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Examining the object-based and pixel-based image analyses for developing stand volume estimator model

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ABSTRACT

In the last two decades there has been significant leap on the spatial resolution of the satellite digital images which may be very useful for estimating stand parameter required for forest as well as environment management. This paper describes development of stand volume estimator models using SPOT 6 panchromatic and multispectral images with an object-based digital image analysis (OBIA) and conventional pixel-based approaches. The data used include panchromatic band with1.5m spatial resolution, and multispectral band with6m spatial resolution. The proposed OBIA technique with mean-shift algorithm was functioned to derive a canopy cover variable from the fusion of the panchromatic and multispectral, while the pixel-based vegetation index was used to develop model with an original pixel-size of 6 m. The estimator models were established based on 65 sample plots both measured in the field and images. The study found that the OBIA provides more accurate identification with Kappa Accuracy (KA) of 71% and Overall Accuracy (OA) of 86%. The study concluded that the best stand volume estimation model is the model that developed from the canopy cover (C) derived from OBIA i.e., $v = 13.47e^{0.032C}$ with mean deviation of only 0.92%, better than the model derived from conventional pixel-based approach, i.e., $v = 0.0000067e^{16.48TNDVI}$ with a mean deviation of 5.37%.

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1. INTRODUCTION

Development of stand-volume models based on remote sensing data usually involves measurements of independent variables through visual interpretation method on the image [1, 2]. The visual interpretation mainly relies more on the capability of interpreters that are quite varied from person to person, depending on the their skill and experiences that may provide inconsistence results. So that, to reduce inconsistence in performing measurement and interpretation the images, then it is necessary to develop a more quantitative approach that apply automatic and / or semi-automatic methods.

One of commonly used quantitative approaches are the pixel-based and/or the object-based algorithms. In the classifying medium resolution images, the pixel-based image is widely used and proven to be more practical and accurate. However, detection and identification of objects in high and very high resolution images, approaches that are only based on the pixel values tend to be less accurate, because most reflectance and radiation objects are less sensitive to the dimensions of the object. Some studies, proven that the object-based approach may provide better accuracy [3-5].

In the last two decades, in line with the availability of high and very high resolution images and digital image analysis techniques, classification of high and very high resolution images have led to the use of the object-based algorithms [6, 7]. This object-based classification method uses three main parameters as object detectors, namely spatial radius, range radius, and minimum region size. This classification method performs detection and delineation, not only based on pixel but also based on object segmentation. Image segmentation techniques using the algorithm Mean-shift [8-10] have been used in several forest resource studies, such as the use of unmanned imagery in the inventory of nipah vegetation with overall and kappa accuracy of 76.6 % and 55.7% [11] and environmental management monitoring [12]. Detection of land use changes images Synthetic Aperture Radar (SAR) with mean shifts shows better detection and identification capabilities than classic log ratios [13], detection of forest changes due to storms using OBIA [14].

Recently, three are a lot of high resolution images available for forest measurement. However, only few studies were conducted by using quantitatives approach. The segmentation method with the algorithm mean shift may increase the accuracy value by 40.9% when compared with other methods such as region growing, and k-means [15], the mean shift algorithm also reduces work time by 40% when compared to the algorithm kmeans [16].

In this study, there are several research questions that need to be studied, namely:

a) What is the reliability of pixel-based and object-based approaches for forest cover detection in lowland forests?; and
b) How do the performance of classification using the combination of pixel-based and object-based approaches, particularly on estimating stand stock?.
c) Which combination of object-based method parameter provide the most accurate assessment for detecting stand variables?

The main objective of this study is to develop a mathematical model and test its reliability base on pixel-based and object-based approaches, as well as to find out the best estimate of stand volume model using very high resolution satellite imagery.

2. RESEARCH METHOD

2.1. Site describtion

The study site was located in Bintuni Bay District, West Papua Province, while data processing was carried out in the Laboratory Remote Sensing and Geographic Information System (GIS), Forest Planning Division, Department of Forest Management, Faculty of Forestry, Bogor Agricultural University, from December 2016 to August 2018. The geographical location of the study site is located at coordinates between 132 ° 59 '- 133 ° 46' BT and 01 ° 26 - 02 ° 11 'LS (Figure 1).

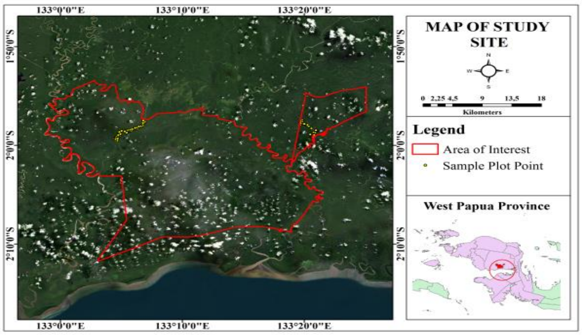


Figure 1. Map of research locations

2.2. Data and softwere

Main data used in the study were the SPOT 6 image having spatial resolution of 1.5 meters and 6 meters, field measurements consisted of diameter at breast high (dbh), tree height, spesies name and regeneration. During data processing and data analysis, some software's were applied, namely the ERDAS Imagine Ver. 14 for image analysis, Microsoft Excel 2007 for performing statistical analysis, and QGIS 2.18 which was equipped with tool Orfeo Toolbox for performing spatial operation and segmentation. Measurement of stand dimensions used *phi*-band, distance meter, compass, Global Positioning System (GPS), plastic/mine rope, Suunto, flagging tape, tally sheet, writing instruments, and digital cameras.

The SPOT 6 multispectral image consisted of Red, Green, and Blue bands (band 321) which may produce natural colors having spatial resolution of 6 meters. The panchromatic band of SPOT6 image have spatial resolution of 1.5 meters. During the analysis, SPOT6 image having 6 meter spatial resolution was pansharpened using the Brovey Transformation. The Brovey's method is the most popular method for combining two types of images spatial resolution [17] developed by an American scientist to improve the visual appearance of an image.

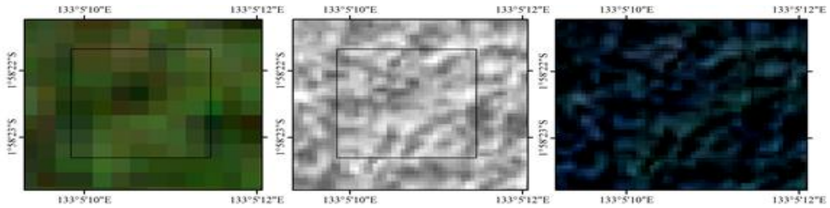

(a) (b) (c)

Figure 2. (a) SPOT 6 multi-spectral image, (b) panchromatic, (c) pansharperning

2.3. Research procedure
2.3.1. Pre processing image
Prior to any further analysis, several pre-processing activities were performed, namely geometric correction, image-sharpening, visual interpretation process (on screen digitizing) to identify the land cover class (forest, road, and body of water) and defining general description of canopy cover class.

2.3.2. Field measurement
For dry land forest, measurement of stand parameters was carried out by measuring all tree size, starting from the small size trees (dbh $\geq$20 cm) up to the large size trees having dbh larger than 30 cm. The small size tree were measured within the sub-plot of 25 m x 25 m, while the large tree was measured within 50 m x 50 m plot. The total number of sample plots measured in the field was 65 plots, where 33 sample plots were used to establish a model and the rest of 32 sample plots were used on model validation process. The all sample plots was selected purposively based on the characteristics of the image and accessibility consideration.

Furthermore, the volume of each trees was calculated by using the equation published on the monograph of allometric models issued by the Forestry Research and Development Agency in 2012. The applied model was Vol (m^3) = 0.000309421 $dbh^{2.13873}$having R^2 of 93% [18].

2.3.3. Vegetation index transformation
On pixel-based approach, the original band were transformed into several indices, by applying several combination of spectral bands, such as green, red and near infrared (NIR). Vegetation index is optical measurement of greenness of vegetation canopy, composite properties of leaf chlorophyll, leaf area, structure and cover of vegetation canopy. In this study, several vegetation indices applied are as follows:

a. Soil Adjusted Vegetation Index (SAVI)

$$SAVI = \frac{(NIR-RED)*(1+L)}{(NIR+RED+L)} \quad (1)$$

b. Difference Vegetation Index (DVI)

$$DVI = NIR - RED \quad (2)$$

c. Normalized Difference Vegetation Index (NDVI)

$$NDVI = \frac{NIR-RED}{NIR+RED} \quad (3)$$

d. Vegetation Index ratio (RVI)

$$RVI = RED / NIR \quad (4)$$

e. Red Green Index (RGI)

$$RGI = \frac{GREEN-RED}{GREEN+RED} \quad (5)$$

f. Renormalized Difference Vegetation Index (RDVI)

$$\mathrm{RDVI} = \frac{\mathrm{NIR-RED}}{\mathrm{SQRT\ (\ RED\ NIR)}} \quad (6)$$

g. Transformed Difference Vegetation Index (TNDVI)

$$\mathrm{TNDVI} = \left[\frac{\mathbf{NIR-RED}}{\mathbf{NIR+RED}} + \mathbf{C}\right]^{\mathbf{1/2}} \quad (7)$$

where L = ground background adjustment factor in canopy; C = constant (0.5).

2.3.4. Object-based image classification

The process of segmentation is an initial process of object-based images or also called object base image analysis (OBIA). In image segmentation, pixels were mapped into a color space (filtering) and grouped (clustering), where each cluster describes a homogeneous area (similar spectral values and spatial characteristics) in the image. In this study, the segmentation process uses mean-shift algorithms with parameters spatial radius, radius ranges, and minimum size regions. Spatial radius (Hs) is a parameter that has a function to control distance, measured by a number of pixels. Spatial radius will group a number of pixels into one segment or one object, while range radius (Hr) is a segmentation parameter that matches the spectral value of each pixel. The radius range refers to spectral variability (distance in n-dimensional spatial space) to group a number of pixels into one segment. Furthermore, it is also defined that the minimum region size (M) is a parameter associated with the minimum size of the number of pixels that make up a single object. Objects that have a number of pixels below the parameter value will be combined with the closest object. This study examined 27 combinations of means of parameter shift in each cluster to obtain canopy cover values and vegetation gaps (Table 1).

Table 1. SPOT 6 Image Segmentation Parameter Combination in 2016

No	Code Combination	Hs	Hr	M	No	Code Combination	Hs	Hr	M
1	K-01	2	21	4	15	K-15	5	28	49
2	K-02	2	21	20	16	K-16	5	35	4
3	K-03	2	21	49	17	K-17	5	35	20
4	K-04	2	28	4	18	K-18	5	35	49
5	K-05	2	28	20	19	K-19	11	21	4
6	K-06	2	28	49	20	K-20	11	21	20
7	K-07	2	35	4	21	K-21	11	21	49
8	K-08	2	35	20	22	K-22	11	28	4
9	K-09	2	35	49	23	K-23	11	28	20
10	K -10	5	21	4	24	K-24	11	28	49
11	K-11	5	21	20	25	K-25	11	35	4
12	K-12	5	21	49	26	K-26	11	35	20
13	K-13	5	28	4	27	K- 27	11	35	49
14	K-14	5	28	20					

Notes: Hs: spatial radius (pixels), Hr: range radius (brightness value), M: minimum region size (pixel)

The further step of the OBIA was the classification of canopy cover and gap (see illustration on Figure 3(a)). For classifying the canopy cover and gap, then the pixel-based classification, i.e., a supervised classification using the algorithm maximum-likelihood classifier was applied. The pixel-based classification stage consisted of determining the training area and class signature. The supervised classification result is shown in Figure 3(b).

(a) (b) (c) (d)

Figure 3. Steps of classification process of segmentation results; (a) results of segmentation; (b) supervised classification results; (c) overlay results of segmentation and supervissed classification results; (d) labeling of segmentation results based on supervissed classification results

2.3.5. Accuracy Assessment

Some methods used in assessing the results of segmentation include using fragmentation indices [19], area fit index [20], and use of area, perimeter and shape index [21]. Accuracy analysis in this study, was assessed by using a confusion matrix principle, to provide the Overall and Kappa Accuracy. The matrix was filled out by comparing the reference data obtained from visual interpretation (on screen digitizing) and the classified image (the results of OBIA). The formulas used to calculate Overall Accuracy (OA) and Kappa Accuracy (KA) [22] are:

$$\text{Overall Accuracy(OA)} = \frac{\sum_{i=1}^{r} X_{ii}}{N} 100\% \tag{8}$$

$$\text{Kappa Accuracy(KA)} = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r} X_{i+}X_{+i}}{N^2 - \sum X_{i+}X_{+i}} 100\% \tag{9}$$

where:
Xii = number of pixel in the diagonal element of the confusion matrix in the i line and i column,
Xi + = total pixel (grid) in the i column,
X + i = total pixel in the i row, N = total pixels

The results of the accuracy assessment for all segmentation combinations were used to select the best combination of segmentation parameters. The selection of the best segmentation results was based on the overall accuracy value and the largest kappa accuracy.

2.3.6. Canopy cover and vegetation gap

The measurement canopy cover in the forestry was a common work, particularly when the stand analysis was done using image analysis. In this study, the stand variable observed was canopy cover and gap of the stand. Canopy cover can be defined as the size of many leaves, twigs, branches or branches in stands that cover a certain area. While the gap in this study is interpreted as an empty area or image between branches, branches or branches in stands (Figure 4).

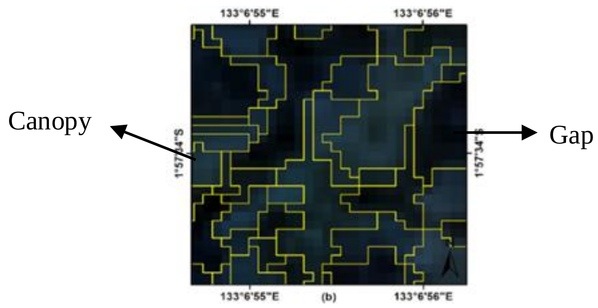


Figure 4. Differences in canopy and gap

2.3.7. Volume estimator model

Stand volume estimator models developed in this study express the relationship between stand volume per unit area and stand variables that could be interpreted or measured through satellite images. The model is expressed in the form of mathematical equations or regression equations. The stand variable measured from the SPOT 6 images was percent canopy cover (C) that derived based on object-based method and vegetation indices that processed using the pixel-based algorithm namely NDVI, TNDVI, SAVI, RGI, RDVI, DVI and RVI. The form of the regression model examined were:

a. Linear model : $V = a + bX$
b. Exponential model : $V = ae^{bX}$
c. Logarithmic model : $V = a.\ln.X + b$
d. Polynomial model : $V = a + bX + cX^2$

2.3.8. Validation Model

Validation was done intended to obtain the best model [22-25]. The validation of the estimator model was done by using half of the sample plot samples taken in the field. Validation measures that used to evaluate the models were the average deviation (SR) and aggregate deviation (SA). The average deviation is the percentage of the absolute value of the sum of results for the difference between the estimated value and the actual value with the estimated value of example (n). A good model would have an SR value of less than 10%.

$$SR=\left[\frac{\sum_{i=1}^{n}\left|\frac{\sum \hat{yi}-\sum yi}{\sum \hat{yi}}\right|}{n}\right] \text{ x } 100\% \quad (10)$$

The aggregative deviation is the difference in the number of actual values with estimated values as proportional to the estimated value. A good estimation model usually has an SA value between -1 and +1.

$$SA=\left[\frac{\sum \hat{y}-\sum y}{\sum \hat{y}}\right] \quad (11)$$

Notes:
SR : average deviation, SA : aggregate deviation, $\hat{yi}$: i estimate value, yi: i actual value, n :number of sample.

3. RESULTS AND ANALYSIS

3.1. Volume Estimator

3.1.1. Volume estimator model using vegetation index

Based on the analysis of variance, analysis of correlation and validation test, the pixel-based regression equations of each model with their associated *p*-value, R^2, SA and SR are summarized in Table 2. These stand volume estimation models were developed based on several typed of vegetation indices derived from SPOT 6 images. It was shown that most of the *p*-values are less than 0.005, except model M6, M21, M24 and M27.

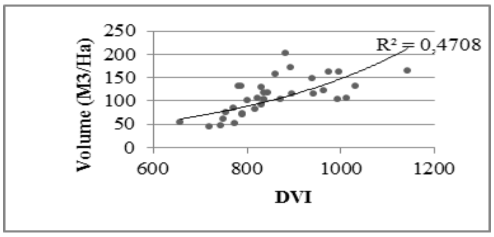
Table 2. Volume Estimator Model with SPOT 6 Image Vegetation Index in 2016

No	Model Code	Model type	Equation	*P-value*	R2	Validation measure SA	SR
1	M1	TNDVI_exp	$V = 0.0000067e^{16.48TNDVI}$	0.000013	0.50	0.12	5.34
2	M2	SAVI_exp	$V = 0.402e^{5.450SAVI}$	0.000014	0.49	0.12	5.37
3	M3	NDVI_exp	$V = 0.402e^{8.175NDVI}$	0.000014	0.49	0.13	5.42
4	M4	RDVI_exp	$V = 1.415e^{0.139RDVI}$	0.000020	0.48	0.13	5.60
5	M5	RVI_exp	$V = 555.6e^{-9.38RVI}$	0.000011	0.50	0.13	5.74
6	M6	RGI_exp	$V = 377.9e^{-0.78RGI}$	0.058481	0.14	0.07	7.28
7	M7	RVI_log	V = -72.4ln (RVI) - 53.57	0.000011	0.46	0.14	8.92
8	M8	DVI_lin	V = 0.061DVI - 25.63	0.000030	0.44	0.14	9.08
9	M9	RDVI_lin	V = 3.376RDVI - 42.90	0.000020	0.45	0.14	9.49
10	M10	SAVI_lin	V = 132.9SAVI - 73.82	0.000014	0.46	0.14	9.52
11	M11	TNDVI_poly	$V = -5204TNDVI^2 + 10876TNDVI - 5644.$	0.000013	0.50	0.99	9.54
12	M12	NDVI_lin	V = 199.3NDVI - 73.84	0.000014	0.46	0.14	9.54
13	M13	TNDVI_lin	V = 401.9TNDVI - 375.9	0.000013	0.46	0.14	9.55
14	M14	NDVI_log	V = 103.0ln (NDVI) + 97.44	0.000014	0.47	0.14	9.57
15	M15	TNDVI_log	V = 405.3ln (TNDVI) + 26.02	0.000013	0.47	0.99	9.58
16	M16	SAVI_log	V = 103.0ln (SAVI) + 55.67	0.000014	0.47	0.14	9.60
17	M17	RVI_lin	V = -228.6RVI + 102.4	0.000011	0.47	0.15	9.63
18	M18	RDVI_log	V = 72.80ln (RDVI) - 193.3	0.000020	0.47	0.15	9.81
19	M19	DVI_log	V = 55.90ln (DVI) - 349.6	0.000030	0.46	0.15	9.83
20	M20	DVI_poly	$V = -0.00018DVI^2 + 0.39160DVI- 170.40680$	0.000030	0.51	0.15	10.04
21	M21	RGI_lin	V = -17.52RGI + 87.33	0.058481	0.11	0.10	10.20
22	M22	NDVI_poly	$V = -1392NDVI^2 + 1630NDVI - 440.1$	0.000014	0.50	0.15	10.21
23	M23	SAVI_poly	$V = -618.8SAVI^2 + 1087SAVI - 439.9$	0.000014	0.50	0.15	10.21
24	M24	RGI_log	V = -59.8ln (RGI) + 100.8	0.058481	0.11	0.10	10.33
25	M25	RVI_poly	$V = -1431.RVI^2 + 700.2RVI - 47.02$	0.000011	0.49	0.15	10.36
26	M26	RDVI_poly	$V = -0.493RDVI^2 + 24.43RDVI - 265.7$	0.000020	0.51	0.16	11.08
27	M27	RGI_poly	$V = -43.84RGI^2 + 287.3RGI - 440.8$	0.058481	0.14	0.12	12.01
28	M28	DVI_exp	$V = 2.868e^{0.002DVI}$	0.000030	0.47	-0.45	-53.10

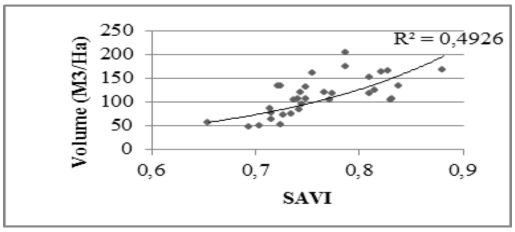
Note: Exp : exponential, Log : logarithmic, Lin : linear, Poly : polynomial

Based on the results of the significance of *p*-value and correlation value, it was found that the statistical performance of using RGI is weak, where it has a *p*-value greater than 0.05 and very low $R^2$of only 11%. Then, it is concluded that the RGI based model could not be used for assessing the stand model. In general, the regression model developed using TNDVI, NDVI, DVI, SAVI, RDVI, and RVI have a *p*-value below 0.05 with R^2 values ranging between 11% and 51%. The study results also show that the models obtained from the several forms of vegetation index have an SA values between -1 and 1 with SR less than 10%. These means that the model could be statistically acceptable and implementable. Of the models, the TNDVI-based model provides the highest R^2 value of 50% with excellent validation, having SA value of 0.12 and SR value of only 5.34%, it is also shown in the estimation of pine stands using the vegetation index which shows a value of accuracy of 51% [26].

As shown in Figure 5, there are close relationships between the stand volume and the TNDVI, NDVI, DVI, SAVI, RVI, RDVI, and RGI. In general, the higher the vegetation index value tend to have the higher the volume. The TNDVI, NDVI, DVI, SAVI, and RDVI in particular the higher the vegetation index value would provide the higher the stand volume. Different trend is shown by the RGI and RVI, where the lower the vegetation index value would mean the higher the stand volume. This is due to [27] Red band and Green band values inversely proportional to the vegetation while the value is Infrared band directly proportional to the vegetation.



(a)



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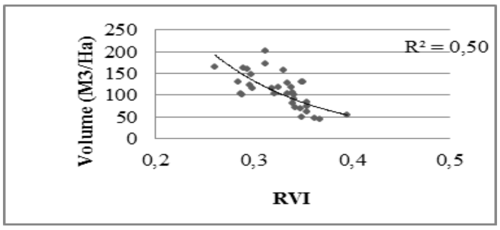

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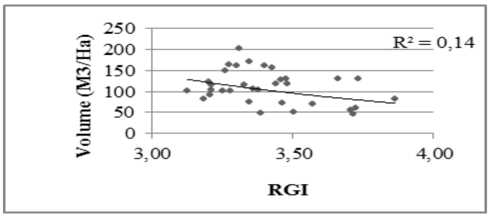

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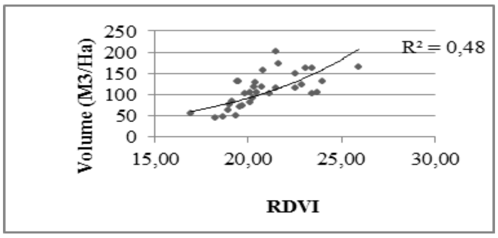

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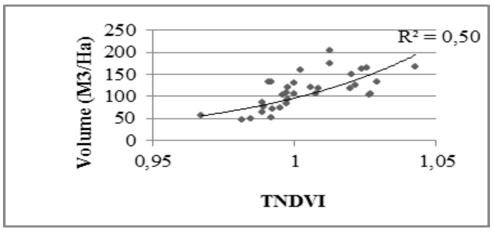
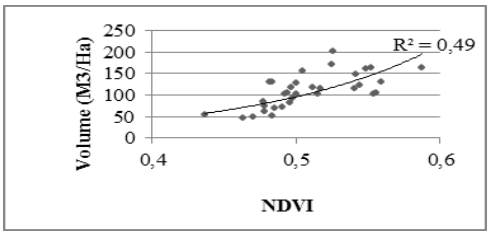


(f)



(g)

Figure 5. Scatter diagram between (a) stand volume and DVI, (b) stand volume and SAVI, (c) stand volume and RVI, (d) stand volume and RGI, (e) stand volume and RDVI, (f) stand volume and the TNDV, (g) stand volume and the NDVI

3.1.2. Object-Based Volume Estimator Model

3.1.2.1. Segmentation Combination Selection

The best combination of segmentation parameter was done by evaluating the overall accuracy value (OA) and Kappa (KA) accuracy of all segmentation combinations examined. This accuracy testis crucial to provide information regarding the coincidence between the segmentation result and actual class in the field [28]. The recapitulation of OA and KA accuracy values of parameter segmentation combination tested in this study are summarized in Figure 6. The accuracy values were obtained by comparing the results of segmentation and the results of visual interpretation and field observations as reference data.

Of the 27 tested combinations of segmentation parameters, the combination that give the highest accuracy was provided by K-10 (5-21-4), while the lowest accuracy value was in provided by K-09 (2-35-49). The Kappa and Overall accuracies of K-10 are 71.2% and 86.6%, while the Kappa and Overall accuracies of K-09 are 8.8% and 64.8% (Figure 6). This is in line with several previous studies which stated that the accuracy of the results of object-based classification has a fairly high value [29-32].

As shown in Figure 7, the variation of spatial radius and minimum region size did not give any significant variation of the segmentation accuracy. The significant difference of accuracy was due to the variation of range radius, where when the radius range increases then the accuracy decreases. From the overall combination of parameters, the study shows that the parameter range radius is the determinant factor that affect the detection of canopy cover and stand gap. In the best combination of parameters, the value radius range used is 21. If the radius range is increased to 28, then there is a decrease in the Overall accuracy value and Kappa accuracy. Different study results were shown by [11] that the most significant segmentation parameter is the minimum size region.

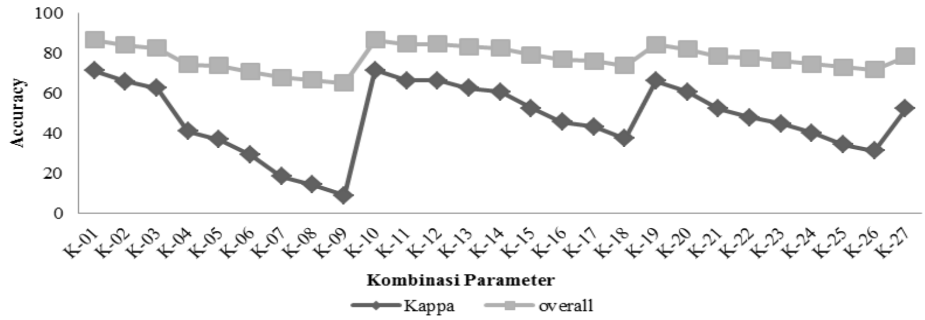


Figure 6. Value of overall accuracy and accuracy of kappa

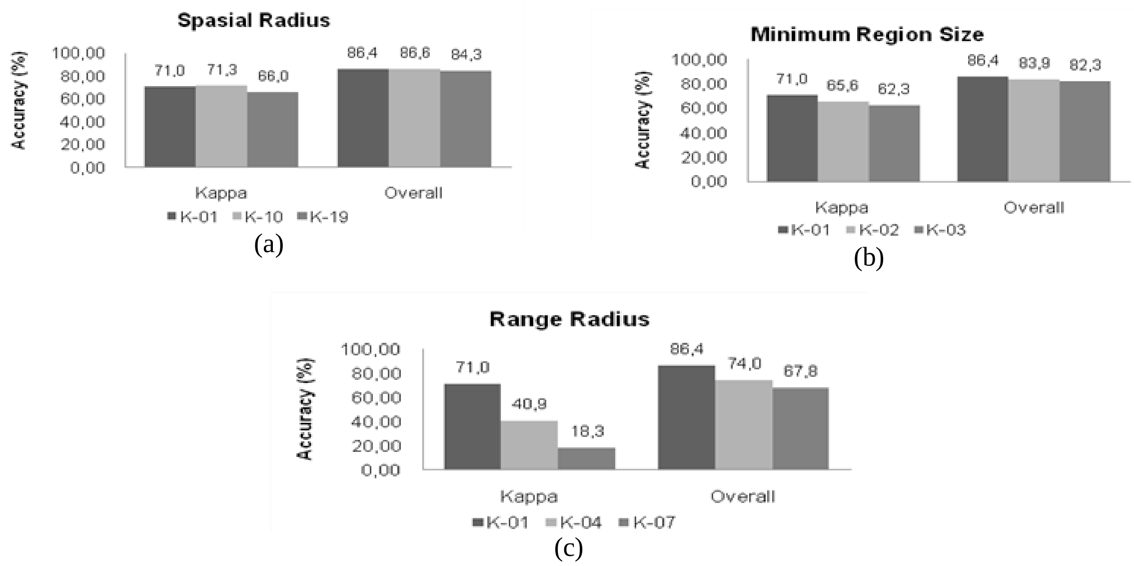
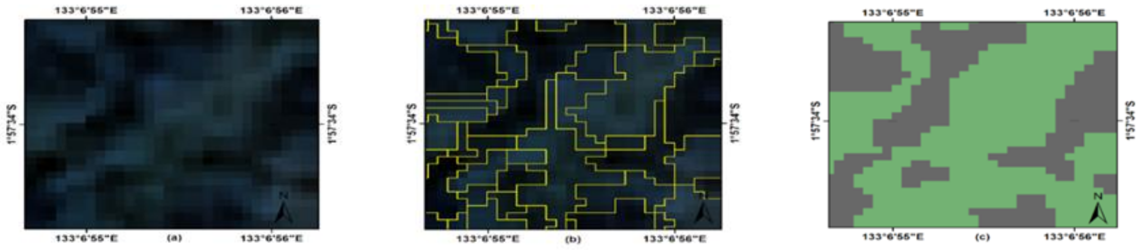


Figure 7. The Kappa and Overall accuracies for parameters (a) spatial radius, (b) minimum size region, and (c) radius range

Figure 8 shows the results of segmentation and OBIA from SPOT6 images with a combination of K-10 parameters. If observed in detail there will be differences in shape, size and the color between the gap and canopy cover. The results of image segmentation can separate canopy objects and gaps properly.



(a) (b) (c)

Figure 8. (a) SPOT 6 image, (b) segmentation results, and (c) OBIA results

3.1.3. Volume estimator model with OBIA

The percentage of canopy cover derived from the OBIA was then used to develop a stand volume estimator model. In the OBIA, the delineation of canopy and gap was obtained from the segmentation process. Furthermore, the canopy cover (percent) was the used to develop a regression model, where the response variable is standing stock per unit area.

In the plot used to construct the model, canopy cover in the image ranges from 40% - 80% and the stand volume ranges from 40 m^3 - 200 m^3 (Figure 9). Based on the results of the study, the higher the percentage of canopy cover in a digital image eat the higher the stand volume.

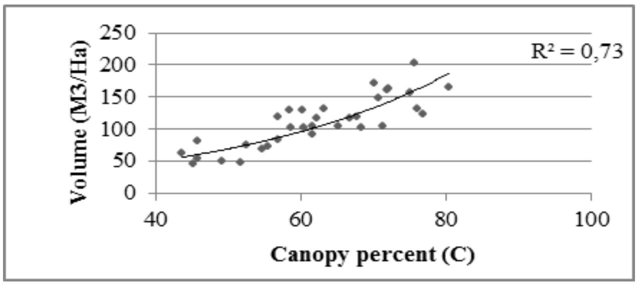


Figure 9. Scatter diagram between volume and canopy cover

From the stand volume estimator models as shown in Table 3, it is shown that the exponential model (Model code S1) is the most accurate model, having the highest R^2 and the smallest SA and SR. The study found that the stand volume could be predicted using the canopy cover derived from SPOT 6. Model S1 has other factors that affect the formation of regression relationship with canopy cover volume on a relatively small image that is less than 30%, it is seen from the magnitude of the coefficient of determination (R^2), which defines the biggest factor is of variables tested so this equation is worth using. Based on the equation model tested, the S1 model is the one that best meets the requirements with the aggregative deviation value (SA) being 0.16 and the average deviation (SR) is 0.92%.

Table 3. Model Volume Estimator with OBIA Image SPOT 6 in 2016

No	Code Model	Form Model	Equation	P-value	R2	Validation SA	Validation SR
1	S1	Exp	$V = 13.47e^{0.032C}$	0.00000000068	0.73	0.16	0.92
2	S2	Log	V = 194.9ln (C) - 692.1	0.00000000068	0.71	0.18	5.91
3	S3	Lin	V = 3.257C - 92.28	0.00000000068	0.71	0.17	4.67
4	S4	Poly	$V = -0.0030C^2 + 3.6257C - 103.3021$	0.00000000068	0.71	0.18	5.79

Note: Exp : exponential, Log : logarithmic, Lin : linear, Poly : polynomial

3.2. Map of Volume Distribution

From the selected models, then a spatial volume distribution of stand volume was made.

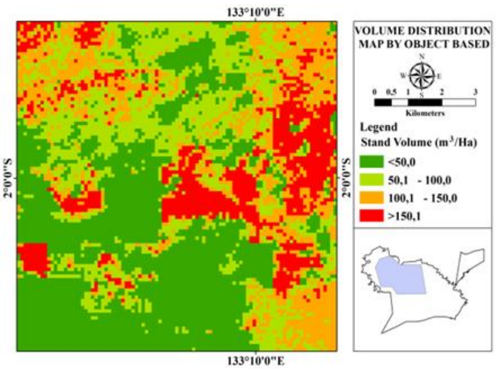


Figure 10. Stand volume derived by the OBIA

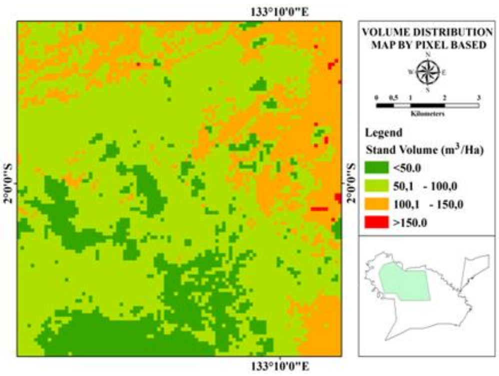


Figure 11. Stand volume derived by the pixel-based

4. CONCLUSION

Object-based image analysis (OBIA) with a mean-shift algorithm could detect and identify canopy cover and gap of low land forest accurately, having accuracy OA of 73% and KA of 86%. The stand volume estimator model using canopy cover derived from the OBIA is significantly more accurate than those model developed using vegetation indices derived from the pixel-based approach. The estimator model with the OBIA approach is $V = 13.47e^{0.032C}$which has SA = 0.16 and SR on only 0.92% less than 1% while the estimator model with the vegetation index approach is $V = 0.0000067e^{16.48TNDVI}$ with SA values = 0.12 and SR = 5.34%.

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