

Assessing the Crown Closure of Nypa on UAV Images using Mean-Shift Segmentation Algorithm

Robert Parulian Silalahi¹, I Nengah Surati Jaya², Tatang Tiryana³, Fairus Mulia⁴

¹Bogor Agricultural University, Campus IPB Dramaga, Bogor, Indonesia

^{2,3}Department of Forest Management, Faculty of Forestry, Bogor Agricultural University, Campus IPB Dramaga, Bogor, Indonesia

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ABSTRACT

Utilization of very high-resolution images becomes a new trend in forest management, particularly in the detection and identification of forest stand variables. This paper describes the use of mean-shift segmentation algorithm on unmanned aerial vehicles (UAV) images to measure crown closure of nypa (*Nypa fruticans*) and gap. The 27 combinations of the parameter values such as spatial radius (hs), range radius (hr), and minimum region size (M). Gap detection and nypa crown closure measurements were performed using a hybrid between pixel-based (maximum likelihood classifier) and object-based approaches (segmentation). For evaluation of the approach performance, the accuracy assessment was done by comparing object-based classification results (segmentation) and visual interpretation (ground check). The study found that the best combination of segmentation parameter was the combination of hs 10, hr 10 and M 50, with the overall accuracy of 76,6% and kappa accuracy of 55.7%.

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Corresponding Author:

Robert Parulian Silalahi,
Bogor Agricultural University, Campus IPB Dramaga,
Bogor, Indonesia 16680
Email: ins-jaya@apps.ipb.ac.id

1. INTRODUCTION

Indonesia is one of the tropical countries having a wide variety of ecosystems, starting from coastal forest/lowland (mangrove, swamp forest, peat swamp forest), dry-low land forest, up to mountainous forests, sub-alpine and alpine). To obtain a sound basis forest management planning, there is a need to provide accurate and timely supporting data related to ecosystem type, forest classes, forest density, biodiversity, standing stock, etc. One of the unique ecosystem types, which economically, ecologically, socially and culturally plays an important role is the mangrove ecosystem. In Indonesia, this mangrove ecosystem is a highly vulnerable ecosystem to conversion. One of the vegetation that goes into an association of mangrove ecosystem is nypa (*Nypa fruticans*). Nypa vegetation is common in estuary areas affected by tide [1]. In Indonesia, the information on the dynamic growth, status and potential of nypa has not been much studied, since the nypa ecosystem is less attractive and even frequently considered as wasteland. Some researchers indicate that nypa vegetation can provide potential economic value, either at small-scale or large-scale business. Nypa is one type of vegetation that may provide daily need product for household consumption. Several of nypa research found that nypa has a potential to be a source of food because of its have high carbohydrate and protein [2], even according to the study [3], nypa contains an ethanol to produce fuel energy.

Currently, the use of remote sensing technology in natural resource management is a must, and even for a small scale forest management. Now, there is a trend of using very high-resolution images for detailed forest management up to the tree-level forest management. Since the launch of natural resources satellites for

civilian use in the 1970s, the development of remote sensing technology has grown rapidly, starting from a low, moderate to very high resolutions. In line with their development, the remote sensing has been also widely used for supporting either regional level, national level or individual tree level forest inventory. Today, the advent of the high and very high resolution had provided a good opportunity as well as a challenge all at once. The higher the spatial resolution, the more detailed information could be derived, the more complex and reliable approaches are required.

In a very high-resolution imagery, the use of ordinary pixel-based approach such as supervised and unsupervised classifier is often provided less accurate information, since the classification is solely based upon the brightness values (reflectance) of the object. The advent of object-based classification technique often called the object-based image analysis (OBIA), which consider not only the brightness values of the object but also the spatial aspect of the object being analyzed has offered a promising solution to overcome the drawback of the existing pixel-based analysis. The object-based processing is considered to have a better performance in processing high-resolution digital image because, in addition to considering the value of the pixel itself, it also considers the size (area) and shape of the object within the image.

In the last few decades, the spatial resolution of images has been improved rapidly. In addition to satellite imagery, one of the imaging platforms that produce very high-resolution images is UAV (Unmanned Aerial Vehicle). The UAV is also called to as drone (dynamic remotely operated navigation equipment). Now camera technology used in the UAV is mainly conventional camera that may provide spatial resolution up to 5 cm. However, its recording platform is very perspective because it can be flown under the cloudy weather (fly below the cloud), unmanned, low cost, fast and relatively low risk. Thus, the UAV technology becomes a good alternative because the data obtained would be very detail and real time, as well as could be obtained easily with cheaper price. The utilization of UAV technology has been widely used to in many aspects such as mapping activity [4], quantifying spatial gap pattern [5], change detection [6], forest inventory activities [7], canopy spectral mapping [8], measuring stand variables such as crown diameter, canopy percentage and number of trees [9, 10] as well as estimation of the standing stock and site index quality of teak sites [11].

The Increasing resolution of the digital images from low resolution to very high resolution have encouraged a development of image processing. The current image processing trends are the use of object-based classification methods, as a complimentary of the pixel-based approach. A pixel-based approach can be used as long as a pixel is the same size as a particular object [12]. An object-based approach is now a popular approach in high and very high-resolution image processing.

Basically, the object-classification method consists of two parts namely segmentation and classification. Conventionally, the segmentation is the initial process of an object-based classifier, then followed by classification. Image segmentation is generally defined as a process of dividing an image into groups which are spatially or spectrally uniform [13]. Object-based approaches have been applied in some works such as classification of agricultural land using SPOT-5 [14], exploration of the urban information in Cianjur [15], mapping of coral reef habitat [16], mapping land covers changes changes in mangrove ecosystems [17], detecting of forests changes caused by hurricanes [18], the object-based classification of land use in Ontario, Canada had also be examined by [19].

In this study, the authors focused on examining the appropriate object-based classification parameters for analyzing the nypa crown closure dan gap. This study integrated the pixel-based approach with maximum likelihood classifier and the mean-shift algorithm in segmentation method. The use of the mean-shift segmentation algorithm is widely used in earlier studies for benthic mapping [20], environmental management monitoring [21], land cover classification [22], change detection in SAR image [23], medical diagnosis [24]. Although the mean-shift algorithm had been successfully examined in classifying building objects in suburban area [25], the application in classifying nypa vegetation is still challenging. Up to now, very high-resolution image utilization research for nypa ecosystem assessment is still very rare. The main objective of the study is to develop a classification technique for assessing the nypa crown closures and their gap by combining the mean-shift segmentation algorithm and maximum likelihood classifier of the pixel-based classification.

2. RESEARCH METHOD

2.1 Site description

The research was conducted within the concession area of IUPHHK PT Kandelia Alam, geographically located between 109°34'10,82" E & 109°41'14,85" E; and between 0° 35'18,21" S & 0°39'53,45" S. Administratively, the study site is located within Kubu Raya Regency, West Kalimantan Province (Figure 1). Field observation and field measurements were conducted in 2016, especially in areas covered by UAV (Unmanned Aerial Vehicle) imagery.

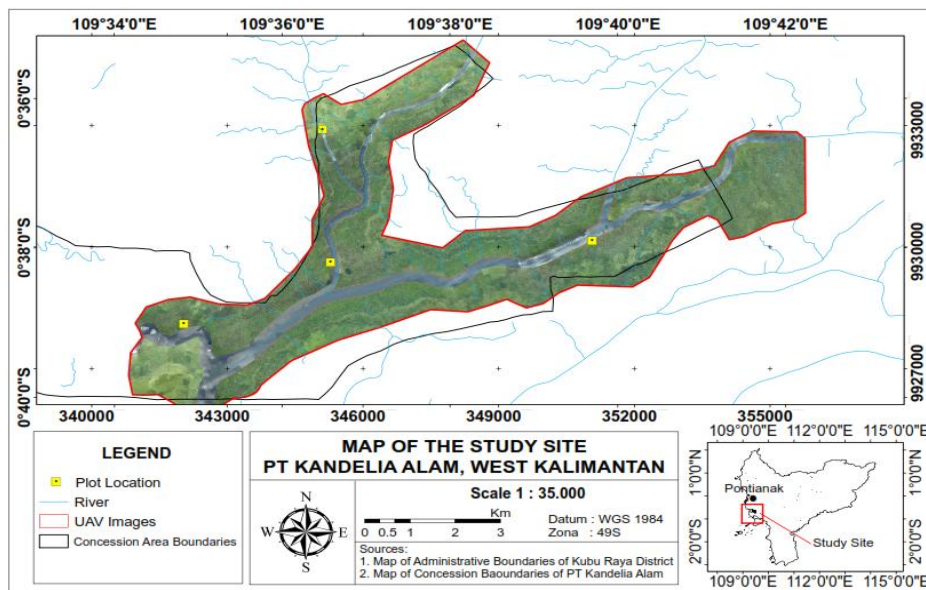


Figure 1. Study site map

2.2 Data and Software

The main data used in this study is a UAV image having 10 cm spatial resolution, 8 bits radiometric value, 4 bands, namely Red, Green, Blue, and Alpha. The preprocessing work such as rectification, radiometric correction, and geometric correction was done by data supplier. The used UAV images which cover approximately 4087 ha, were recorded in February 2016. Other supporting data used in this study are the data collected from ground measurements such as an individual diameter of nypa, length and diameter of leaves, a number of leaves, a number of stump and weight of sample nypa (100-200 gram). The processing and data analysis were done using some software such as QGIS 2.18, Orfeo Toolbox / Monteverdi 1.24, ERDAS Imagine 9.1 and Microsoft Excel 2010.

2.3 Field Measurement and Data Processing

2.3.1 Field measurement

For comparison and accuracy assessment purposes as well as to obtain quantitative and qualitative information about the actual condition of vegetation in the field, then ground observation and measurement were performed. These field observations and measurements were conducted on four cluster plots having a size of 60 m x 100 m. Each cluster was divided into 15 sub clusters (cluster elements), having a size of 20 m x 20 m each. The position of the cluster was made in such a way so that its position relatively perpendicular to the river flow.

2.3.2 Pre-processing

Preprocessing of UAVs includes image cropping that fit the selected cluster locations. Cropping was done to facilitate the process of segmentation and classification. The size of the UAV image for each area of interest is 1100 x 1100 pixels or approximately 110 x 110 meters in size. The area of interest was selected to cover three classes namely mangrove, nypa and gap. Each cropping process of the area of interest (AOI) image was carried out by firstly removing the alpha band, so that the image only has a Red band, Green band, and Blue band.

2.3.3 Segmentation

Segmentation process is the initial step in object-based image classification (OBIA), where its classification algorithm was done by merging smaller segments into larger objects based on its homogeneity (i.e., a similarity of spectral value and spatial characteristics) of the image. The segmentation method used in this research is using a mean-shift algorithm of Orfeo Toolbox/Monteverdi 1.24. In this study, the segmentation approach used was based on spectral and spatial approaches. The mean-shift algorithm was first introduced by [26] and has been proven that this method is a versatile, non-parametric method for estimating gradients in the clustering process. Some research successfully implemented the method for

solving problems at low-level vision [27]. The parameters used in segmentation process using mean-shift algorithm are the spatial radius, range radius, and minimum region size. In this study, the authors examined 27 combinations of segmentation parameters to obtain segmentation information on canopy and gap of nypa vegetation at research location (Table 1).

Table 1. Combination of the parameter examined on the segmentation

No	Setting	hr	hs	M	Combination	No	Setting	hr	hs	M	Combination
1	Setting 01	5	10	50	5-10-50	15	Setting 15	10	20	150	10-20-150
2	Setting 02	5	10	100	5-10-100	16	Setting 16	10	30	50	10-30-50
3	Setting 03	5	10	150	5-10-150	17	Setting 17	10	30	100	10-30-100
4	Setting 04	5	20	50	5-20-50	18	Setting 18	10	30	150	10-30-150
5	Setting 05	5	20	100	5-20-100	19	Setting 19	15	10	50	15-10-50
6	Setting 06	5	20	150	5-20-150	20	Setting 20	15	10	100	15-10-100
7	Setting 07	5	30	50	5-30-50	21	Setting 21	15	10	150	15-10-150
8	Setting 08	5	30	100	5-30-100	22	Setting 22	15	20	50	15-20-50
9	Setting 09	5	30	150	5-30-150	23	Setting 23	15	20	100	15-20-100
10	Setting 10	10	10	50	10-10-50	24	Setting 24	15	20	150	15-20-150
11	Setting 11	10	10	100	10-10-100	25	Setting 25	15	30	50	15-30-50
12	Setting 12	10	10	150	10-10-150	26	Setting 26	15	30	100	15-30-100
13	Setting 13	10	20	50	10-20-50	27	Setting 27	15	30	150	15-30-150
14	Setting 14	10	20	100	10-20-100						

Remarks: hs : Spatial radius (pixel), hr : Range radius/spectral value (DN) and M : Minimum region size (pixel)

Spatial radius is a parameter that has a function to control the distance, measured by a number of pixels. The spatial radius will group a number of pixels into one segment or one object, whereas the range radius is a segmentation parameter that corresponds to the spectral value of each pixel. The range radius refers to spectral variability (distance in n-dimensional spatial space) to group a number of pixels into a single segment. Furthermore, it is also defined that the minimum region size (M) is a parameter related to the minimum size of the number of pixels that form a single object. Objects that have the number of pixels below the parameter value will be combined with the nearest object. After the parameter values are determined, the segmentation process is performed on all four research clusters. At the end process, since the segmentation was processed on the raster-formatted data, an output of the segmentation would also raster format. Finally, it is needed to convert raster data into a vector format.

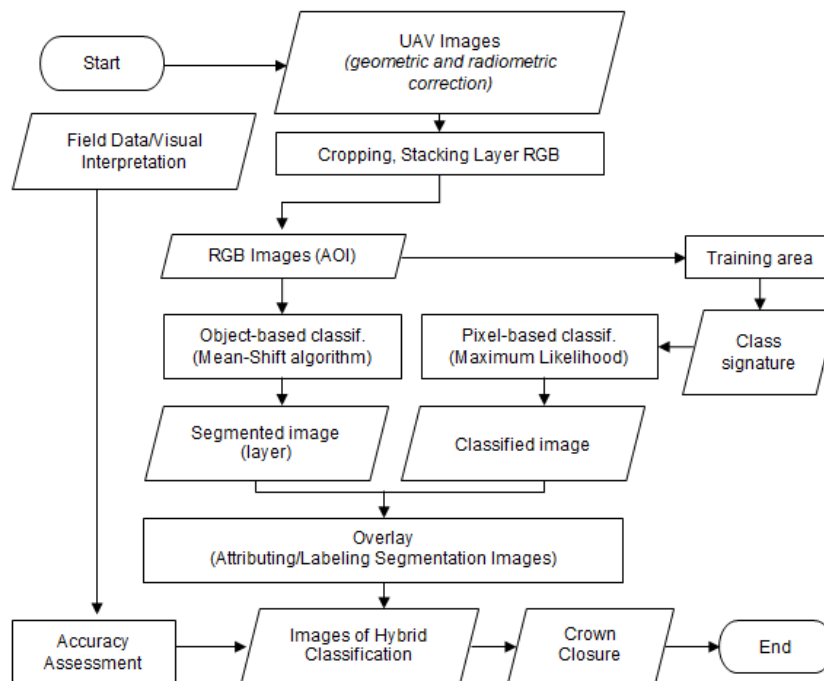


Figure 2. Flow diagram of the study process

2.3.4 Classification

In this study, the author applied the hybrid between the object-based (segmentation, OBIA) and pixel-based maximum likelihood classifier (MLC). The results of segmentation classification results of segmentation run using Orfeo Toolbox/Monteverdi was then incorporated with the results of supervised classification run using ERDAS imagine. During the classification using MLC, several classes were defined, namely nypa canopy, mangrove canopy, bare land, gap, and water body. The results of supervised classification have then used an attribute of each polygon obtained during segmentation. The classification step outlined in this study is depicted in Figure 2.

2.3.5 Accuracy Assessment

One of the important issues in determining the optimal segmentation is in the accuracy assessment. Although there are some method to assess the performance of segmentation such as fragmentation index [28], the area fit index [29] and there is also another method to evaluate the segmentation result using area, perimeter and shape index (SI) [30]. This study used a comparison between the segmentation results with reference area.

To identify the most accurate segmentation parameter for assessing the nypa crown closure and gaps, the conventional confusion matrix analysis was performed. The data reference used for expressing the actual crown closure and gaps derived is the data derived from visual interpretation and ground observation. The comparison between the automated classification (OBIA and MLC) was then used to calculate the overall accuracy (OA) and kappa accuracy as the follows [31].

$$OA = \left[\frac{\sum_{i=1}^f X_{ii}}{N} \times 100\% \right] \quad (1)$$

$$K = \frac{N \sum_{i=1}^f X_{ii} - \sum_{i=1}^f X_{i+} X_{+i}}{N^2 - \sum_{i=1}^f X_{i+} X_{+i}} \times 100\% \quad (2)$$

Remarks:

- OA : Overall accuracy (%)
- K : Kappa accuracy (%)
- X_{ii} : Coincided value (number of pixel)
- N : Total pixel
- K : Kappa accuracy (%)
- X_{i+} : The sum of column j
- X_{+i} : The sum of row i

2.3.6 Crown Closure

The results of the accuracy assessment for all combinations of the parameter setting were used to identify the optimal segmentation parameters. The best combination of segmentation parameter was then used to calculate the value of crown closure (Cc) of nypa in each cluster. Prior to any further process, the cluster was simulated into several plot forms according to the shape and size of the field plot. Selection of the most optimal plot size simulation was done by considering the coefficient of covariance (CV) value of the biomass, volume and nypa density variation. The percentage of crown closure is the ratio between total crown coverage (m^2) and plot size (m^2).

3. RESULTS AND ANALYSIS

The selection of the best segmentation parameters is done by evaluating the average value of overall accuracy (OA) and kappa accuracy (KA) for all four clusters. Recapitulation of accuracy values of OA and KA are summarized in Figure 3. The accuracy value was derived by comparing the segmentation and visual interpretation as well as field observation as reference data.

Of the 27 combinations of the segmentation parameter examined, we found that the relatively high accuracy in predicting the crown closure of nypa were provided by the setting-10 (10-10-50), setting-01 (5-10-50), setting-04 (5-20-50) and setting-19 (15-10-50) having overall accuracy between 76.5% and 76.6% and kappa accuracy between 55.6 and 55.7% (Figure 3). The classification accuracy obtained by applying the combination of mean-shift algorithm and pixel-based maximum likelihood classifier is slightly lower than the accuracy of the combination mean-shift algorithm and support vector machine (SVM) classification

examined by [25]. This is mis due to the size, shape and brightness value of the nypa vegetation more complicated than size, shape and brightness value of the building objects.

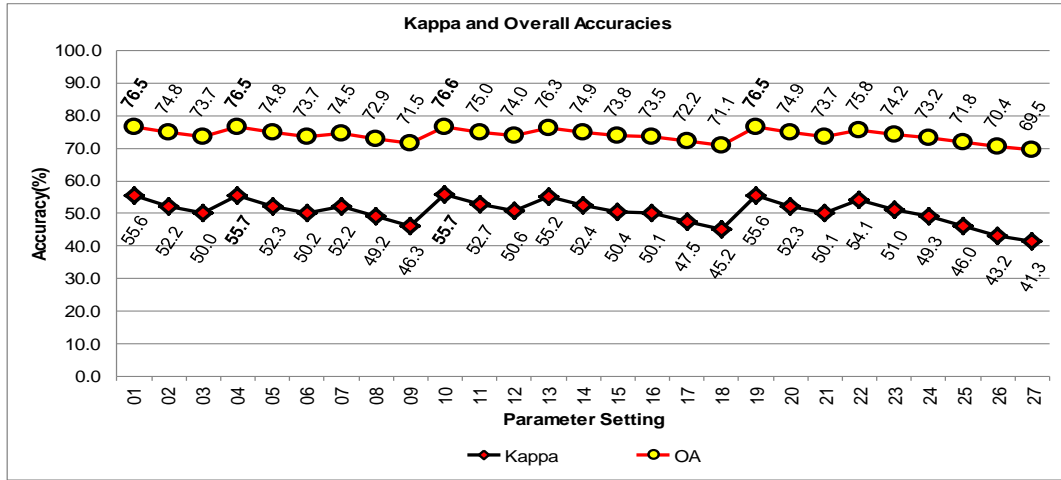


Figure 3. Overall and Kappa Accuracy for all combination of segmentation parameter

From these accuracy values, it is noted that the variation in the values of spatial radius and range radius does not provide a significant difference of accuracy (Figure 4). No significant difference in accuracy was obtained when the spatial radius was increased or decreased. Of all setting, it seems that the most accurate spatial radius parameter for predicting the crown closure is 10 pixels. When the spatial radius is changed to 15 then the accuracy decreased. From the range radius point of view, the increase of range radius from 10 to 20 causing the decline in OA from 76.6% to 76.3%, very tiny change (see setting-10 (10-10-50) and setting-13 (10-20-50)) (Figure 4b). The range radius differed significantly when it raised from 20 to 30 pixels (Figure 4b), causing a decrease of overall accuracy 2.8% and kappa accuracy of about 5.1%.

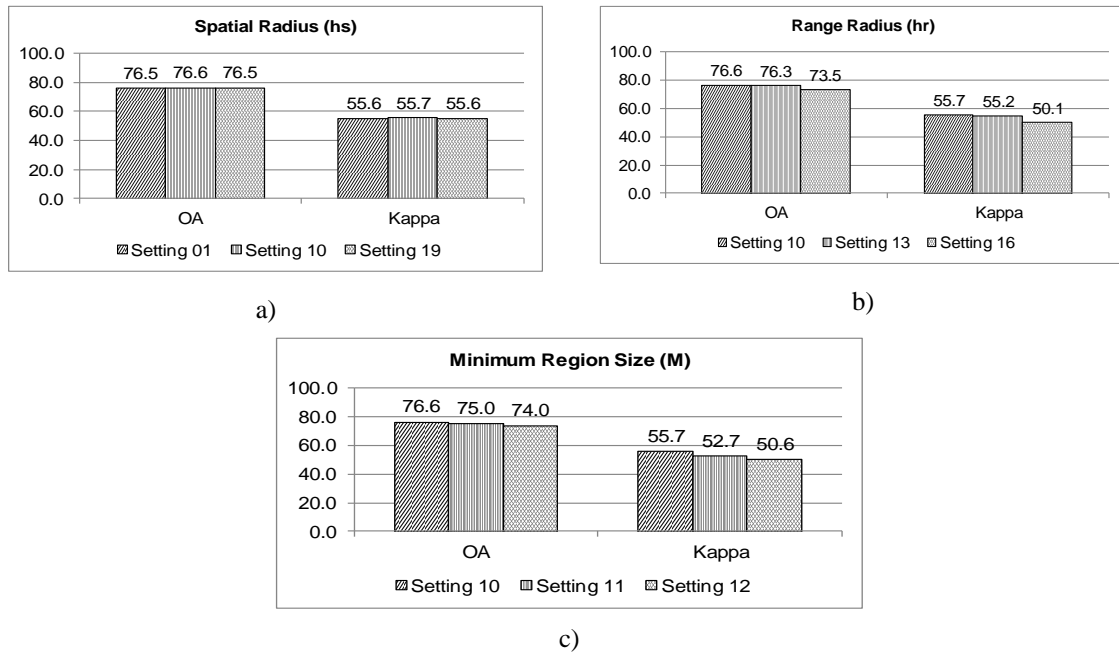
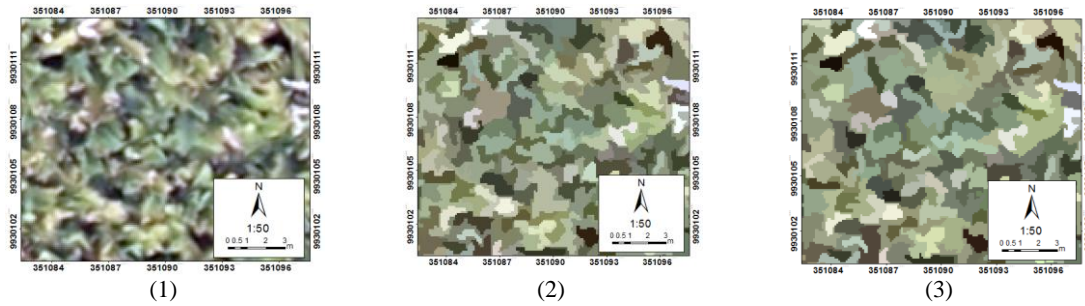


Figure 4. Overall and Kappa accuracy for all parameter

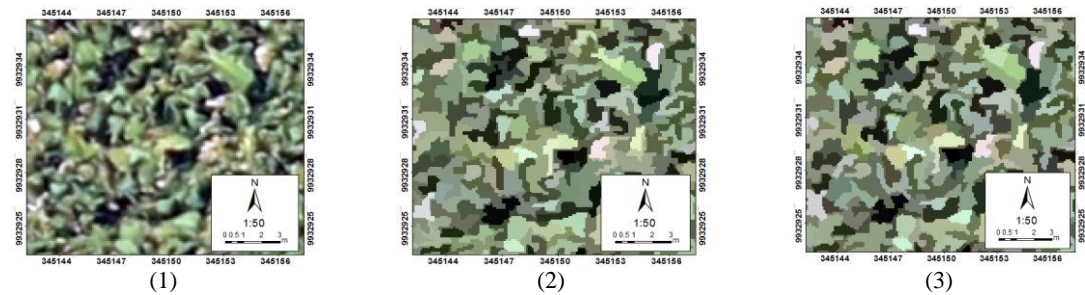
The third parameter we observed was the minimum region size (M). This M parameter determines the number of pixels that may compose a single segment (object). We set up the M size on the basis of the

individual diameter of nypa tree, that ranging from 0.5 m² ~ 1.5 m². These M values are from 50 to 150 pixels. The study found that the high accuracy settings are obtained from the value M of 50 pixels. The M having size more than 50 pixels reduce the overall accuracy. The minimum region size differed significantly when it raised to 100 pixels (Figure 4c), and causing a decrease of overall accuracy 2.6% and kappa accuracy 5.1%.

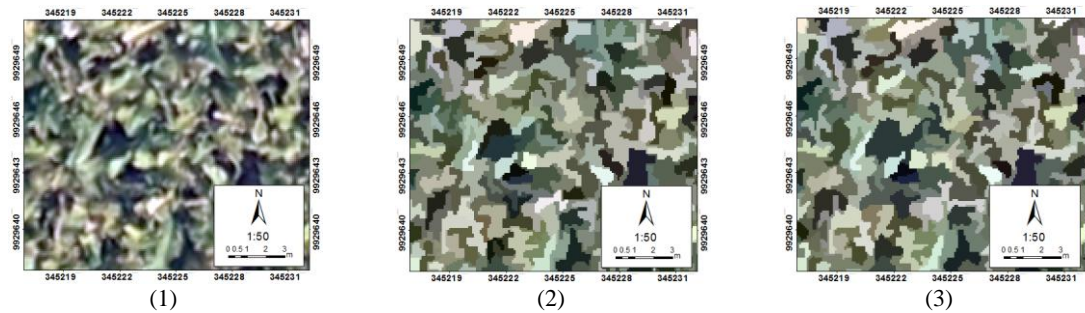
Among the three segmentation parameters evaluated, it is shown that the M is the most affecting parameters, larger than the spatial radius and range radius. This is in line with the study carried out by [27], expressing that spatial radius was less sensitive than the other segmentation parameter. The M is expressing the nypa size (crown coverage). The radius range which expresses the range of spectral is less sensitive in distinguishing the nypa leaves and gap. Thus it causes less significant in segmentation processes of the crown closure analysis of the nypa.



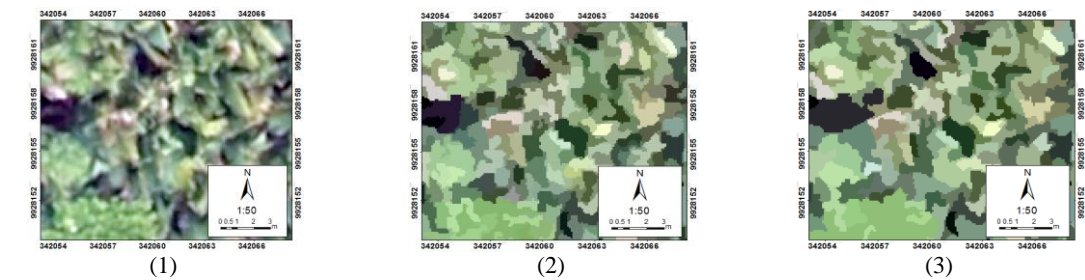
a) Cluster 1



b) Cluster 2



c) Cluster 3



d) Cluster 4

Figure 5. Comparison between sample of original image of the UAV (left column : 1) with segmentation results using setting-10 (middle column : 2) and the setting-04 (right column : 3) at cluster 1 (a) ~ cluster 4 (d).

To increase the accuracy of crown closure delineation, the authors also applied a pixel-based classifier that relies on its spectral signature. The segmentation result was then combined with the classification result obtained from the supervised classification. This is in line with the study of [20] for identification of benthic habitat. However, his finding provided a very low overall accuracy of only 27.7%. His study noted that low accuracy may be due to the gap from segmentation process when integrating photo-transect and cluster. Besides, the low accuracy may be due to the sample location that does not match with the object in the map.

The examination on the use of a pixel-based method to classify crown closure and the gap was also performed. However, the study results show that its ability to identify the object is still low. One of its drawbacks is in the labeling of objects, which is only based on the brightness value or color of the object, without considering the spatial aspects such as location, size, shape, texture, etc. The success or failure of pixel-based classification is solely determined by its brightness value. Thus, the quality of the object classification results depends on the quality of pixel-based qualification results. The difficulty in determining the spectral separation of a class also becomes a challenge in pixel-based classification particularly in using the high-resolution data. The low accuracy of using spectral range (radiometric) might be due to the image quality (blurring/image motion and low spectral resolution) [32, 33]. The image blurring due to the high image motion affect the ability of UAV image in identifying the object of interest [32, 33]. The presence of noise also reduces the accuracy of segmentation. In the very high-resolution imagery, it is quite common that the small size of gaps among trees, branches, twigs, and leaves causing “salt and pepper” noise. The other source of noise may come from the misregistration and geometric correction during pre-processing stage. Based on the best-selected parameter segmentation setting-10, the crown closure of nypa within the sampling plot are ranging from 38.4% to 61.6%.

4. CONCLUSION

From the foregoing results and discussions, this study concludes that the most optimal segmentation parameters in measuring the crown closure of nypa and gap is provided by the setting-10, which has 10 for spatial radius, 10 for range radius and 50 for minimum region size. The accuracy of this segmentation parameter combination provides approximately 76.6% of overall accuracy and 55.7% for kappa accuracy. This study also concluded that variation of minimum region size (M) contribute a significant variation in accuracy assessment, greater than another parameter spatial radius (hs) and range radius (hr). The classification technique by combining of pixel-based and object-based has given a promising result in delineating a very small feature within the nypa vegetation.

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