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Drone image-based parameters for assessing the vegetation condition the reclamation success in post-mining oil exploration

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ABSTRACT

This paper examines drone-based parameters for assessing the success of reclamation activities in post-mining oil-exploration area. The applied drone-based images were multispectral images having visible light and infrared wavelength regions with 5 cm spatial resolution. The main objective of the study is to develop a mathematical model to estimate a reclamation success, through development of success indices. The model were developed by analyzing the relationship between the vegetation success and the digital number values of original and/or synthetic images of drone-based images using 70 sample plots. The mathematical models were developed using a regression analysis, where responses are biomass, volume, and basal area, while the independent variables were original digital number value of images and their derivative synthetic images. The study found that there is a close relationship between parameter biomass stock (ton/ha) and basal area (cm) with both, i.e., original digital number and vegetation indices.

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1. INTRODUCTION

Mining is one of the sectors that has a significant role in economic development in Indonesia. On the other hand, mining also contributes to negative impacts on the environment, such as loss of forest vegetation (deforestation) and land damage (land degradation) including disruption of the balance of the forest ecosystem. Either on areas of post-exploration and/or post-mining activities, reclamation must be followed. The reclamation activity is intended to restore the environmental conditions, especially forest vegetation that close to its original condition [1]. Forest reclamation activities provide many benefits for the sustainability of forest functions through revegetation [2-5]. Revegetation in reclamation is aimed to increase biodiversity, increase canopy cover, canopy stratification, increase soil fertility, accelerate colonization and entry of wild animals, and improve the condition of the forest environment.

Monitoring activities after reclamation aim is intended to provide multi-date data/information and estimate the rate, as well as direction of change [6]. Commonly, monitoring activities use criteria and indicators that enable evaluator to asses the reclamation vegetation easily, consistently, and accurately. Hence, the success of post-mining forest reclamation requires an assessment mechanism through monitoring activities. Monitoring the success of mine land reclamation has been carried out by using several key indicators ofreclamation success both in terrestrial and remote sensing such as vegetation (plant growth, wood volume, and tree basal areas), fauna, soil, and water. Monitoring the success of current post-mining reclamation through terrestrial conventional method has several limitations, including high costs, laborious, time consuming, low accessibility and scattered mining site. while information on the reclamation success is expected to be in hand of decision maker timely, with low cost, accurate and transparent. Therefore, monitoring using remote sensing, particularly drone-based remote sensing data will be very helpful because data acquisition could be performed quickly as the drone could flies under the cloud, fast, comprehensive, having very high spatial resolution, amendable (digital format), easily understood by end user with a reasonable cost. The image of the drone with a sub-meter spatial resolution (5 cm) is capable to measure vegetation parameters quickly and accurately. Research related to the use of drone imageries has been widely carried out for inventorying vegetation [7-9].

Researches on monitoring the success of reclamation in the ex-mining areas could be found in [10], includes monitoring land rehabilitation in Bukit Asam mining area using vegetation parameters such as plant growth, land cover percentage, and species composition, native faunas (insects, birds, amphibians, reptiles, and mammals), soil, and ground and surface water quality. Abubakar [11] evaluated the revegetation success in the ex-nickel mine in Soroaku using growth parameters (plant height, stem diameter, canopy cover, and root development), and growing condition parameters (litter and biodiversity). Puspaningsih, *et al*. [12] monitored the reforestation success in mining areas using the soil index model. From the biodiversity aspects, canopy cover and canopy stratification as well as site quality could demonstrate the success of revegetation activities in the ex-mining area. In addition, the revegetation success to support the stability of the surrounding environment could be assessed from the biomass content as an indicator of forest productivity. Syaufina and Ikhsan [13] noticed that the higher the success rate of revegetation activities in the ex-mining area, the greater the potential of carbon sequestration or biomass storing from the land. Previous studies have shown that there is a significant relationship between original digital values, or synthetic imagery and biomass stock above ground Rakhmawati [14] stated that the relationship value of land cover biomass and NDVI is 60%, and Ren, *et al.* [15] stated that the relationship value of biomass on grass and SAVI is $L = 0.2$ of 64%.

In this study, assessing reclamation in ex-mining area using key indicators of biomass, volume, and basal area is examined. The biomass, volume and basal area is estimated using vegetation variables obtained from unmanned aerial vehicles (UAV) images. The use of biomass, volume, and basal area as key indicators with variables obtained from UAV images to assess the reclamation success is expected to facilitate monitoring reclamation in areas of ex-post-mining applicable which is accurate, consistent, transparent and cheaper. The objective of this study is to develop a mathematical model that capable to estimate the reclamation success indicators using very high resolution images from multi-spectral drone images.

2. RESEARCH METHOD

2.1. Study sites

The data were collected in 6 ex-wells of PetroChina International Jabung Ltd Jambi Province. An overview of sampling locations is presented in Figure 1. The study encompassed the reclamation activities in PetroChina that already since 2013. This reclamation was done following the Jambi Governor Letter No. S-525/1457/SETDA-EKBANG-4: V/2013 dated May 13, 2013 concerning Rehabilitation and Reclamation of bare and abandoned Land Activities, on an ex-well managed by Petro China International Jabung Ltd as shown in Table 1. Field data collection was done since February 2019, then followed by data analyses of biodiversity, soil, water, fauna, canopy structure, environmental quality, community perceptions, spatial analysis and model development in the period of February to May 2019. The analysis was carried out at the Soil Laboratory of the Faculty of Agriculture, IPB, Soil Physics, Chemical Laboratory and Soil Fertility Laboratories of the Faculty of Agriculture of Jambi University, Regional Environmental Laboratories of the Provincial Environment Office of Jambi, and Remote Sensing Laboratory and GIS of the Faculty of Forestry, IPB.

Table 1. The location of the 6 ex-wells of gas exploration of Petro China International Jabung Ltd

Description	Oil and gas ex-wells					
	Ripah	Kajen	Sarinah	North Kabul	Gerbang	NW Lambur
Exploration Year	2003	2004	2004	2006	2008	2010
Planting Year	2016	2016	2016	2016	2016	-
Villages	Sungai Toman	Simpang Tuan	Sungai Bungur	Purwodadi	Teluk Nilau	Kota Baru
Districts	Mendahara Ulu	Mendahara Ulu	Kumpeh	Tebing Tinggi	Pengabuan	Geragai
Regencies	Tanjabar	Tanjabtim	Muaro Jambi	Tanjabar	Tanjabar	Tanjabtim
Plant Age	3 Years	3 Years	3 Years	3 Years	3 Years	0 Years

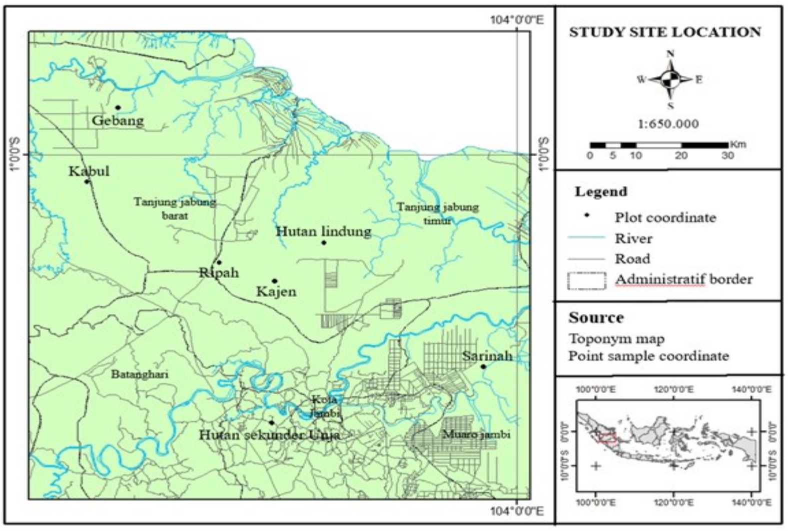


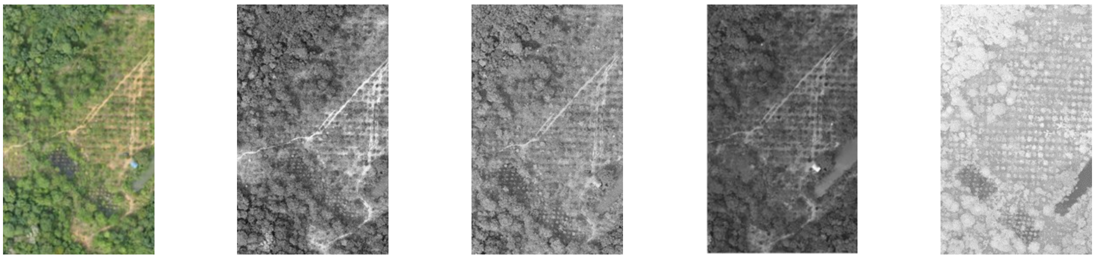
Figure 1. Study site map

2.2. Data, tools, software, and hardware

The tools used to conduct field measurements were drones to record images of each area of interest, GPS, distance tape measurer, phi-band (tape diameter), hypsometer gauges, ropes, poles, book register, machetes, compass, hygrometers, plastic bags, labels, scales, litter ovens, calculators, conventional cameras and DSLR cameras to measure the dimensions of vegetation growth in the field. Data analysis was performed using a set of computers and Agisoft photoscan software for drone image processing, geographic information systems (ArcGIS 10.3) for spatial operation processing, ERDAS IMAGINE 2014 for image processing and analysis, and data processing (SPSS version 24) for statistical analysis (model development).

The main data used in this research include the UAV image data (Figure 2) and vegetation indices derived from image processing (Figure 3), and the primary data taken from the field included aboveground biomass. The measurement data were divided into two data sets in which one set was used to build the success model of reforestation, while the other set was used to test the model accuracy. Other data supporting this research were work maps and reclamation reports.

UAV image | Red | Green | Blue | NIR



UAV image | Red | Green | Blue | NIR

Figure 2. Comparison of UAV visual images with its each respective band

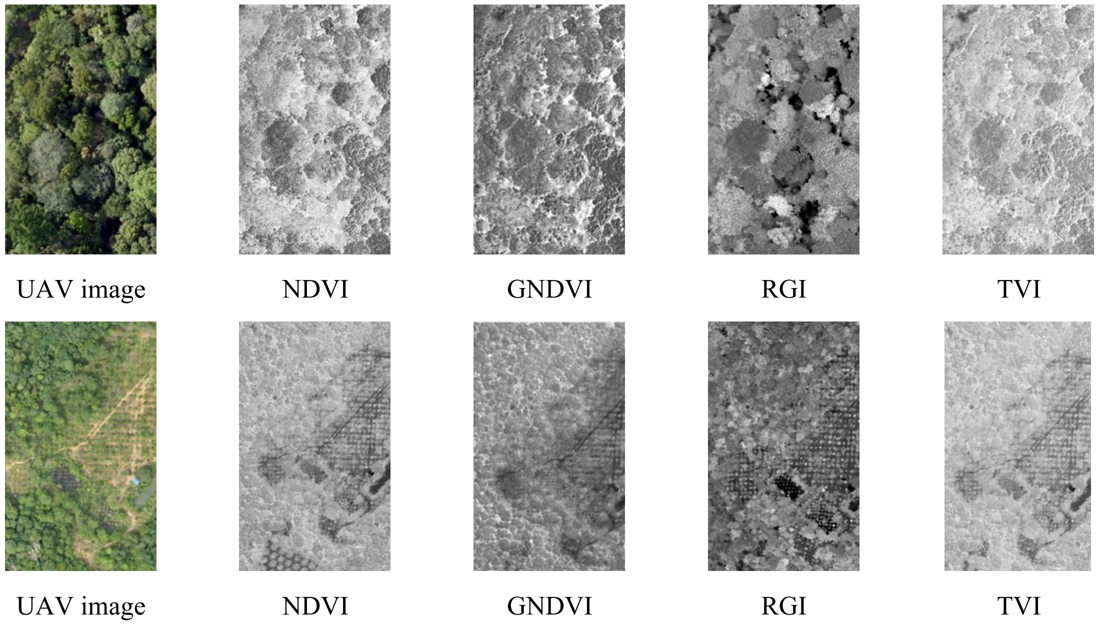


Figure 3. Comparison of UAV visual image and its respective index

2.3. Data processing

2.3.1. Estimation Indicators of the success of forest reclamation

Indicators used as an estimation of the success of forest reclamation are indicators that could describe the level of growth and productivity of the forest. Some common and consistent indicators of the success in forest reclamation with site conditions and biological processes of forest growth include the average basal area (LBDS), average volume of aboveground biomass, and average growth rate of stand/increment dimensions [16]. In this study, the indicator used as a key indicator in the success of reclamation was biomass. In estimating the value of biomass, several variables were used including the value of the red, green and blue channels of UAV images and the value of synthetic image channels constructed from UAV images.

2.3.2. Parameters and variables

The parameters for the success of post-mining reclamation used in this study included basal (LBDS), volume, and biomass. The basal area (LBDS) was calculated using the following formula:

$$Lbds = 0.25\,\pi\,D^2$$

D = diameter at breast height
Stand stocks (volume) were calculated using the following formula:

$$Volume = basal\ area\ x\ tree\ height\ x\ convertion\ constanta$$

Carbon stocks are stored in 3 main components, namely biomass, necromass, and soil organic matter. The three components can be divided into 2 groups: aboveground and below ground biomasses [17]. In this study, the calculated biomass estimation was aboveground biomasses of tree, bush, litter and necromass. The components other than tree biomass were dried in the oven to determine their dry weight, while tree biomass was calculated using the following formula:

$$Biomass = volume * specific\ gravity$$

The variables used in the model development were divided into independent and dependent variables. The dependent variables used included basal area (LBDS), volume, and biomass, while the independent variables included red, green, blue, NIR bands and vegetation indices of NDVI [18], GNDVI [19], TVI [20], and RGI [21].

2.3.3. Transformation of vegetation index

Vegetation Index is the amount of vegetation greenness value obtained from processing digital signal data of brightness values of several satellite sensor data channels. Peng, *et al.* [22] stated that vegetation index is an optical measurement of the greenness level of the vegetation canopy, composite properties of leaf chlorophyll, leaf area, structure, and vegetation canopy cover. According to Jaya, *et al*. [23], vegetation indices are values obtained from mathematical operations using pixels that come from several channels or bands contained in the image. There are other applications of vegetation index in forestry purposes, such as the use of vegetation index for detected degradation and deforestation [24]; and for measuring land cover changes in burned area [25]. Transformation of vegetation index was used to obtain new images using certain mathematical equations that involved specific spectral bands of images emphasizing the appearance of vegetation. Vegetation indices used in this research included NDVI, GNDVI, RGI, and TVI, obtained by using these following formulas:

Normalized difference vegetation index (NDVI) $NDVI = \frac{NIR-RED}{NIR+RED}$

Red green index (RGI) $RGI = \frac{GREEN-RED}{GREEN+RED}$

Transformed vegetation index (TVI) $TVI = \left[\frac{\mathbf{NIR-RED}}{\mathbf{NIR+RED}} + \mathbf{C}\right]^{\mathbf{1/2}}$

Green normalized difference vegetation index (GNDVI) $GNDVI = \frac{NIR-GREEN}{NIR+GREEN}$

Note:
Red : is band with a wavelength of 600-700nm
Green : is band with a wavelength of 500-600nm
NIR : is band with a wavelength of 700-1000nm
C : is a constant to remove imaginary numbers (negative numbers) with a value of 0.5

In addition to the development of post-mining exploration model, there are other mine success indices that had also been developed to assess post-mining success. Puspaningsih, *et al.* [12] used a soil index determined by using indicators of litter, soil physics, soil biology, and soil chemistry indices to determine the success of nickel mine reclamation; furthermore, Muis, *et al.* [26] used LBDS (basal area), biomass, and mean annual increment (MAI) indices.

2.3.4. Formulation of estimation model of biomass, LBDS, and timber volume

The remote sensing image parameters used in estimating the biomass, basal area (LBDS), and volume were the bands of UAV image namely red, green, blue, and NIR. The study also examined the synthesis band in the form of a vegetation indices obtained from the UAV image, namely NDVI, GNDVI, RGI, and TVI. in which B was the predicted value, namely biomass, volume, and basal area, *a* is constant of regression, *b & c* are regression coefficients, *e* is a mathematical constant, also called Euler's number, x is independent variable that derived from digital number of the original and/or synthetic bands, e.g., NDVI, GNDVI, RGI, and TVI. The constant values of *a, b* and/or *c* were obtained from the process of statistical analysis with the least squared method. In this study the models examined were as follows:

- Linear model : $B = a + bx$
- Exponential model : $B = a\,eb^{\cdot X}$
- Logarithmic model : $B = a\,ln\,x + b$
- Polynomial Model : $B = a + bx + cx^2$
- Power Model : $B = ax^b$

2.3.5. Model validation

Model reliability testing was conducted by comparing the results from field observations of the sample plots and the results of estimation using the developed estimation model. Model validation was done to obtain the best model among the models developed [6, 26-28]. There were 24 sample plot data used for the model validation. The validation methods applied in this study included mean deviation (MD), aggregative deviation (AD), root-mean squared error (RMSE) and bias (e). The mean deviation is the percentage of absolute values of the sum of the results of the difference between the estimated value and the actual value with the estimated value of the example (n). The model is good when it has an MD value of less than 10%. The formula for mean deviation is as follows:

$$MD = \left[\frac{\sum_{i=1}^{n}\left|\frac{\sum\widehat{yi} - \sum yi}{\sum\widehat{yi}}\right|}{n}\right] x\ 100\%$$

Aggregate deviation (AD) is the difference of the number of actual values and the estimated values as proportional to the estimated values. The formula is as follows:

$$AD=\left[\frac{\Sigma\hat{y}-\Sigma y}{\Sigma\hat{y}}\right]$$

The formula for RMSE, which expresses an error indicator based on the quadratic total of the deviation between the expected and actual results is written as follows:

$$MSE=\left[\frac{\sqrt{\sum_{i=1}^{n}\left(\frac{\widehat{yi}-yi}{yi}\right)^2}}{n}\right] x\ 100\%$$

The following bias (e) formula is describing the errors that occur both in the implementation of measurements and in the measuring instrument. Note: $\widehat{yi}$ is i-estimated value, yi is i-actual value and n is number of samples.

$$e=\frac{\sum_{i=1}^{n}(\widehat{yi}-yi)}{n}$$

2.3.6. Selection of the best model

The selection of the best model was carried out by ranking all examined models based on some validation measures applied. The ranking was given according to the amount of composite score values derived from AD, MD, RMSE and e. The ranked model was only the models that have a high regression coefficient and determination coefficient (R^2 adjusted), have a small standard error value (s), pass the F-calculated value, meet the χ^2 test (χ^2 count < χ^2 table). Where $Score\ R_{out}$, $Score\ R_{min}$, $Score\ R_{max}$ are output, minimum and maximum scores, while E_{min}, $Emax$, and E_{input} are is the minimum, the maximum and original input of deviation values (error). The formula of data standardization to convert the deviation value to score value, used the equation Jaya [6] as follows:

$$Score\ R_{out}=\left[\frac{E_{input}-E_{min}}{E_{max}-E_{min}}x(ScoreR_{max}-ScoreR_{min})\right]+ScoreR_{min}$$

3. RESULTS AND ANALYSIS

3.1. Digital values of UAV original and synthetic images

This research used the original and synthetic bands derived from UAV image as independent variables. The original band of UAV image consisted of green, blue, red, and NIR bands, while the established synthetic bands are NDVI, GNDVI, RGI, and TVI. Table 2 summarizes the statistical values of the bands.

Table 2 Statistical values of UAV image derived from sample plots

Source	Range (min – max)	Mean	Standard Deviation	Coefficient Variation (%)	Standard Error
Green	63.7 - 186.9	117.5	z	20.71	3.14
Blue	74.2 - 159.3	130.6	16.9	12.97	2.19
Red	52.3 - 123.0	87.4	14.4	16.44	1.85
NIR	85.9 - 247.7	196.8	47.6	24.17	6.14
NDVI	-0.042 - 0.439	0.242	0.1237	51.17	0.016
GNDVI	-0.152 - 0.345	0.187	0.1126	60.08	0.0145
RGI	-0.118 - 0.141	0.059	0.0562	95.85	0.0073
TVI	0.677 - 0.969	0.858	0.074	8.62	0.0095

3.2. Estimation model development of the key indicators for success

The results of the correlation analysis between independent variables with biomass, volume, and LBDS show strong relationship; hence, the equation model was built based on this relationship. The establishment of biomass estimation models was made based on 70 sample plots of data in which 70% of plot data was used for model development, while the rest and 30% was used for the model validation. Establishment of the biomass estimation models also referred to the Lu [29]. Wahyuni [30], establish the estimation model for biomass referred to the correlations between field survey and digital parameters in the image. The biomass estimation model was built based on the correlation between the biomass value, volume, and or field basal area (LBDS) with the independent variables derived from vegetation indices and original band values of the UAV images). During the development of the model, a correlation coefficient test was also performed.

The results of the coefficient of determination test in Table 3 show that some developed models could estimate biomass, volume, and LBDS as shown with R^2 values in some equation models greater than 40%. This highlights that some independent variables used had a considerable effect in estimating biomass. However, there were some models with R^2 values lower than 40%. The biomass estimation model using NIR as the x variable had the highest R^2 value at 90%, while LBDS estimation model using GNDVI as the x variable had the lowest R^2 value at 30%.

Table 3. Results of estimation models

Independent variables	Model Codes	Models type	Functions	R^2
		y is basal area (cm^2)		
Red	M1	Linier	$y = -0.465\ red + 61.417$	0.7
Green	M2	Linier	$y = -0.470\ green + 67.992$	0.7
Blue	M3	Logarithmic	$y = -34.014 \ln (blue) + 159.052$	0.4
NIR	M4	Logarithmic	$y = -23.581 \ln (NIR) + 130.901$	0.7
GNDVI	M5	Linier	$y = -28.571\ GNDVI + 13.724$	0.3
RGI	M6	Logarithmic	$y = -29.008 \ln (RGI) - 39.591$	0.6
TVI	M7	Linier	$y = -94.530\ TVI + 96.051$	0.5
NDVI	M8	Quadratic	$y = 196.213\ NDVI^2 - 99.297\ x + 13.097$	0.7
		y is volume (m^3/ha)		
Red	M9	Logarithmic	$y=-833.535 \ln(red)+4045.366$	0.8
Green	M10	Logarithmic	$y=-987.191 \ln(green)+4880.916$	0.7
Blue	M11	Quadratic	$y=0.146\ blue^2-32.246\ blue +1777.927$	0.5
NIR	M12	Logarithmic	$y=-462.388 \ln (NIR)+2513.090$	0.8
GNDVI	M13	Quadratic	$y=328.049\ GNDVI^2-730.409+231.867$	0.4
RGI	M14	Quadratic	$y=34076.679\ RGI^2-15923.895\ RGI+1846.098$	0.7
TVI	M15	Linear	$y=-1855.996\ TVI+1831.992$	0.5
NDVI	M16	Quadratic	$y=3583.720\ NDVI^2-1778.552 NDVI+181.648$	0.8
		y is Biomass (kg/ha)		
Red	M17	Quadratic	$y=0.109\ red^2-32.266\ red+2352.002$	0.9
Green	M18	Quadratic	$y=0.109\ green^2-35.128\ green+2811.985$	0.8
Blue	M19	Quadratic	$y=0.232\ blue^2-47.677\ blue+2460.116$	0.6
NIR	M20	Quadratic	$y=0.022\ NIR^2-11.112\ NIR+1422.294$	0.9
NDVI	M21	Quadratic	$y=5046.479\ NDVI^2-2800.201 NDVI+353.412$	0.9
GNDVI	M22	Exponential	$y=238.272\ exp^{-12.532GNDVI}$	0.6
RGI	M23	Quadratic	$y=6455.356\ RGI^2-4299.76\ RGI +707.033$	0.4
TVI	M24	Exponential	$y=2.703\ exp^{10e-22.511TVI}$	0.6

Note: R^2: Determination coefficient

3.3. Model validation test

The model validation is aimed to measure the degree of discrepancy between the field data and the estimated data from the model. The validation test is used to compare the facts obtained from observations and facts derived based on theories. Validation test of the estimation models were assessed based on aggregate deviation (AD) values, mean deviation (MD), bias values (e), and RMSE values, as presented in Table 4. The model validation test in Table 4 shows that the models were reliable to estimate key indicators of reclamation success in the study area. Based on aggregate deviation (AD) values, most validated models met the AD rules by not exceeding an interval value between -1 to 1. The smaller the AD and MD values are, the better the results will be. The results of the bias test (e) indicated a systematic error that occurred due to errors in the measurement results ranging from 0.1 to 36.5 in which the lowest bias value belongs to M1 model. The lower the bias value is, the more accurate model will be. The lowest RMSE (Root Mean Square Error) value is in M4 model by 0.9.

The model validation test in Table 4 shows that the models were reliable to estimate key indicators of reclamation success in the study area. Based on aggregate deviation (AD) values, most validated models met the AD rules by not exceeding an interval value between -1 to 1. The smaller the AD and MD values are, the better the results will be. The results of the bias test (e) indicated a systematic error that occurred due to errors in the measurement results ranging from 0.1 to 36.5 in which the lowest bias value belongs to M1 model. The lower the bias value is, the more accurate model will be. The lowest RMSE (root mean square error) value is in M4 model by 0.9.

3.4. Selection of the relible model

The selection of the best model was conducted by considering the results of model validation assessment. The best three models are summarized in Table 5. For biomass estimation, the most accurate model come from model M20, having average deviation of about 15.2%, while for the basal area (LBDS) estimation is obtained from M8, with average deviation of about 11.3%.

Table 4 Results of the model validation of biomass estimation

Model Codes	%AD	%MD	%RMSE	%e	Average (%)	Model Codes	%AD	%MD	%RMSE	%e	Average (%)
M1	20.0	20.0	10.1	0.4	12.6	M13	80.0	80.0	1.5	1.2	40.7
M2	20.0	20.0	5.6	1.1	11.7	M14	80.0	70.0	2.4	1.0	38.4
M3	50.0	50.0	6.7	2.2	27.2	M15	70.0	80.0	1.7	0.9	38.1
M4	20.0	20.0	3.4	1.1	11.1	M16	60.0	90.0	0.9	0.1	37.7
M5	50.0	50.0	6.0	4.5	27.6	M17	70.0	0.0	6.2	2.1	19.6
M6	40.0	40.0	10.8	3.0	23.5	M18	70.0	90.0	10.0	3.8	43.4
M7	30.0	30.0	6.7	2.6	17.3	M19	80.0	10.0	8.8	3.8	25.7
M8	20.0	20.0	4.1	1.1	11.3	M20	28.0	28.0	3.7	1.2	15.2
M9	60.0	90.0	2.0	0.1	38.0	M21	60.0	90.0	8.0	3.1	40.3
M10	10.0	90.0	1.2	0.2	25.4	M22	10.0	90.0	1.2	0.4	25.4
M11	80.0	50.0	1.5	0.0	32.9	M23	30.0	40.0	4.3	1.8	19.0
M12	50.0	60.0	0.8	0.3	27.8	M24	10.0	90.0	1.9	0.5	25.6

The results indicate that the NIR was the most significant independent variable to estimate the biomass content of vegetation in post-mining exploration area. The similar result was shown by Hunt, *et al*. [31], where NIR give strong correlation with biomass (Figure 4). For estimating the basal area, the NDVI which is derived from NIR dan red band is the best variable [32] (Figure 4). The NDVI have a close correlation with canopy structure. Hence, the success of post-mining can be detected by utilizing UAV images using Red and NIR bands. No one of the model that could be accurately estimate the standing stock of volume, since the average deviation is larger than 20%.

Table 5. Results of calculating the model scores

Model Codes	Functions	Average % of deviation
M20	Biomass = $0.022NIR^2 - 11.112NIR + 1422.294$	15.2
M8	LBDS = $196.213\ NDVI^2 - 99.297\ NDVI + 13.097$	11.3

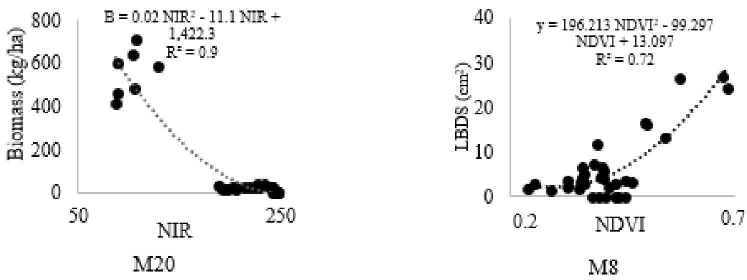


Figure 4. Scatter diagram of the best models

4. CONCLUSION

From the foregoing findings and discussion, the study concluded that the biomass content of vegetation within the post-mining exploration area could be estimated by using the NIR bands with the model of $0.022\ NIR^2$-$11.112NIR + 1422.294$ with the average of deviation of about 15%. For estimating the basal area, the most reliable model type is polynomial of $196.213\ NDVI^2 - 99.297\ NDVI + 13.097$ with the average of deviation about 11.3%. In general, it is concluded that the drone-based images having 5 cm spatial resolution is highly potential to assess the either biomass and/or timber volume stock that would be beneficial to be used for evaluating the early growth condition of vegetation. No one of the model could be used for estimating the standing volume of early growth vegetation.

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