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Assessing the Capability of Sentinel-2A Data for Mapping Seagrass Percent Cover in Jerowaru, East Lombok

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Abstract Remote sensing technology has been widely used in various applications related to natural resources and environment monitoring. In this paper, we evaluated the capability of new Sentinel-2A image to map the distribution and percent cover of seagrass in optically shallow water of Jerowaru coastal area, East Lombok. Seagrass distribution map was produced from radiometrically and geometrically corrected Sentinel-2A image with overall accuracy of 61.9%. Using empirical model, seagrass percent cover was predicted with maximum coefficient of determination (R2) of 0.51 and standard error of estimate (SE) of 19.4%. The results suggest that Sentinel-2A image can be used to perform seagrass mapping time and cost-effectively and can be further improved by incorporating more robust empirical modeling technique.

Key words: Remote sensing, Sentinel-2A, Seagrass, Mapping

Abstrak *Teknologi penginderaan jauh telah banyak digunakan dalam berbagai aplikasi terkait inventarisasi sumberdaya alam dan pemantauan lingkungan. Pada penelitian ini, kemampuan data penginderaan jauh Sentinel-2A diuji untuk memetakan distribusi dan persentase tutupan padang lamun di perairan laut dangkal Kecamatan Jerowaru, Lombok Timur. Peta distribusi padang lamun dihasilkan dari citra Sentinel-2A terkoreksi radiometrik dan geometrik dengan akurasi 61,9%. Menggunakan model empiris, persentase tutupan lamun diestimasi dari citra Sentinel-2A dengan koefisien determinasi (R^2) sebesar 0,51 dan standard error (SE) sebesar 19,4%. Hasil penelitian ini menunjukkan data penginderaan jauh Sentinel-2A dapat digunakan untuk dalam pemetaan padang lamun dengan waktu dan biaya yang efektif.*

Kata kunci: *Penginderaan jauh, Sentinel-2A, Padang lamun, Pemetaan*

1. Introduction

The coastal zone is essential to marine life and support a large part of the world's living marine resources [Short & Coles, 2001]. One of the most valuable resources in the coastal area is seagrass. Seagrass habitats provide various ecological services such as fish feeding and nursery grounds, sediment stabilizer, and carbon storage [Hogarth, 2015]. Despite its importance, seagrass habitats are exposed to pressure and threat from anthropogenic and natural impact [Nadiarti, et al., 2012]. A study found that Indonesia has lost 30% area of its seagrass beds [UNEP, 2004].

In order to reverse the degradation trends, there is a growing need to map and monitor distribution and abundance of seagrass beds. This may provide useful information for management and conservation strategy in coastal area. For decades, remote sensing technology has been widely used for mapping and monitoring coastal and shallow sea environment because of its cost-effectiveness and large area coverage [Hartono, 1994; Mumby, et al., 1997]. Several studies succesfully used remote sensing data to map seagrass area and percentage cover [Pu, et al., 2012], species composition [Fyfe, 2003], and other biophysical properties such as leaf area index [Wicaksono & Hafizt, 2013], biomass [Knudby & Nordlund 2011], and above-ground carbon stock [Wicaksono, 2015].

The capability of moderate spatial resolution remote sensing data such as Landsat (30 m pixel size) and ASTER-VNIR (15 m pixel size) has already been demonstrated for mapping and monitoring seagrass biophysical characteristics [Armstrong, 1993; Mumby, et al., 1997; Wicaksono & Hafizt, 2013; Pu, et al., 2014]. Those data are available for free, and has high revisit capability, and thus very useful to map large area cost effectively. Recently, a new earth-observation satellite named Sentinel-2A was launched on June 2015 as part of Sentinels mission and Europe's Copernicus programme to provide data continuity for environmental

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monitoring of earth surface. Sentinel-2A satellite carries mult-ispectral imager (MSI) onboard with 13 spectral bands at visible, near-infrared, and shortwave-infrared wavelength with 10, 20, and 60 m spatial resolution, respectively. Moreover, the multispectral imager is capable of covering wide swath of 290 km, has frequent revisit time, and can be obtained freely, which make it very potential to be used in wide range of applications [ESA, 2015]. However, mapping seagrass abundance has never been done using Sentinel-2A data. This study aims to evaluate the performance of Sentinel-2A image to understand its potentials and usefulness for mapping seagrass biophysical properties. Seagrass percent cover was selected as the parameter of interest to be mapped, since it is currently recognized as a key parameter for seagrass monitoring effort [McKenzie, et al., 2001]. Seagrass percent cover is defined as the area of substrate which is covered by seagrass when observed directly from above [Phinn, et al.. 2008].

2. The Methods

Study area

This research was carried out in part of north coastal area of Jerowaru District, East Lombok Region, Nusa Tenggara Barat Province. Seagrass are located in optically shallow water (<3 m depth) on sand and mud substrate and dominated by species such as *Enhalus acoroides*, *Thalassia hemprichii*, and *Cymodocea rotundata*. Several less-dominant species such as *Halophila ovalis* and *Halodule universis* are also present. The condition of seagrass beds vary from continous beds with single species and mixed species to patchy beds. Seagrass beds in this study area are associated with other benthic organisms such as micro benthos and coral reefs.

Field methods

Fieldwork was carried out from 22 – 25 May 2016. Prior to field survey, visual and digital image interpretation was performed to determine field data location. Point-based field data of substrate type, seagrass species composition, and percent cover were collected with photo-quadrat and photo-transect method [Roelfsema, et al. 2014] by snorkeller using digital underwater camera and 1 m^2 quadrat. A handheld global positioning system device (GPS) was towed to a snorkeller to acquire field data position. Photos taken from field survey were interpreted in the laboratory.

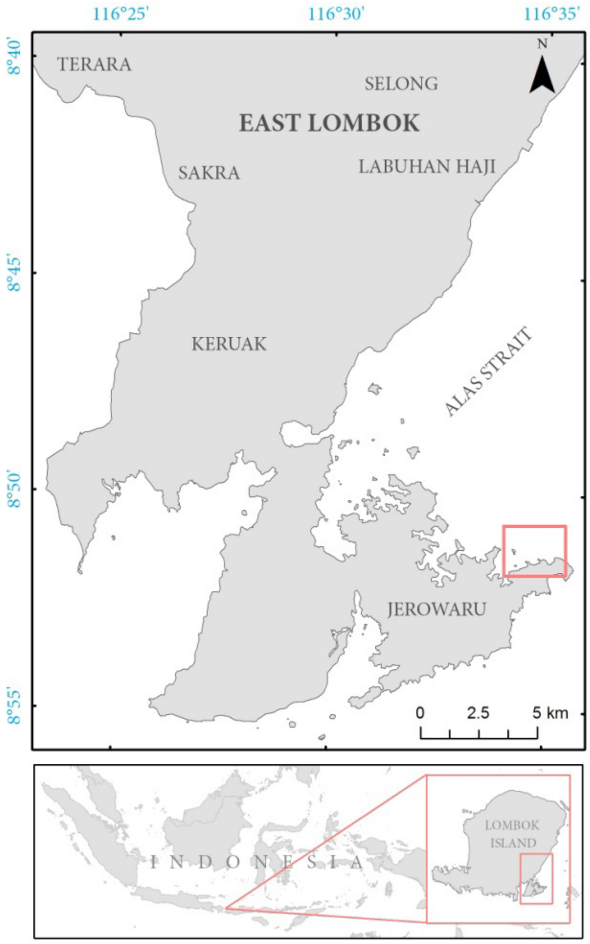


Figure 1. The location of study area

A total of 253 data points were collected and generalized into 96 samples to match Sentinel-2A image pixel size, which are presented in Figure 2. From all these samples, 80 samples are seagrass, and 16 others are non-seagrass. Half of seagrass samples were used to train the maximum likelihood classification algorithm and develop the empirical model, while the other half was used for accuracy assessment.

Image data and pre-processing

Remote sensing data used in this study is Sentinel-2A Level-1C (top-of-atmosphere reflectance) image, covering Jerowaru District, and acquired on 18 May 2016 from Sentinels Scientific Data Hub (http://scihub.copernicus.eu). Only visible spectral bands with 10 m pixel size (band 2, band 3, band 4) were used in this study. These bands were selected because of their capability of penetrating water body, so that the features on the optically shallow water can be detected by the imaging sensor [Green, et al., 2000]. Atmospheric correction was applied to the data using dark object substraction method [Chavez, et al., 1977] performed. Water column effect was compensated using method developed by Lyzenga [1981], producing single depth-invariant bottom index from each pair of spectral bands. In this study, we named these depth-invariant bottom index (DII) bands as b2b3, b2b4, and b3b4, representing the pair of the origin spectral bands being used. These three DII bands no longer contains reflectance information of seabed objects but the normalized index value invariant to the variation of depth.

Benthic habitat mapping

Digital supervised image classification with Maximum Likelihood algorithm was applied on three DII from Sentinel-2A image to produce benthic habitat map. This habitat map was used to distinguish seagrass and non-seagrass area, since only seagrass pixels were used to map seagrass percent cover. Since seagrass biophysical properties were controlled by species [Wicaksono, 2015], it was necessary to differentiate seagrass based on its morphology or canopy structure [Wicaksono & Hafizt, 2013]. The classification scheme used consists of six classes, which are bare substrate, coral reefs, *Ea*-seagrass, *EaTh*-seagrass, *ThCr*-seagrass, and optically deep water. Details of seagrass classes are presented on Table 1. Confusion matrix analysis [Congalton, 1991] were used to assess the classification accuracy of benthic habitats map.

Seagrass percent cover mapping

Empirical modelling approach was performed to estimate seagrass percent cover by calibrating DII values with corresponding field seagrass percent cover data. We developed four linear regression models, three models for each class of seagrass (*Ea, ThCr, EaTh*) and one model for all class of seagrass regardless of their species and canopy structure. Seagrass percent cover data were used as the dependent variable while DII values were as the independent variable. From three DII bands, only bands that produced significant correlation at 95% confidence level (95%CL) with field data were used as input in the empirical modeling of seagrass percent cover using regression analysis. The accuracy of the estimated seagrass percent cover was calculated using standard error of estimate (SE).

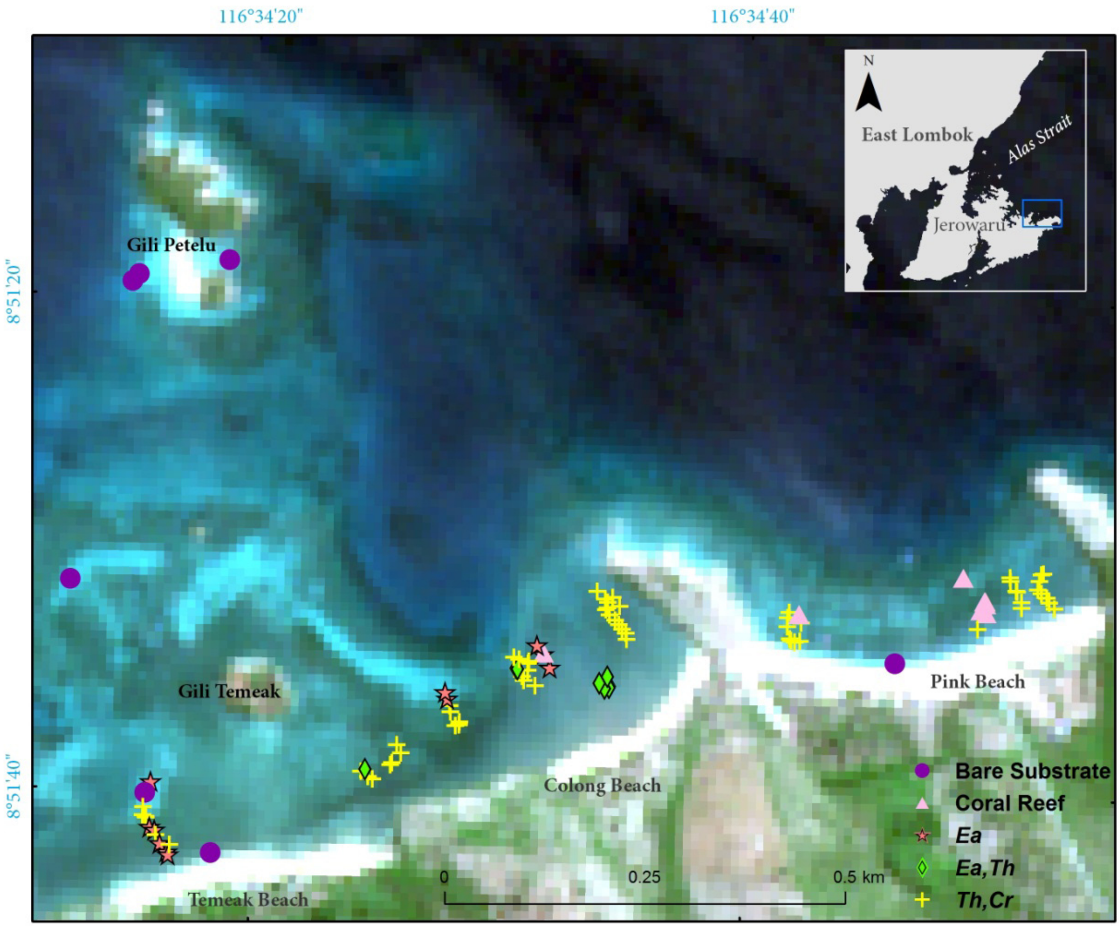
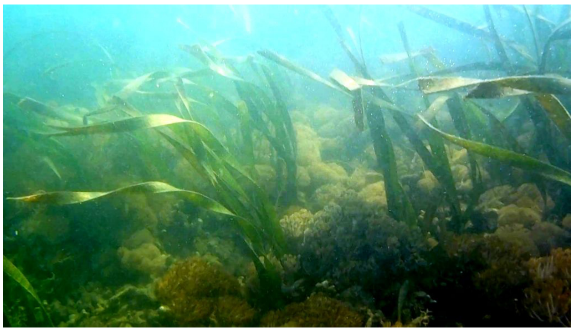
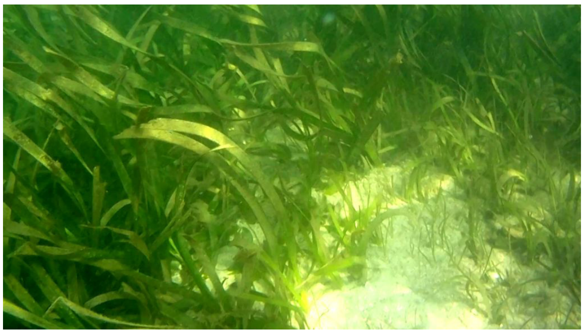


Figure 2. Field data distribution at study area

Table 1. Seagrass classification scheme based on morphology or canopy structure

Class name	Dominant species	Additional information	Picture
Ea	*Enhalus acoroides*	Leaf extends vertically within water column	
ThCr	*Thalassia hemprichi, Cymodocea rotundata, Halophila ovalis., Halodule uninervis*	Leaf covers the substrate and not significantly extending vertically within water column	
EaTh	*Enhalus acoroides, Thalassia hemprichi, Cymodocea rotundata, Halophila ovalis., Halodule uninervis*	A mixed between *Ea*-type and *ThCr*-type at significant proportional coverage	

Source: Wicaksono & Hafizt [2013]

3. Result and Discussion

Mapping seagrass distribution

The result of Maximum Likelihood classification is shown in Figure 3. An overall accuracy of 61.9% was obtained. The class with the lowest user and producer accuracy is *Ea*, where the user accuracy is zero percent (0%), which mean that there is no chance that the *Ea* class in the classified image is actually seagrass in the field. In addition, 0% of *Ea* class producer accuracy also means that no *Ea* class in the field is correctly classified. *EaTh* class, which contains *Ea* species, was also tend to be missclassified as *ThCr* class. Both bare substratum and coral reef class also suffered from similar misclassification, where most of them were classified as *ThCr*. Optically deep water is the only class that was classified correctly, suggesting that it was spectrally distinct compared to benthic habitats in optically shallow water.

These errors may come from various factors. The first factor could be the environmental conditions of our study site. Our study site is a complex environment, where multiple species of seagrass and other benthic covers such as coral reefs and macro algae are present. During the high tide, the wave is likely causing a turbulance, which increases the water turbidity, due to the presence of limestone cliffs which separates one beach to another. The suspension caused by wave turbulance may affect the reflectance from water column and limit the penetration capability of Sentinel-2A visible bands.

The second factor is the spatial resolution of Sentinel-2A image. At 100 m^2, reflectances from objects in the corresponding pixel were generalized. In addition, it is also problematic when different benthic objects are located adjacent to each other. The bandwidth and wavelength sensitivity of Sentinel-2A spectral bands may also incapable of detecting the difference of unique reflectance from each seagrass class. Previous study shows that at less complex environment with homogenous benthic type, multispectral data have better performance in mapping benthic habitats [Green, et al., 2000; Goodman, et al., 2013].

Third, these high misclassification rates of seagrass classes are mainly due to the limitation of samples available. Given more samples, we may yield better results as in Wicaksono & Hafizt [2013]. The last factor, even though the probability is small, the error may be caused by the misidentification and inconsistencies of interpreter in interpreting the field photos, suggesting that mapping benthic habitats as well as seagrass species composition in complex environment using remote sensing is still a difficult task.

Mapping seagrass percent cover

The empirical modeling of seagrass percent cover using Sentinel-2A image was performed using linear regression analysis. Linear regression models between Depth-invariant bottom index (DII) and field seagrass percent cover data produced high coefficient of determination (R^2). Linear regression graphics of the strongest relationship between DII and field seagrass percent cover for each seagrass class are presented in Figure 4. The accuracy of the estimated seagrass percent cover was provided at Table 3.

Table 2. Confusion matrix for classification of nearshore benthic habitats at the study area. Field data in columns, classification results in rows

	Ea	*EaTh*	*ThCr*	Bare substrate	Coral reef	Optically Deep water	Total	User accuracy (%)
Ea	**0**	1	8	0	0	0	9	0.0
EaTh	0	**1**	3	0	0	0	4	25.0
ThCr	1	0	**8**	0	1	0	10	80.0
Bare substrate	1	0	1	**2**	0	0	4	50.0
Coral reef	3	0	8	0	**2**	0	13	15.4
Optically Deep water	0	0	0	0	0	**31**	31	100.0
Total	5	2	28	2	3	31	**71**	
Producer accuracy (%)	0.0	50.0	28.6	100.0	67.0	100.0		Overall accuracy = 61.9

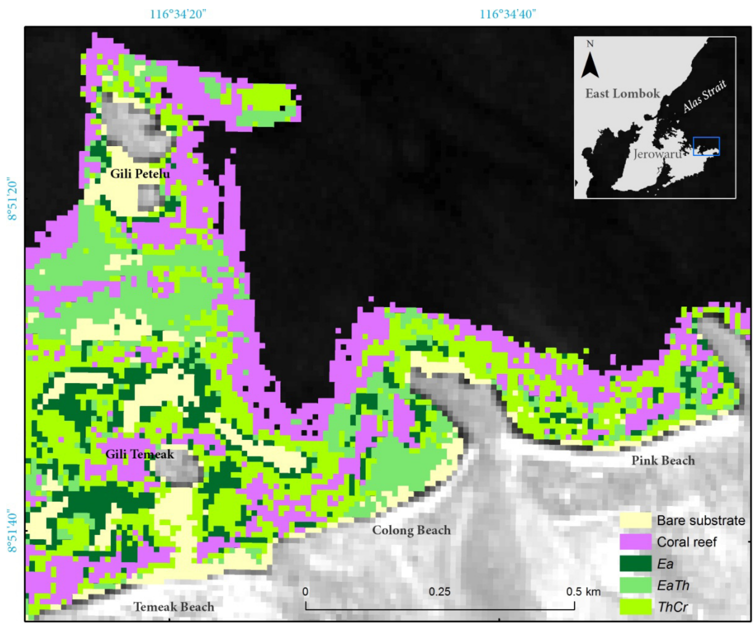


Figure 3. The result of Maximum Likelihood classification with 61.9% overall accuracy

The resultant regression function obtained from these empirical models can only be applied on the corresponding seagrass pixels. Thus, we have four different seagrass percent cover models based on the empirical model of each seagrass class. Table 3 shows the SE of the estimated seagrass percent cover from the model. Because the habitat map produced from multispectral classification was not capable to distinguish seagrass with different type of canopy structure, it was not possible to map seagrass percent cover for each seagrass type separately using these three empirical models. Hence, the only model used to map seagrass percent cover is the model developed from DII b2b4 for all seagrass class. In this complex environment where the water is slightly turbid and multiple seagrass species and associate benthic habitats are present, empirical model created from DII b2b4 derived from Sentinel-2A image had R^2 of 0.51 with SE of 19.4%.

The accuracy of seagrass mapping of this research is lower than the result obtained by Topouzelis et al. [2016]. Nevertheless, the accuracy of seagrass percent cover model obtained in this research is not comparable to the research conducted by Topouzelis, et al. [2016] although they used similar sensor, especially since their class complexity is lower than in our research. Their classification scheme consists of seagrass, soft bottom and hard bottom, while in this research we mapped the species composition.

Table 3. Accuracy assessment for seagrass percent cover model

Validation sample	Band	SE (%)
Ea (n=5)	DII b2b4	37.8
ThCr (n=28)	DII b2b4	18.0
EaTh (n=3)	DII b3b4	63.8
Total seagrass (n=36)	DII b2b4	19.4

Separating seagrass from other benthic habitats is more feasible than differentiating various seagrass species. However, our accuracy is comparable to other several studies that utilized different sensors. Using hyperspectral EO-1 Hyperion data with 30 m spatial resolution, Pu, et al. [2012] achieved R^2 of 0.78 and SE of 15.7% at shallow clear water Northwest coastline of Florida. Landsat 5 TM data produced lower result with R^2 of 0.59 and SE of 21.2%.

When mapping seagrass percent cover, Phinn, et al. [2008] suggested a classification method with several classes of percent cover range in case the correlation between spectral band reflectance and seagrass percent cover is not significant to enable the development of percent cover estimation based on regression analysis. At the same spatial resolution as Sentinel-2 data, SPOT-5 data managed to map monobed *Posidonia oceanica* seagrass at Laganas Bay, Greece with four

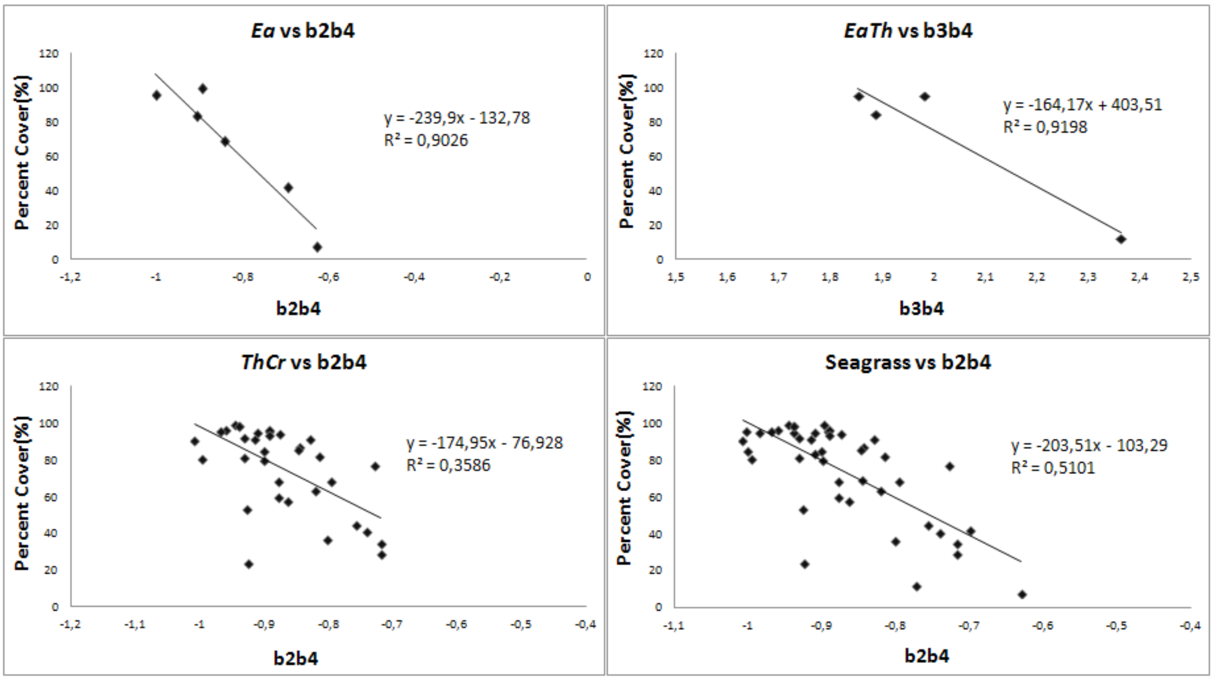


Figure 4. Linear regression analysis between DII value and field seagrass percent cover showing mild (b2b4 - *ThCr*) to strong (b2b4 – *Ea*, b3b4 – *EaTh*, b2b4 – all classes) prediction power

benthic classes including dense cover seagrass, sparse cover seagrass, algae, and sand with high classification accuracy of 96% [Pasquialini, et al., 2005]. This research also revealed that increasing the spatial resolution does not always have a positive impact in the accuracy of classification. In fact, pan-sharpened SPOT-5 image with 2.5 m spatial resolution at the same region and classification scheme produced lower classification accuracy of 73% [Pasquialini, et al., 2005]. Phinn, *et al*. [2008] used Landsat 5 TM, CASI, and Quickbird image with spatial resolution of 30 m, 4 m, and 2.4 m respectively, to map four categories of seagrass percent cover at multi-species seagrass bed of Moreton Bay, and resulted in classification accuracy not larger than 45%, suggessting the ineffectiveness of these images in distingusihing seagrass percent cover class using digital classification.

Most of seagrass percent cover mapping approach used digital classification and resulting in classes of seagrass percent cover range, or simpler class such as dense or sparse class of seagrass. However, mapping seagrass percent cover with empirical model results in more precise information since every pixel will have its own percent cover value. This model later can be used as the baseline for deriving another seagrass biophysical properties such as standing crop or above-ground biomass and leaf-area index, which are the properties that highly correlated with seagrass percent cover [Wicaksono, 2015]. The resulting seagrass percent cover map is presented in Figure 5.

4. Conclusion

North coastal area of Jerowaru District is a complex environment, with the presence of several species of seagrass and associate benthic habitats. We found that even in the complex environment such as our study area, Sentinel-2A image can be used to map seagrass habitat distribution up to 61.9% overall accuracy and seagrass percent cover with SE of 19.4%. The accuracy could be better given more samples used to train and calibrate the image. Applying additional spectral transformations such as Principle Component Analysis (PCA) or Independent Component Analysis (ICA) [Wicaksono, 2016] might increase the accuracy and robustness of empirical modelling result. Hence,

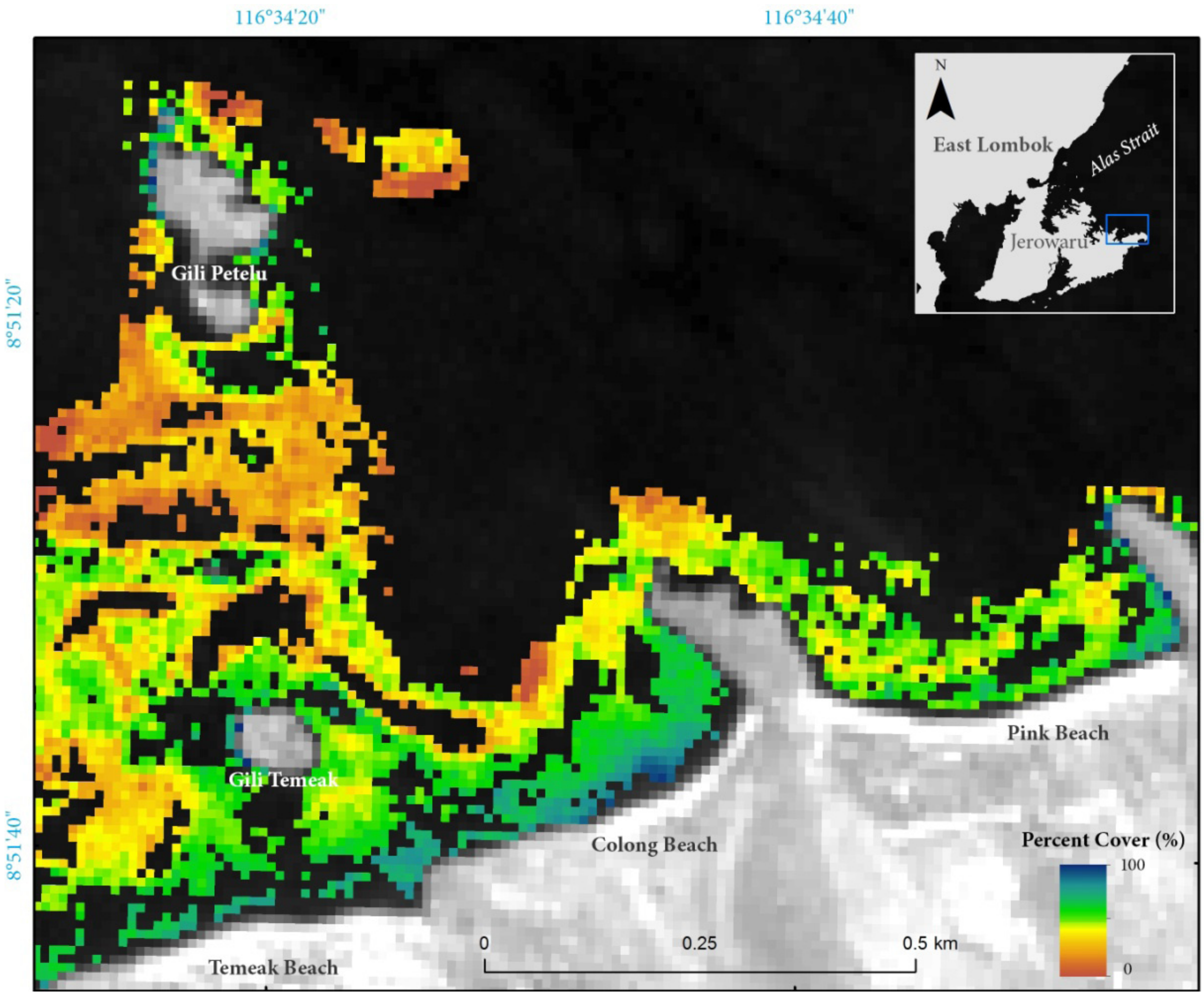


Figure 5. Seagrass percent cover map modeled from DII b2b4 with SE 19.4%

we concluded that Sentinel-2A could be a good data source for mapping and monitoring resources in coastal and nearshore optically shallow water environment over large area overtime cost-effectively.

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