Object-based image analysis (OBIA) for mapping mangrove using Unmanned Aerial Vehicle (UAV) on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta Province

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Abstract. Tidung Kecil Island is a conservation and mangrove cultivation area. Therefore, the potential of mangrove ecosystems on Tidung Kecil Island will have a direct role in coastal ecosystems. Accurate mangrove mapping is necessary for the effective planning and management of ecosystems and resources because mangroves function as protectors of ecological systems. The utilization of remote sensing technology that is near *real-time* can be used as an alternative in providing spatial data effectively. Mapping earth's surface objects method is growing especially after the development of design, research, and production of flexible Unmanned Aerial Vehicle (UAV) platforms. The use of object-based classification methods is currently an alternative in classifying an object of the Earth's surface using both satellite and aerial photo imagery data (orthophoto) that has a high accuracy value. This research aim is to map object based mangrove ecosystems using UAV technology on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta. The K-NN algorithm result was a good classification with 81.081% overall accuracy (OA) at the optimum value of the MRS segmentation scale 300;0,1;0.7 and divided into two classes which are mangrove and non-mangrove for 0.381 ha and 20.912 ha respectively.

Keywords: accuracy, mangrove mapping, object-based, Tidung Kecil Island, UAV

1. Introduction

Mangroves are coastal ecosystems that have functions as protectors of ecological systems such as protection from abrasion, wind, and waves [1]. The characteristics of mangroves that can live on land and sea are one of the potentials in planning the management of coastal areas to support the economy [2-3]. Tidung Kecil Island itself is a conservation and mangrove cultivation area. Therefore, the potential of mangrove ecosystems on Tidung Kecil Island will have a direct role in coastal ecosystems. There are 18 species of mangroves with *Rhizophora stylosa*, and the level of mangrove diversity is relatively low compared to other vegetation [4]. However, the function of mangroves located on Tidung Kecil Island directly impacts the balance of the ecosystem.

Accurate mapping techniques are needed effectively to monitor and manage mangrove resources. Conventional field surveys will take a long time and cost a lot of money so the usage of remote sensing technology that is near-real-time is an alternative in providing spatial data effectively [5]. The utilization of remote sensing technology for mapping earth's surface objects is growing, especially after the development of the design, research, and production of Unmanned Aerial Vehicle (UAV) platforms. Remote sensing with satellites has a variety of sensors with spectral resolution from medium (multispectral) to high (hyperspectral), unlike UAV because generally UAV sensors have the spectral resolution that is still relatively low, but this is balanced with the UAV's ability to produce very high spatial resolution data compared to satellite imagery [6]. Using UAV technology can produce images with a spatial resolution of less than 5 cm compared to high spatial resolution satellite imagery at only 50 cm [7]. The use of UAV is also more flexible and faster data acquisition processed [8] and can be done anytime and anywhere following the wishes and data needs of UAV users themselves, while the needs of satellite imagery data cannot be adjusted to the needs of the image data users.

UAV technology has been widely used in small-scale forest inventory with benefits, low cost, and high flexibility [9]. The very high spatial resolution imagery derived from the UAV system has the potential to identify mangrove species [10]. Identifying mangroves using high spatial resolution satellite imagery cost more financial needs than UAV images [11].

The usage of satellite imagery or aerial photo imagery to map coastal ecosystems is certainly inseparable from the process of classification or digital analysis of the image. In general, digital analysis of remote sensing data has two approaches: pixel-based and object-based [6]. The use of object-based classification methods is currently an alternative in classifying an object of the Earth's surface using both satellite and aerial photo imagery data (orthophoto) that has a relatively higher accuracy rate than pixel-based [12].

There are many chances to develop a management system using this technology-based, especially on mangrove ecosystems. The usage of remote sensing technology, especially UAV, is one of the solutions that are needed to improve it. This research aim is to map mangrove ecosystems using UAV technology.

2. Material and methodology

2.1. Location

This study was conducted on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta Province which was conducted from June 12 - July 27, 2021. Geographically, Tidung Kecil Island are located 5°48'5.69"S - 5°48'16.90"S and 106°30'57.62"E - 106°31'48.58"E (Figure 1).

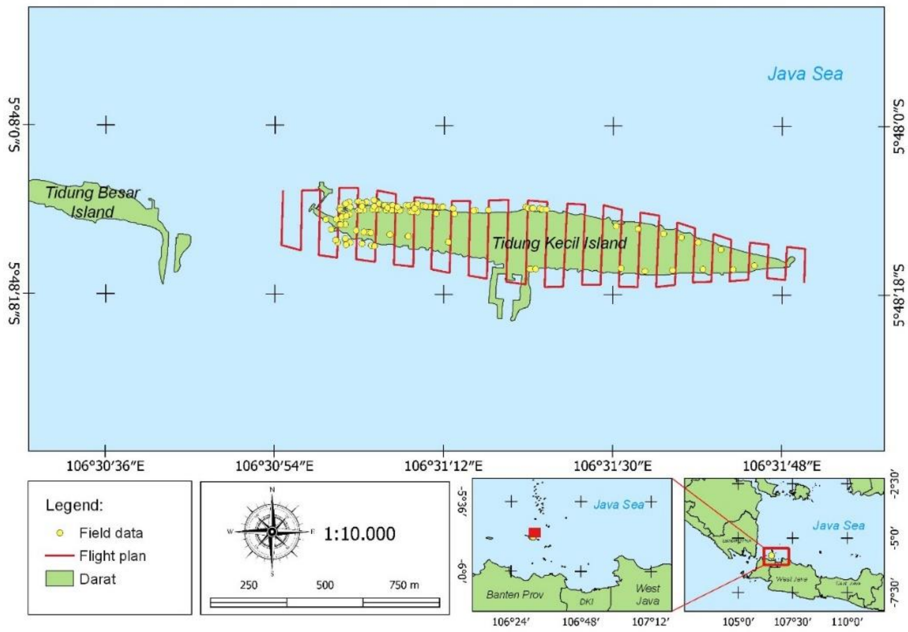

Figure 1. Study area location on Tidung Kecil Island.

2.2. Data source
In this study, field observations were made on mangrove land cover using UAV and it took numbers of Ground Control Points (GCP). Land cover data retrieval using UAV technology, the UAV product is DJI Mavic 2 Pro. The UAV data acquisition is carried out at an altitude of 150 m and side lap and front lap arrangements are 70% each. There are 116 GCP used with 82 GCP for training data and 34 GCP for validation data.

2.3. Data processing
2.3.1. Data preparation (orthophoto)
At this stage, aerial photography is acquired using combined UAV images resulting in a single photo/orthophoto image using Agisoft Metashape software. There are several stages of the processing carried out sequentially to produce an image, namely: (1) Add photo; (2) Align photo; (3) Optimize camera alignment; (4) Build dense cloud; (5) Build mesh; (6) Build texture; (7) building Orthomosaic; and (8) Orthomosaic export.

2.3.2. Segmentation
The segmentation process uses multiresolution segmentation (MRS) and chessboard segmentation (CS) algorithms. MRS is an optimization procedure by grouping objects using certain parameters, it has three important parameters: scale, shape, and compactness. Shape regulates the spectral homogeneity and object shape related to digital values affected by color. Compactness plays a role in balancing or optimizing the compactness and smoothness of the objects to determine smooth borders and compact edges. Scale manages the size of objects that can be adjusted to the user's needs based on the level of detail. The values used in shape and compactness parameters range from 0 to 1, while scale values are an abstraction in determining the maximum value of heterogeneity to evoke an object. Therefore, there is no standard provision regarding typical parameter values in object-based classifications [13-14].

2.3.3. Classification
The classification process by the OBIA method uses objects/segments built into the image segmentation process, which are then classified based on a predefined classification scheme. The classification on each level used several algorithms to build a rule set, the usage of it is customized depending on user needs to classify objects in certain classes [13]. The concept of multiscale classification built into this study consists of 2 levels of image objects, namely level 1 and level 2. In this study, the classification at level 1 is to use an assigned class with the application of certain value limits (threshold) to produce the class of objects following what is desired. Threshold values are obtained through trial and error to find optimum values. In level 2 classification, it uses a classifier with the application of the K-Nearest Neighbor (K-NN) algorithm with thematic layer input or training area of field data to classify mangrove classes. Mathematically it can be written with the following equation [15].

$$D(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_n - q_n)^2} \tag{1}$$

$D(p,q)$: new object characteristic value
p & q : objects compared
n : number of nearby objects

2.3.4. Accuracy test
Mangrove land cover classification is validated using the error matrix. Accuracy test using the confusion matrix [16] which consists of overall accuracy (OA), producer (PA), user accuracy (UA), and Kappa statistics. For OA, PA and UA mathematically it can be written with the following equation:

$$Producer\ Accuracy\ (PA) = \frac{n_{ij}}{n_{+j}} x\ 100\% \tag{2}$$

$$User's\ Accuracy\ (UA) = \frac{n_{ij}}{n_{i+}} x\ 100\% \tag{3}$$

$$Overall\ Accuracy\ (OA) = \frac{\sum_i^k n_{ij}}{n} x\ 100\% \quad (4)$$

Kappa statistics are the accuracy evaluation values generated by the error matrix and can be mathematically written as follows [16]:

$$Kappa = \frac{n \sum_i^k n_{ij} - \sum_i^k (n_{i+}\, n_{+j})}{n^2 - \sum_i^k (n_{i+}\, n_{+j})} \quad (5)$$

n_{ij} : appropriately classified values
n_{+j} : number of classified values in the field class column
n_{i+} : number of classified grades on the image class row
n : number of observations
$\sum_i^k n_{ij}$: the exact number of classified values
$\sum_i^k (n_{i+}\, n_{+j})$: number of multiplication values classified on image class rows with classified values in field class columns

3. Results and discussion

3.1. Classification scheme
Based on 348 photos of observations in the field produced by UAV (Figure 2), the scheme was produced as many as two classes of level 1 and same as level 2 that has two other vegetation classes, namely: Level 1 (Vegetation (V) and Non-Vegetation/Water(A)) and Level 2 (Mangrove (M) and Non-Mangrove (NM)).

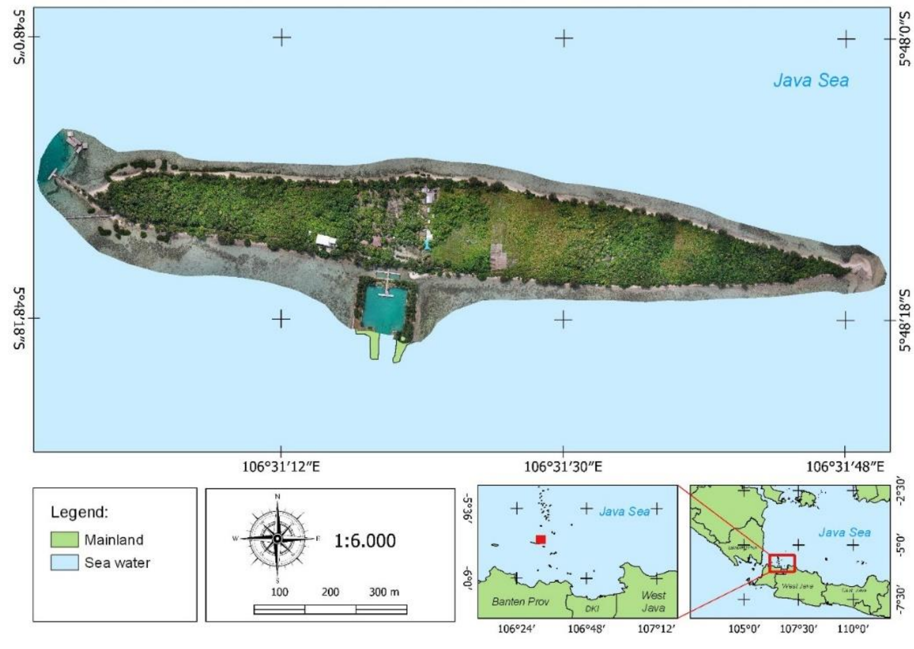

Figure 2. UAV Mosaic Imagery on Tidung Kecil Island.

3.2. Classification
As can be seen in Figure 3, the results of the level 1 classification are divided into two classes, namely the vegetation and non-vegetation classes, where water is also included in the non-vegetation class. The result of level 2 classification can be seen in Figure 4. Level 2 classification divides vegetation class only that been classified before. In level 2 classification vegetation class will be divided into two other

classes, which are mangrove and non-mangrove classes. It can be seen the difference between mangrove and non-mangrove in that image.

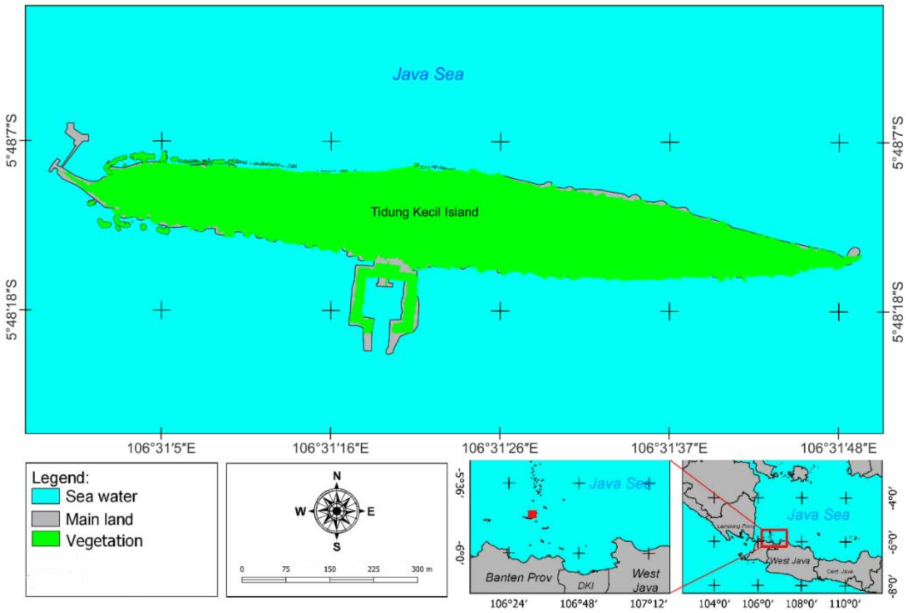

Figure 3. Vegetation and Non-Vegetation Classification (Level-1).

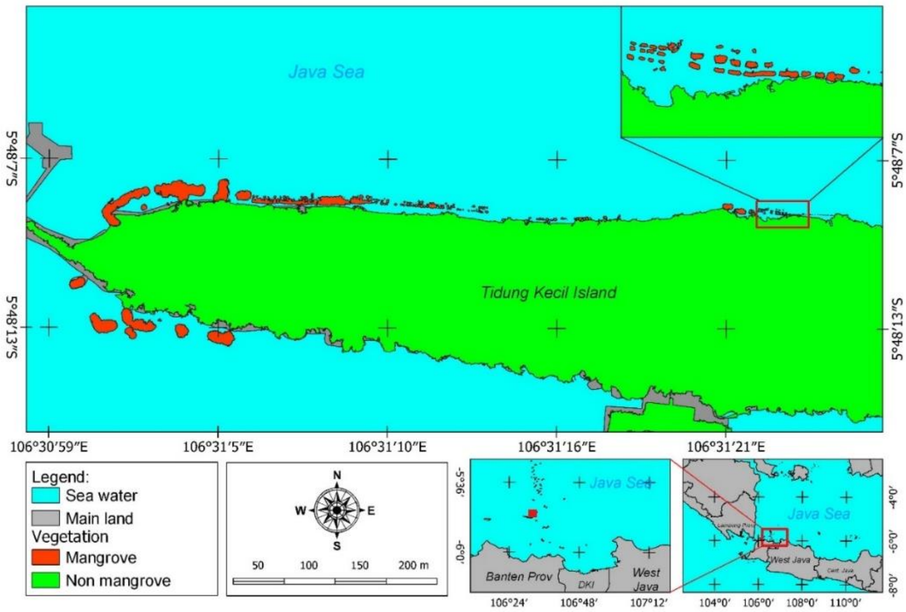

Figure 4. Mangrove and Non-Mangrove Classification (Level-2).

The relationship between the scale parameters, the number of objects, and the resulting accuracy is presented in Figure 5. It is seen that the size of the scale greatly affects the number of objects produced. The larger the value of the specified scale the less the number of objects produced. While the overall accuracy of object-based classification using K-NN algorithms is influenced by segmentation parameters. Based on Figure 5, the segmentation optimization process will result in optimum accuracy. The scale of 200 to 300 results of accuracy increases with the increase in the value of the scale applied. The optimum accuracy of segmentation obtained is 81.081% with a scale value of 300, shape 0.1, and compactness of 0.7. The segmentation parameters value on UAV imagery with scale 250–350, shape 0.1, and compactness 0.5–0.9. Segmentation parameter values are obtained based on trial and error and there are no absolute values [17]. The application of segmentation scale optimization in the process of object-based mangrove land cover classification using the K-NN classification algorithm produces 81,081% overall accuracy (OA) divided into two classes which are mangrove and non-mangrove for 0.381 ha and 20.912 ha respectively.

Mangroves can be mapped/separated by the land cover class around mangroves with high user accuracy (UA) and producer accuracy (PA). UA and PA in successive mangrove classifications were 72.22% and 86.67%. The kappa value of the classification is 0.62 (good category), based on the kappa value it shows that the applied classification result is significantly different (see Table 1). Kappa values indicate the level of relationship between field data and significant processing data [18]. Based on the OA value and significance test also refers to the standardization, the mangrove classification accuracy has been very satisfactory and this study showed the UAV accuracy is better than satellite imagery classification. Another study showed that the usage of high spatial resolution satellite such as Worldview-2 satellite imagery with the same classification method and algorithm resulting 69.56% OA [19] and the usage of low-resolution satellite imagery such as Landsat 5 TM and Landsat 8 OLI with the 30-meter spatial resolution resulting 60.71% OA [20].

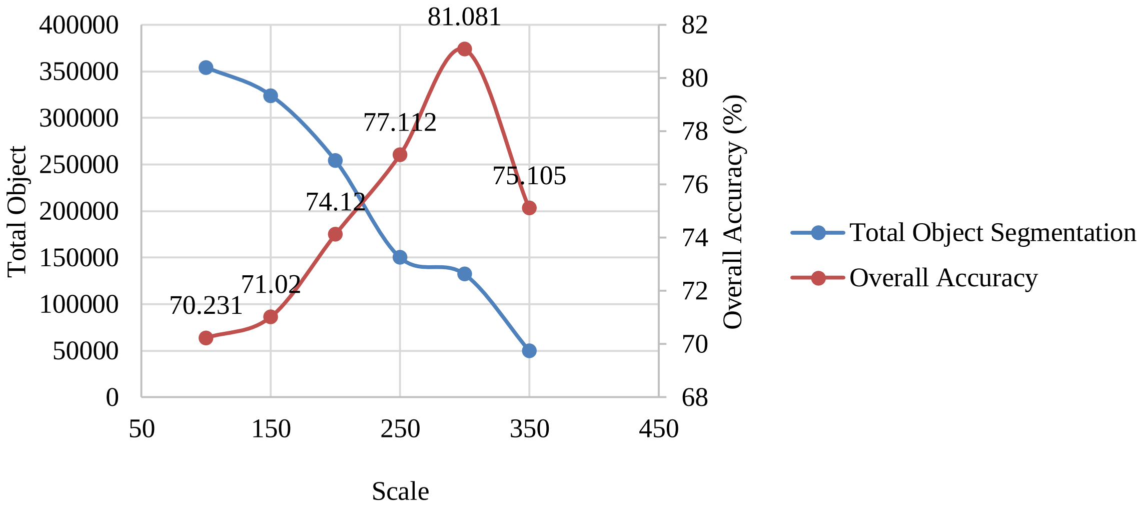

Figure 5. Effect of the segmentation optimization process.

Table 1. The accuracy of mangrove classification.

Class	Producer Accuracy (PA) %	User Accuracy (UA) %	Producer Accuracy (PA) (Pixels)	User Accuracy (UA) (Pixels)
Mangrove	86.67	72.22	13/15	13/18
Non Mangrove	77.27	89.47	17/22	17/19
Overall Accuracy		81.08 %		
Kappa		0.62		

4. Conclusion
The utilization of UAV technology and object-based image analysis can be used to determine mangrove and non-mangrove on Tidung Kecil Island, Kepulauan Seribu, DKI Jakarta Province. A High value of

overall accuracy (OA) for about 81.081% shows that this method is very useful and proved as one of the best options in mangrove mapping.

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