Shallow water habitat mapping with unmanned aerial vehicle (UAV) technology in Serena Island, Bitung city, North Sulawesi, Indonesia

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Abstract. The objective of the study was to apply the photogrammetric technique in aerial photography caught by a drone in mapping the shallow water habitat of Serena Island, Bitung City. The object images were made at the phase of two-level multiresolution segmentation, classified based on the information given by the object, and the accuracy test. There were 99 photos recorded in the study site, where all were effective to be aligned to produce the aerial photography at the resolution of 2.61x2.61 cm pixel^{-1}. Five classes of shallow water bottom habitats were recorded, namely algae, live corals, dead corals, coral debris, and sand with a classification area of 6.77 Ha consisting of 2.42 Ha live corals (35.73%) and then 2.21 Ha sand (32.64%). The accuracy test of the map was 86.15% (OA) and Kappa accuracy was 82.69%.
Key Words: aerial photography, bottom, coral reef, photogrammetry, topology.

Introduction. Recently the need for renewable technology is developing with the need for good quality of an information system, such as geographic information system (GIS) in the field of coastal and marine resources. In its development, the spatial information system of natural resources stems from the use of space technology, such as airplanes, and even satellite technology. The satellite image data, as one of the instruments, are highly restricted based upon the resolution, such as spatial, temporal, and radiometric resolutions (Narayanan et al 2002; Johnson & Jozdani 2018). Besides, the quality of satellite image data is still limited by several factors, such as weather conditions and geographic location of data recording, and obtaining high-resolution image data is sometimes expensive (Boyle et al 2014; Malarvizhi et al 2016; Xiang et al 2019).

The use of remote sensing that benefits the unmanned aerial vehicle (UAV) technology has developed very fast. The use of UAVs by civilians has also increased with the increasing availability of vehicles, small sensors, GPS, inertial measurement units and other supporting hardware (Patterson & Brescia 2008; Rango et al 2008). The use of drone has developed and been applied to mapping of the coastal resources, such as small islands, mangrove, coral reefs, seagrass bed, nursery ground of coastal fishes, and tide-induced beach image (Ramadhani et al 2015; Ventura et al 2016; Ruwaimana et al 2018; Wahidin & Abdullah 2018; Hudi & Romadhon 2020; Kabiri et al 2020).

The use of unmanned aircraft for mapping activities is generally of low cost, easy to carry anywhere, speed and altitude can be adjusted according to research objectives. This vehicle can be operated unnoticed and under the cloud cover that always becomes an obstacle for aeroplanes and satellite for the same mission. The photographic data recorded in drone have bridged the gap between field observation and remotely sensed image obtained from conventional vehicles, aeroplane, and satellite (Wahidin & Abdullah 2018). Drone has several benefits, since it can be operated fast and repeatedly, needs relatively cheaper expenditure and is safer than the use of aeroplane, has more flexible

flying height and time, and can collect very high resolution spatial image (Rango et al 2006; Boyle et al 2014; Malarvizhi et al 2016; Wahidin & Abdullah 2018).

Image classification is a pixel grouping process into certain classes based on brightness value/BV/digital number of the image. According to Navulur (2006) and Blaschke (2010), the image classification technique is divided into two bases, the image-based image and the object-based image (object base image analysis/OBIA). OBIA is a new paradigm in object-based image classification. This analytical method is segmentation and imagery analysis based on spatial, spectral, and temporal characteristics (Blaschke 2010). It is capable of simultaneously analyzing the object classes based on the spatial and spectral aspects (Danoedoro 2012). The implementation of OBIA can also significantly increase the accuracy compared with that of pixel method (Wahidin et al 2015).

The application of the UAV and the OBIA in coastal resources mapping, particularly shallow water marine ecosystem in North Sulawesi Province, including Bitung City, is still rare and relatively new. Meanwhile, immediate and accurate information on coastal resources in the context of management and policy is urgent, and one of the approaches is spatial information. This study identifies the photogrammetric technique applied to the aerial photography using the UAV drone and the object classification based on the high resolution aerial photographies of shallow water habitats in Serena Island, Bitung city.

Material and Method

Data collection. This study was carried out in the coral reef area of Serena Island, Bitung city, North Sulawesi (Figure 1). Data collection of aerial photography and field checks were done during August 2021. The former used DJI Phantom 4 Pro Ver. 2.0-typed UAV drone equipped with 1-inch CMOS camera of 20 M effective pixels and FOV 84° 8.8 mm/24 mm lense type (35 mm format equivalent) f/2.8 - f/11 auto focus at 1 m - ∞; maximum tilt angle of each flying mode is Smode 42°. The battery capacity of DJI P4A has maximum flyng time length of 30 min. DJI P4A has been equipped with a remote control equipment to monitor the drone route and performance during the operation and satellite-based position system GPS/GLONASS.

Before conducting the aerial photography, the flight planning was set. It used a Pix4D *Capture* application. The flight planning comprised the flight coverage, height, direction, photo overlay, maximum flying speed and viewpoint position (Joyce et al 2018). The flight area was prepared using area format *.shp data area designed using Arcmap 10.4.1 software. The flying height was set at 100 M with the direction of -90°, P-mode 25°, and A-mode 35 or from the south to the north. To collect the desired image of an area, the drone flied along a straight line, then moved to the next lane without altering the direction and flied back along the entire flying lane. To prevent the gap of the coverage along the lane, the recorded images were overlapped as 80% frontlap and 70% sidelap. The aerial photography was done at the daytime between 13.00-14.00 pm of Central Indonesian Time.

Bottom substrate data collection used shallow water substrate geotagging technique developed by Rondonuwu (unpublished) through the dives at the depth where the coral reef was still recorded (± 8 m depth). The surveyor dove near the bottom while taking pictures of bottom substrate using underwater digital camera while pulling the GPS-attached float on the surface and set with each 3 min tracking mode. This technique is the development of georeference transect photographic technique (Roelfsema & Phinn 2008) in free swimming observation using snorkel (Figure 2).

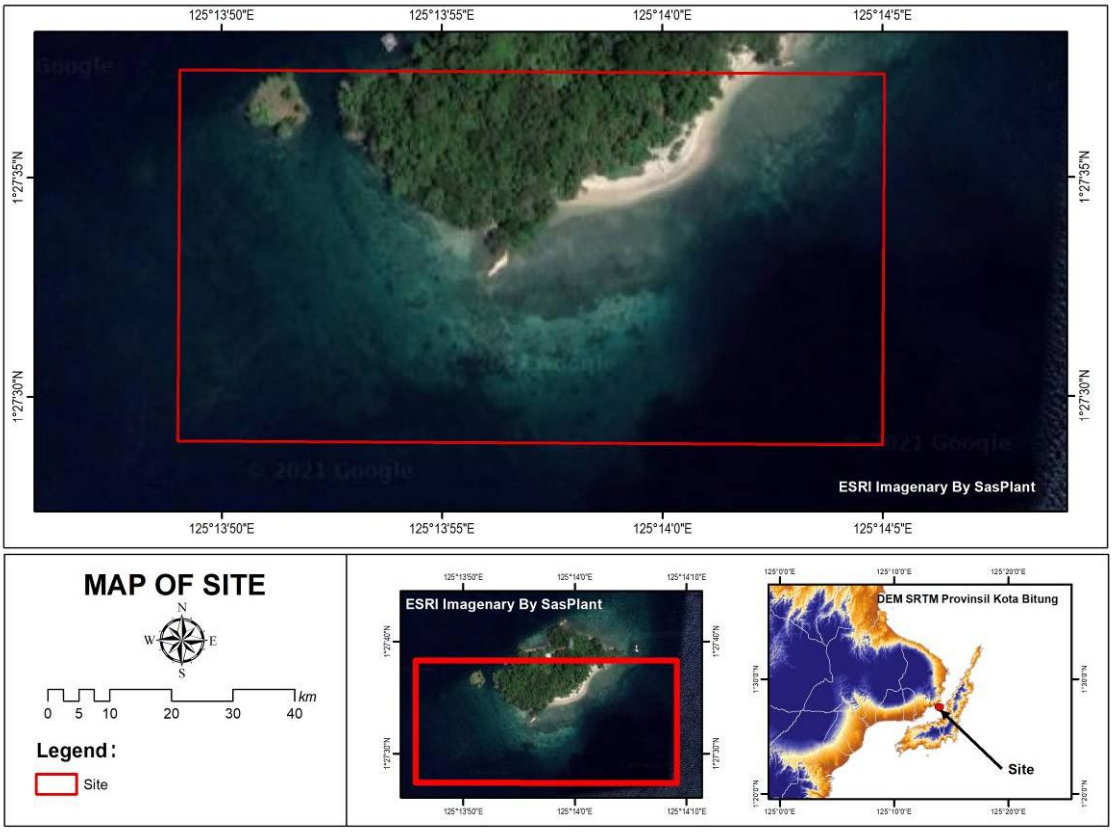


Figure 1. Study site.

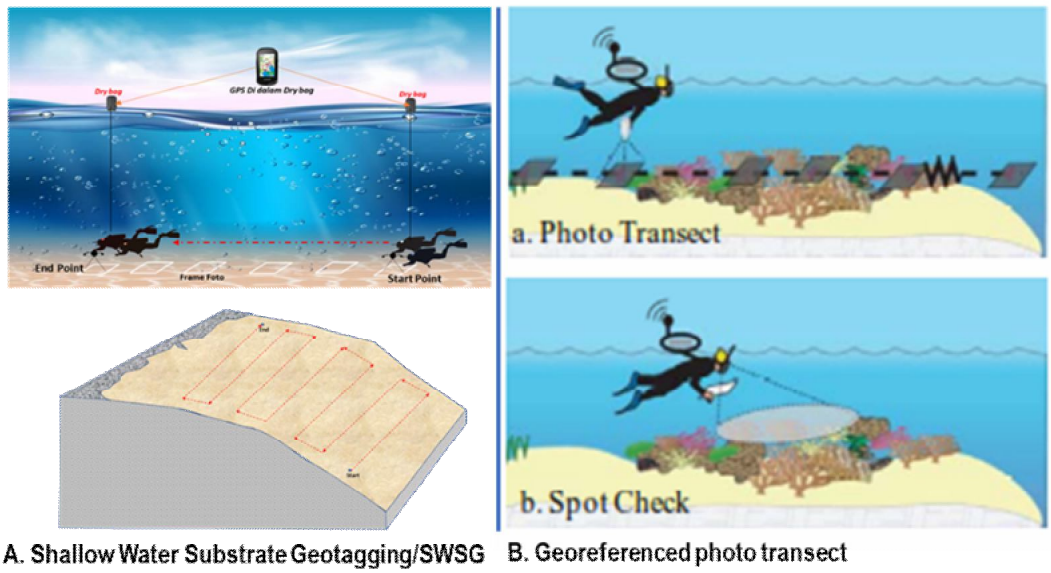


Figure 2. A. Photographical technique developed by Rondonuwu (unpublished); B. Photographical technique developed by Roelfsema & Phinn (2010).

Data analysis. The aerial photographs were analyzed using Agisoft Photoscan software (http://www.agisoft.com) with algoritma stereo multiview to construct the ortho-photomosaic and 3D point cloud of the aerial photograph overlay. The photogrammetric technique-based ortho-photomosaic and 3D point cloud followed Casella et al (2016). At the initial step, Agisoft determined the photo aligns using algoritma structure from motion (SfM) that identifies the photo point feature, then monitors the point position along the photo dataset. The result of the first step is 3D point cloud that geometrically

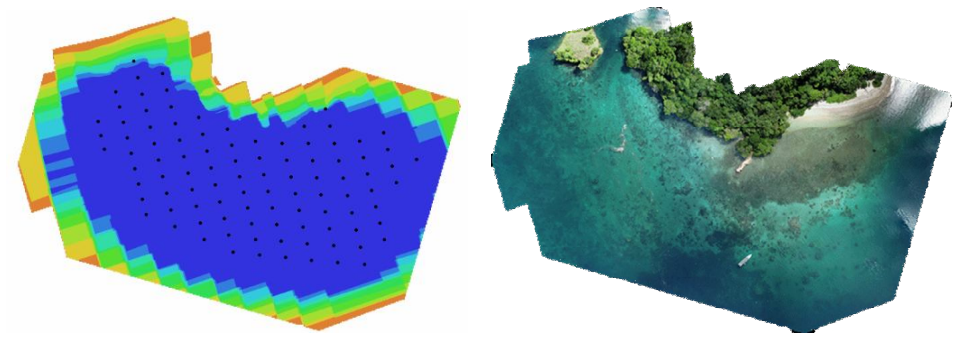
represents the study area, the camera position relative to each photo acquisition moment, and the internal camera calibration parameter (focal length, principal point location, three radial, and two tangential distortion coefficients).

Step 2 was to build a dense point cloud. Step 3 was to operate the algorithm of pixel value to build the majority of geometric details. Agisoft software applies algorithms based on computational capabilities that provide high-quality 3D modeling from a series of overlapping aerial photographs (Verhoeven 2011). Step 4 is the classification of shallow water substrates using object-based classification techniques (Blaschke 2010; Phinn et al 2012). The classification of shallow water bottom substrates with an object-based approach was applied to the Nearest Neighbor algorithm (Wahidin et al 2015; Zang 2015). Step 5 was to test the accuracy of the digital classification results with test samples from the results of field activities. The accuracy test was then applied using overall accuracy (OA), producer accuracy (PA), user accuracy (UA) and Kappa accuracy (McCoy 2005; Jhonnerie et al 2015; Wahidin et al 2015).

Results and Discussion

Multiresolution segmentation. The total area recorded based on the planned flight covered an area of 0.0925 sq. km, with a mean height of 110 m above sea level and flying time of 13 min and 27 sec. There were 99 photos recorded, all of which were effective to combine (orthophoto mosaic) in the overlapping process of aligning photos. It indicates that every point spreading on this process (phase 1 SfM process) can be combined in all outcomes of the aerial photography (Figure 3A). Casella et al (2017) found > 90% of photos that can be processed in the orthophoto mosaic phase. Meanwhile, Wahidin and Abdullah (2018) found that only 150 (87.72%) of 171 photos can be used in the overlay process of the photo-alignment phase. This difference could result from several factors, such as flight height and drone-recorded area or object (Casella et al 2016).

The overlay of the aerial photography based on the camera recording locality at mean flying height yields the surface resolution of 4.43 cm pixel^{-1} and the projection error level of 1.35 pixels. After going through the process of merging orthophoto mosaic with photogrammetric techniques, aerial photos were produced with a resolution of 2.61x2.61 cm pixel^{-1}.



(a) (b)

Figure 3. Ortho photo mosaic processing: (a). Site and photo overlay; (b) Ortho-photo mosaic.

Object-based classification (OBIA). Object-based classification in this study utilized several algorithms in eCognition software. This classification process needs several additional information other than the spectra of worldview-2 image. The additional information on the object could enrich the user to define the object into certain classes. This classification yields two thematic maps separated into two-level segmentation. The developed rule set is to connect the interscalar segments at each level (parent child relationship) by building an object defining concept. Parent child relationship is used to connect the segments form at each level. This relationship was processed with the algorithm of copy image object level as sample of classification copy at the level 1 with

class filter parameter to make peripherial area for smaller segmentation of the shallow water class at the level 2.

Level 1 utilizing the multiresolution segmentation (MRS) algorithm with the scale parameter = 50, shapes = 0.1, compactness = 0.5 yielded 65,042 objects segment^{-1}. These were classified using an assign class algorithm with different thresholds into two classes, terrestrial and shallow water. The MRS algorithm of level 2 with parameters of scale = 25, shapes = 0.1, compactness = 0.5 yielded 12,883 objects segment^{-1}. The algorithm used for segment classification at levels 1 and 2 was the classification algorithm. It executes the spectral information and the close relationship between segment classes to be classified with Nearest Neighbor Classification (Figure 4).

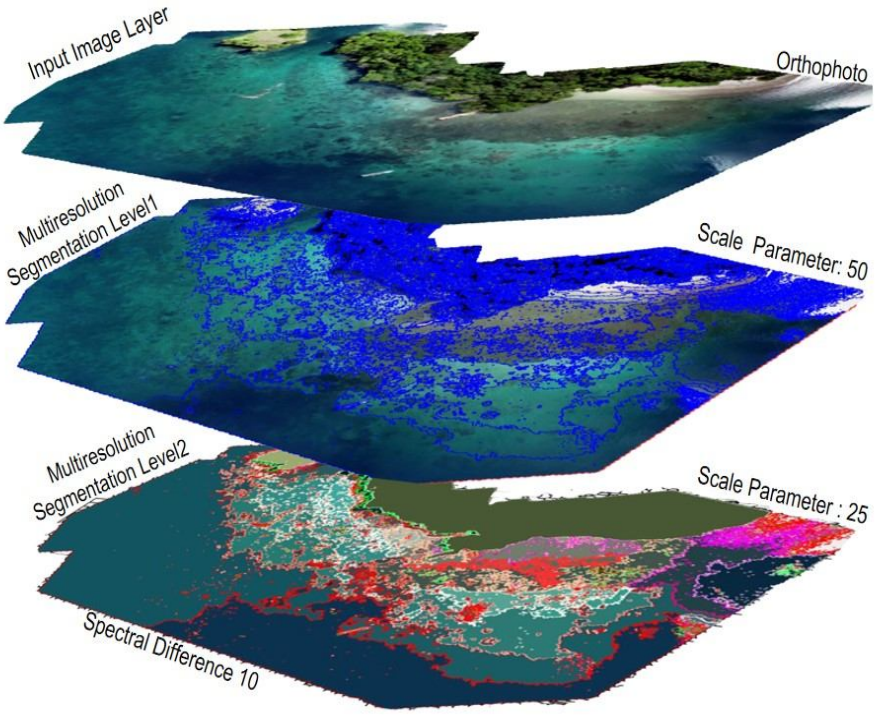


Figure 4. Ortho-photo mosaic and multiresolution segmentations.

Based on image classification, there were 5 classes of shallow water bottom habitats in the southern part of Serena Island, like algae, live corals, dead corals, rubble, and sand with a classification area of 6.77 Ha. Live corals had the widest area, 2.42 Ha (35.73%) and followed by sand, 2.21 Ha (32.64%), whereas algae covered only a small area (Table 1 and Figure 5).

Table 1

Habitat coverage

Habitat class	*Area*	
	Ha	*%*
Algae	0.31	4.63
Live corals	2.42	35.73
Dead corals	1.30	19.21
Sand	2.21	32.64
Rubble	0.53	7.79
Grand total	6.77	100

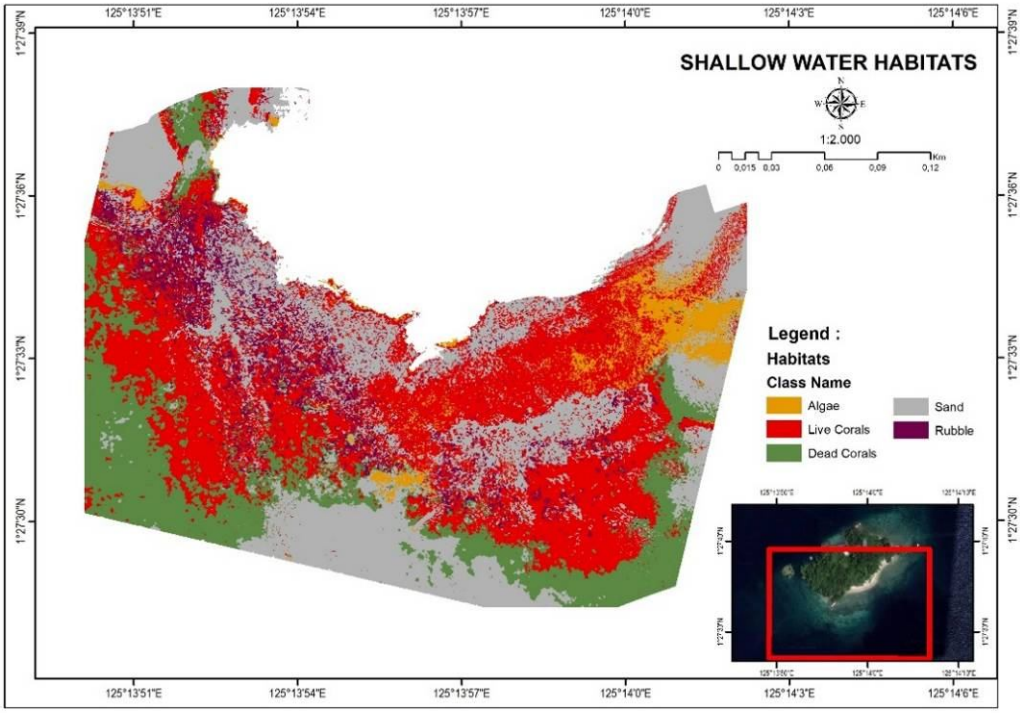


Figure 5. Shallow water habitat classification.

Table 2 demonstrates that the total accuracy of the map based on the classification technique and field observation is 86.15% (OA) and the Kappa index is 82.69%. According to Green et al (2000), the acceptable benthic habitat mapping accuracy is > 60% for OA. Besides, McCoy (2005) claimed that there is no standard practical rule to predict the accuracy of the final map, but there are several elements necessarily considered, such as the number of map classes, and the homogeneity of habitat coverage affects the map accuracy. Errors in accuracy estimation could result from the reference data, the sensitivity of classification to the observer's variability, inconsistency of the satellite image data spatial resolution, and failures in the mapping process (Congalton & Green 2009).

Table 2

Matrix of level-2 accuracy test

Classification	*Ground truth*						*PA (%)*
	Algae	*Live corals*	*Dead coral*	*Rubble*	*Sand*	*Total*	
Algae	12	1	1	0	0	14	85.71
Live corals	0	12	1	1	0	14	85.71
Dead coral	0	1	10	1	0	12	83.33
Rubble	0	1	1	10	0	12	83.33
Sand	0	0	0	1	12	13	92.31
Total	12	15	13	13	12	65	
UA (%)	100	80	76.92	76.92	100		
OA (%)						86.15	
(K) Kappa accuracy (%)						82.69	

Notes: UA = user accuracy; PA = producer accuracy; OA = overall accuracy.

Phinn et al (2012) who mapped the benthic community yielded a total of 78% accuracy in Heron area, 52% in Ngderack, and 65% in Navakavu, for geomorphological zone mapping with > 80% mapping. Roelfsema et al (2013) reported the accuracy between 76 and 82% in geomorphological zone mapping using OBIA method and between 52 and 75% total accuracy in benthic habitat mapping. Zhang et al (2013) who mapped benthic

habitat using OBIA algorithm random forest classifier (RF) method on the AVIRIS (airborne visible/infrared imaging spectrometer) image yielded the highest accuracy of 86.3%.

Conclusions. Object-based aerial photography (OBIA) classification of 99 photos could yield shallow-water marine habitat maps of the southern part of Serena Island with 86.15%. The classification up to level 2 only yields the map of shallow water habitat types and spread, but could not explain the quality of each habitat, such as coral reef condition. Hence, the ideal habitat-based shallow water classification is up to level 3.

The implementation of OBIA method in benthic habitat mapping on small area coverage becomes the best choice to obtain accurate information compared with the pixel approach method.

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

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