Monitoring the seagrass ecosystem using the unmanned aerial vehicle (UAV) in coastal water of Jepara

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Abstract. Seagrass ecosystem in the world were highly sensitive to environmental changes. They were also in global decline and under threat from a variety of anthropogenic factors and global climate change. There was now an urgency to establish robust monitoring methodologies so that change in seagrass abundance and distribution in these sensitive coastal environments can be understood. Typical monitoring approaches have included remote sensing from satellites and airborne platform, ground base ecological survey. The techniques can suffer from temporal and spatial inconsistency, or were very localised, making it hard to assess seagrass meadows in a structurer manner. The aim of this research was to present the technique of using a lightweight drone and consumer grade cameras to produce very high spatial resolution mosaic of intertidal site in Bandengan, Jepara waters, Indonesia. The data collection methodologies followed by digitation method techniques to produce coverage estimates, with ground check at location, with data drone analysis. This result showed that digitation method can show between the observed and classified low coverage seagrass 7-12% (<25%) compare to middle coverage seagrass 34-48% (between 25< and <50%), also was able to detect the other biotic features, such as colonies of macroalgae, massive coral, the flat sand and coral rubble at the observation location.

1. Introduction

Seagrass meadows are a productive shallow marine ecosystem and have an important role in the ecosystem in coastal areas. The seagrass ecosystem has an ecological function as a spawning area, a nursery ground for various fish with important economic value and carbon sequestration [1, 2]. The seagrass bed ecosystem also has a function as sediment traps to clear the waters needed for the growth of coral reefs. Despite their evident ecological importance, the seagrass ecosystem has been declining three decades [3], with one in five seagrass-habitat-associated species on some risk of extinction with threats of disturbance and damage by activities of coastal communities, also because of global warming. The threats, such as human disturbance (i.e. mechanical damage and release of a toxic compound, changes in water quality) likely caused such decline the services of seagrass ecosystem. Therefore it is a clear need to develop methods to monitor the condition of seagrass meadows [4].

Monitoring efforts to date have been conducted using a range of in situ approaches, including scuba/snorkeling surveys, ground-based sampling, and hovercraft-based mapping [5]. Active and passive remote sensing approaches are also used frequently to estimate the coverage and quality of seagrass habitats. Using active acoustic remote sensing methods such as side-scan sonar, it has been shown effective to estimate the condition of coral and densities and coverage of macroalgae. Mapping using remote sensing could be used for interpreting preliminary data before field observation. In addition, it can be used as comparison of the field observed data with satellite image and increase credibility of the result of the research. Collecting ultra-high-resolution image (<5cm) across multiple
Spectrum channels can be used for real-time management proposes and to validate remote sensing data from satellites [6]. In drones, areal photographs produced have 4 channels (bands 1, 2, 3, and 4), namely channels at the visible wavelength (bands 1, 2, and 3) with wavelength at the value of 0.4-0.7 µm and NIR (band 4) with a wavelength of 0.7-1.3 µm.

With attributes and channels in such a way for each photo produced, data processing is carried out on visible channels for shallow water-extracting needs and for NIR channel to differentiate land and water. Special processing needs to be carried out on objects underwater columns such as seagrass meadows, corals, macroalgae as well as suspended or dissolved objects because the water column absorbs, dissipates, and continuous some electromagnetic waves [7]. The minimum absorption in wavelengths with a range of 0.48 µm and low absorption in the range 0.4-0.6 µm. Based on this data and the support of the number of channels and wavelengths of each channel, the drone image has a potential to be used to detect objects both under the surface and in the water column. The research aimed to obtain an overview of the structure and map seagrass meadows ecosystems at Bandengan waters in Jepara Regency Central of Java Indonesia, by using aerial photographic imaging from the drone unit of the DJI Phantom 4 Pro. Bandengan coastal water was chosen because it has a community of coastal, coral reefs, and seagrass meadows ecosystem to test the aerial photo data collection.

2. Materials and Method

2.1. Study site
Coastal areas are regions of remarkable relevance for humans, providing essential components for social and economic development from the local to the national scale [8]. The study region located on the Jepara Regency (shown Figure 2), as specific on Bandengan waters, North Java Sea. Geographic location projection was at 110°39′6″ E – 110°39′11″ E and 6°33′45″ S – 6°33′51″ S. This region presents an irregular coastline with a low slope. Bandengan waters have a widespread of seagrass beds. This area is an intertidal area, the formation of a "green belt" between coral reefs, seagrass and mangroves can be found in these waters. The high tourism activity in this area [9] as well as the concern on the increasing release of carbon into the air, have made the objective of monitoring in this area of the seagrass beds as one of the stock providers to be considered by using the technology for monitoring with high efficiency and effectivity.

2.2. Drone as UAV Module and data collection
Unmanned aerial vehicle (UAV) for remote sensing coastal areas was used in present works as representing low-cost technology with good performance [10]. A Phantom 4 Pro quadratic drone rotor with low-weight was used in this study. Some activities with custom and adjustment has to be done. Aerial surveying was performed using this drone with 1.388 Kg and 1” 20MP CMOS Sensor. The flight mission was done by the Drone Deploy Application on mobile (free software). It was established 20 meters of flight height because it makes high-resolution. As seagrass has a thin leaf, it needs a clear pixel to justification analysis, with small format camera it is possible to get the good pixel to coverage leaf of seagrass.

2.3. Image processing as data analyze
The photogrammetric process resulting from drone imagery is combined using the ortho-mosaic method [11]. Drone at a recent study was a good choice to select as a survey tool of ecologists, monitoring, environmental applied, etc, drone photo has good contrast at accurate on pixel [7]. Drone imagery in advance can complement traditional field measurements, ensuring almost continuous synoptic coverage with a good trade-off between spatial and temporal resolution, thus allowing for a timely characterization of coastal environment dynamics. In particular, the availability of a multitemporal historical series of remote sensing data can provide useful information on the spatiotemporal variability of hydrological (sea surface currents, river runoff/discharge), biological (phytoplankton blooms, primary productivity) and physical (temperature, salinity, and turbidity) properties of coastal waters as
well as on human-induced land cover mutations (deforestation, surface urban islands) [6]. The high-level resolution of the photo results is obtained from the height of the drone and the camera’s specifications. The altitude of the drone when the flight plan is 20 meters and the calibration was done before the photo flight implementation. All processes about image analyze shown in Fig1. This is done to ensure that the photos are quite good and accurate.

The images from imagery drones were processed by AgiSoft Photoscan, commercial software for free users. Combining photos with an ortho-mosaic was done using AgiSoft photoscan v 1.2.5 software [12]. In the first process, photos were collected next alignment photo, generating a cloud point, dense of cloud, develop digital elevation model (DEM), hence to orthophoto mosaic was generated [13] [10] [6]. Steps before the result of the merger were generated, among others, the photo aligning was carried out to create a mesh cloud, dense calculation, so that it can be done ortho-mosaic.

Ground check collection for seagrass coverage (%) refers to the LIPI method [14]. Calculation are carried out along the 100m long transect line form the coast to the sea. Calculation of seagrass coverage as using a 50x50m quadrant transects placed every 10m along the transects line. There are 3 line transect with a distance between the lines as far as 50m, so that the observed area of the seagrass beds is 100x100m squared. Illustration of the method of calculating seagrass coverage (%) can be seen in Fig 2.
3. Results and Discussion

The aerial photograph data collection survey was carried out on September 2019 at Bandengan coastal area, Jepara Regency with the work area at coordinates 6°33'52.6" - 6°33'50.3" S and 110°39'17.6" - 110°39'13.4" E as shown in Figure 4. Retrieval of photo data at the research location by drone was carried out at 07.00-09.00 in the morning with sunny weather. Tracking drone for taking field photo data and area collecting for seagrass coverage can be seen in Figure 3.

![Figure 3. Tracking Drone for Taking Field Photo Data and area collecting for seagrass coverage](image)

This research was carried out with three technical stages in analyzing aerial photographs. This method was used to obtain the best result in analyzing aerial photographs with a higher resolution. From one photo, three optical bands can be obtained, namely red, green and blue, and one band NIR for further data processing.

Variation in the complexity of image analysis processing in each method approaches is quite varied. The processing technique is a method that is often used in remote sensing data processing with several adjustments to maintain better objectivity.

3.1. Unsupervised Red bands – NIR (NDVI)

Some optical band RGB as unsupervised in combination with the NIR band is often used for processing to detect vegetation area so that the optimal shallow water vegetation area is obtained. Combining the aerial drone photos results in higher pixel accuracy. The NDVI is a vegetation index widely used to evaluate the health conditions of vegetation, whether preserved or derived from anthropic actions, such
as agriculture. NDVI's estimation of drones is still quite precarious as it requires different studies to assess their accuracy. The aim of this study is to evaluate the NDVI estimate obtained with images of visible attention to radiometric calibrations [15]. Spatial processing to obtained data on the extent of seagrass meadows is carried out with the NDVI equation to produce 2 classes. As a vegetation class and a non-vegetation class. The resulting vegetation class is then analyzed visually so that it can adjust the appropriate value in interpreting the condition of seagrass meadows. The results of the value of seagrass cover were tested with the results of a ground check using a quadratic transect that had been carried out in the field to obtain the correction value.

3.2. Supervised Optical bands

Supervised optical bands were a type of classification analysis by combining 3 bands of optical red, green, and blue bands (RGB). The optical band was composite from red green and blue, R and B represent normalized surface reflected averaged over orange of wavelength, visible red had wavelength 0.6um and visible blue had 0.4 um [16]. The supervised approach uses training sample classes to get the classification as good as desired. False vegetation, rock area, sand area, seagrass, sand, and rubble (refer to coral) can be well classified. This method divided shallow marine habitat into 5 classes of training samples. These five classifications became clusters in the assessment of the desired land cover yield. The result of land was carried out for analysis by RMSD (%) of the quadrant transect data from measurements in the field.

3.3. Segmentation OBIA Classification

Image segment processing was done by using multi-resolution segmentation in Trimble’s eCognition Developer 64 software by minimizing the object value with an average heterogeneity of image values at a certain resolution. With the scale parameter that was the reference in making the segment, the maximum value of heterogeneity allowed in producing the image object to be analyzed was determined. Scale parameters were tested at several values to get the optimal number based on the variability of the class or land coverage in the image [17]. As a result, object-based image analysis (OBIA) techniques had emerged to address these issues. The OBIA technique had now replaced the traditional pixel-based method as the new standard method that facilitated land-cover classification from high spatial resolution remote sensing imagery [18] [19]. Step of OBIA which applying in this research following, extraction with unsupervised classification, using NDVI classification to the divided objective area.

The result of field data collection from the ground sampling area consists of an area with of total area of 100000 (length tx width: 100 x 100 m Transect), line transect along 100 m, the transect using quadrant size 50x50 cm, the distance between line transect is 50m. Ground check data result for coverage (%) of seagrass in Bandengan coastal waters can be seen in Table 1.

Table 1. Ground check data of seagrass coverage (%) in Bandengan waters, Jepara regency

| No. | Seagrass species            | Coverage (%) |
|-----|----------------------------|--------------|
| 1   | *Enhalus acoroides*        | 9.13         |
| 2   | *Thalassia hemprichii*     | 20.45        |
| 3   | *Cymodocea serrulate*      | 21.98        |
|     | Total Coverage (%)         | 51.56        |

The ground check result data was combined with the aerial photo area with the accuracy of each analysis method from Unsupervised Red bands - NIR (NDVI), Supervised optical bands, and segmentation of OBIA, sequentially 0.64 cm/px, 0.55 cm/px, and 0.98 cm/px. This value then acquired, for each area that had a value against the seagrass code justification, that an estimate of the land cover value of seagrass meadows could be obtained. Bandengan waters had a photo area of 14239.75m². This study area was a shallow water (Table 2).
Figure 4. Orthomosaic drone photo with image taken from 20 meters altitude and resolution of 0.5 cm/px.

The unsupervised NDVI is shown in Figure 5 with the analyzing method refer to 2.3.1, which shows the total area analyzed is in the amount of 14239.75 m². When analyzing the class is divided into 3 classes with class values, non-vegetation (areas in grey), vegetation (area in light green), and false vegetation (areas in dark green). The cover size of the seagrass meadows in the analysis by applying unsupervised NDVI is 6680.84 m², with a total cover of 46.92% of the total area recorded by the result of the orthomosaic of an aerial photograph. The area cover used as the study process at the time of the ground check was 5113.94 m² or 45.56% of the area of the transect area. Unsupervised NDVI had been tested with field measurements having an error deviation of 3.602%.

Table 2. The result of the analysis of the three method (unsupervised NDVI, supervised optical band, RGB-OBIA) processing of aerial photograph (orthomosaic) of seagrass cover in Bandengan Waters, Jepara.

| Image Analysis       | Class | Total Area Cover (aerial) | Total Area (transect) | Seagrass cover (aerial) | Seagrass coverage (transect image result) | RMSD (%) | Estimated Cover (%) |
|----------------------|-------|--------------------------|-----------------------|------------------------|------------------------------------------|----------|--------------------|
| Unsupervised NDVI    | 3     | 14239.749                | 10000                 | 6680.841               | 5113.937                                 | 3.602    | 46.917             |
| Supervised Optical Bands | 5     | 14239.749                | 10000                 | 6911.051               | 5290.154                                 | 0.280    | 48.534             |
| OBIA Classification  | 3     | 14239.749                | 10000                 | 7497.301               | 5738.907                                 | 3.850    | 50.544             |
Figure 5. The result analysis using the unsupervised Red bands-NIR (NDVI) method in the drone flying area in Bandengan waters. Colour class classification of seagrass (light green), non-seagrass (dark green), and sand (grey).

The application of drones to the utilization of aerial photographs with high resolution was also analyzed using supervised optical bands, by method 2.3.2. shown in Figure 6, with the following colour classification, i.e. false vegetation (dark-green), rock area (black), sand area (grey), seagrass (light green), sand, and rubble (refer to coral) can be well classified (pink). The results of the analysis showed that the value of the seagrass cover area was known to be 6911.051m$^2$ or 48.53$m^2$ of total area covered by drones. The transect area of the analysis results shown that the total cover area of the seagrass area was 5290.154$m^2$ or 48.49%, the error value of the test result obtained was 0.28% for the RMSD test analysis.

Figure 6. The result analysis using Supervised Optical bands method, in the drone flying area in Bandengan Waters. Colour class classification of seagrass area (light green), sand and rubble area (pink), sand area (grey), rocks area (black), and false vegetation (dark green).
The result of image analysis using the approach method, as the third method was the OBIA classification segmentation analysis, which was shown in Figure 7. The classification result showed 3 classes, including seagrass vegetation with bright green colour, false vegetation with dark green colour, and un-classification with grey colour. Segmentation was done with multiresolution, optimizing the object value by minimizing the mean acquired heterogeneity. The result of this analysis has got the largest deviation value for error, which was 3850m² with a cover of 50.544%. The coverage area showed a value of 5738.91m².

Figure 7. The result analysis using the Segmentation OBIA Classification method in the drone flying area in Bandengan waters. Colour class classification of seagrass (light green), non-seagrass (dark green) and non-classification (grey).

The use of drone products to estimate NDVI was quite promising. But it was necessary to study more robust radiometric calibration procedures, increasing the quality of data products from drones and making it more comparable between sites, sensors, and schedules, previous study about NDVI to estimate vegetation result same result [15]. Supervised analysis with optical bands were shown higher resolution from drone imagery. The image generally provided a more detailed map. In order to examine the accuracy of the classification products, accuracy assessment was applied to the results accuracy assessment provided producer’s accuracy, which occurred when we have omitted certain categories that actually existed on the ground, user’s accuracy, which occurred when we have identified categories that did not exist on the ground, and finally, overall accuracy, which was the total number of correct pixels [20]. Supervised analyze can provide image raw with high resolutions as drone imagery. On supervised analysed, the descriptions of training samples in different areas were inconsistent, it was differs from other analyses, it was why supervised analysis could reach good accuracy than other analyzes. For example, the description of some studies used some sample objects, whereas other studies employed the proportion of samples. For easy comparison and analyses, training sample proportion was uniformly used here to delineate the size of training samples in supervised classification. For simplicity, with an increase in the size of training samples, the classification accuracy increased accordingly. A positive correlation existed between classification accuracy and size of the training sample [19]. This study described for the first time an approach to intertidal seagrass mapping using the lightweight drone to obtain very fine spatial resolution data. A wide variation between classification was found when measuring the difference between classified and observed cover within the quadrat sample collected. Given that the addition of texture layers has improved classification accuracy in the past in similar habitat such as salt mars [21], we expected to see reduce on RMSD scores in this study. It may be that
the classification of the very fine spatial resolution data shown in this study can only be improved by the addition of more spectral, rather than textural layers. The spectral complexity found in hyperspherical optical remote sensing studies on *Zostera nolti* leaves ([22] suggested that the addition of further spectral bands may produce better discrimination between seagrass shoots and background sediments. Different texture measures were selected during the layer selection phase for each site. This highlighted the importance of treating each mosaic individuals when selecting layers to input to a classification scheme. Variables such as the spatial resolution of the images, and the meteorological conditions (e.g. cloud cover) allowed for the identification of meadows features such as other biotic features, like the colonies of macroalgae, massive coral, also the flat sand and coral rubble at the observation location.

### 4. Conclusions

This research used high-resolution aerial photographic images and developed an object-based identification method by developing the neared neighbour method and index vegetation in its application. Based on the method used in this study, the information in the object-based classification and emphasizing that the object-based classification method produced effective and efficient outputs compared to the commonly used visual classification method. In developing this classification method, it was necessary to conduct a more in-depth study of the parameter scale used at different image resolution values so as to produce a more accurate segmentation according to the image data used.

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