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RESEARCH ARTICLE

Object-Based Mangrove Mapping Comparison on Visible and NIR UAV Sensor

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Abstract. Mangrove ecosystems are natural resources that have potential value for development due to their high productivity. Mapping and identification of mangroves have always played a crucial role in mangrove ecosystem conservation efforts, especially to support the sustainable development goal of coastal resources and climate change issues. Several attempts have been made using Unmanned Aerial Vehicle (UAV) techniques acquisition of high spatial resolution aerial images data with various sensors and object-based classification for image processing with various levels of success. This study aims to identify mangrove objects using UAV with true color and NIR false-color sensors using the OBIA approach. The UAV used in this study was DJI Phantom 3 Pro with a true-color sensor (default) and NIR false-color (modified Canon IXUS 160 cameras). The comparison between the two types of sensor of aerial photographs as a source for mangrove mapping proved that the latter performed better than the former because of the near-infrared band can optimally discriminate between mangrove and non-mangrove objects. This will assist future research directions in the mangrove ecosystems mapping method.

1. Introduction

Mangrove forests are one of the ecosystems that have high productivity and play an important role in ecological, environmental, biological, and economic aspects around coastal areas. (Ibharim, et al., 2015). This ecosystem has essential environmental services that are very important including protection of coastal areas from ocean currents and winds, providing habitat and spawning grounds for marine organisms, maintaining the quality of coastal waters, and tourism (Green et al., 1998; Kamal et al. al., 2016). Mangrove forests can also generate enormous economic value through the use of habitats as a medium for aquaculture for various kinds of marine biodiversity, including fish, crabs, shrimp, and other marine fauna (Nagelkerken et al., 2008). Indonesia is one country with highly abundant mangrove forests in the world (Nehren and Wicaksono, 2018). This makes Indonesia as one of the countries that have a major role and contribution in addressing the issue of blue carbon storage that can support the realization of sustainable development goals related to coastal resources as well as climate change (Duncan et al., 2016). This shows that it is very important to provide up-to-date and accurate information about mangroves (Buditama, 2016).

The warning status of global mangrove forest degradation requires a cost-effective and accurate method for obtaining mangrove information (Nehren and Wicaksono, 2018). The latest technological developments of Unmanned Aerial Vehicle (UAV) aerial mapping, allowing a more flexible data acquisition, detailed, accurate, and up-to-date (Wang, et al., 2019). This technology has been widely used in the last two decades and can support the remote sensing images' work performance, which produces a limited information scale for monitoring environmental conditions (Matasci et al., 2018). UAV can also be applied with a variety of sensors that can support more accurate mangrove information acquisition, including true color, multispectral, hyperspectral, LiDAR, microwave, and thermal data sensors, with very high spatial resolution and more flexible data acquisition periods (Bhardwaj et al., 2016). This technology is more flexible and controllable than remote sensing satellite imagery in terms of flying altitude, viewing angle, acquisition time and the percentage of overlap (Candiago et al., 2015). This technology has also been used and has different success rates for species identification (Cao et al., 2018), tree height estimation (Panagiotidis et al. 2017), leaf area index (LAI) estimation (Yao et al. 2017), vegetation density (Jin et al. 2017) and other relevant studies.

To obtain mangrove information systematically, the use of different sensors will produce different information, so that the selection of the best sensor for mangrove identification will give optimal results (Zimudzi et al., 2019). The use of modified Near-Infrared (NIR) sensors is very helpful in identifying mangroves because they have a unique spectral response from the other coastal vegetation types (Jensen, 2007; Bendig et al., 2015; Ballari et al., 2016). The use of this sensor is very effective because it can support the results obtained from the default UAV (true color) sensor

(Ballari et al., 2016; Khakhim et al., 2020). Pixel and object-based classification methods have been frequently used in mapping applications (Tian et al., 2017; Cao et al., 2018). The use of the pixel-based classification is often applied at medium to small satellite images spatial resolution with a high spectral resolution and gives optimal results. Implementing pixel-based classification in very high spatial resolution imagery, especially UAVs, presents a complex challenge. That is, the quality of the predicted results will decrease when the spatial resolution is high, the dimensions of very detailed aerial photographs require longer computation time, and the UAV has limited spectral resolution that is the less optimal result when using pixel-based classification (Zimudzi et al., 2019). In this context, object-based image classification (OBIA) has better performance than pixel-based classification (Blaschke et al., 2014). Object-based classification has received great attention for more efficient object identification, especially mangroves (Cao et al., 2018). Several previous relevant studies concluded that OBIA is a classification method that has a very good performance in mangrove identification (Kamal et al. 2014; Ma et al., 2017; Cao et al., 2018).

The main objective of this research is to assess the ability of the NIR sensor modified by a standard camera for mangrove-non-mangrove mapping using the OBIA method. In this study, the UAVs used were operated with two different sensors. The first sensor is a standard UAV camera (DJI Phantom 3 Pro) with a true-color sensor, while the second sensor uses a modified NIR camera that produces false colors aerial photos. This is important to do because it can answer the challenges related to the comparison of the performance of the two sensors in providing better results. Thus, this research hopefully can contribute to the academic fundamentals, on the use of UAV technology and NIR sensors for accurate and detailed information acquisition of mangroves.

Baros is one of the coastal conservation areas of the Special Region of Yogyakarta (DIY) which has a high potential for mangrove ecosystems (Figure 1). The Mangrove area in Baros, Kretek, Bantul Regency is dominated by Rhizophora *sp.* and Avicennia *sp.* This ecosystem is quite developed, due to the mangrove planting program support by the local community. Until now, the mangrove ecosystems development has formed a habitat with high biodiversity. Several living things that use mangroves as a habitat, such as, mangrove crabs, types of shellfish, birds, snakes, fish, and so on can be found in this ecosystem. Improvement of environmental conservation programs, making the Baros mangrove ecosystem used as ecotourism for the education and environmental preservation benefits. Currently, the Baros mangrove ecosystem is experiencing environmental pressure due to human activities, which seriously threatens the mangroves ecosystem existence. The threat is sand mining at beach ridges which serves as a barrier to protect the stability of the mangrove substrate and protect coastal areas. Therefore, mangrove mapping in Baros is very necessary to evaluate the status of mangrove forest cover against environmental pressures.

2. Methods

This study used object-based classification (OBIA) to identify mangroves using true-color and NIR false-colour aerial images. OBIA has received extensive attention lately for the processing of images for object identification and can provide high accuracy maps (Zimudzi et al., 2019). Several previous studies have concluded that OBIA has better performance than pixel-based classification (Kamal et al., 2014; Cao et al., 2018). OBIA is a classification method that groups pixels in an image based on their spatial patterns into segments that represent geographical objects in the field (Blaschke et al., 2014). It allows the outcome of the

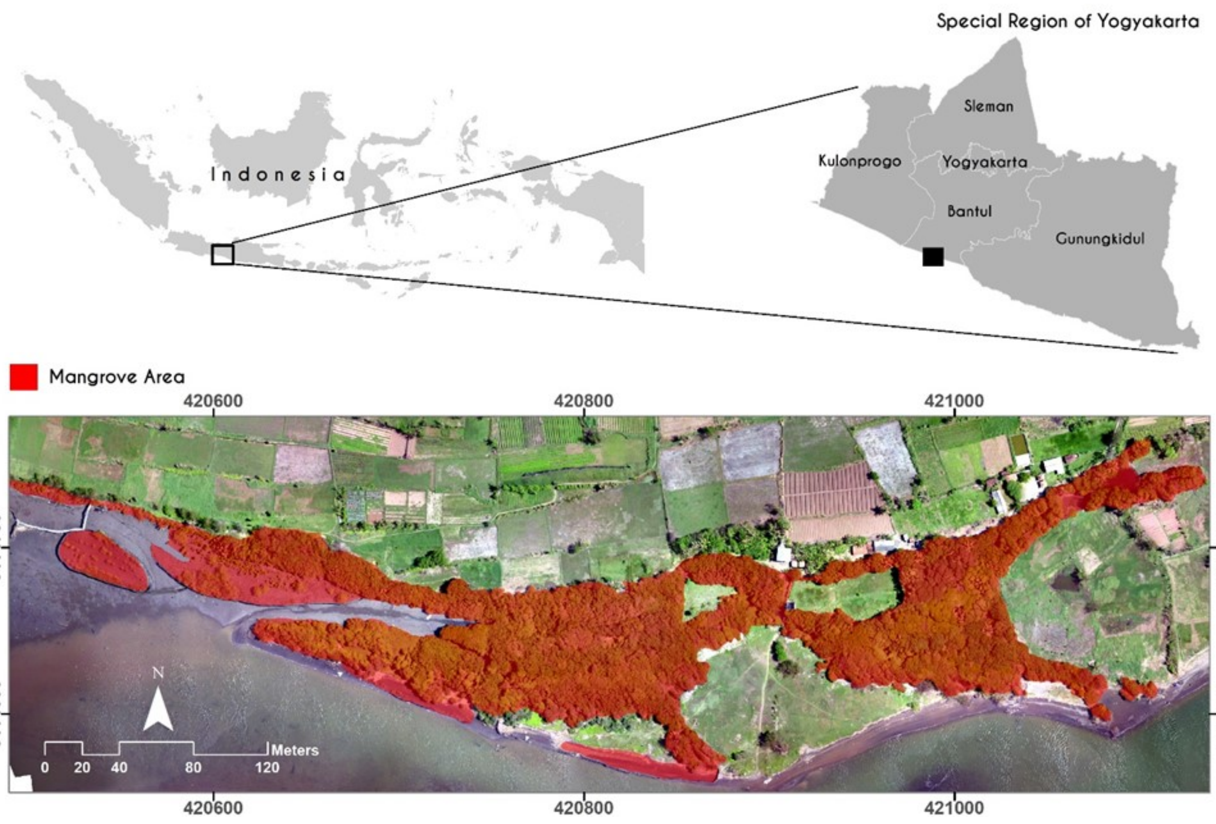

Figure 1. Baros Mangrove Conservation Area.

classification to have the smallest mapping unit in the form of a geographical mapping object and, accordingly, the results have the most likeliness to the original conditions on the field.

DJI Phantom 3 Pro built-in camera is used for true color photos and a modified Canon IXUS 160 for a false-color photo. DJI Phantom 3 Pro camera has Sony EXMOR 1/2.3" CMOS sensor with 6.16 x 4.62 mm in size, 12.4 megapixels, FOV 94° 20mm lens with f/2.8, and 4 mm focal length. Canon IXUS 160 has Canon 1/2.3" CCD sensor with 6.17 x 4.55 mm in size, 20 megapixels, 28 mm lens with f/3.2 – f/6.9, and 5 mm focal length. Gam Color 890 Dark Sky Blue is used to substitute the infrared-blocking filter on Canon IXUS 160, which has a size of 6.17 x 4.55 mm to fit with Canon IXUS 160 sensor size. Photos of both cameras use the same altitude and are taken almost at the same time for aerial photography, which is 100 meters and around 08.00 a.m.

The results of the classification of the two aerial photographs were then calculated using the segmentation accuracy-test introduced by Clinton et al. (2010). This test uses the principle of comparing the generated segments with reference polygons that are considered correct. The reference polygons were created using manual digitization. Afterward, both segmented polygons and reference polygons were overlaid to compute the two parameters in the segmentation accuracy test, namely Area Fit Index (AFI) and shape similarity (D), using the following equation. The research method is depicted in the flowchart below (Figure 2).

$$AFI = \frac{segment - reference}{segment} \quad (1)$$

$$D = \sqrt{\frac{\left(1 - \frac{(segment \cap reference)}{segment}\right)^2 + \left(1 - \frac{(segment \cap reference)}{reference}\right)^2}{2}} \quad (2)$$

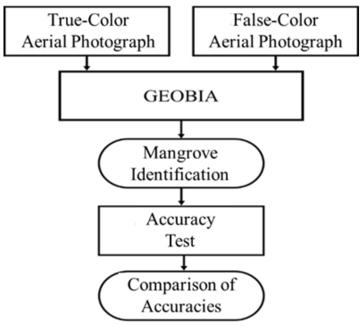

Figure 2. The method flowchart

3. Result and Discussion

The classification using OBIA divided the objects into two classes, namely mangrove and non-mangrove. The non-mangrove class was ignored because the research focused on mangroves. The images below show the appearance of the true-color and false-color aerial photographs and the results of mangrove identification using each photograph (Figure 3). The results of the identification showed that both aerial photographs successfully distinguished mangroves and non-mangrove objects. In general, both objects nearly have the same appearance. However, the identification results of the false-color aerial photograph are smoother than the true color. This is because non-vegetation objects are easier to distinguish in the near-infrared band compared to vegetation objects, in this case, is mangroves. The near-infrared band has characteristics of high spectral response in vegetation objects, low in soil objects, and very low in water bodies (Ballari et al., 2016). The high spectral response to vegetations is caused by the spongy tissues on the leaves, which reflect the infrared waves that they receive at a high intensity (Roy, 1989). Spectral properties of mangroves are not only influenced by the chlorophyll content but also the prevailing environmental condition and background reflectance of soil and water (Kannan and Kumar, 2008).

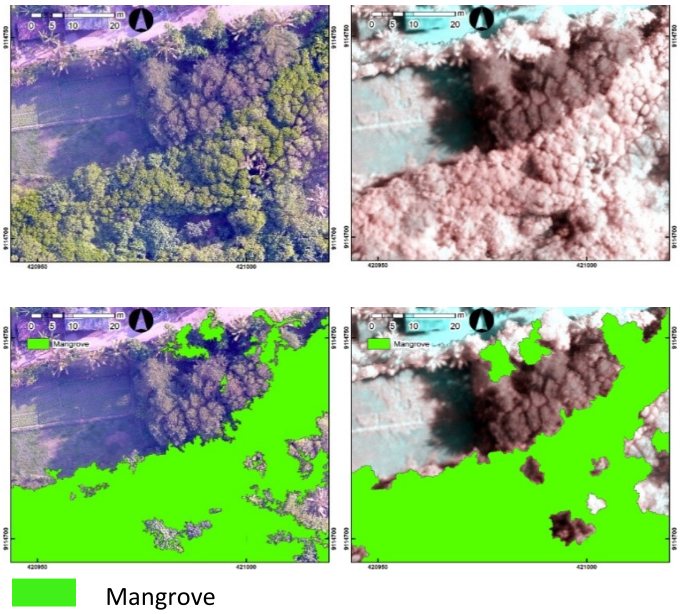

Figure 3. The aerial photographs of part of the Baros Mangrove Conservation Area and the Mangrove objects were identified using OBIA. On the left side are true-color aerial photographs, while on the right are false-color aerial photographs

Another factor is the difference in the quality of sharpness on the image produced (Gilbertson et al., 2017). The modified cameras have a weakness; that is, they tend to be more difficult to achieve focus. It makes the false-color aerial photography was not as sharp as the true-color one, even though both techniques have the same spatial resolution, 3 cm. The difference in image quality is also caused by the difference in the camera sensor. DJI Phantom 3 Pro with a built-in camera and Sony EXMOR 1/2.7" CMOS sensor (DJI, 2017) was used for a true-color aerial photograph and a modified Canon IXUS 160 camera with Canon 1/2.3" CCD (Canon Inc., 2015) sensor was used for a false-color aerial photograph. Most of digital camera sensor is sensitive to a wavelength between 350 nm and 1100 nm, which includes visible and near-infrared wavelengths (Brooker, 2009). A filter is used to block infrared wavelength so the camera can only produce a photo in the visible wavelength, which is between 400 nm and 700 nm. This filter needs to be removed or substituted so the sensor can also capture near-infrared wavelength. The filter that is used as a substitute for the infrared-blocking filter is Gam Color 890 Dark Sky Blue filter. This filter uses a deep-dyed polyester base as its material and can pass blue wavelength with a range of 380 nm to 520 nm and infrared more than 680 nm (Rosco, 2013). The results of the identification were tested for accuracy based on the results of manual digitization which are considered correct. The digitization process is carried out after the aerial photos were taken, in which the actual field conditions are known during the photo was taken. So that distinguishing between mangrove and non-mangrove can be done properly without having to do a field test again. The digitization results were used as ground-truth for accuracy assessment of mangrove OBIA results from true- and false-color photos. The images below are the results of manual mangrove digitization, which were used as a reference. (Figure 4).

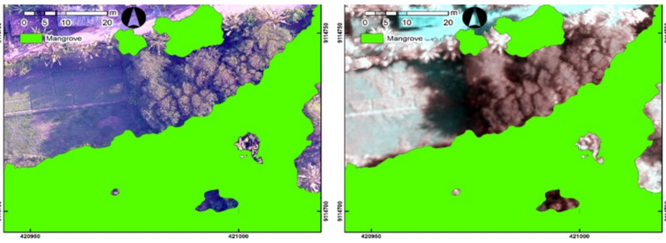

Figure 4. The results of manual digitization on mangrove objects that are used as a reference

The calculation process used the formula introduced by Clinton et al. (2010) which later produced the values presented in Table 1.

Table 1. Accuracy Test Results of the Object Based Mangrove Identifaication

Aerial Photos	AFI	D
True Color	-0.087	0.140
False Color	-0.07	0.126

Judging from the AFI values, the classification results of the two photos turned out to be under segmentation. It means that the identified mangroves are narrower than the ones in the reference. However, the AFI value of the true color is lower than the false color, or in other words, the identification results of the former are more under-segmented than the latter. The D values show the similarity level to the object of reference. The 0 value denotes a perfect value, which signifies that the identification results using OBIA are the same as the reference. The D value of the false color is closer to 0 than that of the true color. It means that the OBIA of the false-color aerial photographs likely results in a more accurate mangrove identification than that of the true color.

The results show that both types of cameras can be used to identify mangroves properly. Although the photos from the modified false-color camera is not as sharp as the built-in UAV true-color camera, but able to provide better performance in distinguishing mangrove from non-mangrove. This allows th use of a modified camera to be used in false-color aerial photography at a more affordable cost compared to using a camera that is specifically made for false -color photography. This modified camera can also be used for other things, such as the classification of plant species and estimating carbon stocks. Much needs to be explored again so that false color can be used for further perspective.

4. Conclusion

Mangrove objects can be identified using GEOBIA from both true- and false-color aerial photographs. The Area Fit Index (AFI) and shape similarity (D) of the identified mangrove objects on the former were -0.087 and 0.140, while the ones on the latter were -0.07 and 0.126. These figures show that the false-color aerial photographs produce better identification of mangrove objects than the true-color ones.

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