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COMPARISON OF SEAGRASS COVER CLASSIFICATION BASED-ON SVM AND FUZZY ALGORITHMS USING MULTI-SCALE IMAGERY IN KODINGARENG LOMPO ISLAND

KOMPARASI KLASIFIKASI TUTUPAN LAMUN BERDASARKAN ALGORITMA SVM DAN FUZZY MENGGUNAKAN CITRA MULTI-SKALA DI PULAU KODINGARENG LOMPO

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ABSTRACT

Seagrass beds play an ecological role in the shallow marine environment, such as a habitat for biota, primary producers, and sediment traps. They also act as nutrient recyclers. Since they have such an important role, this natural resource needs to be preserved. Therefore, continuous monitoring and mapping of seagrass beds, especially by remote sensing methods, is paramount. The current rapid development of satellite sensor technology, especially its spatial and spectral resolutions, has improved the quality of the seagrass distribution map. The use of proper classification methods and schemes in the classification of seagrass distribution based on satellite imagery can affect the accuracy of the map, which is why various alternative algorithm studies are required. In this study, the Support Vector Machine and Fuzzy Logic algorithms were used to classify the WorldView-2 and Sentinel-2 satellite imageries on Kodingareng Lompo Island with four classes of seagrass cover, sparse (0–25%), moderate (26–50%), dense (51–75%), and very dense (76–100%). The result showed that the Fuzzy Logic algorithm applied to WorldView-2 imagery has the best overall accuracy of 78.60% seagrass cover classification.

Keywords: accuracy, mapping, seagrass condition, sentinel-2, worldview-2

ABSTRAK

Padang lamun mempunyai peranan ekologi bagi lingkungan laut dangkal yaitu sebagai habitat biota, produsen primer, penangkap sedimen serta berperan sebagai pendaur zat-zat hara. Mengingat pentingnya peranan ekosistem padang lamun maka kelestarian sumber daya alam ini perlu dijaga, oleh karena itu pemetaan dan pemantauan yang terus-menerus terhadap keberadaan padang lamun sangat penting dilakukan. Metode penginderaan jauh merupakan metode yang dapat digunakan untuk memetakan dan memantau kondisi padang lamun. Perkembangan teknologi sensor satelit yang pesat saat ini, khususnya resolusi spasial dan spektral sensor meningkatkan kualitas peta sebaran lamun. Penggunaan metode dan skema klasifikasi yang kurang tepat dalam klasifikasi kondisi lamun dari citra satelit juga termasuk hal yang dapat memengaruhi akurasi peta, sehingga dibutuhkan berbagai alternatif kajian algoritma yang digunakan. Pada penelitian ini digunakan algoritma Support Vector Machine dan Logika Fuzzy menggunakan citra satelit WorldView-2 dan Sentinel-2 di Pulau Kodingareng Lompo dengan empat kelas tutupan lamun yaitu jarang (0-25%), sedang (26-50%), padat (51-75%), dan sangat padat (76-100%). Hasil yang diperoleh adalah algoritma Logika Fuzzy menggunakan citra WorldView-2 memiliki akurasi keseluruhan klasifikasi tutupan lamun yang paling baik sebesar 78,60%.

Kata kunci: *akurasi, kondisi lamun, pemetaan, sentinel-2, worldview-2*

I. INTRODUCTION

The seagrass ecosystem is an ecosystem that has an important role in coastal waters as a filtration medium, a barrier to erosion, a place of fish spawning, a place to maintain saplings of various types of marine biota, a place to feed for marine biota, and is part of a shallow marine area (Rahmawati *et al.*, 2014). The current seagrass cover in Indonesia is 42.23% of the total area is 293464 ha (Sjafrie *et al.*, 2018), which is in the unhealthy category based on the criteria set by the Ministry of State and the Environment Republic of Indonesia No. 200 (2004). Regarding the importance of the role of the seagrass ecosystem, the preservation of these natural resources needs to be maintained, therefore continuous mapping and monitoring of the existence of seagrass beds is very important.

The remote sensing method is one method that has been widely used to map and monitor the conditions of seagrass beds. The existence and distribution of seagrass can be identified and mapping using satellite images through the appearance of the difference in color and texture of the substrate (Larkum & West, 1990); (Patty, 2016). The current rapid development of satellite sensor technology, especially its spatial and spectral resolutions, improve the quality of the seagrass distribution map. The level of accuracy of the classified map depends on the spatial resolution of the satellite imagery used (Wang *et al.*, 2018).

Using inappropriate classification methods and schemes in the classification of benthic habitats (including seagrass) from satellite images is one thing that can affect the accuracy of the map (Siregar *et al.*, 2018a). Various alternative studies of algorithms and classification methods to be used in order to improve the accuracy of seagrass mapping are things that still need to be done. More than a decade ago, most satellite image classification approach is used based on pixel information where each pixel was classified into one category (Murmu & Biswas, 2015). The pixel-based classification technique in benthic habitat mapping is still misclassified because of the high diversity of habitats in one pixel so it becomes mixed pixels (Wahidin *et al.*, 2015), which causes difficulty in determining the class of these pixels. Classification with a Fuzzy Logic approach provide more precise, accurate representation and allows partial membership, which is interpreted closely to the mixed pixel problem (Murmu & Biswas, 2015).

There are several algorithms used in the classification of satellite images. Pixel-based classification algorithms include Maximum Likelihood, Support Vector Machine, Minimum Distance, Mahalanobis Distance, and Parallel Piped. These algorithms have been carried out by several previous researchers with good results. The SVM algorithm used for seagrass classification in Tunda Serang Island, Banten applying WorldView-2 imagery has an accuracy value of 76.4% with four classes of seagrass cover (Aziizah *et al.*, 2016). Other studies that produce fairly good accuracy values are Traganos & Reinarzt (2017) and Poursanidis *et al.*, (2018). The Fuzzy Logic algorithm has also been widely used in remote sensing image classification (Nedeljkovic, 2004; Lizarazo & Elsner, 2009; Eastman, 2012). In Indonesia, several studies have been conducted using Fuzzy Logic for the classification of shallow-water habitats, Ampou *et al.* (2017) and Sangadji *et al.* (2018).

Water depth is also an important factor that contributes to the accuracy of the classification of satellite images. A water column correction needs to be done to improve accuracy in extracting shallow-water benthic habitat information by eliminating the influence of water depth which will exponentially reduce the reflected signal from benthic habitats as water depth increases. The water column correction method that has been widely applied in shallow water habitat mapping is the Depth Invariant Index (DII) (Lyzenga, 1981).

Kodingareng Lompo Island is one of the Island in Spermonde Archipelago that has seagrass distribution with different condition and density. In this area, study on seagrass identification and mapping is very limited, therefore it is important to conduct a study on mapping seagrass distribution and classification. This study aims to analyse the accuracy of seagrass classification based on pixel-based using Support Vector Machine and Fuzzy Logic algorithms and WorldView-2 and Sentinel-2 imageries are used.

II. RESEARCH METHODS

2.1. Time and Place of Research

This research was conducted in the waters of the Kodingareng Lompo Island, Kodingareng Village, Ujung Tanah District, Makassar, South Sulawesi (Figure 1). Geographically, the Kodingareng Lompo Island is situated at 119˚16'00" East Longitude and 05˚08'54" South Latitude. A field survey was conducted from 21st to 25th June 2020.

2.2. Material and Data

The equipment used during the field survey comprised the Global Positioning System (GPS), 50 x 50 cm^2 quadrant transects, basic diving equipment, and underwater cameras. In this study, WorldView-2 satellite imagery with a spatial resolution of 1.85 meters and Sentinel-2 with a spatial resolution of 10 meters were used (Table 1) which was acquired on January 25th, 2020.

2.3. Sampling Points

Prior to field survey, a working map

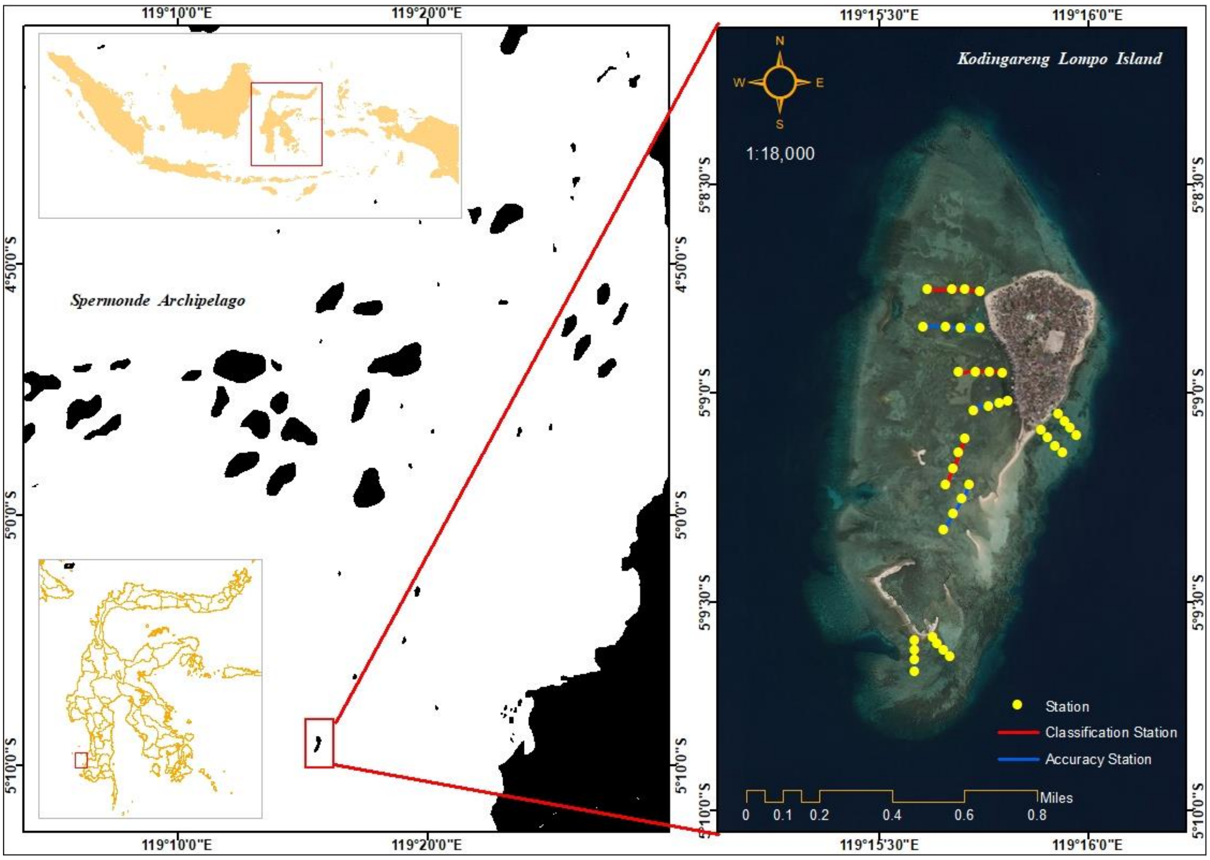

Figure 1. The study site and sampling stations on Kodingareng Lompo Island, Spermonde Archipelago, South Sulawesi.

Table 1. Characteristics of WorldView-2 and Sentinel-2 imagery.

Band	WorldView-2		Sentinel-2	
	Wavelength (nm)	Spatial Resolution (m)	Wavelength (nm)	Spatial Resolution (m)
Blue	450–510	1.85	398–594	10
Green	510–580	1.85	515–605	10
Red	630–690	1.85	626–702	10
NIR	770–895	1.85	790–980	10

Source: DigitalGlobe (2010) and ESA (2015).

was made from the unsupervised classification of satellite imagery of the site which is used to select point sampling. Meanwhile, the field observation sampling points was determined using the Systematic Random Sampling method. Seagrass cover photos were taken perpendicularly from above of a transect using the Underwater Photo Transect (UPT) technique. The coordinates of the sampling point are used as reference points in the classification and accuracy test of both images. Total number of sampling points collected from five sampling stations is 240 points, which is divided into 120 points for input in the classification and 120 points for input in the accuracy test.

2.4. Image Pre-Processing

Satellite image processing started with image cropping, geometric correction, radiometric calibration, and atmospheric correction. The images were cropped based on the Region of Interest (RoI) includes the waters around Kodingareng Lompo Island. The geometric correction used the Ground Control Point (GCP) transformation technique of 10 points which are spread on each side of the study area. The study area was mapped using Universal Transverse Mercator projection (50 SUTM). The Top of Atmosphere (ToA) correction is carried out by changing the Digital Number (DN) to a radian or reflectance value using the parameters of the e-sun value, the zenith angle of the sun, and the distance from the earth to the sun. This aims to eliminate the radiometric distortion caused by the position of the sun. From the radiometric calibration process, it is followed by atmospheric correction using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercube (FLAASH) method which can reduce the effects of atmospheric disturbances and produce more accurate reflectance of the physical surface on the image (Siregar *et al.*, 2018b). The parameters used for the correction are the coordinates of the study location, date and time of the acquisition, aerosol model, and image resolution.

Water column correction was used to eliminate the influence of water depth by reducing the influence of water column attenuation, which will exponentially decrease with increasing water depth. The method used is the DII method that produced a bottom index of the shallow waters benthic habitats such as corals, seagrass, rubbles, and sand. Commonly used algorithm is (Lyzenga, 1981):

$$DII = ln(Li) - [(Ki/Kj) * ln(Lj)] \quad \text{.........(1)}$$

Information: *Li* was digital value in i band, *Lj* was digital value in j band, *Ki/Kj* was the ratio of the attenuation coefficient in the i and j band pairs.

2.5. Image Classification

The class objects used in this study were seagrass, coral, sand, and rubble, and the algorithms used were Support Vector Machine (SVM) and Fuzzy Logic. The basic concept of the SVM algorithm is an effort to find the best hyperplane that functions as a separator of two classes in the input space. The hyperplane is determined by measuring the hyperplane margin to find the maximum point. The margin is the distance between the hyperplane and the closest pattern from each class, which is called a support vector. The largest margin can be found by maximising the value of the distance between the hyperplane and its closest point, which is one (Saputro, 2015).

In Fuzzy Logic classification, there are three steps i.e. fuzzification, if-then rule, and defuzzification. Fuzzification is changing the fuzzy input into fuzzy variables which are presented as fuzzy sets with a membership function of each. The input used is a signature statistical value, namely the mean value and standard deviation. These values will define the membership function (Nedeljkovic, 2004). Then change the membership value by using the rules or what is called the if-then rule process. It makes the rules based on benthic and seagrass habitat classes from each satellite image. Each class is created in one input variable for the water column corrected image. It structures the relationship between the respective input and output variables. Then the defuzzification stage, which is to change the fuzzy output to a crisp value based on a predetermined membership function or can also be called transforming the results of fuzzy reasoning into the output value. The fuzzy output will be included in the defuzzification process to produce a crisp output (Thendean & Sugiarto, 2008).

2.6. Accuracy Test

The purpose of the accuracy test is to find out how accurate the classification results are, using an error matrix. The accuracy test parameters comprise Overall Accuracy (OA), User Accuracy (UA), Producer Accuracy (PA), Kappa statistic, and the Z-test, which are calculated using the following formula (Green *et al.*, 2000):

$$OA\ (\%) = \frac{\text{the number of pixels correctly classified}}{\text{the number of samples overall accuracy test}}\ x\ 100 \quad \text{.....................} (2)$$

$$UA\ (\%) = \frac{\text{the number of samples in the classification row that are classified correctly}}{\text{the number of samples classified as that class}}\ x\ 100 \quad \text{............} (3)$$

$$PA\ (\%) = \frac{\text{the number of samples in the classification column that are classified correctly}}{\text{the number of samples classified as that class}}\ x\ 100 \quad \text{............} (4)$$

KHAT-based Z-test or K statistic is used to describe the agreed value of the field data with the results of the satellite image classification. The Kappa coefficient values are in the range 0–1 and are usually less than the overall accuracy value, which can be calculated using the equation Green *et al.* (2000) below:

$$\kappa = \frac{N\sum_{i=1}^{k} n_{ij} - \sum_{i=1}^{k} n_{i+}n_{+j}}{N^2 - \sum_{i=1}^{k} n_{i+}n_{+j}} \quad \text{..................} (5)$$

Information: *k* was the number of rows in the matrix, *nij* was the number of observations in *i* row and *i* column, *ni+* and *n+j* were the total margin of *i* rows and *i* column, *N* was the total number of observations (overall accuracy).

Kappa values grouped into five based on the range of Kappa coefficient values which is presented in the Table 2.

The statistical test to test if the two error matrix results from different classification methods using the Z-test as follow:

$$Z = \frac{k_1 - k_2}{\sqrt{var\ k_1 + var\ k_2}} \text{..............................} (6)$$

Information: Z was the standardised value and normal distribution of the Kappa coefficient, $k1$ and $k2$ values were the kappa statistical calculations of each error matrix with the hypothesis H0: (k1-k2) = 0, alternative H1: (k1-k2) ≠ 0, H0 rejected if $Z \geq Z\alpha/2$. At the 95% confidence level, if the Z-test result value is greater than 1.96 then the result is significant (Congalton & Green, 2009).

Table 2. The range of Kappa coefficient values (Richards, 2013).

κ	Classified as
< 0.4	Bad
0.41–0.60	Moderate
0.61–0.75	Good
0.76–0.80	Very good
> 0.81	Almost perfect

III. RESULTS AND DISCUSSION

Pixel-based classification using the SPV algorithm and Fuzzy Logic algorithm applied to seagrass conditions comprised sparse with 0-25% cover, moderate with 26-50% cover, dense with 51-75% cover, and very dense with 75-100% cover classes based on to the density of seagrass cover.

Table 3. Seagrass density classification (Amran, 2017).

Density	Coverage (%)
Sparse	0–25
Moderate	26–50
Dense	51–75
Very Dense	75–100

3.1. Support Vector Machine (SVM) Classification

Based on seagrass classes, the classification using the Support Vector Machine algorithm in terms of the sparse (0–25%) and dense (51–75%) seagrass density classification has a relatively different area from the two satellite images (Table 4) and is viewed from the PA and UA have low accuracy values in the sparse (0–25%) and dense (51–75%) classes of seagrass density classification (Table 8). The high misclassification of the SVM algorithm is because many of the seagrass classes were covered by sand substrate when collecting data in the field so that the SVM algorithm cannot detect seagrass condition and detect it as another class that is approaching its pixel value. This is especially the case in the sparse class where the situation in the field is often mixed with sand. There is a high probability that the signal from the condition of the seagrass is mixed with the substrate that is around it (Bayyana *et al.*, 2020), the substrate can be a type of rock or mud-sand, seagrass growing on rocks, dead coral, or some areas with high turbidity causing a similar spectrum of reflection between seagrass and mud or rock (Ni *et al.*, 2020).

Based on theory, the SVM algorithm defines a hyperplane from the supporting vector which is the only point closest to the hyperplane (Traganos *et al.,* 2018). This possibility is also a factor that causes a high level of misclassification in the sparse class of seagrass because it is often mixed with sand so it is difficult to distinguish. A classification problem is an attempt to find the line (hyperplane) that separates the two classes. The likelihood of the classification results for most classes is positive (sand class), therefore the discrimination boundaries approach class +1 and cause a high misclassification in the rare seagrass class, the same concept also occurs in other classes of seagrass density classification. The weakness of the SVM algorithm is that it is difficult to apply to many classes (Puspitasari *et al.,* 2018).

Besides, visually the results of pixel-based classification for seagrass cover using the SVM algorithm on both satellite images show noise as salt and pepper effect which causes seagrass class in the middle of coral and deep water (Figure 2). The SVM classification has a lot of noise (salt and

Table 4. The area extent of the classification results on WorldView-2 and Sentinel-2 imageries using the SVM algorithm on Kodingareng Lompo Island.

Seagrass Density	WorldView-2 Image (ha)	Sentinel-2 Image (ha)
Sparse (0–25%)	18.93	33.71
Moderate (26–50%)	19.64	26.18
Dense (51–75%)	36.56	6.04
Very dense (76–100%)	33.00	40.05
Total	108.13	105.98

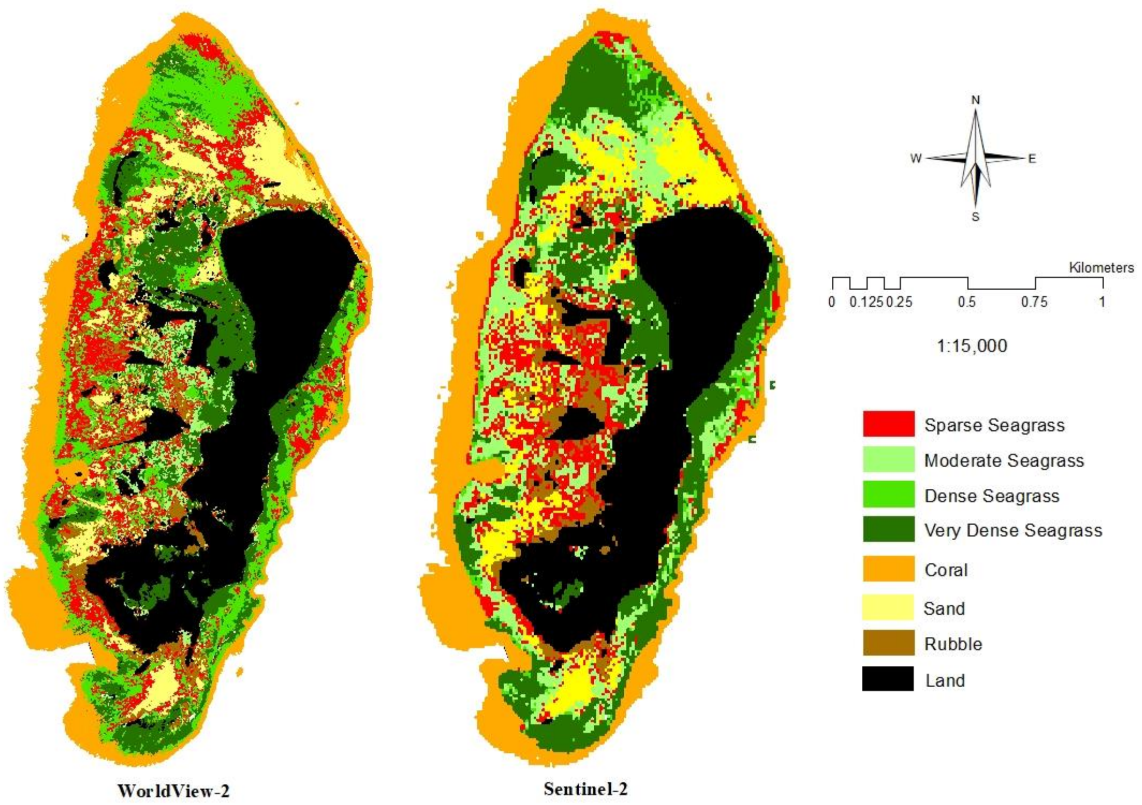

Figure 2. The results of the classification of seagrass cover using the SVM algorithm on WorldView-2 and Sentinel-2 imageries on Kodingareng Lompo Island.

pepper) and misclassification between deep water class and seagrass (Poursanidis *et al.*, 2018). There needs to be another approach to overcome the shortcomings of pixel-based classification which often gives results that still contain salt and pepper effects (Maksum *et al.*, 2016), one solution to the problem is the use of object-based classification (Blaschke, 2010).

When viewed from the total area (Table 4), the area of the seagrass class in the WorldView-2 image is wider than in the Sentinel-2 image (108.12 ha vs 105.98 ha). This area difference is probably because of the difference in the spatial resolution of the two satellite images. This shows the importance of spatial resolution for detecting benthic habitats and seagrass cover, where WorldView-2's spatial resolution is higher than Sentinel-2. The smaller pixel size, the more vegetation that can be identified (Kamal *et al.*, 2014). Another factor is the difference in the acquisition hours of the two satellite images, even though they were taken on the same day and date. The WorldView-2 imagery was acquired at low tide at 14:27, while Sentinel-2 was acquired at high tide at 10:30. An increase in water volume will increase the attenuation and spectral absorption of seagrass received by satellites (Phinn *et al.,* 2008). Therefore, the water column correction needs to be done to increase accuracy in the extraction of shallow water benthic habitat information and to reduce the effect of water column attenuation which will exponentially decrease with increasing water depth.

Visually, the pixel-based classification results for seagrass density using the SVM algorithm from the WorldView-2 image are more visually appropriate to the conditions in the field than the benthic habitat map generated from the Sentinel-2 image, where a few seagrass classes are still found after coral reef zoning with a depth of about ten meters to the East of Kodingareng Lompo Island (Figure 2). The distribution of seagrass in Indonesia is closest to the coastline and extends to a depth of ≤ 3 meters (Fauzan *et al.,* 2018), at this depth, seagrass can still receive sunlight optimally to carry out photosynthesis (Short *et al.,* 2007).

Water quality and the combination of spectral and radiometric resolutions image are other sources of error. The water condition of the Kodingareng Lompo Island has a high level of turbidity (up to 34 NTU) and is included in a complex environment where there are many species of seagrass and other benthics cover such as coral reefs and macro-algae. In complex environments where waters are almost turbid, it can affect reflection from the water column and limit the penetration ability of the Sentinel-2 bands. Its spectral wavelength may not detect the difference in reflectance of each class of seagrass (Fauzan *et al.,* 2017). Unlike WorldView-2, which has a better spectral band that penetrates the water (Baumstark *et al.,* 2016).

3.2. Fuzzy Logic Classification

In the classification using a Fuzzy Logic algorithm, there are three steps carried out in this Fuzzy Logic algorithm, namely fuzzification, if-then rule, and defuzzification. The results of the training area extraction for each class on WorldView-2 and Sentinel-2 imageries are presented in Table 5.

In the Fuzzy Logic model at the if-then rule we made stage using seven classes:

If (*Input is Sparse Seagrass*) then (*Class is Sparse Seagrass*)
If *(Input is Moderate Seagrass*) then (*Class is Moderate Seagrass*)
If (*Input is Dense Seagrass*) then (*Class is Dense Seagrass*)
If (*Input is Very Dense Seagrass*) then (*Class is Very Dense Seagrass*)
If (*Input is Coral*) then (*Class is Coral*)
If (*Input is Sand*) then (*Class is Sand*)
If (*Input is Rubble*) then (*Class is Rubble*)

Based on the classification results on the two satellite images, it shows that the results of Fuzzy Logic are better than the SVM algorithm. We can see this event in the sparse seagrass and sand classes, where these two classes are difficult to distinguish and are considered a mixed class between sparse seagrass and sand. This is showed by the accuracy value per class of seagrass density classification, both by PA and UA (Table 8). The Fuzzy Logic algorithm is very suitable for mapping benthic habitats, which are characterised by mixed features (Da Silva *et al.,* 2016). Therefore, Fuzzy Logic is suitable for situations where the detected classes are quite diverse (Eastman, 2012). When viewed from the total area (Table 6), the area of the seagrass class in the WorldView-2 image is wider than in the Sentinel-2 image (147.79 ha vs 108.53 ha). The higher spatial resolution of an image, we can identify the more vegetation.

Table 5. The digital values of each seagrass condition class on WorldView-2 and Sentinel-2.

Benthic Habitat and Seagrass Classes	WorldView-2		Sentinel-2	
	Mean	StdDev	Mean	StdDev
Sparse Seagrass	-179.03	58.40	-0.58	0.03
Moderate Seagrass	-128.56	48.70	-0.52	0.04
Dense Seagrass	-91.68	47.13	-0.48	0.04
Very Dense Seagrass	4.10	49.11	-0.39	0.04
Coral	184.66	70.12	-0.25	0.10
Sand	-141.94	93.09	-0.59	0.02
Rubble	-195.56	56.40	-0.57	0.02

Table 6. The area extent of the classification results on WorldView-2 and Sentinel-2 imageries using the Fuzzy Logic algorithm on Kodingareng Lompo Island.

Seagrass Cover	WorldView-2 Image (Ha)	Sentinel-2 Image (Ha)
Sparse (0–25%)	58.31	37.45
Moderate (26–50%)	27.81	18.61
Dense (51–75%)	30.21	24.19
Very dense (76–100%)	31.46	28.28
Total	147.79	108.53

Judging from the distribution of seagrass classes, the classification results of WorldView-2 imagery has more variety distribution of seagrass density classification than Sentinel-2, where at 5th station (East of Kodingareng Lompo Island) there are four conditions of seagrass (sparse, moderate, dense, and very dense), whereas in the Sentinel-2 imagery only one seagrass condition was detected, namely the very dense class (76–100%) (Figure 3). Despite the time difference between image acquisition and the field survey was ± 5 months, this difference did not impact the identification results because the area of the seagrass habitat on the Kodingareng Lompo Island did not transform from time to time. In areas with a high level of disturbance and seagrass dynamic, differences between image acquisition date and field survey may cause significant differences in seagrass identification (Wicaksono & Hafizt, 2013). Therefore, one problem found in Sentinel-2 imagery is that when different classes are located close to each other, it can affect the reflection from the water column and limit the penetration ability of the spectral bands so that it is difficult to distinguish between one class of seagrass density classification and another. In less complex environments with homogeneous benthic types, multispectral data performed better in mapping benthic habitats (Green *et al.*, 2000); (Goodman *et al.*, 2013).

Water column correction also affects the classification results using this Fuzzy Logic algorithm. The condition of the waters of the Kodingareng Lompo Island has a fairly high level of turbidity (up to 34 NTU) in several observation stations. The variation in depth and turbidity affects the water column, a water column correction or DII transformation is carried out by the Lyzenga algorithm to reduce the depth effect on the spectral reflection of bottom water objects so that the information got is clearer and shows the characteristics of the shallow bottom (Thalib *et al.*, 2018). The application of the water column correction method with the Lyzenga transformation proves an increase in the accuracy of the two satellite images.

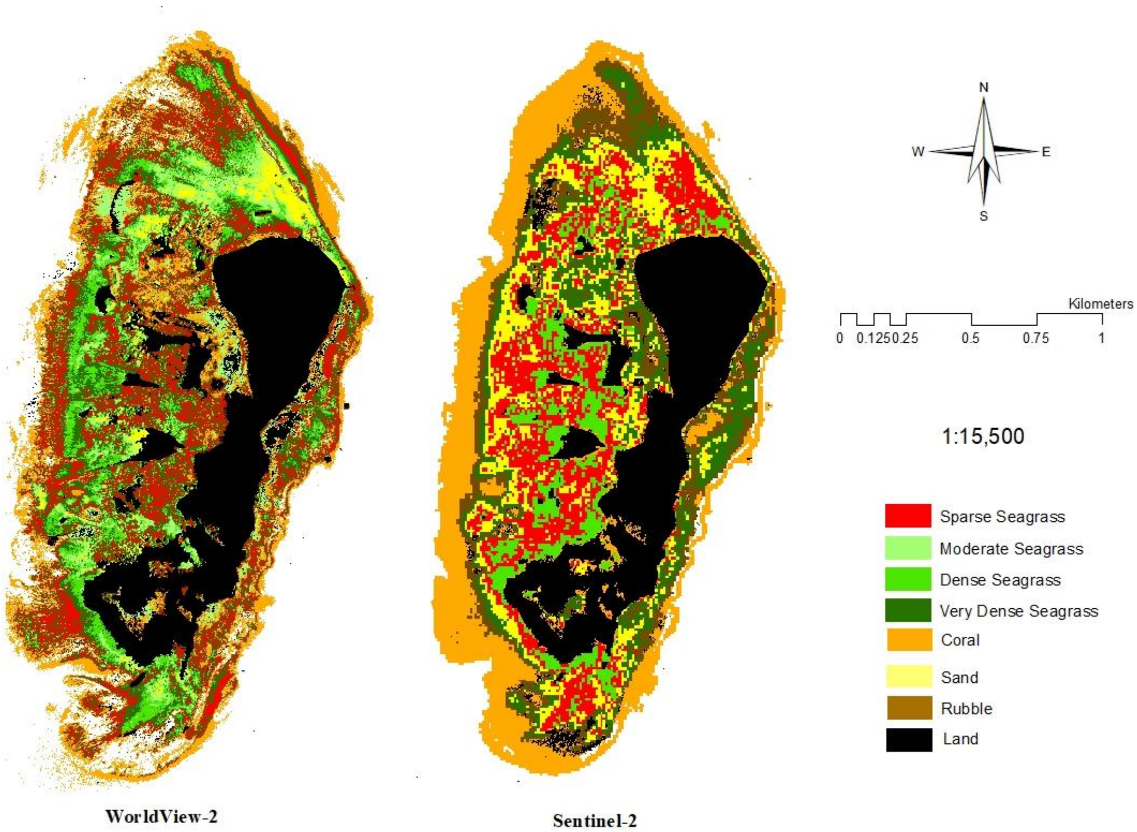

Figure 3. The results of the classification of seagrass cover using the Fuzzy Logic algorithm on WorldView-2 and Sentinel-2 imageries on Kodingareng Lompo Island.

3.3. Accuracy Test

The overall accuracy test showed that the Fuzzy Logic algorithm using WorldView-2 imagery has a good accuracy compared to the classification of the SPV algorithm (Table 7). One cause of the lower accuracy value generated by the SVM algorithm can be the spectral similarity factor, which is difficult to avoid in the classification process. Pixel-based methods cannot avoid the spectral similarity between benthic habitat classes (Wahidin *et al.*, 2015). Thus, in this study, Fuzzy Logic can distinguish benthic habitat classes with their complexity and ecosystem biodiversity. The use of Fuzzy Logic can improve accuracy with OA of 70% for benthic habitat mapping (Topouzelis *et al.*, 2018) and with OA of 76.3% for seagrass mapping (Urbanski & Szymelfenig, 2003). The application of water column correction also shows good results for both algorithms. It is necessary to correct the water column in its application, which is considered to increase the accuracy value of the resulting benthic habitat map (Green *et al.*, 2000).

Apart from the overall accuracy values, performing these two classification algorithms can be seen from the Kappa coefficients and Z statistics. The *k* value is used to assess the classification accuracy of an error matrix. In this study, the *k* value of the Fuzzy Logic algorithm using WorldView-2 imagery is 0.75 which is categorised as a good category based on the Kappa coefficient value range by Richards (2013) and means that the classification process is carried out to keep away from 75% random classification errors. The Z statistic-value shows that the use of the Fuzzy Logic algorithm in WorldView-2 imagery is better than other application with the highest Z

Table 7. The results of the accuracy test on WorldView-2 and Sentinel-2 imageries use the SVM and Fuzzy Logic algorithms.

Satellite Imagery	Algorithm	OA (%)	Kappa	Z	Sig. SVM vs Fuzzy	Sig. WV2 vs S2
WorldView-2	SVM	74.00	0.70	12.08	WV2 = 0.84	SVM = 0.60
	Fuzzy	78.60	0.75	50.38		
Sentinel-2	SVM	68.57	0.63	8.88	S2 = 0.02	*Fuzzy* = 0.76
	Fuzzy	75.02	0.71	10.96		

Table 8. The accuracy of seagrass density classification uses the SVM and Fuzzy Logic algorithms in Kodingareng Lompo Island.

Seagrass Class	WorldView-2				Sentinel-2			
	SVM		*Fuzzy*		SVM		Fuzzy	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Sparse	63.14	60.00	82.52	82.52	66.67	71.43	74.00	76.47
Moderate	66.67	68.75	61.54	87.72	71.43	66.67	68.40	71.43
Dense	46.15	76.92	92.65	68.33	64.29	75.00	77.69	63.10
Very Dense	85.71	80.00	82.22	77.89	78.57	78.57	99.75	64.58

statistic-value of 50.38. This value is greater than the Z-value table (1.96), so the results of the overall Z-value are statistically significant. Also, based on the significance test carried out to see the difference between the two images and the two algorithms in classifying seagrass density, it shows that the WorldView-2 and Sentinel-2 imagery with a significance value of 0.84 and the Fuzzy Logic and SVM algorithms with a significance value of 0.76.

Several factors can influence the result of seagrass density classification in this study. First, the classification algorithm performance. Misclassification of the using SVM algorithm is because many of the seagrass classes are covered by the sand substrate as we see it in the field so that the SVM algorithm cannot separate the different seagrass cover. The results of the SVM algorithm visually showed several noises, known as of salt and pepper effect which showed the appearance of seagrass class in the middle of corals and deep waters. SVM is an algorithm that does not take spatial aspects into account and classifies the object-based solely on the extracted feature representation. By using the SVM classification algorithm sparse seagrass and sand classes which is difficult to distinguish is considered as a mixed class. Meanwhile, the classification using Fuzzy Logic algorithms showed better results than the SVM algorithm. This can be seen from the accuracy value of each class of seagrass density classification show by PA and UA (Table 8). The fundamental problem of traditional classification like SVM is to create boundaries on classes randomly and often cause errors, therefore Fuzzy Logic classification is used to solve this problem by assigning classes based on its membership values (Huang *et al.*, 2011). Fuzzy Logic is not only handled noise but also can assign the data into over one cluster.

Second, the different spatial resolution of satellite data used in classifying the distribution of seagrass. The total area of benthic habitat and seagrass density from the SVM and Fuzzy Logic algorithms on WorldView-2 imagery is wider than Sentinel-2. This shows the importance of spatial resolution for better detection of benthic habitats and seagrass density, where the spatial resolution of WorldView-2 is higher than Sentinel-2 data, i.e. the smaller pixel size so that the more feature can be identified. The difference in the area may also because differences in acquisition hours for the two satellite images. WorldView-2 imagery acquired in the period of low tide and Sentinel-2 of high tide. Besides, the satellite sensor capability also depends on their respective wavelengths. Sentinel-2 spectral band may not detect differences in reflectance for each class of seagrass, whereas WorldView-2 has a shorter spectral band and can detect reflection from specific bottom waters (Wicaksono *et al.*, 2017). The difference in the characteristics of the wavelengths of the two satellite images can be seen in Table 1. Light attenuation increases when it enters the deeper water column (Traganos & Reinartz, 2017). The smallest attenuation is in the blue band of WorldView-2 imagery (450–510 nm), the highest attenuation is in the 600–700 nm, which is the location of the red band (630–690 nm) and the reflectance of seagrass leaves is in the 550 nm peaks lie in the green band range (510–580 nm). WorldView-2 wavelengths are shorter in each band than compare to the Sentinel-2 wavelength, theoretically allowing a more accurate classification of seagrass, and in turn increase in the area mapped (Wicaksono *et al.*, 2017).

IV. CONCLUSION

Classification of seagrass using the Fuzzy Logic algorithm gives better results than the Support Vector Machine algorithm. The classification of seagrass using WorldView-2 imagery have a higher accuracy than compare to Sentinel-2 imagery. Overall accuracy test showed that the Fuzzy Logic algorithm using WorldView-2 satellite imagery has the best level of accuracy. Based on the significance test of using both images and both algorithms, it is shown that the WorldView-2 and Sentinel-2 imageries have a significance different of 0.76, and the SVM and Fuzzy Logic algorithms have a significance different of 0.84.

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