Information Required for Estimating the Indicator of Forest Reclamation Success in Ex Coal-Mining Area

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Abstract

This paper describes how the information of the key indicators for assessing the degree of forest reclamation success in ex coal-mining area was identified. Those indicators were analyzed using the descriptive statistic as well as the discriminant analysis on the basis of biophysical data representing age class of vegetation after reclamation. The main objective of the study was to find out the predominant key indicator that determines the success of forest reclamation in ex coal-mining areas. This study found that the variance of basal area, green biomass and increment was relatively high between young plantation and old plantation. The study confirmed that the variation of the success of reclamation was strongly influenced by site quality. The study concluded that the best indicators to be used for assessing the success of forest reclamation was the increment providing accuracy more than 79.6% either for indicator five or three classes.

Keywords: discriminant analysis, ex-mining area, forest productivity, forest reclamation, site quality

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1. Introduction

Mining activities in forest area have been one of the direct causes of forest degradation and deforestation. During the last decade, the number of mining activities within the forest area had been doubled. In the mainland of Sumatera, it has been reported that the forest utilization permits (IPPKH) for mining activities increase sharply at about 67% during the 2013-2014 period, or increase about 5142.5 ha. Approximately 28.8% of the total use permit (2909.9 ha) is located in South Sumatra Province [1]. In general, the mining with open pit mining system had causing the destruction of the forest stand it self as well as its environment [2, 3]. Forest degradation will have direct and indirect negative impact to forest stands or sites [4], decreasing species composition, forest productivity, and biodiversity [5, 6], disturbance of land stability [7-9], increasing soil erosion, sedimentation, and damaging catchment area [10], and decreasing soil fertility which influence the physical, chemical, and biological soil characteristics [8], [11-12].

Reducing the negative impact of forest degradation from mining activities requires an improvement activity through forest reclamation. The forest reclamation is aimed to restore and repair the damaged lands and its vegetation so the forest has been put back to its initial functions [7], [13-14]. However, restoring forest ecosystem, particularly in a damaged ex mining area is difficult to do [15], a heavy challenge that requires integration of reclamation techniques that are suitable with the site's condition [16]. This must be supported by effective monitoring and evaluation on the success of the reclamation activities. Effective means choosing the precise method, criteria, and indicator used in assessment [17].

A number of researches were done to review the indicators used for monitoring and evaluation of forest reclamation's success in ex mining area. Soil index such as physical, chemical, and biological characteristics of the soil, and litter index are important factors in monitoring the success of reforestation in ex nickel-mine [11]. The ex-mine soil quality indicator consists of soil's organic carbon, CO_2 flow, dehydrogenase activity, sand fraction, water content, and base saturation become the key parameters to evaluate the success of reclamation in coal

mine area [17, 18]. Soil characteristics such as soil texture, content of organic materials, and cation exchange capacity are important factors considered in assessing ex mine restoration [19]. Monitoring of *collembola* (invertebrates) abundance index is an indicator of soil fertility in ex gold mine area [20]. Nutrient cycle and litter decomposition are indicators to assess the restoration of ecosystem function [21]. Biodiversity measurement is used in evaluating mining area, based on the database on land cover, protected area, mining activities, and habitat value measurement [5, 22], while forest health assessment uses vegetation as indicator to continuously monitor the change [6, 23].

Measuring the success of revegetation in ex mining area is one of the important processes on the monitoring of the reclamation. The success of assessing the achievement of reclamation is required by the decision-maker in a fast, cheap and easy ways. The previous studies [7-8], [10-11] show that the indicators being used to monitor the success of revegetation varied widely, depending on the mining system as well as the biophysical conditions of the premining regions. Although several researches on the assessment on the success of forest reclamation in ex mining area with their various indicators have been conducted, the assessment of forest reclamation and its relation to forest growth and productivity function that use spatial growing factors as variables is still limited. Whereas, the function of stands' growth is a functional relation of the stands, such as diameter, basal area, height, volume, biomass, and stands' age [24-27]. In the research, authors conducted a spatial review on the key factors that can be used to have a quick, consistent, and accurate assessment on forest reclamation. The analysis of this functional relation will then become the determining indicator of forest reclamation's success. The objective of this research was to identify the estimating indicator of forest reclamation's success in ex coal mining area. The authors examine some important indicators to monitor the success of revegetation, which includes basal area, biomass and increment. The indicator that provides high consistency estimate will be used as a determinant of the success of revegetation.

2. Method

2.1. Site and Date

This research was conducted within the reclamation area of PT Bukit Asam (Persero) Tbk. ex coal mining. Historically, in 2014, the revegetation covered a total of 1.456,2 ha area wide (Figure 1). Administratively, the research was conducted in Tanjung Enim Sub District, Muara Enim District, South Sumatra Province. Geographically, the location was at 103°40'– 103°45'Eastern Longitude and 3°35'–3°45' Southern Latitude [28].

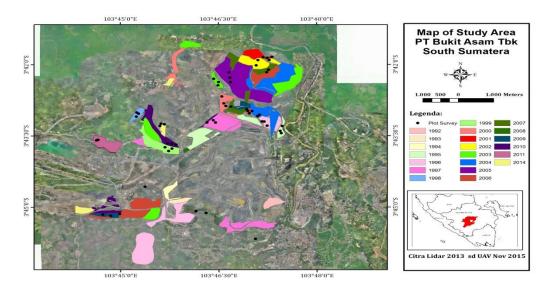


Figure 1. Map of the Study Site

Field data collection was conducted from April to May 2015 representing stand age from 1 to 20-years-old revegetation area and natural forest (HA). The details of revegetation area are as depicted in Table 1.

	Tab	ie T. Age Di	SINDULIO	n of Revege	lation Area	in ex iviin	ing Sile	
No	Age (year)	Year of planting	No	Age (year)	Year of planting	No	Age (year)	Year of planting
1.	1	2014	7.	10	2005	13.	16	1999
2.	2	2013	8.	11	2004	14.	17	1998
3.	5	2010	9.	12	2003	15.	18	1997
4.	6	2009	10.	13	2002	16.	19	1996
5.	8	2007	11.	14	2001	17.	20	1995
6.	9	2006	12.	15	2000	18.	HA	-

Table 1. Age Distribution of Revegetation Area in ex Mining Site

2.2. Number of Plots and Variables Measured in the Field

There were 54 plots measured in the field, while the number used for model development was 49 plots. Limited data have caused model verification to use the same data that were used for model development.

The variables measured in the field in each plot include vegetation condition, soil characteristics and land surface condition. Vegetation condition includes diameter at breast height (*dbh*), plant height, litter, canopy cover percentage, number and type of vegetation. Soil samples collected from the field consist of undisturbed soil sample and disturbed soil sample, which were analyzed in June 2015 at Soil Laboratory, Soil and Land Resource Department, Faculty of Agriculture, Bogor Agricultural University. Soil characteristics data consist of physical characteristics (bulk density, sand, clay, and silt fraction) and chemical characteristics which focused on macro nutrients (Ca, Mg, K, Na, cation exchange capacity, C organic, N and P). Land surface condition data include the shape and depth of soil erosion.

2.3. Estimating Indicator of Forest Reclamation Success

The indicator used to estimate forest reclamation success consists of several variables that can describe the growth rate and forest productivity. Several common estimating indicators that are consistent with the biological process of forest growth are mean basal area per width unit [11], mean biomass volume per width unit or mean stands dimension growth rate (Mean Annual Increment/MAI) with the following details:

1. Basal area (BA) is the cross sectional area at diameter breast height (*dbh*) per area width unit. Basal area unit is $m^2 ha^{-1}$.

2. Biomass (ton ha⁻¹) calculated is the total of litter biomass and above ground biomass (AGB). The ABG is calculated using biomass estimation allometric based on the specific gravity difference of tree [29] and species allometric equation.

3. Mean Annual Increment (MAI) is the ratio between tree volume at year t and tree age per width unit [27]. MAI unit is $m^2 ha^{-1} t^{-1}$.

The three parameters chosen as indicator were then classified into five class (very small, small, medium, big and very big) and three class (small, medium, big). This classification was done to obtain high accuracy at various estimating indicators of forest reclamation success. The classification in this research used equal interval with the following equation:

Equal Interval = <u>Maximum value – Minimum value</u> Number of class

Value interval and distribution of data number for each basal area, biomass and MAI class for five class classification can be seen in Table 2, while three class classification is served in Table 3.

Increment is defined as the increase of dimension or size of a chosen characteristic of a tree individual or stands in a certain time interval. The level of MAI may also give a crucial information on the success and failure of the revegetation. One of the models of increment function has the objective to estimate the dimension of a stand at a certain age or time as the basis to determine the precise silviculture treatment [25, 27].

		Basal a	rea	Biomass	MAI		
Notation	Description	Interval (m ² ha ⁻¹)	Number	Interval (ton ha ⁻¹)	Number	Interval (m³/Ha/Y)	Number
	Very small	<4.71	7	<38.44	15	<1.05	11
II	Small	4.71–9.15	10	38.44-49.61	6	1.05–1.91	8
111	Moderate	9.16-13.60	15	49.62-60.78	10	1,92–2.76	13
IV	Large	13.61–18.05	9	60.79-71.95	5	2.77-3.62	5
V	Very large	>18.05	8	>71.95	13	3.62-4.48	12

Table 3. Basal Area Three Class Classification MAI Basal area Biomass Notation Description Interval Interval Interval Number Number Number $(m^2 ha^{-1})$ (ton ha⁻¹) (m³/Ha/Y) Small <9.16 17 <49.62 21 19 T <1.92 9.16-13.60 Ш Moderate 15 49.62-60.78 10 1,92-2.76 13 >13.60 >60.78 >2.76 Ш Large 15 18 17

2.4. Determinant Indicator of Forest Reclamation Success

Forest reclamation success is determined by several indicators which specifically analyzed in this research. The indicator reflected the characteristics of growth media quality, which were described into several independent variables as listed in Table 4.

Table 4. Determinant Factors (Independent Variable) of Forest Reclamation Success	3
in Ex Coal Mining Area	

Indicator	Variables	code
Soil index		
	 Soil physical properties: 	
	 Bulk Density (Bd) 	X1
	 Sand fraction (Ps) 	X2
	 Clay fraction (Li) 	X3
	 Silt fraction (De) 	X4
	 Soil chemical properties: 	
	 Calsium (Ca) 	X5
	 Magnesium (Mg) 	X6
	 Potassium (K) 	X7
	Sodium (Na)	X8
	 Cation exchange capacity (CEC) 	X9
	 Organic carbon (C-organic) 	X10
	Nitrogen (N)	X11
	Fosfor (P)	X12
	- Litter	
	 litter thickness (KS) 	X13
	 Dry litter mass (BKS) 	X14
Land Surface condition	,	
	 Soil erosion shape (E) 	X15
Biodiversity status		
	 Shannon diversity index (H') 	X16
	 Margalef richness index(DMg) 	X17
Stand structure	 Stand density (Kr) 	X18
	 Canopy stratification (St) 	X19
	 Percentage of canopy cover (C %) 	X20
Recolonization		
	 Colonization/initial vegetation (KL) 	X21

2.5. Data Analysis

2.5.1. Multivariate Normality Test

Prior to any further analysis, to fulfil statistics principles, the normality of all independent variables used in discriminant analysis was analyzed. The result of multiple normality test showed that data distribution follows a linear line. The same with many $d_j^2 \le x_{p0.5}^2$ value for independent variable, which is 55.1 % (>50.0%). This shows that the data follows multiple normal distribution [30].

2.5.2. Multi-Collinearity Analysis

Furthermore, the multicollinearity test was applied to fulfil statistics principles in discriminant analysis. The objective of multicollinearity test is to see the relation between independent variables (predictor variable). Discriminant analysis was done to avoid multicollinearity issues. The level of relation proximity between predictor variables was calculated using Pearson correlation coefficient. The value of Pearson correlation coefficient is between -1 to 1. The value, whether it is positive or negative, shows the level of relation between variables. The value of correlation coefficient used in this research is 0.65. The value was made as limit in choosing variables [31].

The result of multicollinearity test showed that 4 out of 21 variables were excluded due to strong proximity between variables (r value <0.65). The correlating variables are sand (Ps) and clay (Li) fractions have high correlation with dust (De) fraction, calcium (Ca) correlates with magnesium (Mg), potassium (K) correlates with sodium (Na), and biodiversity index (H') has strong correlation with vegetation species richness (DMg). One of the correlating variables must be excluded from the model, and those are De, Mg, Na, and DMg. Those variables have weak significance value (discriminating power) compare to other variables. Excluding weak variables will result in good model [32].

2.5.3. Discriminant Function Analysis

A stepwise discriminant analysis method was to classify groups or classes on the basis of a set of independent variables (predictor). The tested independent variables were in form of quantitative data with interval or ratio data type; while the predicted (dependent) variables were in form of qualitative data with ordinal scale (class name). A vector X ($X_1, X_2, ..., X_n$) is the value of independent variable which will be inserted and evaluated by each discriminant function. Since, the algorithm of discriminant function was to get the maximum likelihood, then the class or group was determined by the the highest value derived from each discriminant function [30, 32]. The class predicted were developed on the basis of basal area, MAI and biomass.

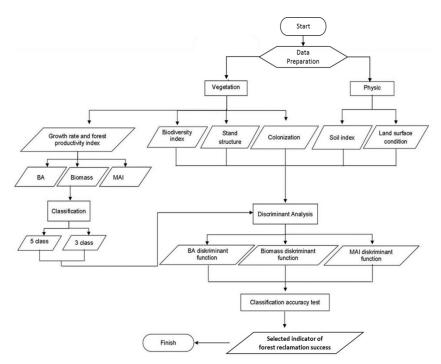


Figure 2. Flowchart of Research Step

2.5.4. Classification Accuracy Assessment

According to [33], accuracy test is conducted to see the error in the classification of estimating parameter of forest reclamation success stated in percent. In this study the accuracy

assessment was done by using confusion matrix or also known as contingency matrix by comparing the actual basal area class and the predicted classes derived from discriminant analysis. The accuracy calculated in this research is the overall accuracy. To summarize all of the work above, the research step is depicted in Figure 2.

3. Result and Discussion

3.1. Basal Area

Basal area was calculated for both the natural forest and each stand age of revegetation area except for the young plantation having age less than eight years, i.e., for age class of seven years (planted in 2008), four years (planted in 2011) and three years (planted in 2012). The basal area shown in Table 5 is the mean of each plot per planting year.

					N	/iining					
No	No. Planting		l	Basal area		No	Planting	٨٣٥	E	Basal area	а
INO	year	Age	mean	Std	CV	No	year	Age	mean	Std	CV
1	2014	1	0.41	0.16	39.13	10	2002	13	8.82	5.89	66.73
2	2013	2	0.93	0.40	43.10	11	2001	14	8.97	2.09	23.25
3	2010	5	14.89	3.25	21.82	12	2000	15	10.28	6.05	58.84
4	2009	6	9.31	6.56	70.50	13	1999	16	14.92	4.90	32.85
5	2007	8	12.02	10.23	85.12	14	1998	17	12.24	0.85	6.92
6	2006	9	7.86	2.82	35.81	15	1997	18	17.06	6.84	40.10
7	2005	10	10.65	3.01	28.25	16	1996	19	14.33	8.75	61.07
8	2004	11	11.91	6.07	50.96	17	1995	20	19.31	3.05	15.79
9	2003	12	13.29	5.34	40.18	18	HA	HA	21.36	7.12	33.34

Table 5. Basal Area Mean (m² ha⁻¹) in Natural Forest and in Revegetation Area of ex Coal-

Table 5 shows that the highest mean of basal area in natural forest is approximately 21.36 m2 \pm 7.12 m²ha⁻¹. The high basal area in the natural forest is highly correlated to density, type of vegetation, and litter abundance on the forest floor. The decomposed litter has important role to the productivity and nutrient cycle in forest ecosystem, particularly tropical forest. Litter has the role to store nutrient stock, reduce bulk density, increase the soil's cation exchange capacity, form protection shield to soil surface, and manage micro climate condition [34-36].

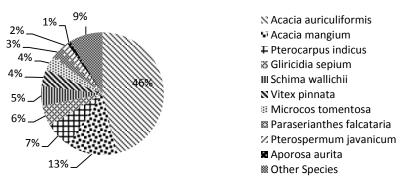


Figure 3. Proportion of Dominant Tree and Pole Vegetation in Natural Forest and Revegetation Area

In the revegetation area, it was found that them coefficients of variance (CV) of basal area data were ranging from 6.9% to 85.1%. This means that the basal area data of revegetation has been varied widely. However, in general, the common trend of basal area is in line with the plant's age, the increase in age is followed by the increase in diameter [11]. The highest mean of the basal area mean is provided by the 20 year-old stands, with mean and standard deviation of 19,31 and 3,05 m²ha⁻¹. The lowest mean basal area was found in the youngest stands of aged 1-year-old with 0,412 \pm 0,161 m²ha⁻¹ and 2-year-old with 0,930 \pm 0,401 m²ha⁻¹. It is noted that the high basal area of revegetation area is influenced by the thickness of

top soil [37]. The field measurement that the sowing of top soil in revegetation area in mean is about 50-80 cm above the soil embankment. Precise top soil management is very beneficial for nutrient cycle and biodiversity improvement [16].

The study result also shows that other factor that influences basal area is the composition of vegetation species. The dominant species found in this research was fast growing species, including acacia (*Acacia auriculiformis*), brown salwood (*Acacia mangium*), amboyna wood (*Pterocarpus indicus*), gliricidia (*Gliricidia sepium*), schima or needlewood (*Schima wallichii*), *Vitex pinnata*, *Microcos tomentosa*, white albizia (*Paraserianthes falcataria*), bayur (*Pterospermum javanicum*), *Aporosa aurita* and other species (Figure 3).

In the ex mining area, a direct planting with endemic (local) tree species in revegetation area does not work well compare to introducing pioneer species. The local tree species, particularly those has a high economic value usually require shades in its early planting years. When planted in open land, the growth is stunted or even dead [38]. Fast growing species are needed for potential reclamation in ex coal-mining area. The choosing of fast growing vegetation is based on its ability to adapt with soil condition in reclamation area [39].

3.2. Biomass

As mentioned in the method, the biomass that consisted of poles and trees (dbh \geq 10 cm) and litter biomass was also examined as a parameter of the revegetation. From the sample plots measured, the statistical values of biomass both in natural forest and revegetation area for each planting year is shown in Table 6. It is noted that the standard deviations (std) of biomass are ranging between 0.03 and 57.59 and the coefficient of variance (CV) is ranging between 0.55% and 82.50%, which shows high value for several planting year. This means that the mean of biomass measured in both natural forest and revegetation area plots have relatively high variability.

No	Planting	000	Biomass		,	No	Planting	0.00	Biomass		
INU	Year	age	mean	Std	CV	INO	year	age	mean	Std	CV
1	2014	1	1.97	0.71	36.08	10	2002	13	65.17	53.77	82.50
2	2013	2	5.52	0.03	0.55	11	2001	14	57.46	10.30	17.93
3	2010	5	68.85	14.64	21.26	12	2000	15	34.79	19.70	56.61
4	2009	6	47.08	11.07	23.51	13	1999	16	51.75	31.91	61.67
5	2007	8	26.13	8.43	32.25	14	1998	17	53.27	13.17	24.73
6	2006	9	46.17	15.49	33.55	15	1997	18	63.15	17.67	27.98
7	2005	10	43.85	21.41	48.83	16	1996	19	84.56	37.43	44.26
8	2004	11	77.55	14.23	18.34	17	1995	20	93.13	17.89	19.20
9	2003	12	71.22	16.71	23.47	18	HA	HA	98.70	57.59	58.35

Table 6. Biomass Mean (ton ha⁻¹) in Natural Forest and Revegetation Area

The highest mean biomass was found in natural forest with 98.70 ± 57.59 ton ha⁻¹. While in revegetation area, the highest biomass mean value was 93.13 ± 17.89 ton ha⁻¹ belongs to 20 years old stands; while the lowest biomass mean was 1.97 ± 0.71 ton ha⁻¹ in 1 year old stands. The older the stand, the higher biomass value is found. Due to the variation of the revegetation success, the biomass value obtained in this research did not perfectly depend on the age of forest stands.

The research found that biomass production positively correlated with the proportion of trees having tree $dbh \ge 20$ cm with r of 0.81, on contrary, biomass has negative correlation with the proportion of plants having dbh < 20 cm with r= -0.81. The research suggested that the higher biomass tends to be determined by trees having $dbh \ge 20$ cm (Figure 4). This is in line with the research done by Basuki *et al.* 2009, suggesting that biomass content in mixed dipterocarps forest has strong correlation (r = 0.89) with dbh. In addition, the factor of tree density which represented by the number of trees (≥ 20 cm) per area unit also has relatively high correlation with biomass having r of about 0.73. Some researchers also found that there is a relationship between above ground biomass and tree density and dbh [40, 41].

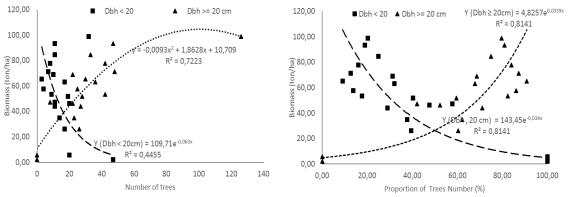


Figure 4. Relation between Biomass and the Proportion of Number of Trees

3.3. Mean Annual Increment (MAI)

The sample data collected expressed that the CV value for each MAI is also very wide, ranging from 4.09% for 20 year old stands to 88.13% for the stands under 10 years old. This means that the 20 year-old stand is relatively stable, so that the stand is relatively homogenous. In contrast, the young plantation is quite unstable, some parts have high MAI while the others have a relatively low MAI. The summary of the MAI value in natural forest cover and revegetation area cover is tabulated in Table 7.

No	Planting	A a a		MAI		No	Planting	Ago		MAI	
INU	year	Age	Mean	Std	CV	INU	year	Age	Mean	Std	CV
1	2014	1	0.08	0.02	21.44	10	2002	13	3.02	2.66	88.13
2	2013	2	0.11	0.06	55.25	11	2001	14	2.34	0.36	15.40
3	2010	5	4.70	1.21	25.83	12	2000	15	1.28	0.56	43.31
4	2009	6	1.89	1.52	80.20	13	1999	16	2.15	1.13	52.62
5	2007	8	1.11	0.48	43.49	14	1998	17	2.13	0.77	36.30
6	2006	9	3.07	2.36	76.96	15	1997	18	2.70	0.84	31.26
7	2005	10	2.31	1.85	80.10	16	1996	19	2.14	0.57	26.45
8	2004	11	3.99	1.23	30.91	17	1995	20	2.39	0.10	4.09
9	2003	12	4.56	1.28	27.98	18	HA	HA	4.60	0.26	5.75
9	2003	12	4.56	1.28	27.98	18	HA	HA	4.60	0.26	

Table 7. MAI (m³ha⁻¹t⁻¹) in Natural Forest and Revegetation Area

Table 7 shows that the highest MAI volume was found in natural forest with mean and standard deviation of $4.60 \pm 0.02 \text{ m}^3\text{ha}^{-1}\text{t}^{-1}$. In revegetation area, the highest MAI volume was found in planting year 2010 or 5 year old stands with mean and standard deviation of $4.70 \pm 1.21 \text{ m}^3\text{ha}^{-1}\text{t}^{-1}$. The lowest MAI of volume was found in the young planting year of 2014 (1 year old stands) and 2013 (2 years old stands), respectively $0.08 \pm 0.02 \text{ m}^3\text{ha}^{-1}\text{t}^{-1}$ and $0.11 \pm 0.06 \text{ m}^3\text{ha}^{-1}\text{t}^{-1}$. The high MAI value is influenced by the plant species. The dominant species found were fast growing species such as white albizia (*Paraserianthes falcataria*) and amboyna wood (*Pterecarpus indicus*).

Volume MAI of a stand also depends on stand density, vegetation species and soil fertility. Volume increment of a tree can was derived from the growth rate of the *dbh*. Each species has different diameter growth rate. For all species, high growth rate takes places in the early age. The older the plant, the slower the rate, until it finally stops [26, 27].

3.4. Classification and Determination of the Estimating Indicator of Forest Reclamation Success

Parameter value of each indicator for forest reclamation success (basal area, biomass, and MAI) was classified into five classes and three classes. The parameter classification was related to the variables of growth quality using discriminant analysis mentioned previously. The result of discriminant analysis shows that there are 17 sets of variable combination in each classification of forest reclamation success estimating indicator (basal area, biomass and increment). The order of variable combination for each indicator is different both in five classes

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and three classes. Furthermore, the significance value and accuracy of variable combination obtained in each indicator classification was summarized in Table 8, 9, and 10.

		Basal area	a 5 classes				Basal area	a 3 classes	
No	Variable (IN)	Number of variables	Sig.	Accuracy	No	variable (IN)	Number of variables	Sig.	Accuracy
1	X20	1V	< 0.0001	38.78	1	X20	1V	< 0.0001	57.14
2	X14	2V	0.00	51.02	2	X16	2V	0.01	57.14
3	X16	3V	0.02	63.27	3	X14	3V	0.01	67.35
4	X5	4V	0.15	73.47	4	X13	4V	0.11	71.43
5	X13	5V	0.11	75.51	5	X12	5V	0.21	75.51
6	X18	6V	0.35	71.43	6	X3	6V	0.32	81.63
7	X2	7V	0.24	71.43	7	X5	7V	0.41	79.59
8	X19	8V	0.31	71.43	8	X2	8V	0.45	79.59
9	X3	9V	0.34	71.43	9	X7	9V	0.58	79.59
10	X7	10V	0.39	67.35	10	X19	10V	0.61	77.55
11	X12	11V	0.50	71.43	11	X11	11V	0.53	79.59
12	X15	12V	0.71	71.43	12	X21	12V	0.57	81.63
13	X11	13V	0.76	71.43	13	X9	13V	0.81	79.59
14	X21	14V	0.85	77.55	14	X10	14V	0.81	83.67
15	X1	15V	0.91	75.51	15	X18	15V	0.86	81.63
16	X9	16V	0.95	77.55	16	X1	16V	0.77	83.67
17	X10	17V	0.91	77.55	17	X15	17V	0.96	83.67

 Table 8. The Accuracy Value of Estimating Indicator of Forest Reclamation Success Using

 Basal Area in Five Classes and Three Classes

Table 9. Accuracy Value of the Estimating Indicator of Forest Reclamation Success Using Biomass in Five Classes and Three Classes Classification

		Biomass	5 classes			Biomass 3 classes				
No	variable (IN)	Number of variables	Sig.	Accuracy	No	variable (IN)	Number of variables	Sig.	Accuracy	
1	X20	1V	< 0.0001	46.94	1	X20	1V	0.00	61.22	
2	X14	2V	0.10	59.18	2	X14	2V	0.05	69.39	
3	X11	3V	0.30	55.10	3	X13	3V	0.22	71.43	
4	X2	4V	0.24	59.18	4	X12	4V	0.18	67.35	
5	X1	5V	0.42	61.22	5	X5	5V	0.26	71.43	
6	X13	6V	0.21	65.31	6	X9	6V	0.25	77.55	
7	X10	7V	0.39	67.35	7	X19	7V	0.33	73.47	
8	X16	8V	0.51	69.39	8	X11	8V	0.34	71.43	
9	X18	9V	0.55	69.39	9	X2	9V	0.42	71.43	
10	X12	10V	0.63	69.39	10	X21	10V	0.52	73.47	
11	X5	11V	0.67	71.43	11	X7	11V	0.63	73.47	
12	X9	12V	0.35	75.51	12	X16	12V	0.59	75.51	
13	X21	13V	0.73	73.47	13	X1	13V	0.72	75.51	
14	X19	14V	0.74	75.51	14	X10	14V	0.93	75.51	
15	X7	15V	0.84	77.55	15	X18	15V	0.91	79.59	
16	X15	16V	0.99	77.55	16	Х3	16V	0.97	79.59	
17	X3	17V	0.99	79.59	17	X15	17V	0.99	79.59	

Note: Variables (V), bulk density (X1), sand (X2), clay (X3), Ca (X5), K (X7), CEC (X9), organic carbon (X10), N (X11), P (X12), litter thickness (X13), dry litter mass (X14), soil erosion (X15), biodiversity index (X16), stand density (X18), canopy stratification (X19), the percentage of canopy cover (X20, recolonization (X21)

Table 8 shows that the accuracy value of each variable combination is generally varied, both for five classes and three classes of basal area. The highest accuracy using basal area for five classes and three classes are 77.6% and 83.7% respectively. Variable combination with five classes of basal area is provided using the combination of 14 variables. Those fourteen variables are sand fraction, clay fraction, calcium, potassium, sodium, phosphorus, litter thickness, dry litter mass, erosion, biodiversity index, tree density, canopy stratification, crown cover percentage, and colonization. While the highest accuracy of variable combination for three classes of basal area classification was also provided by 14 variable combinations. The research also noted that one variable that differentiate between three and five classes was erosion in five classes and cation exchange capacity in three classes classification.

In addition, there are only several variables which could well differentiate the classification of basal area (five classes and three classes). The calculation was based on the

significance value ($Sig \le 5\%$). The result shows that significant variables in five classes of basal area has similarity with significant variables in three classes. There are only three significant variables, namely dry litter mass, diversity index, and crown cover percentage.

The highest accuracy value (79.6%) was also obtained in biomass classification with five classes and three classes (Table 9). For five classes, the highest accuracy was obtained from the combination of all variables (17 variables), while the highest accuracy value in three classes was obtained only from the combination of 15 variables out of 17. The two variables excluded were clay fraction and erosion.

		MAI 5 c	lasses				MAI 3 c	lasses	
No	variable (IN)	Number of variables	Sig.	Accuracy	No	variable (IN)	Number of variables	Sig.	Accuracy
1	X20	1V	< 0.0001	49.98	1	X20	1V	< 0.0001	59.18
2	X9	2V	0.07	51.02	2	X9	2V	0.01	67.35
3	X2	3V	0.05	59.18	3	X2	3V	0.01	75.51
4	X21	4V	0.12	61.22	4	X10	4V	0.14	73.47
5	X14	5V	0.13	63.27	5	X12	5V	0.23	75.51
6	X15	6V	0.30	63.27	6	X13	6V	0.17	77.55
7	X10	7V	0.20	67.35	7	X14	7V	0.25	79.59
8	X19	8V	0.44	69.39	8	X15	8V	0.08	79.59
9	X11	9V	0.47	75.51	9	X5	9V	0.31	81.63
10	X13	10V	0.48	71.43	10	X7	10V	0.35	81.63
11	X5	11V	0.51	75.51	11	X19	11V	0.62	85.71
12	X3	12V	0.59	77.55	12	X16	12V	0.56	83.67
13	X16	13V	0.73	77.55	13	X3	13V	0.58	81.63
14	X12	14V	0.73	75.51	14	X21	14V	0.62	83.67
15	X7	15V	0.82	77.55	15	X18	15V	0.67	83.67
16	X18	16V	0.80	77.55	16	X11	16V	0.87	85.71
17	X1	17V	0.95	79.59	17	X1	17V	0.97	85.71

Table 10. Accuracy Value of the Estimating Indicator of Forest Reclamation Success Using MAI in Five Classes and Three Classes Classification

Based on the significance value, there were several variables that could well differentiate between five and three classes of biomass. There was one significant variable in five classes, i.e., crown coverage (Sig = < 0.0001). Whereas in three classes there were two significant variables (Sig = 0.05), namely dry litter mass and crown coverage.

For the increment (MAI), the highest accuracy in five classes classification was 79.6%, obtained from the combination of all variables (17 variables), while for three classes the highest accuracy value was 85.7% and obtained from the combination of 11 variables (Table 10). Those variables were sand fraction, calcium, potassium, cation exchange capacity, C organic, phosphorus, litter thickness, dry litter mass, soil erosion, canopy stratification, and crown cover percentage. It is also shown that several variables could well differentiate between five and three classes of MAI. The statistical *Sig* (0.05) shows that there were three significant variables in five classes, which were sand fraction, cation exchange capacity, and crown cover percentage. Significance result obtained for three classes also showed three significant variables with *Sig* value of 0.01. The three variables for three classes are the same with those in five classes.

From all the above, the study shows a very promising findings, where the overall accuracy value for predicting the forest reclamation success with five classes and three classes was higher than 75%. It is noticed that the most consistent and accurate parameter applied as estimating indicator of forest reclamation success is increment (MAI). The accuracy assessment obtained from using increment (MAI) parameter is quite high, i.e., about 85.7% for three classes. It is quite logic that the rate of MAI is depended mainly on the site quality. A proper land preparation which include recontouring and restoring top soil may cause better site quality, improving physical and chemical properties of soil.

This research then suggested that the difference of forest reclamation success rate is highly influenced by growth media quality of which variables are soil physical and chemical characteristics, litter, and crown cover. The quality of growth media is the level of soil fertility which will influence the tree growth and productivity. The trees that grow on fertile soil will give faster MAI compare to those that grow in less fertile soil [19]. The soil quality, that is influenced by the soil physical condition and nutrient content is an important factor that influences soil fertility [42].

4. Conclusion

The study concludes that the success of reclamation are varied widely, indicated by a wide range of the CV in various age class, i.e., CV of 6.9% – 85.1% for basal area, CV of 0.6%-82.5% for biomass and CV of 4.1% –88.1% for MAI. The most consistent and accurate indicator for assessing the forest reclamation success in ex coal-mining area is increment (MAI). The MAI gave consistently higher accuracy assessment of 85.7% for three classes, higher than basal area (83.7%) and biomass (85.7%). The main factors that could well differentiate the success of reclamation indicators for increment (MAI) is sand fraction, cation exchange capacity, and crown cover percentage (for five classes and three classes). This study suggessted that to reduce the CV of reclamation success then the criteria of reclammation should be grouped into several age classes. The lesser the CV the more accurate assessment will obtained. The success of reclamation were depend on the each age class after plantation.

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