Mangrove land cover classification using unmanned aerial vehicles in Jailolo Bay, West Halmahera, Indonesia

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Abstract. Coastal environment remote sensing and geographic information systems (GIS) technologies are currently developing rapidly. Both of these technologies can be used to determine near real time conditions of coastal ecosystems. One method used for coastal ecosystem mapping is aerial photomapping by using unmanned aerial vehicles (UAV) or commonly known as drones. Remote sensing techniques are known to be fast and efficient for monitoring mangrove ecosystems when compared to conventional field observations, which are expensive, time consuming, and sometimes unachievable due to poor accessibility of mangrove areas. This study aimed to investigate the ability of drone aerial photography to classify mangrove land cover using an object-based approach in Jailolo Bay, North Maluku Province, and to analyze the accuracy of land cover mapping resulted. Mangrove ecosystem classification carried out using the nearest neighbor (NN) algorithm was able to identify 7 classes of mangrove land covers. The classification accuracy obtained was very high and the mangrove classes could be accurately mapped.
Key Words: aerial photo, drone, mapping, North Maluku, vegetation.

Introduction. Coastal area ecosystems are experiencing dynamic environmental changes. Key ecosystems in Indonesia's coastal areas include mangroves, seagrass beds, estuaries, coral reefs, and seaweed beds. Mangrove forests are important ecosystems and environmental buffers for coastal areas. Mangroves are woody plants that are tolerant of salt water of vegetation consisting of seedlings, trees and shrubs that can grow and develop on tropical and subtropical intertidal areas relatively protected from strong waves (Wang et al 2019).

Mangroves live on land – sea interface zones. These ecosystems are sensitive not only to changes in the physical environment but also to anthropogenic processes of urbanization and economic development (Meijer et al 2021). Increasing community knowledge and understanding can be a viable option in mangrove protection related to climate change (Nining et al 2021). In order for mangrove ecosystem to remain sustainable, development activities around mangrove forest areas need to be accompanied by efforts to conserve, rehabilitate, and even restore damaged areas.

Remote sensing and geographic information systems (GIS) technologies are developing rapidly nowadays (Nugroho & Al-Sanjary 2018). Both of these technologies can be used to determine near real time condition of coastal ecosystems. One of the methods used to obtain this imagery is by using an unmanned aerial vehicle (UAV) or commonly known as a drone. UAV is an aircraft equipped with a flight control system through precision global positioning system (GPS) waves and electronic controls so that it can fly according to the flight plan made by the drone pilot. This allows the UAV to obtain high-resolution spatial data (Muliady & Subagya 2019). Drone aerial photography technology is supported by special software that can be adapted to a specific area or ecosystem. High resolution aerial photography provides many advantages because it can help survey activities in difficult areas (Colomina & Molina 2014).

Remote sensing techniques are known to be fast and efficient for monitoring mangrove ecosystems when compared to conventional field observations, which are expensive, time consuming, and sometimes impossible due to the poor accessibility of mangrove areas. Multispectral sensors on satellite platforms such as Landsat-TM and SPOT-XS have been widely used for mapping mangroves on a global or regional scale (Giri et al 2011; Giri et al 2014; Green et al 1998; Held et al 2003). Due to the poor spatial or spectral resolution of those multi-spectral images, their abilities to classify mangrove land cover are not very good. With the development of high spatial resolution satellite sensors, such as IKONOS, Quickbird, and WorldView-2, which have high spatial resolution, they are gradually being used for mangroves identification even down to the species level because of their detailed spatial characteristics, such as structure and texture (Tang et al 2015; Wang et al 2004; Wang et al 2008).

Based on the development of sensor technology and remote sensing platforms, more accurate and timely satellite imagery with high spectral and spatial resolution, positive impact on identification accuracy, can be obtained more easily. Drones as an emerging unmanned aircraft system are increasingly being used as remote sensing platforms (Colomina & Molina 2014).

Most studies on the classification of mangrove species have been carried out using pixel-based methods such as spectral angle mapper (SAM), maximum likelihood classification (MLC) and spectral unmixing (D'iorio et al 2007; Yang et al 2009), or object-based classifications, such as nearest neighbor (NN), random forest (RF), and support vector machine (SVM) (Duro et al 2012; Kamal et al 2015; Zhang et al 2016).

This study aims to investigate the ability of drone aerial photography to classify mangrove land cover using an object-based approach in Jailolo Bay, North Maluku Province, and analyze the accuracy of land cover mapping resulted.

Material and Method

Research site. This research was conducted in a mangrove forest area in Jailolo Bay, Jailolo District, West Halmahera Regency, North Maluku Province (Figure 1). Field surveys and data collection were carried out in March 2022 by selecting two villages having mangrove areas.

Aerial photo data collection. Aerial photo data collection was carried out by using drone type DJI Mavic 2 Pro which runs with the DJI Go and Drone Deploy applications on the iOS device iPad Mini 4. The DJI Go 4 application is available for free on the App Store, used for settings drone features such as cameras, sensor systems, and GPS systems. The drone camera was set in automatic mode (auto) so that all photos recorded were automatically set to the same brightness level on the drone camera. Drone Deploy is also an app available on the App Store that is used to create aerial photo recording flight plans. Collecting aerial photo data was undertaken by making flight plans at two locations flying area with a flight altitude of 100 meters, camera angle 90^{o}, and 80% of photo overlay both front and side overlap, so that each location took 14 minutes to fly with the number of photos 242 and 252 respectively (Figure 2).

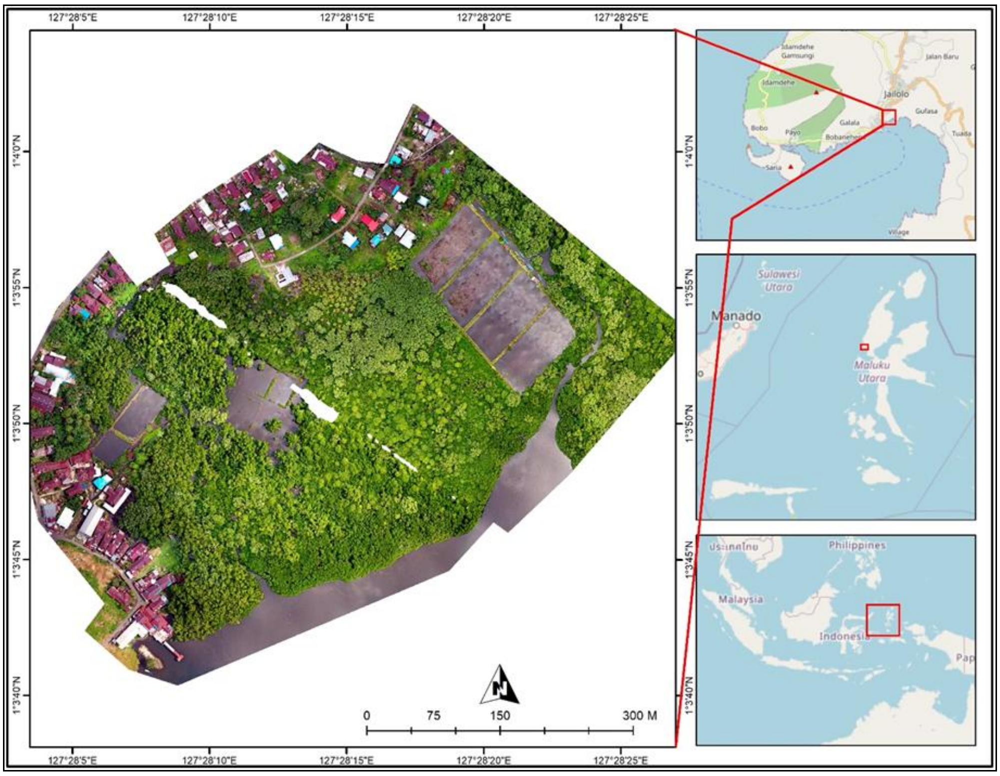

Figure 1. Study area in Jailolo Bay, North Maluku, Indonesia (map generated using QGIS 3.10).

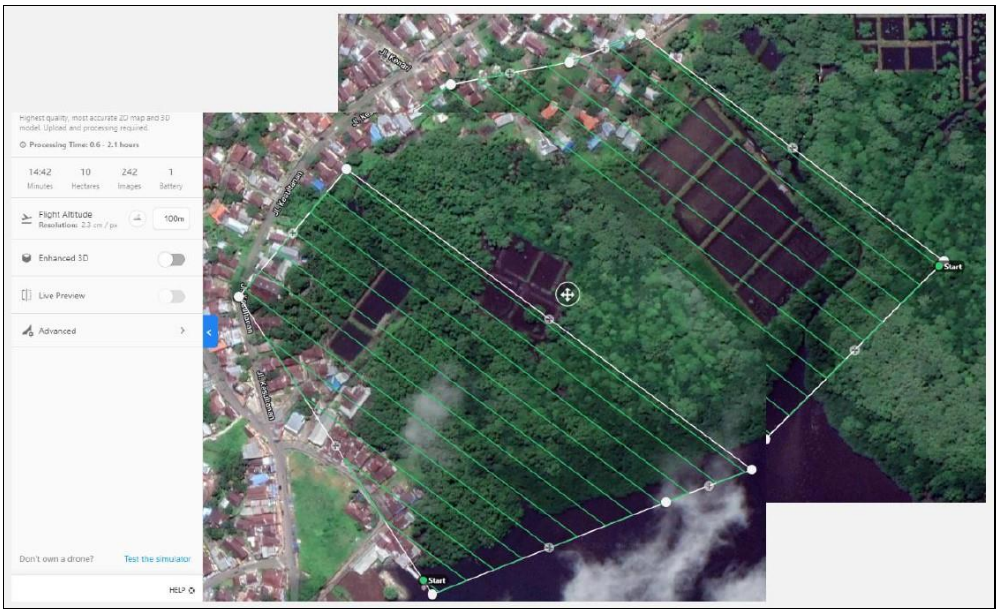

Figure 2. Flight plan for drone aerial mapping (figure generated using DroneDeploy).

Aerial photo processing. Processing of 513 aerial photographs collected by drone mapping used Agisoft Metashape Professional Program with medium processing quality. Aerial photo processing used a structure from motion (SfM) technique with a stereo multiview algorithm to create ortho photomosaics and 3D point clouds from overlapping photos. Point cloud data processed in the software produced ortho-corrected photomosaics and interpolated digital elevation models (DEM) using conventional kriging techniques (Casella et al 2014, 2016).

Data analysis. Data processing of drone aerial photos for mangrove land cover classification used object-based image analysis (OBIA) classification techniques referring to land cover classes issued by the Geospatial Information Agency (SNI 2010). The object-based classification technique (OBIA) is an approach that consists of two stages, namely segmentation and assigning classes to areas that have been segmented (Blaschke 2010). Object-based classification was implemented using the multi-resolution segmentation (MRS) technique using the nearest neighbor (NN) classification algorithm based on three parameters: scale, shape, and compactness. The shape and compactness parameters used fixed values of 0.1 and 0.5, respectively (Wahidin et al 2015), while the scale as a segmentation size parameter used a value of 500.

The results of mangrove land cover classification were then assessed for its classification accuracy that included 123 samples. The accuracy test that is commonly performed on remote sensing classification results is an error matrix (error matrix/confusion matrix or contingency matrix). This is done by comparing the results of the classification map to the actual class. The actual class is obtained from samples on orthophoto processing results by applying a stratified random sampling technique. The accuracy test was applied referring to Congalton and Green (2008) which consists of overall accuracy (OA), producer accuracy (PA), user accuracy (UA), and Kappa coefficient. Percentage of accuracy of a class is obtained from the comparison of samples numbers that are correctly covered in training samples with number of classes of training samples. The percentage of classification accuracy as a whole is calculated from the comparison between the number of correct classes and the total number of classes in the entire training area.

Results and Discussion. Results of drone aerial photo data processing had an effective overlap of 1646 points per pixel. This meant that each point in the point cloud (the initial stage of the SfM process) was visible or matched in an average all of 513 photos collected. This is a high value compared to most other photogrammetric studies; typically, good results are obtained with an effective overlap of 10, depending on the type of object recorded (Cassela et al 2016). The final result of drone aerial photo processing was photomosaic orthorectification (RGB) and DEM data in raster format, with final surface resolutions of 2.3 and 9.19 cm/pixel, respectively (Figure 3). The orthophoto surface resolution in this study had higher quality than that of Pranata et al (2020) who analyzed the accuracy of forest land cover using drones which obtained surface resolutions between 2.52 – 3.00 cm/pixel at a flying altitude of 100 meters. This difference could be caused by differences in camera resolution on drone devices and the quality of orthophoto data processing.

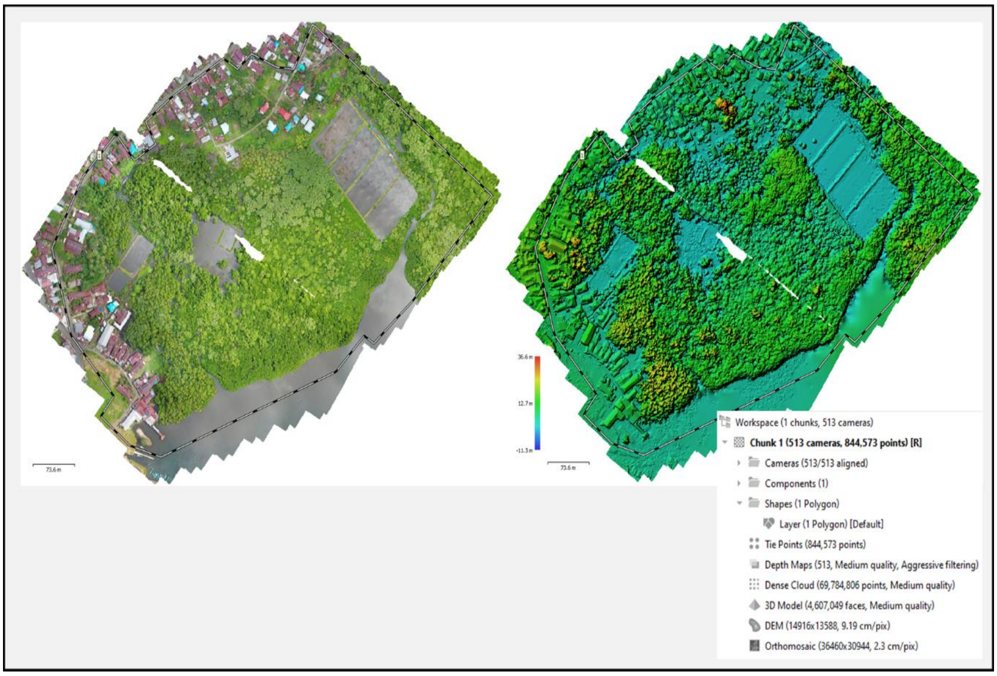

Figure 3. RGB ortophoto (left) and DEM data (right) (figure generated using Agisoft Metashape).

Mangrove land cover classification resulted from drone aerial imagery obtained 7 classes of land cover, namely bodies of water, buildings, shrubs, roads, mangroves, ponds, and non-mangrove vegetation (Figure 4).

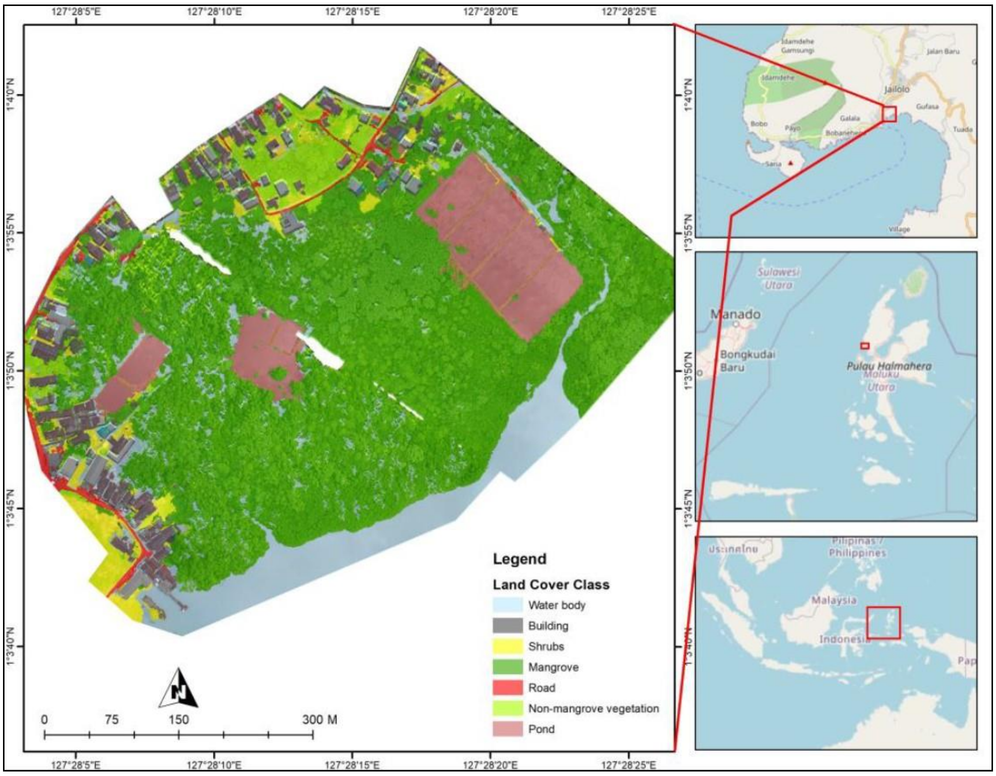

Figure 4. Land covers classification results (map generated using QGIS 3.10).

The results of land cover classification showed that mangroves were spread from near settlements toward the sea. These results were in accordance with Giesen et al (2006) that mangroves are a type of forest vegetation that is dominated by woody plants and is inundated by sea water or influenced by tides, coastal areas with muddy, sandy, or sandy-muddy conditions. Information on area of each land cover class can be seen in Table 1.

Table 1

Area of land cover classes

No.	*Land cover class*	*Area (ha)*	*%*
1	Water body	3.99	13.54
2	Building	2.21	7.51
3	Shrubs	1.14	3.86
4	Road	0.47	1.60
5	Mangrove	17.31	58.72
6	Pond	2.81	9.54
7	Non-mangrove vegetation	1.54	5.23
	Total	29.48	100.00

Mangroves were found as the most extensive land cover class over the study site mapped with total area of 29.48 ha. The mangrove area covered 58.72% of the total area analyzed or 17.31 Ha. The smallest land cover class was the road class with an area of 0.47 Ha or 1.60%. Pond class that also contained water body was corrected with contextual editing techniques according to the instructions of Mumby et al (1999). Water body and pond classes had an area of 3.99 ha and 2.81 ha respectively. And the final two land cover classes, shrubs and non-mangrove vegetation classes had areas of 1.14 ha and 1.54 ha respectively.

The results of classification accuracy test for mangrove land cover are presented in Table 2. These results indicate that the object-based classification technique (OBIA) using the nearest neighbor classification algorithm had an overall classification accuracy (OA) value of 88.62% and a Kappa coefficient of 84.13. Mangrove classification accuracy value is greater than 90% for both PA and UA. The results of user accuracy (UA) showed that all samples produce mangrove land cover classifications were applicable, namely the water body, shrubs, mangroves, and ponds classes (accuracy values of more than 90%). Producer accuracy results (PA) showed that all land cover classes could be accurately classified using object-based classification techniques except for shrubs and non-mangrove vegetation classes (Table 2).

Table 2

Accuracy test matrix for mangrove land cover classes

Class	*Water body*	*Building*	*Shrub*	*Mangrove*	*Vegetation*	*Road*	*Pond*	*Total*	*UA*
Waterbody	**10**	0	0	0	1	0	0	11	90.91
Building	1	**10**	1	2	0	0	0	14	71.43
Shrub	0	1	**10**	0	0	0	0	11	90.91
Mangrove	0	0	1	**57**	2	0	0	60	95.00
Vegetation	0	0	1	1	**7**	0	0	9	77.78
Road	1	0	0	0	1	**6**	0	8	75.00
Pond	0	0	1	0	0	0	**9**	10	90.00
Total	12	11	14	60	11	6	9	**123**	
PA	83.33	90.91	71.43	95.00	63.64	100.00	100.00		
OA	88.62								
Kappa	84.13								

Similarity of land cover classification results could not be avoided for shrubs and non-mangrove vegetation. Application of the object-based classification technique with the NN algorithm produced a user accuracy value for water body, shrubs, mangroves, and ponds classes which was better than for building, non-mangrove vegetation, and roads classes. The results of the accuracy test for land cover classification in this study were higher than accuracy results obtained by Cao et al (2017) who classified 10 classes of mangrove species using the object-based classification technique on drone hyperspectral aerial photographs. The overall accuracy value (OA) using the nearest neighbor (NN) algorithm with several schemes produced an accuracy value ranging between 71.34-81.79%. Meanwhile, accuracy value using the SVM algorithm obtained the overall classification accuracy value (OA) ranging from 77.61-89.55%. These results were consistent with previous studies by Gomez-Chova et al (2003) and Ma et al (2015) that a selection of features from high-dimensional classifications, such as hyperspectral or object features, could improve performance and efficiency by eliminating redundant information.

Jia et al (2014) combined Hyperion data and SPOT-5 data to distinguish four mangrove species, but this study used drone hyperspectral imagery with narrower bandwidth and higher spatial resolution and could identify more mangrove species. Mangrove species included in the mangrove land cover class with an area of 17.31 ha have been reported from research by Abubakar et al (2022) which identified 11 species. The results of the identification of mangrove species consist of *Rhizophora apiculata*, *R. mucronata*, *Bruguiera gymnorrhiza*, *B. parviflora*, *Ceriops decandra*, *C. tagal*, *Sonneratia alba*, *Avicennia alba*, *A. marina*, and *Xylocarpus granatum*. Regardless of differences between study sites, the classification accuracy reported here is higher than that of Kamal and Phinn (2011), who used CASI-2 data for mapping three mangrove species, especially when incorporating elevation information into the classification features. These results were also consistent with the work of Liu and Bo (2015) who concluded that altitude information in object-based classification of vegetation species could improve classification accuracy.

Conclusions. Drone aerial photos with an object-based approach classification using the nearest neighbor algorithm was able to identify 7 classes of mangrove land cover. The classification accuracy obtained was very high and mangrove classes can be mapped very well.

Conflict of interest. The authors declare that there is no conflict of interest.

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