.42 ton carbon ha^{-1} (reflectance band), and 37.6 ton carbon ha^{-1} (vegetation index).

4. The estimation method using selected models constructed from Landsat 8 satellite imagery has the potential to be used for predicting the nitrogen content and carbon stock of oil palm plantations on a wider scale.

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