

BIOMASS ESTIMATION MODEL FOR MANGROVE FOREST USING MEDIUM-RESOLUTION IMAGERIES IN BSN CO LTD CONCESSION AREA, WEST KALIMANTAN

Sendi Yusandi¹, I Nengah Surati Jaya^{2*}, and Fairus Mulia³

¹Directorate of Biodiversity Conservation, Ministry of Environment and Forestry, Manggala Wanabhakti blok 7 lt 7
Jl. Gatot Subroto, Jakarta Pusat, Indonesia

²Remote Sensing and GIS Laboratory, Faculty of Forestry, Bogor Agricultural University Bogor, Indonesia

³PT Kandelial Alam. Jalan Supadio Pontianak

*e-mail: ins-jaya@apps.ipb.ac.id

Received: 13 June 2017; Revised: 15 May 2018; Approved: 22 June 2018

Abstract. Mangrove forest is one of the forest ecosystem types that have the highest carbon stock in the tropics. Mangrove forests have a good assimilation capability with their environmental elements as well as on carbon sequestration. However, the availability of data and information on carbon storage, especially on tree biomass content of mangrove is still limited. Conventionally, an accurate estimation of biomass could be obtained from terrestrial measurements, but those methods are very costly and time-consuming. This study offered an alternative solution to overcome these limitations by using remote sensing technology, i.e. by using Landsat 8 and SPOT 5. The objective of this study is to formulate the biomass estimation model using medium resolution satellite imagery, as well as to develop a biomass distribution map based on the selected model. The study found that the NDVI of Landsat 8 and SPOT 5 have considerably high correlation coefficients with the standing biomass with a value of higher than 0.7071. On the basis of the values of aggregation deviation, mean deviation, bias, RMSE, x^2 , R^2 , and s , the best model for estimating the mangrove stand biomass for Landsat 8 is $B=0.00023404 e^{(20 NDVI)}$ with the R^2 value of 77.1% and $B=0.36+25.5 NDVI^2$ with the R^2 value of 49.9% for SPOT 5. In general, the concession area of Bina Silva Nusa (BSN) Group (PT Kandelial Alam and PT Bina Ovivipari Semesta) have the potential of biomass ranging from 45 to 100 ton per ha.

Keywords: *mangrove forests, biomass, model, score, NDVI*

1 INTRODUCTION

The increase of carbon dioxide (CO₂) concentration in the atmosphere has been a major factor that affects the global warming. Forests are considered to be one of the important components of the mechanism of carbon emission that may reduce GHG when it managed in a sustainable manner. Forest biomass is also often used as one of the basic considerations in sustainable forest management activities, especially those associated with carbon trading. This is due to the ability of the forest to sequester

the CO₂ in the biomass. The volume of biomass content trapped in the forest depends on stand conditions such as natural regeneration, disturbance conditions and forest allocation (IPCC 2001). Mangrove forests are one of the forests which possibly have the highest carbon storage in the tropics compared to the other forest types in the world (Donato *et al.* 2012). Although mangroves are known to have good assimilation capabilities with environmental components and have high C absorption rates, data and information on carbon

storage for some components, especially for tree biomass are very limited (Komiyama *et al.* 2008), so it is important to know biomass information in a mangrove forest area for sustainable forest management.

Traditionally, the biomass content of forest could be assessed through a direct field or terrestrial survey approaches. However, this method mainly laborious, time-consuming and costly. According to Lu (2006), field or terrestrial measurements are the most accurate way to collect biomass data but require labor-intensive time, difficult to apply in the very wide remotely located areas. Therefore, the use of other approaches using remote sensing technology which is continuously increasing may offer a good alternative. The remote sensing technology provides the information timely, cheaper cost and comprehensive data.

In addition, the use of remote sensing technology in collecting information regarding the potential of mangrove biomass as a CO₂ absorber could be carried out effectively and efficiently.

At a national and global level, research on the uses of remotely sensed data had been widely applied. Several types of research could be found in Qirom *et al.* (2012) and Yuwono (2012) who work with radar data for estimating the biomass contents. While Tank and Chappell (2008) worked with optical data, particularly the use of the Infrared band. However, the researches on biomass estimation in a tropical mangrove forest using satellite imagery is still limited. Cahyaningrum and Hartoko (2014) conducted an estimate of mangrove

biomass in Karimunjawa National Park by predicting biomass in the image through the digital value contained in each band. However, Jaya (2010) estimation method using the value of each band is not effective when it applied in a multi-temporal case, where it needs a spectral improvement or transformation techniques such as vegetation index.

The vegetation indices transformation technique is a simple and very practical technique to detect specific vegetation conditions, as well as to recognize the vegetation density. In this study, the estimation of biomass contents of mangrove forest was performed, then expected to minimize errors and improve the accuracy assessment all at once. The main objective of the study is to develop a mathematical model for estimating the biomass content of mangrove forest using medium resolution satellite imageries. This research is expected to provide a tool for estimating above ground in practical, efficient and timely.

2 MATERIALS AND METHODOLOGY

2.1 Study Sites

The study site was located in the concession area of the PT Kandelia Alam and PT Bina Ovivipari Semesta, Kubu Raya Regency, West Kalimantan (Figure 2-1). Both study areas have the same ecosystem typed and footprint characteristics such as climate type, rainfall, air temperature, air humidity and soil type.

Data pre-processing and processing were carried out at the Remote Sensing Laboratory and GIS, Forest Management Department, Faculty of Forestry, Bogor Agricultural University.

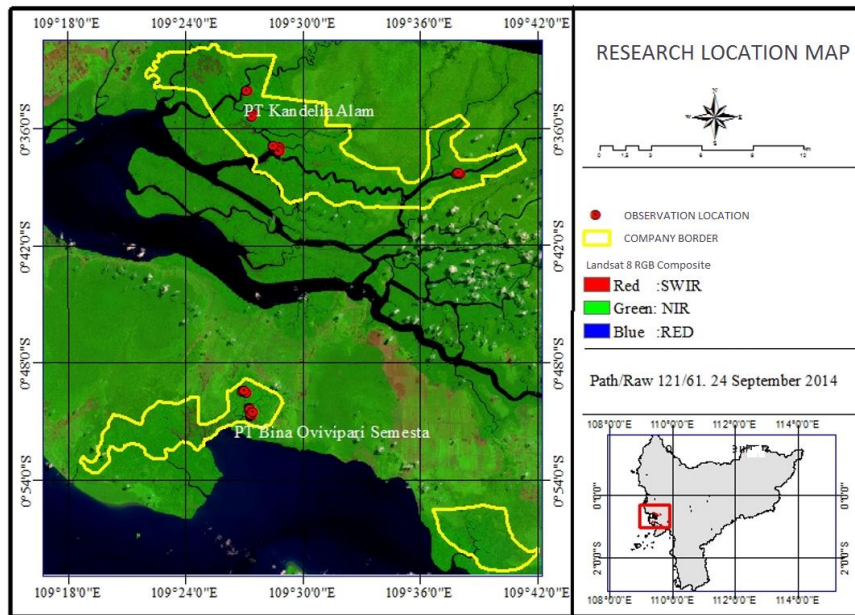


Figure 2-1: Map of the study site

2.2 Data, Software, and Hardware

For ground data collection, the tools used are compass, phi band, clinometer (suunto), rope, camera, scales, oven, GPS, and tally sheet; while for data processing the research applied SPSS V.20, ArcGIS 10.1, and ERDAS Imagine Software version 9.1.

The data used consisted of two types, i.e. primary data and secondary data. Primary data used were: wet and dry weight (BB) of low vegetation, seedling and litter; volume of life and dead standing and collapsed trees; number tree for each sapling, pole and tree; Landsat imageries 8, 8 OLI path/raw 121/61; SPOT 5 imageries, path/raw 287/351 dan 288/351; species name and density of trees; Vegetation type & field plot coordinate. Other supporting data were species-specific density, biomass expansion factor (BEF), forest inventory data of PT Kandelia Alam and PT Bina Ovivipari Semesta, and the Administrative boundary of Kubu Raya Regency.

2.3 Ground Data Collection

Ground data collection was done by developing a purposive sampling method,

which was laid out representing the stand condition. The considered stand condition are logged-over of stands of 1989, 1998, 2002 in PT Kandelia Alam, and stands of 2006, 2008, 2009 in PT Bina Ovivipari Semesta.

For analyzing the Landsat 8 images, 52 uniformly-distributed sampled plots were selected, where 10 sample plots belong to logged over forest (LOF) of 1989 and 1998, 32 plots belong to LOF of 2002, 2006, 2008, and 2009 (eight sample plots for each condition), and 10 sample plots represent the LOF of 1989 and 1998. For analyzing SPOT 5 images, 40 sample plots were used that to represent the LOF of 1989, 1998, 2002, 2006 and 2009.

The above ground biomass of the trees that consisted of standing live trees and necromass (standing and felled down dead trees) were measured within each rectangular sample plot of 25 m by 25 m-width sizes. For forest floor vegetation (ground vegetation), necromass and litter, the measurements were done in the 2 m x 2 m sub-plot; while measurement of the biomass of sapling level, the measurement within 5 m x 5 m sub-plot. For biomass calculation, the stand

variables measured were tree diameter, tree height, root height, species name, the volume of necromass, the weight of litter and sample plot coordinate.

2.4 Data Processing

Data processing covers biomass estimation, spatial analysis, data normality, correlation (collinearity) test, and heteroscedasticity, analysis of variance for each regression coefficient test, validation test, model selection and biomass map development.

1. Mangrove forest biomass estimation

The biomass contents might be estimated either using the allometric equation, BEF coefficient of the stand, or by measuring the wet- and dry-weight. The forest floor biomass (ground vegetation, litter, and necromass) was calculated on the measurement done in plot 2 m × 2 meter sample plot. The total dry weight (DW) was calculated using the following equation in Hairiah and Subekti (2007), then the biomass of the dead trees was calculated by using the formula of Forestry Research Agency (2012), the standing dead tree was calculated using the formula from Hilmi (2003). The biomass of standing dead trees was calculated using:

Root biomass:

$$B = -0.7 - 11.9 \text{ Dbh} + 0.969 \text{ H}^2 \quad (2-1)$$

Biomass stem:

$$B = 80.7 + 0.0333 \text{ Dbh}^2 \times \text{H} \quad (2-2)$$

Where B = biomass (kg), Dbh = diameter at breast height (cm); and H = height of dead tree (m).

The estimation of tree-level biomass was performed using the following allometric altimetry models:

Bruguiera gymnorhiza:

$$\text{Log B} = -0.552 + 2.244 \text{ log Dbh} \quad (2-3)$$

Rhizophora apiculata:

$$B = 0.043 \times \text{Dbh}^{2.63} \quad (2-4)$$

Xylocarpus granatum:

$$B = 0.1832 \times \text{Dbh}^{2.21} \quad (2-5)$$

The biomass volume of the sapling stage was computed using the allometric of Pambudi (2011), as follows:

$$B = 0.027542 \times \text{Dbh}^{3.22} \quad (2-6)$$

2. Vegetation index

The vegetation index developed in this study used the Normalized Vegetation Index (NDVI) on the basis of red (RED) of the visible light and near-infrared (NIR) which is reflected by vegetation. The NDVI would provide values ranges from -1 to 1. The low (negative) NDVI values identify areas of water bodies, rocks, sand, and snow. High NDVI values (positive) identify areas of vegetation in the form of pastures, shrubs, and forests, whereas the NDVI value near 0 generally identifies vacant land (Saputra 2007). This NDVI value can be calculated using the equation:

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad (2-7)$$

3. Assumption Test.

The assumption test includes Normality test, linearity test. The normality test was done using the Kolmogorov Smirnov test

Normality test:

To assess the data normality, the data used was tested using Kolmogorov Smirnov. The test was intended to know whether the data are bell-shaped distribution (normal distribution).

a. Linearity Test

The execution of linearity test is intended to evaluate whether two variables have a linear relationship or not significantly. This states that any changes that occur in one variable will be followed by changes in a parallel manner to the other variables. Test linearity using the formula as applied by Hadi (2004):

b. Heteroscedasticity test

Heteroscedasticity test was conducted to find out whether in a regression model there was a variance inequality of the residual of another observation. To test for the presence of symptoms of heteroscedasticity, then used Glejser test on SPSS.

4. Correlation test

The correlation coefficient (r) is a variable that indicates the closeness of the relationship between two or more variables to its dependent variable (Walpole 1995). In this case, the aims are to determine the relationship between variables or variables used in estimating biomass potential by calculating the correlation coefficient (r).

Correlation test

To perform the correlation significance test, the authors used the z -transformation proposed by Fisher. If $z_{hit} \leq z_{tab}$, then the correlation is not close, while

If $z_{hit} > z_{tab}$, then the correlation between variables is close.

5. Models for estimation of mangrove forest biomass content

The analysis of the relationship between biomass content and NDVI derived from Landsat 8 and SPOT 5 was conducted by developing the regression models with linear, quadratic, power and exponential forms.

6. Evaluation of the regression coefficient

To evaluate the significance of regression coefficient generated in modelling, it is necessary to assess its significance on the basis of the statistical rule. The regression coefficient calculation was done by performing the analysis of variance.

7. Validation of the model

To evaluate the reliability of all models that have been statistically evaluated before, then model validation is done by comparing the estimation result using the developed model and the actual ground observation. In this study, the model validation is done using χ^2 (chi-square), e (Bias), SA (Aggregate Simple), MD (Average Simple) and RMSE (Root Mean Square Error) measures.

8. The Best Model Selection

To find out the best model, it is necessary to rank all statistically accepted models (F -call and R^2 values). The selected model should also pass the Chi-sq test ($(\chi^2_{cal} < \chi^2_{table})$). The rank is expressed by scores of each validation test by considering all the validation values: SA, MD, RMSE, and bias. The rank of the model is derived by summing up all score of each validation valued. The score would be ranging between 1 and 4. The highest score is then selected as the best model.

9. Biomass distribution map

The biomass distribution map is then developed using the selected models the best. The map of biomass distribution is classified into three classes. The procedure for calculating the biomass content could be found in Sutaryo (2009).

3 RESULTS AND DISCUSSION

3.1 NDVI Verification

A total of 52 sample plots in Landsat 8 image and 40 sample plots in SPOT 5 image were analyzed for land cover and NDVI values. It is shown that the observed sample plots have various different NDVI values. The range of NDVI values derived from Landsat 8 is between 0.3 to 0.58 while for Spot 5 is between 0.26 and 0.6. The NDVI values that less than 0.3 for Landsat and less than 0.26 for SPOT 5 mostly belong to the class of bare land, built up and water bodies.

3.2 Correlation between NDVI and Estimated Forest Biomass

The normality evaluation based on Kolmogorov Smirnov test found that both the data for Landsat 8 and SPOT 5 images have P-values of 0.323 and 0.573, larger than 0.05. These mean that the data are normally distributed.

For the test of linearity using F-test, it is also found that the significance value of F (sig) for Landsat 8 image and for SPOT 5 are 0.0004 and 0.039 respectively, smaller than 0.05. These mean that the NDVI values derived from both images have a relationship with the biomass.

Heteroscedasticity was done using Glejser test. The test results show that the significance values for Landsat 8 are 0.066 and for Spot 5 is 0.185. These mean that there is no indication of heteroscedasticity expressing they have a similarity of variance between the residual and observation.

The data analysis shows that there are good correlation coefficients between the biomass contents in the field and the NDVI values derived from Landsat 8 and SPOT 5 images. The values are 0.759 for Landsat 8 and 0.710 for SPOT 5. The correlations are depicted in Figures 3-1 and 3-2.

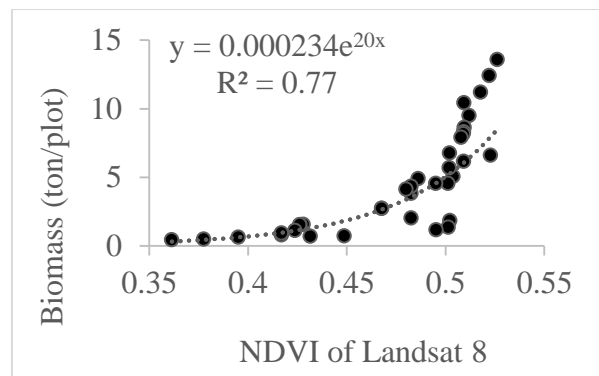


Figure 3-1: Correlation between NDVI of Landsat 8 and mangrove biomass

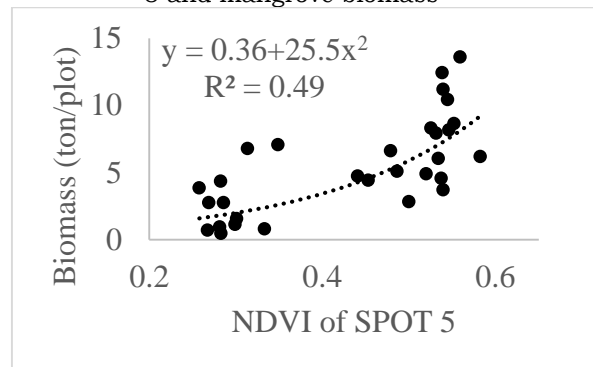


Figure 3-2: Correlation between NDVI of SPOT 5 and mangrove biomass

The scatter diagram and trend lines between the NDVI values of both the images are expressing a positive relationship, i.e., exponential for Landsat 8 and quadratic for SPOT 5. In general, the biomass content will increase when the NDVI increases. To evaluate whether those correlations are significant (can be generalized) or not, the Z-test was performed. It was found the Z-cal for Landsat 8 image is 6,814 and for SPOT 5 image is 5,945. These express that there is a close correlation between NDVI and biomass content having coefficient correlation higher than 0.7.

3.3 Modeling Mangrove Biomass Estimation

Several regression models for estimating the biomass content are developed, as summarized in Tables 3-1 and 3-2. The model forms include linear, quadratic, exponential and power. The coefficient of determination (R^2) is more

than 50% (see Tables 3-3 and 3-4). This means more than 50% of the variation of biomass could be described by the variation of the NDVIs.

Tabel 3-1: Models for mangrove biomass content estimation using Landsat 8.

No	Model equations	Symbol
1	$B = - 25.8 + 64.1 \text{ NDVI}$	M1
2	$B = - 11.8 + 72.1 \text{ NDVI}^2$	M2
3	$B = 2416.317 \text{ NDVI}^{8.91}$	M3
4	$B = 0.000234044 e^{(20 \text{ NDVI})}$	M4

Tabel 3-2: Models for biomass content estimation using SPOT 5

No	Model equations	Symbol
1	$B = - 3.57 + 20.9 \text{ NDVI}$	M5
2	$B = 0.36 + 25.5 \text{ NDVI}^2$	M6
3	$B = 26.843 \text{ NDVI}^{2.15}$	M7
4	$B = 0.3926 e^{(5.41 \text{ NDVI})}$	M8

Evaluation of the regression coefficient

The results of variance analysis of all the constructed models show that all models (M1 ~ M4) have F-call larger than F-tables. Since all models are simple regression model with only one variable, then this test indicates that all models could be accepted statistically. As shown in Table 3-3 and 3-4, standard deviations of each model are come from the models with power and exponential forms, either derived from Landsat 8 or SPOT 5 images.

Regression test results as depicted in Table 3-3 and Table 3-4 explain that the four models constructed using NDVI Landsat 8 and SPOT 5 images could be used for estimating the biomass storage. This is shown by their F-cal values on all types of equation models larger than the F-tab. In other words, the X (NDVI or NDVI 2) variables both in Landsat 8 and SPOT 5 may estimate the biomass value. Tables 3-3 and 3-4 also explain that all models have a wide variation of standard deviation value (s). The higher standard deviation value (s) indicates the higher deviation between the observed value and actual value.

The results of the analysis also show that all the equation models obtained have a varying coefficient of determination (R²). For Landsat 8, the coefficients of determination (R²) are ranging between 57.7% and 77%, while for SPOT 5 the coefficients of determination (R²) are ranging from 49.0% to 51.7%. The coefficient of determination (R²) explains that the higher the coefficient of determination the higher the ability of the regression model to explain the variation of the dependent variables. This means that if R² is 77%, then NDVI can explain 77% of biomass, while the remaining factor is explained by other factors or other variables.

Table 3-3: The analysis of regression coefficient of Landsat 8

No	Symbol	Model	R ²	R ² adj	s	F-cal	F-tab
1	M1	Linear	57.7	56.5	2.4	47.6	5.4
2	M2	Quadratic	60.3	59.1	2.3	53.0	5.4
3	M3	Power	75.7	75.2	0.5	108.8	5.4
4	M4	Exponential	77.1	76.4	0.4	117.4	5.4

Table 3-4: The analysis of regression coefficient of SPOT 5

No	Symbol	Model	R ²	R ² adj	s	F-cal	F-tab
1	M5	Linear	49.0	47.2	2.5	26.9	5.6
2	M6	Quadratic	49.9	48.1	2.5	27.8	5.6
3	M7	Power	51.4	49.7	0.6	29.6	5.6
4	M8	Exponential	51.7	50.0	0.6	29.9	5.6

*remarks: R² = coefficient of determination, R²-adj = adjusted of the coefficient of determination: s = standard deviation, F-cal = value of F-calculation F-tab = value of F-table at the 95% confidence level (α = 0.05).

Model Validation

Based on the model validation results in Tables 3-5 and 3-6, all biomass prediction models generated from Landsat 8 and SPOT 5 provide SA values ranging from -1 to +1. The equation model with Landsat 8 (Table 3-1), has an SA value ranging from -0.22 to 0.03, while for SPOT 5 ranges from -0.02 to -0.19. Based on SA values, all models are acceptable.

In the validation test using the Mean Deviation measure (MD), it is shown that the MD for models of Landsat 8 having MD values less than 10% is obtained only from linear and quadratic model forms. However, for SPOT 5, all models (M1~M4) have MD values less than 10%. These mean that SPOT 5 give better predictor than Landsat 8.

The RMSE (Root Mean Square Error) test which is a combination of bias and accuracy, the models developed using Landsat 8 have RMSE values ranging from 18.90 to 27.50, where the lowest RMSE is provided by the

exponential model. For models developed using SPOT 5 imagery, the RMSE values are ranging from 23.12 to 29.01, where the lowest RMSE value is also generated from the exponential model. In other words, this noted that the exponential model gives a better accuracy value than other model forms.

In this study, the resulting bias values of the Landsat 8 image-based model are ranging from -20.30 to 7.80. The smallest bias value is obtained from the equation in the form of quadratic equation, i.e., is 6.14. In the SPOT 5 image-based equation 5 the resulting bias values range from 0.01 to -19.13, where the lowest bias is provided by a linear equation having a bias of only 0.01.

As summarized in Table 3-5 and Table 3-6, all models developed on Landsat 8 and SPOT 5 have χ^2 -cal < χ^2 -tab in 95% confidence intervals. This means that there is a similarity in the potential value of biomass obtained using actual models and potentials in the field.

Table 3-5: Summary of validation test using SA, MD, bias, RMSE, and Chi-sq based on Landsat 8 data

Sym bol	Model	Validation measures					
		SA	MD	Bias	RMSE	χ^2 - cal	χ^2 - tab
M1	$B = -25.8 + 64.1 \text{ NDVI}$	0.03	7.80	7.80	27.50	5.03	23.68
M2	$B = -11.8 + 72.1 \text{ NDVI}^2$	0.02	6.14	6.14	23.87	4.02	23.68
M3	$B = 2416.317 \text{ NDVI}^{8.91}$	-0.25	21.42	-21.42	19.77	4.31	23.68
M4	$B = 0.0002340e^{(20 \text{ NDVI})}$	-0.22	20.30	-20.30	18.90	3.67	23.68

Table 3-6: Summary of validation test using SA, MD, bias, RMSE, and Chi-sq based on SPOT 5 data

Sym bol	Model	Validation measures					
		SA	MD	Bias	RMSE	χ^2 - cal	χ^2 - tab
M5	$B = -3.57 + 20.9 \text{ NDVI}$	-0.02	0.01	0.01	29.01	4.13	16.91
M6	$B = 0.36 + 25.5 \text{ NDVI}^2$	-0.04	1.46	-1.46	26.25	3.56	16.91
M7	$B = 26.843 \text{ NDVI}^{2.15}$	-0.17	3.88	-17.07	23.96	3.85	16.91
M8	$B = 0.3926 e^{(5.41 \text{ NDVI})}$	-0.19	6.28	-19.13	23.12	3.65	16.91

3.4 Best Model Selection

Model selection was done by considering SA, MD, Bias, RMSE, x^2 , R^2 , and s values. In this study, the Landsat 8 and SPOT 5-based models that produced the largest R^2 are exponential models, which have R^2 of 77% for the Landsat-based model and 51.7% for the SPOT-based image model. The Landsat 8 image-based model has a value of s of 0.48 whereas the SPOT 5 image-based model has s value of 0.63. All model passes the F-test which means the X variable (NDVI) could estimate the Y variable (biomass) precisely. In addition, this exponential model has a high coincidence between its estimation results and actual data in the field. The x^2 test results show that there is no significant difference. The exponential models also provide the lowest RMSE values, i.e. 18.906 for Landsat 8 and 23.120 for SPOT 5 image-based models.

However, for the SA, MD, and bias tests, the best result is in the quadratic

model for Landsat 8 and linear models for SPOT 5 images. This is because the quadratic model of Landsat 8 and the linear model of SPOT 5 have the lowest SA, MD, and bias among the other equations. Therefore, in the selection of the best model, then we calculated the score of each model based on all the tests considered to determine the best model in each image. Score calculations for each model are presented in Tables 3-7 and 3-8.

Based on the scores generated from each test in Tables 3-7 and 3-8, it can be concluded that the best Landsat 8 image-based biomass prediction models potential in the study area is the exponential model of $B = 0.000234044e^{(NDVI * 20)}$. While the SPOT 5 image-based model is a quadratic model of $B = 0.36 + 25.5 NDVI^2$. Both models have the highest scores compared to other models, i.e., 19.89 for Landsat 8 and 20.22 for SPOT 5 based models.

Table 3-7: The rank of Landsat 8-based model.

Symbol	Score								
	x^2 cal	SA	MD	Bias	RMSE	s	R^2	total	ranking
M1	1.00	3.78	3.67	3.67	1.00	1.00	1.00	15.12	4
M2	3.21	4.00	4.00	4.00	2.15	1.11	1.25	19.72	2
M3	2.57	1.00	1.00	1.00	3.69	3.97	3.79	17.02	3
M4	4.00	1.25	1.39	1.25	4.00	4.00	4.00	19.89	1

Table 3-8: The rank of SPOT 5-based model.

Symbol	Score								
	x^2 cal	SA	MD	Bias	RMSE	s	R^2	total	ranking
M5	1.00	4.00	4.00	4.00	1.00	1.00	1.00	16.00	4
M6	4.00	3.71	3.31	3.77	2.41	1.03	2.00	20.22	1
M7	2.46	1.31	2.15	1.32	3.57	3.99	3.67	18.47	3
M8	3.54	1.00	1.00	1.00	4.00	4.00	4.00	18.53	2

3.5 Mangrove Biomass Distribution

For visualization purposes, the map of potential biomass distribution in the study area was made based on the selected model, where the biomass

potential class was divided into 3 classes using natural breaks method (Jenks 1997). In this case, the data classes were calculated from all field plots in the designed previously.

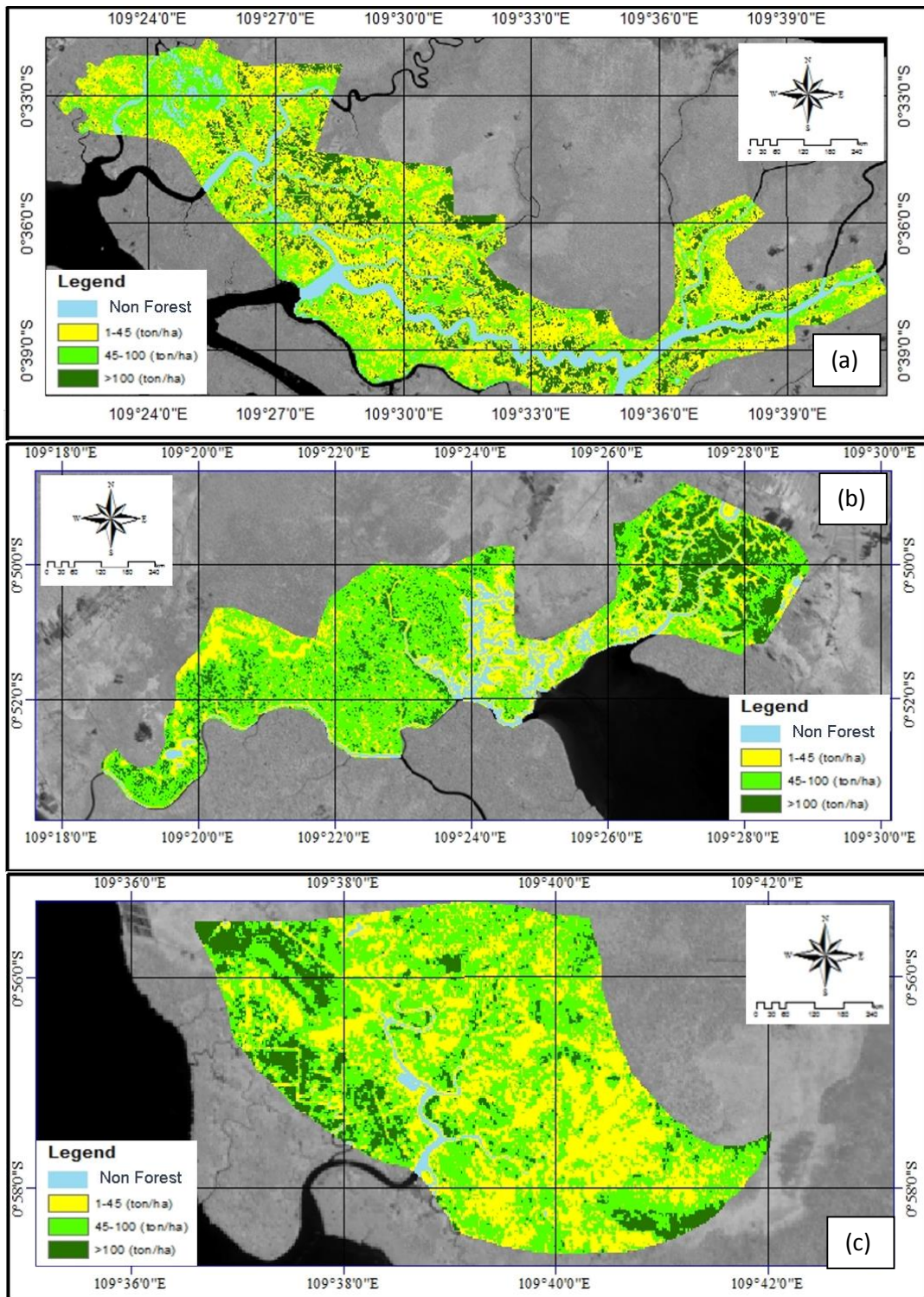


Figure 3-3: (a) Map of biomass distribution, PT Kandelia Alam using Landsat 8; (b) Map of distribution of biomass at PT Bina Ovivipari Semesta, Selat Sekh Block using Landsat 8; (c) Map of distribution of biomass, PT Bina Ovivipari Semesta, Bumbun Strait Block using Landsat 8.

Table 3-9: Biomass stock in PT Kandelia Alam and PT Bina Ovivipari Semesta

Biomass classes (ton/ha)	Kandelia Alam		Bios (Blok Selat Sekh)		Bios (Blok Selat Bumbun)	
	Luas (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Luas (%)
Non forest	1890	9.9	435	7.4	65	1.8
1-45	5659	29.6	1412	24.2	1403	39.0
45-100	8667	45.4	2995	51.4	1701	47.3
>100	2838	14.8	974	16.7	428	11.9

3.5.1 Mangrove Biomass Distribution Based on Landsat 8 Imagery

In composing the map of the biomass distribution using Landsat 8 imagery, we use the natural break method of 3 classes with the class interval of 1-45 ton/ha, 45-100 ton/ha, and > 100 ton/ha. Areas that have biomass below 1 ton/ha are categorized into non-biomass areas since they have non-vegetable land cover or NDVI less than 0.3. Map of biomass potential distribution using Landsat 8 is shown in Figure 3-3.

The results of the map of biomass potential maps as depicted in Table 3-9 show that there is a wide variation of potential biomass in each class of biomass potential. At PT Kandelia Alam, the largest areas belong to the class potential of 45-100 tons/ha, with a percentage of area 45.4%. Similarly, PT Bina Ovivipari Semesta, both at Strait of Sekat Strait and Bumbun Strait Block, the largest percentage area, which is 51.4% in Strait of Sekh Block and 47.3% in Strait of Bumbun Strait has the potential class of 45- 100 ton/ha. In other words, Landsat 8-based biomass estimation yields biomass potential with a dominance range of 45-100 tons/ha.

3.5.2 Mangrove Biomass Distribution Based on SPOT 5 Imagery

Due to the availability of SPOT 5 imagery, the creation of a map of the distribution of biomass in SPOT 5 image

is only done in PT Kandelia Alam. Based on the result of class division using natural break method of 3 classes, the same class hose is made with Landsat 8. Image, that is class 1-45 ton / ha, 45-100 ton/ha, and > 100 ton/ha. The area with biomass of 1 ton/ha is categorized into a biomass area, this is because it has a non-vegetation cover or NDVI less than 0.26 for SPOT 5 image. Map of potential biomass distribution on SPOT 5 can be seen in Figure 3-4.

In tabulation, the potential of biomass using SPOT 5 in PT Kandelia Alam is shown in Table 3-10. The results show that there is a wide variation of potential biomass in each class of biomass potential, similar to the Landsat 8 -based imagery estimates. At PT Kandelia Alam, Potential class of 45-100 tons/ha dominate the areas with a percentage of about 42.8%. This shows that both SPOT 5 and Landsat 8 produce the same dominant area in the class of 45-100 tons/ha.

Tabel 3-10: Biomass stock in PT Kandelia Alam

Biomass classes (ton/ha)	Kandelia Alam	
	Area (ha)	Percentage (%)
Non forest	2698	14.1
1-45	701	3.6
45-100	8155	42.8
>100	7496	39.3

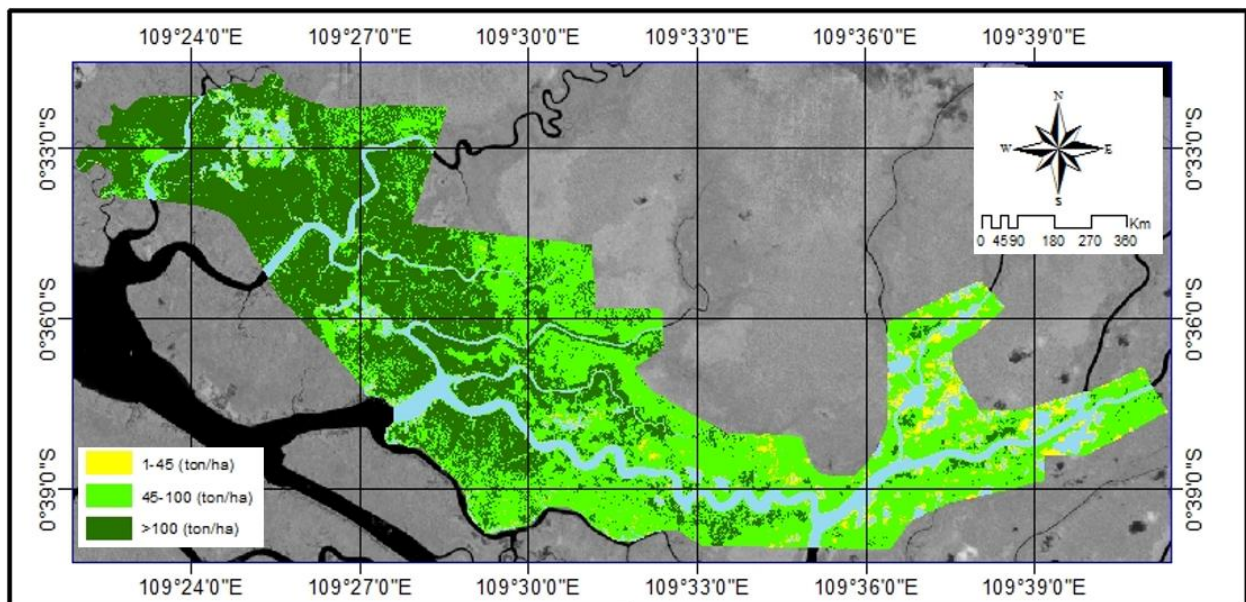


Figure 3-4: Biomass distribution map, PT Kandelia Alam pada SPOT 5.

4 CONCLUSIONS

From the above analysis and discussion on the results, we could conclude that the best Landsat 8 image-based biomass estimation model is the exponential model $B = 0.00023404 e^{(20 \text{ NDVI})}$ with R^2 value of 77.1%, while the best SPOT 5 image-based model is the quadratic model $B = 0.36 + 25.5 \text{ NDVI}^2$ with R^2 of 49.9%. Both models have very small estimation errors. The resulting estimator model using Landsat 8 image and SPOT 5 image can produce biomass distribution map consisting of 3 classes i.e., 1-45 ton/ha, 45-100 ton/ha, and >100 ton/ha. In the study area, the dominant class of biomass potency belongs to the class of 45 - 100 ton/ha.

ACKNOWLEDGMENT

Authors extend sincere thanks to the anonymous reviewer for invaluable comments for improvement of the original manuscripts.

REFERENCES

- Amira S., (2008), Pendugaan biomassa jenis *Rhizophora apiculata* BI, di hutan mangrove Batu Ampar Kabupaten Kubu Raya, Kalimantan Barat. [Skripsi]. Bogor (ID): Departemen Konservasi Sumberdaya Hutan dan Ekowisata, Fakultas Kehutanan Institut Pertanian Bogor.
- Cahyaningrum ST, Hartoko A., (2014), Mangrove Carbon Biomass at Kemujan Island, Karimunjawa Nasional Park Indonesia. *Management of Aquatic Resources Journal* Vol. 3(3): 34-42.
- Donato D., Kauffman JB, Murdiyarso D., *et al.* (2012), Mangrove adalah salah satu hutan terkaya karbon di kawasan tropis (No. CIFOR Infobrief no. 12, p. 12p). Center for International Forestry Research (CIFOR), Bogor, Indonesia.
- Hadi S., (2004), Analisis Regresi. Yogyakarta (ID): Andi Offset.
- Hilmi E., (2003), Model Penduga kandungan karbon pada pohon kelompok jenis *Rhizophora* spp. dan *Bruguiera* spp. dalam tegakan hutan mangrove studi kasus di Indragiri Hilir Riau [Tesis]. Bogor (ID): Program Pascasarjana, Institut Pertanian Bogor.
- [IPCC] Intergovernmental Panel on Climate Change, (2001), *Climate Change 2001: Working Group 1: The Scientific Basis*. New York: Cambridge University Press.
- Jaya INS, (2010), Analisis Citra Digital: Perspektif Penginderaan Jauh untuk

- Pengelolaan Sumberdaya Alam. Bogor: Fakultas Kehutanan IPB.
- Jenks G., (1997), Optimal Data Classification for Choropleth Maps. Occasional paper No. 2, Department of Geography, University of Kansas
- Komiyama A., Ong JE, Pongparn S., (2008), Allometry, biomass, and productivity of mangrove forests. *Aquatic Botany*. Vol. 89: 128-137.
- Lu D., (2006), The potential and challenge of remote sensing-based biomass estimation. *International journal of remote sensing*. Vol. 27(7), 1297-1328.
- Pambudi GP, (2011), Pendugaan biomassa beberapa kelas umur tanaman jenis *Rhizophora apiculata* Bl. pada areal PT. Bina Ovivipari Semesta Kabupaten Kubu Raya, Kalimantan Barat. [Skripsi]. Bogor (ID): Departemen Konservasi Sumberdaya Hutan dan Ekowisata, Fakultas Kehutanan Institut Pertanian Bogor.
- Peraturan Menteri Kehutanan Republik Indonesia. No: P.74/Menhut-II/2014 Tentang: Penerapan Teknik Silvikultur dalam Usaha Pemanfaatan Penyerapan dan/atau Penyimpanan Karbon Pada Hutan Produksi.
- Saputra GR, (2007), Model Penduga Potensi Hutan Rakyat Menggunakan Citra Aster dan Sistem Informasi Geografis di Beberapa Wilayah Kabupaten Bogor Bagian Barat. [Skripsi]. Bogor (ID): Departemen Manajemen Hutan Fakultas Kehutanan IPB.
- Sutaryo D., (2009), Perhitungan Biomassa, Sebuah Pengantar untuk Studi Karbon dan Perdagangan Karbon. Bogor (ID): Wetlands International Indonesia Programme.
- Qirom MA, Saleh MB, Kuncahyo B., (2012), Aplikasi Citra ALOS PALSAR untuk Pendugaan Simpanan Karbon di Hutan Tanaman Akasia. Vol. 1: 121-134
- Talan MA, (2008). Persamaan penduga biomassa pohon jenis Nyirih (*Xylocarpus Granatum* Koenig 1784) dalam tegakan mangrove hutan alam di Batu Ampar-Kalimantan Barat. [Skripsi]. Bogor (ID): Departemen Konservasi Sumberdaya Hutan dan Ekowisata, Fakultas Kehutanan Institut Pertanian Bogor.
- Tangki H., Chappell NA, (2008), Biomass variation across selectively logged forest within a 225-km² region of Borneo and its prediction by Landsat TM. *Forest Ecology and Management*. 256(11), 1960-1970.
- Walpole RE, (1995), Pengantar Statistik Edisi 3 [Terjemahan dari: Introduction to statistics 3rd edition Penerjemah: Sumantri B]. Jakarta (ID): Gramedia.
- Yuwono T., (2014), Model Penduga Massa Karbon Hutan Rawa Gambut Menggunakan Citra ALOS PALSAR [Tesis]. Bogor (ID): Program Pascasarjana, Institut Pertanian Bogor.

