Spatial assessment of seagrass ecosystem using the Unmanned Aerial Vehicle (UAV) in Teluk Awur, Coastal Water of Jepara

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Abstract. Seagrass ecosystem are highly sensitive to environmental changes. They are also in global decline and under threat from global climate change and a variety of anthropogenic factors. There is now, a spatial assessment method for the monitoring of the seagrass beds is needed, so that changes in seagrass condition can be understood. Typical monitoring approaches have included remote sensing from satellites and unmanned aerial vehicle platform, and ground base ecological survey. The techniques can suffer from temporal and spatial inconsistency, or are very localised making it hard to assess seagrass meadows in a structured manner. The aim of research was present the technique using a lightweight drone and consumer grade cameras to produce very high spatial resolution mosaics of intertidal site in Teluk Awur, Jepara water, 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 show that digitation method, can show between the observed and classified low coverage seagrass (<25%), to middle coverage seagrass (between 25< and <50%), also can detect other biotic features, like massive coral, macroalgae also the flat sand and coral rubble.

Keywords: Jepara; seagrass; spatial assessment

1. Introduction
Remote sensing data processing is already a considerable need in the mapping industry, especially high-resolution satellite imagery which is very much used in large-scale mapping. Call it, Ikonos imagery, Quickbird, WorldView, and many more examples of high-resolution satellite imagery that became primadonna in the utilization of remote sensing that has a high accuracy value in the past decade [1].

In addition to using satellite imagery, there is one alternative technology to get faster, cheaper, real time and detailed data that is with aerial photos using a crewless aircraft (UAV) or drone. By using UAVs in mapping activities, there will be many advantages, including the time and duration of the acquisition of fast and flexible data information, operational prices and investment tools that are quite affordable, as well as more real time and detailed results than satellite imagery [2]. Because picture has been taken using UAVs is carried out at altitudes under the clouds, thus
avoiding the results of images with high cloud cover and having sharper results when compared to satellite imagery that is heavily influenced by atmospheric conditions [3].

Along with technological advances in this remote sensing field, practitioners are required to develop methods in the extraction of an image using classification methods to obtain more precise and accurate results [4]. In spatial analysis on remote sensing imagery can be done several analyses to obtain output in the form of maps both general and thematic. One of the analyses conducted to obtain accurate data information and results in representing the suitability between image data and conditions in the field is with classing or classification techniques. In general there are two classification techniques, namely visual classification and digital classification. Visual classification technique is a classification by interpreting and delineating the image directly. Whereas in digital classification, pixels in an image processed with the same spectral characteristics (assuming the same class) are identified and defined in a color either through a supervised method or an unsupervised method (not guided, based on the digital value of the image) using certain software [5].

The most commonly used method of digital asification is a pixel-based method to obtain information-based classing in each image pixel. However, pixel-based methods are less optimal when performed on detailed scale remote sensing data such as high-resolution satellite imagery and UAVs because these methods are commonly used for medium or low scales. In order to get more optimal results on the utilization of this UAV, it is necessary to classify by based on objects because the data that has high resolution objects is quite clearly visible and if using pixel-based methods then the results obtained are less accurate especially in certain objects that have different coefficients [6].

In this study, the method used was object-based classification or Object-Based Image Analysis (OBIA) where this method is based on multiresclusive segmentation into homogeneous areas with parameters such as scale, shape, compactness, and vegetation index information (NDVI) to separate objects from one another. The three main parameters of this multiresclusive segmentation, namely shape, scale, and complexion are then filled with varying values to get segmentation results suitable for digital classification [7]. With segmentation like this will greatly underlie the advancement of image analysis and more efficient processing time, and can produce a good map of land use and cover. Data on land use and cover will be critical in the management planning of an area. The data is useful in the initial identification of land suitability or changes or restoration of a land that wants to be managed further [8].

As an analysis for the accuracy test of this classification method, confusion matrix is used which is an error matrix that compares between categories and the relationship between the reference data and the classification results. In this matrix will be obtained the amount of accuracy of the maker (producers accuracy), user accuracy (users accuracy), overall accuracy (overall accuracy), and coefficient kappa (Kappa coefficient) [9].

This research aims to examine object-based classification methods through NDVI value information for vegetation classification and nearest neighbour methods for land cover in UAV imagery data. Based on this, the study of the estimated land area can be approached by this method.

2. Methods

2.1. Study site
Teluk Awur is located in the Jepara area, Central Java, morphology in the form of a bay facing the northwest. Geographically located 110°37'36.73"E – 110°39'25.16"E and 6°37'11.46"S – 6°35'11.80"S, this area of waters becomes a fairly large area of seagrass beds, integrated with mangrove coasts. This ecosystem represents an integrated ecosystem within the green belt of the ocean. Previous research has shown the majority of seagrass species, including *Enhalus acroides*, *Thalassia hempricii*, *Cymodocea serulata*, and *C. rotundata* as a reference for variations in the
types of seagrass in this area. In this study, seagrass is used as vegetation to be studied in analyzing land cover in a coastal area, using aerial photography approach using drones.

2.2. Fieldwork
Field data retrieval is done on the date 19–21 June 2020. The investigation study was conducted by plotting the area of the transect line with a length of 100 m, and the distance between the transects is 50m, with the total transect line are 3 transect line locations.

Each quadrant transects with a total quadrant of 50 cm x 50 cm, placed on each transect with a distance of 10 m, this is done to see the seagrass coverage area by calcifying the type that dominates the area. The illustration is shown in figure 1.

![Figure 1](image-url)

**Figure 1.** The study area of Teluk Awur, the main inset is an area of interest in conducting drone flight mission, the second inset is Jepara Regency area.

2.3. Area photos acquisition
In the remote sensing approach, to know the area of seagrass cover used by drones. The drone's results from the capture and eventual release of each are analyzed described in Figure 2. Flow chart of the process. Aerial photography uses the DJI Phantom 4 drone, which is equipped with dreadlocks for the stability of the resulting image. The flight track line is set at an altitude of 20m, carried out the acquisition of flight plans on drone deploy software. Using a single camera with an optical band, specification 16-megapixel, wide-angle, focal length 24mm, with CMOS sensor). Since the CMOS sensor does not have a specific spectral range for each RGB band, we consider the RGB value of each pixel to be a band value.

For effective and efficient management and monitoring coastal, in this study seagrass ecosystem and occupation, it is required quality of information, therefore information in advance technique is necessary. Unmanned aerial vehicle (UAV) for remote sensing coastal area represents low-cost with good performance [10]. A Phantom 4 Pro quadratic rotor drone with low-weight was used in this study. We did some activities with custom and adjustment. Aerial surveying was performed using this drone with 1,388Kg 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 made high-resolution. As seagrass has a thin leaf, it needs to clear pixel to justification analysis, with a small format camera it is possible to get the good pixel to coverage leaf of seagrass.

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2.4. Image processing as data analyze

Drones at recent studies were a good choice to be selected as survey tools of ecologists, monitoring, environmental applied, etc. The drone photo has good contrast at accurate pixels [11]. 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) [12]. 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. GPS data is paramount, the next will be synchronized camera and photo to flight track. All process about image analyzing shown in Figure 2.

The region of interest for the water area to be used as an area of analysis and classification as an accuracy test is carried out to carry out ground truthing tests. The total area executed as ROI is 18155.298meters. from here divided several classes according to justification in the implementation of the analysis. The training site is divided into 2–5 polygon classes.

| Band number | Source Camera | Information | Digital Value | Unit       |
|-------------|---------------|-------------|---------------|------------|
| Band 1      | Rgb           | Dem         | -10 – 30      | Metres     |
| Band 2      | Rgb           | Red         | 0 – 255       | 8-bit true color |
| Band 3      | Rgb           | Green       | 0 – 255       | 8-bit true color |
| Band 4      | Rgb           | Blue        | 0 – 255       | 8-bit true color |
| Band 5      | Rgb           | Alpha/NIR   | 255           | -          |

2.4.1. 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 [13].
2.4.2. **Supervised Optical bands.** Supervised optical bands are a type of classification analysis by combining 3 bands optical red, green, and blue bands (RGB). The optical band is composite from red green and blue, R and B represent normalized surface reflected averaged over orange of wavelength, visible red has wavelength 0.6um and visible blue has 0.4 um [14]. The supervised approach uses training sample classes to get the classification as good as desired. Coral coverage, sand, seagrass coverage, unclassified, and false vegetation can be well classified. This method divides shallow marine habitats into 5 classes of training samples. These five classifications become clusters in the assessment of the desired land cover yield. The result of land will be carried out for analysis by RMSD (%) of the quadrant transect data from measurements in the field.

![Flow chart research](image_url)
2.4.3. Segmentation OBIA-nearest neighbour classification. Image segment processing is done by using multi-resolution segmentation in Arcmap on ARCGIS 10.8 software by minimizing the object value with an average heterogeneity of image values at a certain resolution. With the scale parameter that is the reference in making the segment, the maximum value of heterogeneity allowed in producing the image object to be analyzed is determined. As a result, object-based image analysis (OBIA) techniques have emerged to address these issues. The OBIA technique has now replaced the traditional pixel-based method as the new standard method that will facilitate land-cover classification from high spatial resolution remote sensing imagery [15, 16]. Step of OBIA which applying in this research following, extraction with unsupervised classification, using NDVI classification to the divided objective area. In addition, the working time using this classification method is more efficient because the segmentation is based on objects and not pixels. The basic concept of this nearest neighbor method is to look at the distribution pattern of the sample objects referenced or compared using calculations that take into account the distance, number of samples, and area with the following formulas:

\[
R_n = \frac{\bar{D}(\text{Obs})}{0.5 \sqrt{\frac{a}{n}}} \tag{1}
\]

Where:
- \( R_n \): Nearest neighbour value
- \( \bar{D}(\text{Obs}) \): average distance from nearest neighbour observation
- \( a \): Area
- \( n \): number of sample trainings

3. Result

The result of field data collection from the ground sampling area consists of an area with a total area of 10,000 (length x width: 100 x 100 meters-transect), line transect along 100 meters, the transect using quadrant size 50x50 cm, the distance between line transect is 50 m. The ground check result data is 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 will then acquire, for each area that has a value against the seagrass code justification, that an estimate of the land cover value of seagrass meadows can be obtained. Teluk Awur waters have a photo area of 18,155.29 m². This area is a shallow water area which is the study area which can be seen in table 2.

Table 2. The result of the analysis of the three methods (unsupervised NDVI, supervised optical band, RGB-OBIA) processing of aerial photograph (orthomozaic) of seagrass cover.

| Site      | Image Analysis   | No of Class | Total cover area (aerial) (m²) | Total area (transect) (m²) | Seagrass cover (aerial) (m²) | Seagrass coverage (transect image result) | RMSD (%) | Estimated Cover (%) |
|-----------|------------------|-------------|--------------------------------|----------------------------|----------------------------|-------------------------------------------|----------|---------------------|
| Teluk Awur | Unsupervised (NDVI) | 3           | 18,155.298                     | 10,000                     | 4,911.367                  | 2,948.666                                 | 5.302    | 27.05               |
|           | Supervised RGB   | 5           | 18,155.298                     | 10,000                     | 4,820.462                  | 2,894.089                                 | 3.53     | 26.551              |
|           | RGB (OBIA)       | 3           | 18,155.298                     | 10,000                     | 4,871.526                  | 2,924.746                                 | 4.44     | 26.833              |

The ground truth area is an area that is a representation of the land cover of seagrass lading. The width implementation stretches of the transect line as far as 100 m, with the absence of 3 transect lines, with each interval transect studies of 50 m. The total area of the transect study area is 100 x 100 m (10,000 m²). This value will be used as a test value against the cover area in the transect area performed.
The total area swept away by drones are 18155.298 m², this area has been made adjustments by eliminating some unneeded land. The land is coastal to land, docks and ships. The third analysis of aerial photographs shows that the cover of the seagrass field area is approximately 2,948.166 m², the result of unsupervised (NDVI) analysis. Spatially shown in figure 3. The total cover on a percentage point is 27.05% of the drone's photo area. Compared to the total land cover resulting from the transect carried out is 60.03% of the total area swept away by drones. The result of the seagrass field cover of air photos in the area around the transect is 2,948.66 m². Compared with the test area has an error value of 5.302%. Comparing the results of the transect quadrant to the results of the analysis image results in this value. The image quality given by the photograph over the transect area is better. The results are displayed by the Supervised RGB image analysis, which is an analysis with red, green, and blue optical bands. The total class given is 5, with 5 analytical training classes that will be guided to select the areas aimed at the class. The division classes include seagrass (green), sand (gray), sand (brown), false vegetation (dark green), and unclassified (black) more clearly can be seen in figure 4. (Seagrass lading land cover with this analysis is 4,820.462 m² with a total aerial cover of 18,155.298 m². Seagrass field land cover in the transect area shows a total of 2,894.089 m² compared to ground check results showing the total cover of seagrass lading land is 1,838.83 m². Correction of 3.53%. Classing is done by selecting several class combinations that are considered to represent the entire class on the image to be classified on the RGB supervised method. The classification results performed on the drone photos show an average accuracy value of 96.47% (table 3). A previously determined training sample as a test of the accuracy of this classification shows that most classes are classified accurately as shown in table 2 error accuracy shown in table 2 approximately 3.53%. The classes identified and the results of this classification are seagrass (green), sand (gray), coral (brown), false vegetation (dark green), and unclassified (black). In the seagrass coverage class, this segment in the training class identified as seagrass is 96.48%, the rest is identified as false vegetation. This class also allows to contain seagrass, this is because the capture of the photos is a shadow that may be indicated as seagrass.

The results for the management of analysis using Unsupervised RGB OBIA, with 3 class od green seagrass classifications, namely seagrass (green), false vegetation (dark green), and unclassified (gray), can be seen in figure 5 of classification. The total cover of seagrass lading land in this classification gets an error value of 4.447% of the RMSD test. Seagrass lading covers the total temperature of the air pot is 4,870.526 mm², while the result of air photo in the seagrass transect area is 2,924.746 m². The total area covered on the flight plane is 18,155.298 m².

| Classification Results | Classification Results | Classification Results | Classification Results | Classification Results | Classification Results |
|-------------------------|------------------------|------------------------|------------------------|------------------------|------------------------|
| Coral coverage          | 98.77                  | 1.34                   | 0                      | 0                      | 0                      |
| Sand                    | 1.23                   | 93.96                  | 0                      | 0                      | 1.29                   |
| Sea-grass Coverage      | 0                      | 2.68                   | 96.48                  | 0                      | 2.58                   |
| Unclassified            | 0                      | 0                      | 0                      | 100                    | 0                      |
| False vegetation        | 0                      | 2.01                   | 3.52                   | 0                      | 96.13                  |
| Total Accuracy          |                        |                        |                        |                        | 96.4%                  |
Figure 3. Image analysis by Unsupervised Red bands – NIR (NDVI) method, on the drone's flying area in the waters of Teluk Awur, Jepara. Classification of seagrass color class (bright green), false vegetation (dark green), and unclassified (gray).

Figure 4. The results of the analysis using supervised optical bands (RGB) method, on the flying area of drones in the waters of Teluk Awur, Jepara. Classification of color classes coral (brown), sand (gray), seagrass (bright green), unclassified (black), and false vegetation (dark green).
4. Discussion
The use of drone products to estimate NDVI is quite promising. But it is 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 estimation vegetation result same result [13]. Supervised analyze with optical bands shown higher resolution from drone imagery. The image generally provides a more detailed map. In order to examine the accuracy of the classification products, accuracy assessment is applied to the results accuracy assessment provides producer’s accuracy, which occurs when we have omitted certain categories that actually exist on the ground, user’s accuracy, which occurs when we have identified categories that do not exist on the ground, and finally, overall accuracy, which is the total number of correct pixels [14]. Supervised analyze can provide image raw with high resolutions as drone imagery. On Supervised analyzed the descriptions of training samples in different area are inconsistent, it is will different with other analyze, it why supervised analyze can reach good accurate then else analyze. For example, the description of some studies uses some sample objects, whereas other studies employ the proportion of samples. For easy comparison and analyses, training sample proportion is uniformly used here to delineate the size of training samples in supervised classification. As simple, with an increase in the size of training samples, the classification accuracy increases accordingly. Positive correlation exists between classification accuracy and size of the training sample [16]. This study describes for the first time an approach to intertidal seagrass mapping using the lightweight drone to obtain very fine spatial resolution data. We found wide variation between classification 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 salt mars [17], we expected to see reduce 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.

Here are shown 3 methods in drone imagery management, each of which has an estimated cover value on different seagrass beds in Teluk Awur waters. Overall, the average value of seagrass cover in an area with drone of 18,155.298 m² was 26.813%, or 2,681.3 m². Ecologically, the area coverage based on seagrass status according to the Minister of Environment Decree Number 200/2004 concerning standard criteria for damage and guidelines for determining seagrass status based on seagrass cover is divided into three criteria, namely rich / healthy with closure > 60%, less rich / less healthy with closure of 30-59%, and poor <29.9% [18]. The three drone imagery results show a value that is not far from the average value, 27.05%, 26.55% and 26.83%, respectively NDVI, Supervised RGB, and RGB (OBIA) show that the conditions are bad, with a value below 29.9%. Seagrass results (transect image results) show different categories of conditions, namely 29.48%, 28.94%, and 29.24%, respectively for NDVI, Supervised RGB, and RGB (OBIA). It shows that the condition is in the poor category, while with the supervised RGB analysis the seagrass cover condition is bad.

5. Conclusion
The study used high-resolution aerial photo imagery data and developed an object-based classification method by combining the nearest neighbour method and vegetation index in its application. Based on the methods carried out in this study, obtained information in object-based classification has an accuracy yield of 96.4%, emphasizing that object-based classification methods produce a highly effective and efficient output compared to common visual classification methods. Based on standard criteria for seagrass damage of the Decree of Minister of Environment No. 200/2004, seagrass ecosystems in Panjang Island, Teluk Awur, Coastal waters of Jepara were at a moderate level of damage, with variant less healthy to poor.

In the development of this classification method, a more in-depth study is needed on the scale of optimal parameters used at different image resolution values so as to produce more accurate segmentation according to the imagery data used.

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