Mapping Seagrass from Space: Addressing the Complexity of Seagrass LAI Mapping

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Abstract
Information of seagrass LAI is still lacking in most parts of the world due to the high cost of comprehensive mapping. In this paper, we described the use of remote sensing as the cost and time effective solution to perform continuous seagrass LAI mapping, and discussed the issues and difficulties encountered during the mapping. ASTER VNIR and ALOS AVNIR-2 were used to perform the mapping. We proposed at life-form seagrass classification scheme to accommodate the low accuracy of at species level mapping. We also developed sampling mapping unit consist of several factors affecting the distribution of seagrass LAI. The results showed that sensor, method, and environmental limitation contribute to the low accuracy of seagrass LAI mapping.
Keywords: Remote sensing, seagrass, LAI, mapping, ALOS AVNIR-2, ASTER VNIR.

Introduction
Leaf area index (LAI) is one of the most important and influential biophysical components of photosynthesizing organism like seagrass. LAI which generally refers to the total single side leaf area per unit ground is strongly correlated with the extent of photosynthesizing tissue, photosynthesis rate, shoot density, stem density, percent cover, chlorophyll concentration, standing crop, and above ground carbon stock [Bresciani et al., 2011; Dierssen et al., 2010]. At present, LAI has been stated as the essential climate variable by GTOS (Global Terrestrial Observing System), FAO (Food and Agriculture Organization of the United Nations), GCOS (Global Climate Observing System), and FLUXNET [Gosa, 2009]. Therefore, since seagrass LAI affects its carbon sequestration rate, both from atmosphere (CO₂) and water column (bicarbonate ions, HCO₃⁻), it becomes an important variable in the dynamics interaction of energy exchange between atmosphere, hydrosphere, and biosphere. Furthermore, seagrass LAI also represents the abundance of seagrass properties in the area.
at species and at community level.

The availability of seagrass LAI map would be very important for the sustainable management of coastal area where seagrass is located. Seagrass is known to provide various benefits for coastal ecosystems e.g. breeding and nursery ground for coastal and marine biota, sediment stabilizer, pollution filter, water purification, sediment trap, natural food for marine biota, pharmacy and industry uses, coastal barrier from erosion, organic fertilizer, prevent sediment and water column from hypoxic and anoxic condition, carbon sink, and long-term carbon sequestration agent [Hemminga and Duarte, 2000; Bjork et al., 2008]. Special for the adaptation to climate change, seagrass habitat is one of the most effective carbon sink in the earth [Laffoley and Grimsditch, 2009; Nelleman, 2009; Eveleth, 2010]. At present, despite the global small area, seagrass is estimated to constitute 12% of the total oceanic carbon stock due to its ability to perform carbon burial in the sediment [Duarte and Cebrian, 1995; Zimmerman et al., 1997; Invers et al., 2001; Palacios and Zimmerman, 2007; Burdige et al., 2008; Nelleman, 2009]. Moreover, economically, seagrass ecosystem is 33 and 23 times more valuable than the average value of oceanic and terrestrial ecosystem respectively [Bjork et al., 2008]. In short, seagrass is a very important ecosystem, not only for those living within and connected to coastal area, but also for those living in the adjacent ecosystems which rely directly or indirectly on the existence and sustainability of seagrass ecosystem.

Despite the importance, reliable information about seagrass LAI is still lacking in most part of the world, especially in the tropical indo-pacific where the diversity of seagrass is at its maximum. The main reason for this lack of data is the high cost of comprehensive mapping [Dekker et al., 2006; Bjork et al., 2008]. Seagrass habitats are mostly located on difficult-to-access area such as small islands or enclosed and sheltered bay, which limit the effectiveness of traditional field survey to obtain representative information about the diversity of seagrass in the area. Furthermore, even at some accessible area, there is always a part of seagrass habitat which cannot be surveyed due to the potential hazards and environmental limitations.

Remote sensing is the most effective alternative of seagrass mapping which can accommodate the limitation of traditional field survey. Conceptually, seagrass can be seen from space via the ability of visible bands to penetrate water body. Therefore, any satellite or airborne sensor can detect seagrass reflectance as long as they have visible bands on their spectral band configuration. Unfortunately, most NIR energy is absorbed on a few centimeters within water column. Thus, not suitable for seagrass identification unless the seagrass is very shallow or emerging during low tide. At wavelengths beyond NIR, the downwelling energy will be fully absorbed by water with insignificant scattering or transmission.

The depth of penetration is subject to water conditions and geographical conditions [Bukata et al., 1995; Wicaksono, 2010]. The ability of visible bands to penetrate water body is due to the nature of the water itself. Water molecules tend to effectively absorb downwelling energy lower than 400 nm and higher than 580 nm. In addition, water also scatters some EM energies between 400 - 500 nm, which is the reason why water appear blue in human eyes. Therefore, the best spectral range to penetrate water is the region where the scattering and absorption is minimal. The best spectral range for penetrating water is between 460 - 480 nm [Swain et al., 1978].

The upwelling radiance of submerged object including seagrass is the function of seagrass characteristic, water column variation, water surface reflectance, and atmospheric path
radiance [Jensen, 2006]. From sensor perspective, it would be the function of sensor resolutions and noises. Therefore, in order to obtain pixel value which solely represent the variation of seagrass characteristics, EM energies other than seagrass albedo should be minimized. If those radiances can be compensated, it would be acceptable to assume that any changes in seagrass reflectance are due to the changes in the biophysical or biochemical properties of seagrass including LAI. Several works has described the use of remote sensing for seagrass mapping [Pasqualini et al., 2005; Phinn et al., 2008; Lyons et al., 2011; Lyons et al., 2012]. However, these researches were mainly performed using digital classification to map seagrass cover distribution. They have not addressed the issue of mapping continuous seagrass cover or LAI. Information about continuous seagrass LAI can be very useful for the basis of seagrass carbon sequestration modeling and NPP [Dierssen et al., 2010]. Furthermore, they also have not addressed the issue of seagrass mapping accuracy due to species composition within seagrass bed. The empirical model to perform standing crop mapping was also still conducted at community level [Mumby et al., 1997; Phinn et al., 2008]. Therefore, in this paper, we described the use of remote sensing data to map continuous seagrass LAI distribution by considering species and life-form composition. We also explained the complexity of seagrass LAI mapping due to species and life-from variations.

Two multispectral data at different spectral and spatial resolution were used, ASTER VNIR and ALOS AVNIR-2. The purpose of having these two images was to understand the effect of pixel size on the accuracy of LAI estimation. Moreover, since both images have different configuration of water penetration bands, it was interesting to see whether the lack of specific band i.e. the absent of blue band in ASTER, would adversely impact the ability of remote sensing image to map seagrass LAI. In addition, the use of image at different spatial and spectral resolution is important to find out the most effective approach to bridge and accommodate the variation of information composition contained in each pixel size. The approach could be used to obtain the required field information for seagrass LAI modeling that can be applied on image at various resolutions.

**Study area**

Several islands located on Karimunjawa Islands were selected as the study area. These islands were Karimunjawa Island, Kemujan Island, Menjangan Besar Island, and Sintok Island (Fig. 1). In the study area, seagrass habitat was narrowly fringing along the shoreline. There was no vast seagrass meadow in the study area as the extent of back reef and lagoon is also quite narrow. Geomorphologically, benthic area in the study area consist of shallow lagoon less than five meters, back reef, reef crest, fore reef, spur and groove, and escarpment or wall. Seagrass habitat is mainly located on the shallow lagoon less than three meters and associated with sandy substrate, dead coral reefs, rubble, and macro algae.

The seagrass in the study area are *Enhalus acoroides*, *Thalassia hemprichii*, *Cymodocea rotundata*, *Halodule uninervis*, *Syringodium isoetifolium*, and *Halophila ovalis*. Most of these species were concentrated on Kemujan Island. Among those species, *Enhalus acoroides*, *Thalassia hemprichii*, and *Cymodocea rotundata* were the dominant species, while others were found in small portion within the area of the more dominant seagrass species. Bigger seagrass species with narrow and flexible shoots such as *Enhalus acoroides* are usually located on area with high wave exposure, while smaller species with wide and fragile shoots such as *Halophila ovalis* are found on more sheltered area with weak wave exposure.
Figure 1 - True color composite of ALOS AVNIR-2 of the study area. The size of the map is only for viewing purpose. Areas where seagrass is mostly located are indicated by red boxes.

**Methods**

*Sampling design*

Since there were two images used in this study, the field data used in the seagrass LAI model should be able to really correspond with the composition and variation of information contained in each pixel sizes. It is important to make sure that the information collected in the field is comparable and compatible with the information contained in both 100 m² of AVNIR-2 pixel size and 225 m² of ASTER pixel size. Since pixels of ASTER and AVNIR-2 contain different information composition and variation, the selection of sample location was very critical. If not, AVNIR-2 with higher spatial resolution will have a much better chance to deliver better accuracy than ASTER due to its higher data precision. Thus, it would negate the meaningfulness of the LAI modeling results comparison from the two images. In order to bridge seagrass information contained in ASTER and AVNIR-2 pixel size, we proposed a carefully-built mapping unit as the basis for stratified random aligned sampling method.

Prior to field survey, we created mapping unit as the basis for the stratification of sample distributing process. Mapping unit for seagrass sampling will be generated from seagrass spectral class map, seagrass relative density map, bathymetry map, and coastal landscape map. Seagrass spectral class was related to seagrass reflectance as the results of the interaction between downwelling irradiances and seagrass reflecting tissue, therefore, it is relevant with the value in each seagrass pixel. The resulting seagrass spectral classes
represent the distribution of seagrass variation based on its spectral properties. To obtain seagrass spectral class, Isodata unsupervised classifier was applied. Seagrass relative density was related to the amount of seagrass reflecting tissue at area basis where higher density seagrass having a higher rate of interaction with the downwelling irradiances. Map of seagrass relative density was obtained from supervised maximum likelihood classifier using training areas collected on 2010.

Water depth controls the vertical distribution of seagrass due to the amount of available sunlight for photosynthesis. Therefore, it also controls the distribution of seagrass LAI. Bathymetry map was generated from regression analysis between field data and band ratio. Coastal landscape map was interpreted visually and consisted of several factors which control seagrass abundance such as an exposure to waves, beach aspect, and beach material. The aforementioned spectral and environmental factors were synthesized to produce a map in which each unit shows unique information about seagrass condition. Each unit shows seagrass with unique spectral response, at specific density, at particular depth and at specific coastal landscape. The map will be used as the basis for distributing the sample using stratified random aligned sampling design. Those information are adequate to accommodate and bridge the variation of seagrass reflectance at various pixel sizes.

**Field measurement**

During the first field survey conducted on April 2011, we harvested 40 seagrass samples used to identify the relationship between seagrass biophysics. For each species, the strength of relationship between percent cover (PC) and LAI was analyzed. Seagrass PC was calculated visually from the picture taken from each sample using on-screen digitization. Shoot density (SD) for each species within the quadrat was calculated by counting the number of harvested shoot. LAI for each sample were calculated by multiplying SD and the average leaf area for each species. The total LAI of each sample would be the sum of LAI of each seagrass species found on sample site. Our LAI measurement approach was almost similar with Dierssen et al. [2010]. There is another approach to calculate seagrass LAI as described in Yang and Yang [2009]. However, the parameters to obtain seagrass LAI were only SD and shoot height, which in our opinion do not consider the total photosynthesizing area and all the related components. Furthermore, we also identified species composition within the quadrat. This analysis was very important to safely quantify seagrass LAI of the 218 modeling samples via seagrass PC measured from photo quadrat technique in the second field survey. Figure 2 shows the relationship between seagrass biophysics.

**Image corrections**

In order to obtain pixel value which solely represents the variation of seagrass condition, the reflectance of seagrass should be isolated from other additional reflectance. Image corrections, especially radiometric corrections were intended to remove that additional reflectance. At surface reflectance image of ASTER and AVNIR-2 were generated from MODTRAN4 algorithm. The inputs for MODTRAN4 algorithm were several basic information about the climatic and meteorological conditions of Karimunjawa area such as meteorological visibility and aerosol type. Sunglint in both images were minimized via NIR band using the approach developed by Hedley et al. [2005]. Sub-surface volumetric reflectance was compensated using Inverse model formulized by Wicaksono [2010].
The basic of Inverse model was the interaction of electromagnetic (EM) energy within water column. Therefore, this model requires all information about the component which affects the passage of EM energy from sun to sensor such as deep water reflectance, bathymetry, and water column attenuation coefficient for each band [Eq. 1]. Pixels of inversed band should only contained information about seagrass properties variations.

\[ R_b = 10^{(\log(R_w - R_\infty) + 2kz)} + R_\infty \]  

Where \( R_b \) is bottom reflectance without water column attenuation in band \( i \), \( R_w \) is bottom reflectance as recorded by sensor in band \( i \) (sunglint-free), \( R_\infty \) is the mean reflectance of optically deep water in band \( i \), \( k \) is water column attenuation coefficient for band \( i \), and \( z \) is water depth at each pixel.

Variable \( k \) for water in Karimunjawa Island has been calculated by Wicaksono [2010] (Tab. 1). As comparison, general value of \( k \) based on various sources that was summarized by Bukata et al. [1995] is also presented. Certainly, there are differences in the \( k \) values given by Wicaksono [2010] and Bukata et al. [1995]. The differences are the result of the different approach used to quantify the \( k \) values. The \( k \) values given by Wicaksono [2010] was derived mainly from the analysis of optically deep water reflectance and water depth without involving any direct optical measurement of \( k \) in the field. Consequently, the result of \( k \) is highly dependent to the degree of sun illumination, sensor characteristics, weather condition, and water condition during image acquisition. In contrast, \( k \) values described in Bukata et al. [1995] were measured using a real field instrument independent to atmospheric and image condition. Hence, the differences are expected between the two values.
Table 1 - Water column attenuation coefficient ($k$) for Karimunjawa coastal water in comparison with $k$ values obtained in different areas (m$^{-1}$).

| Spectral band range | $k$ in Karimunjawa [Wicaksono, 2010] | $k$ from Bukata et al. [1995] |
|---------------------|-------------------------------------|------------------------------|
| 450 – 520 nm        | ± 0.0184                            | 0.0072 – 0.0156              |
| 520 – 600 nm        | ± 0.0717                            | 0.0156 – 0.209               |
| 630 – 690 nm        | ± 0.1781                            | 0.2408 – 0.3805              |
| 760 – 900 nm        | ± 0.6222                            | > 2.5604                     |

Bathymetry map was created from the image itself by empirically deriving bathymetry from field data using band ratio technique. Band ratio technique was preferred because the field bathymetry data were collected at various benthic covers. If the data is collected at homogenous benthic cover i.e. seagrass, linear algorithm would perform better for bathymetry mapping. Bathymetry data was collected using echo sounder mounted on small Kano so that we can cover shallow water area where seagrass is located. Since most of the seagrass in the study area is located in water less than the depth of two meters, there was no limitation in the maximum DOP of each band. Thus, all spectral bands can be used to model bathymetry data. For ASTER, since there were only two available water penetration bands, the ratio can only be derived from the combination of green and red band.

**PCA transformation**

PCA transformation was intended to compile information from the input spectral bands into several effective components. The inputs for PCA transformation were original bands and inversed bands. PCA transformation was calculated based on correlation matrix using ENVI software. The advantage of performing PCA transformation was its unique information contained within the resulting PC bands. Information contained in each PC band was the integrated unique contribution from blue, green, and red band. Moreover, that unique information can be used complementary to each other. In other word, PC1 band contains information not contained by PC2 and vice versa. Therefore, if PC1 failed to model seagrass LAI, PC2 will have a better possibility to success. In addition, PCA transformation might be able to emerge unique and intrinsic information about spectrally and spatially complex object like seagrass.

**Mapping seagrass LAI**

The main idea in seagrass LAI mapping is how to isolate seagrass reflectance from other additional reflectance such as free surface layer reflectance, sub surface volumetric reflectance, and atmospheric path radiance, which we attempted to remove using image correction techniques. The inversed bands have already contained values which represent the variation of seagrass including the LAI. Therefore, theoretically, inversed bands should be able to explain the variation of seagrass LAI using the empirical models. The datasets used for seagrass LAI mapping were the original bands, inversed bands, PC bands from original bands, and PC bands from inversed bands.

Seagrass LAI modeling was performed at species and at community basis, and thus, it was important to build the most representative and suitable seagrass species classification scheme based on the variation of species found on the study area and the dynamics interaction between downwelling lights and seagrass tissue. Since that interaction is controlled by species type and growth type, we used those parameters to build the scheme. Basically,
there are two main growth types of seagrass. First, the shoot of seagrass extending into water column and sometimes reaches the surface. In our study, *Enhalus acoroides* has this kind of life-form. For seagrass habitat dominated by this type of species, since there is always a gap between the clone of *Enhalus acoroides* shoot, the substrate may still give significant contribution to the overall reflectance of the corresponding pixel. We named this class *Ea*. Second, the shoot of seagrass grows horizontally and effectively covering the substrate. Most seagrass have this kind of life-form i.e. *Thalassia hemprichii*, *Cymodocea rotundata*, *Syringodium isoetifolium*, *Halodule uninervis*, and *Halophila ovalis*. Therefore, at higher density, in contrast to *Ea*-like species, those seagrass species only leave minimum space for the substrate to contribute any reflectance. Hereafter, we named this class *Th,Cr*. However, there were also seagrass habitat consists of mixed species with different life-form or growth type. In the study area, several seagrass habitat were dominated by *Enhalus acoroides* with *Thalassia hemprichii*-like species in between. The existence of the smaller seagrass species under *Enhalus acoroides* canopy has suppressed the reflectance of background substrate. Thus, the characteristic of reflectance of this seagrass species composition is somewhere between *Enhalus acoroides* and *Thalassia hemprichii*, and it should be put as standalone class. Hereafter, we named that class *Ea,Th*. Table 2 provides qualitative descriptor of each class in the seagrass life-form scheme.

During field survey, we also collected independent samples to perform accuracy assessment. The accuracy of the resulting seagrass LAI maps will be assessed using standard error of estimates (SE) technique. This technique calculates the error of prediction from regression analysis that we used during seagrass LAI empirical modeling.

### Table 2 - Class descriptor of at life-form level seagrass classification scheme.

| Class Name | Species Composition | Additional Information |
|------------|---------------------|------------------------|
| *Ea*       | *Enhalus acoroides* | Species growing and extending vertically within water column. Sometimes reach the surface. Other life-forms may present within this class with insignificant coverage |
| *Th,Cr*    | *Thalassia hemprichii*, *Cymodocea rotundata*, *Halodule uninervis*, *Syringodium isoetifolium*, *Halophila ovalis* | Species growing covering the substrate and not significantly extending vertically within water column. Other life-forms may present within this class with insignificant coverage |
| *Ea,Th*    | *Thalassia hemprichii*, *Cymodocea rotundata*, *Halodule uninervis*, *Syringodium isoetifolium*, *Halophila ovalis* | A mixed between *Ea*-type and *Th,Cr*-type species at significant proportional coverage |

### Results

**Seagrass biophysical measurement**

Totally, there were 218 samples taken during field survey conducted on April and November 2012. 134 samples were used to perform LAI modeling and 84 samples were used to assess the accuracy of LAI map. Among 134 calibration samples, 48 samples belong to
Ea class, 31 samples belong to Ea, Th, class and 55 samples belong to Th, Cr class. The 84 validation samples consist of 32 Ea samples, 19 Ea, Th samples, and 33 Th, Cr samples. In each plot, we took several pictures of each sample within the mapping unit to accommodate GPS and image spatial displacement. In addition, we also took several shoot from each seagrass species found on each sample site to help species composition identification in the laboratory. Shoot sample for each seagrass species was collected because some seagrass species found on the study area are visually similar when identified from the picture. The relationship between seagrass PC and LAI at species level was used to obtain seagrass LAI on sample collected at the second field survey. However, we also calculated the relationship between seagrass PC and LAI at community level. At community level analysis was important because the picture of seagrass quadrate might be distorted due to surface ripple, and thus it was difficult to accurately determine the type and boundary between seagrass species within the quadrate. At this condition, the relationship between seagrass PC and LAI at community level was a better option.

**Water column correction**

The most important image correction in this study was the correction of water column effect which intended to isolate seagrass pixel from any additional reflectance. The main inputs to perform water column correction were deep water reflectance, bathymetry, and water column attenuation coefficient. Deep water reflectance values were obtained for each band by visually selecting the most noise-free deep water pixels on sunglint-free image (Tab. 3).

| Image         | Band |
|---------------|------|
| ALOS AVNIR-2  | Blue | 0.000684 | Green | 0.001146 | Red | 0.000381 |
| ASTER VNIR    | -    | 0.00046  |       | 0.000874 |

To generate water depth information on each pixel, we modeled field bathymetry data using log-transformed band ratio. The best bathymetry model for ASTER was obtained from the ratio of green and red band (Fig. 3). The bathymetry map was only effective up the depth of around 10 m. However, it was not a problem since the majority of seagrass in Karimunjawa is located within the depth of five meters. In addition, the accuracy of bathymetry map was much better than AVNIR-2, especially at water shallower than 2 m (SE = 0.73 m, n = 33). It seems that the increase in accuracy was due to the spatial resolution of ASTER which has managed to partially normalize the intra-habitat variation and minor depth fluctuation. Unfortunately, although the R^2 of AVNIR-2 bathymetry model was quite good, the error was quite high (SE = 3.76 m, n = 158) especially for the depth where seagrass are mostly located (SE = 4.23 m, n = 38). In fact, the ratio of AVNIR-2 was saturated at shallow (<5 m) and deep water (>10 m). The R^2 was high was due to the differences between the two ranges of depth; however, the changes were not gradual enough to make the model accurate. Consequently, the map from AVNIR-2 was not used to produce inversed bands. Instead, the bathymetry map used to derive AVNIR-2 inversed bands was interpolated from ASTER which has better bathymetry accuracy.
Using the value of $k$ from Table 1, the modeled bathymetry map, and the reflectance of pure optically deep water from Table 2, inversed bands were produced for each image (Fig. 4 and Fig. 5). Due to the nature of the algorithm, red band tends to produce higher value than the lower wavelengths. Therefore, color composite between blue, green, and red inversed band was visually obscured, especially at deeper water beyond the maximum DOP of red band. Nevertheless, it was not a problem since it was beyond the depth where the majority of seagrass are located.

It is important to note that this water column correction method was only effective up to the maximum DOP of the corresponding band. It is because beyond the maximum DOP, there is no information to begin with. Any emerging information beyond the maximum DOP would be mostly due to algorithm noises.

**Seagrass LAI mapping**

At community level mapping, the best LAI map was obtained from AVNIR-2 IM-PC1 band with SE of 0.72. For ASTER the best LAI map yielded SE of 0.76 from PC1 band. At species level, the $R^2$ and SE were not significantly better. Only $Ea$ produced better model with slightly lower SE. There was no improvement in the accuracy of $Ea$, $Th$ and $Th,Cr$ class. Although $Th,Cr$ consist of species with similar life-form, the variation between species still exhibit serious complexity for remote sensing data. Therefore, modeling the LAI of $Ea,Th$ and $Th,Cr$ were just as difficult as modeling seagrass LAI at community level.

Figure 6 and Table 4 show that the application of water column correction is beneficial for seagrass mapping. Tough, the descriptive resolution of both images also limits the $R^2$ from being high. The SE of seagrass LAI model at community level derived from AVNIR-2 inversed bands ($R^2 = 0.339$, SE = 0.74) and IM-PC bands ($R^2 = 0.358$, SE = 0.72) was lower than the SE of seagrass LAI map modeled from Deglint bands ($R^2 = 0.406$, SE = 0.9) and PC bands ($R^2 = 0.403$, SE = 0.78). Similarly, the quality seagrass LAI map from ASTER improved as water column correction and PCA transformation applied. At species level, IM and IM-PC was also the better performer with lower SE (Tab. 4). Although the decrease in the SE was not much, this condition is understandable as the variation of water depth for seagrass habitat in the study area is not much varied. Basically, water column correction
would provide significantly better result when the seagrass being modeled is located at significantly various depths. However, at which depth water column correction start to give positive impact on the quality of the model still need to be explored.

![Figure 4 - AVNIR-2 inversed blue band (left), green band (middle) and red band (right).](image)

![Figure 5 - ASTER inversed green band (left) and red band (right).](image)

The compilation of spectral band information via PCA was beneficial for the limited band of ASTER. It was shown by the $R^2$ and SE of ASTER’s PC band which was comparable with those from inversed bands. Moreover, on AVNIR-2, the application of PCA on inversed bands yielded the highest accuracy for mapping seagrass LAI at community level and seagrass $Th, Cr$, and thus highlights the fact that PCA may reveal and provide unique and intrinsic information about complex object under investigation. For more general seagrass
mapping, the application of PCA on sunglint-free band was more effective as it does not requires analytical input i.e. bathymetry, water column attenuation coefficient.

![Figure 6](image)

**Figure 6 - SE of seagrass LAI map at community and at species level using ASTER and AVNIR-2. Lower SE values represent more accurate seagrass LAI map.**

| Community (n = 134) | ALOS         | ASTER       | Ea (n = 48) | ALOS         | ASTER       | Ea (n = 31) | ALOS         | ASTER       |
|---------------------|--------------|-------------|-------------|--------------|-------------|-------------|--------------|-------------|
| Deglент             | R² 0.406 SE 0.9 Band Green 0.378 SE 0.8 G-R        | Deglент       | R² 0.367 SE 0.7 Band Red-ALL 0.193 SE 0.74 G-R |             |             |             |             |             |
| IM                  | R² 0.339 SE 0.74 Band INV-B 0.24 SE 0.78 INV-R-G    | IM            | R² 0.386 SE 0.71 Band INV-G-ALL 0.19 SE 0.72 INV-G-R |             |             |             |             |             |
| PC                  | R² 0.403 SE 0.78 Band PC1 0.345 SE 0.76 PC1-2       | PC            | R² 0.379 SE 0.71 Band PC1-ALL 0.11 SE 0.73 PC2-1 |             |             |             |             |             |
| IM-PC               | R² 0.358 SE 0.72 Band PC1 0.398 SE 0.78 PC2         | IM-PC         | R² 0.313 SE 0.72 Band PC1-3   0.182 SE 0.74 PC2 |             |             |             |             |             |

**Table 4 - Resume of seagrass LAI model derived from AVNIR-2 and ASTER.**

Scatter plot between modeled LAI and field LAI at species level and at community level are shown in Figure 7 and Figure 8 respectively.
Figure 7 - Scatter plot between modeled LAI and field LAI at species level. \( Ea \) model came from AVNIR-2 inversed green band (SE 0.71, n = 32), \( E_a, Th \) was modeled from ASTER inversed red band (SE 0.61, n = 19), and \( Th, Cr \) was obtained from AVNIR-2 IM-PC1 (SE 0.75, n = 33).

Figure 8 - Scatter plot (n = 84) between modeled LAI and field LAI at community level. The model from AVNIR-2 IM-PC1 yielded SE of 0.72 while from ASTER PC1 yielded SE of 0.76.

The results also show that at 10 m and 15 m spatial resolution, the quality of seagrass model at community and at species level was not that different. The spatial resolution of AVNIR-2 and ASTER partly generalized the uniqueness of interaction between downwelling irradiances and seagrass with specific species and life-form composition. The fact that \( Ea \) was modeled at higher accuracy was due to the nature of \( Ea \) class. This class consists of single species and life-form, and the area was also quite homogenous. Other classes such as \( E_a, Th \) and \( Th, Cr \) consisted of various species and life-form, and thus, they were modeled as if they were seagrass at community basis. This was shown
by the accuracy of $Th, Cr$ and $Ea, Th$ which is relatively similar with the accuracy of seagrass LAI model at community basis. The results of seagrass LAI mapping are shown in Figure 9.

The distribution of seagrass LAI from both images was relatively similar. Seagrass with LAI between 1.5 and 2 was lining parallel along the shoreline in the northern part of Kemujan Island. At the transition between seagrass habitat and sand or coral reefs, the LAI tend to decrease gradually. The main difference between LAI map from AVNIR-2 and ASTER was the detail in which the two images could provide. Although the spatial distribution pattern of LAI was similar, the intra habitat variation of LAI derived AVNIR-2 was more prominent. It was shown by the LAI of seagrass in the northwestern part of Kemujan Island. In this part, which is dominated by *Enhalus acoroides*, *Thalassia hemprichii*, and *Cymodocea rotundata*, there were patches of seagrass with LAI less than 1.5 and higher than 2. AVNIR-2 was able to provide more precise LAI distribution map due to its higher spatial resolution. For ASTER, the resulting LAI map was more generalized.

**Discussion**

In order to obtain adequate representative samples for seagrass LAI mapping, a good mapping unit for stratified random sampling design should be built. A good sampling mapping unit can be obtained if we considered several factors which affect the variation in seagrass LAI distribution. In this study, we managed to obtain good distribution of sample which may accommodate and bridge the variation of information contained on image with different pixel size. The integration of seagrass distribution factors such as seagrass spectral class, seagrass relative density, bathymetry, and coastal landscape were proved to be an
effective sampling mapping unit for images at various resolutions. Generally, seagrass habitat is composed of single species, mixed species with similar life-form or growth type and mixed species with different life-form or growth type. In this study, those three classes were represented by $E_a$, $E_a, Th$, and $Th, Cr$. Ideally, seagrass LAI mapping, based on the regression analysis, should be performed at species level. However, due to the limitation in the data precision and spectral resolution of the two images, they were not good enough to map seagrass species accurately. Previous studies using Quickbird and CASI hyperspectral reported that seagrass species mapping with 8 classes only yielded 22.69% and 28.11% accuracy respectively [Phinn et al., 2008]. In addition, the narrow strip of seagrass in the study area may further decrease the ability of ASTER and AVNIR-2 to produce accurate seagrass species map. However, at vast seagrass meadow with homogenous species or distinct boundary between species, medium resolutions data may be able to produce good seagrass species map. Therefore, when using medium spatial resolution data on area with small seagrass coverage, it is better to perform the mapping at community level since the accuracy will not differ significantly compared to at species level mapping.

Mapping the distribution of seagrass with multispectral data in optically shallow water with various benthic cover is difficult. At low coverage, seagrass are mostly misclassified as sand, especially at medium or lower spatial resolution data due to the relatively low proportion of seagrass compared to the bare substrate. Sands also have much higher reflectance than seagrass at any depth. In contrast, at high coverage, seagrass would be confused with optically deep water or high density coral reefs at deeper water. The accuracy of seagrass mapping is also not consistent due to the differences in the classification scheme being used. Separating seagrass from sand or other habitats can be quite accurate at medium to high cover density [Mumby and Green, 2000; Pasqualini et al., 2005; Sagawa et al., 2007; Sagawa et al., 2008]. Unfortunately, further seagrass properties mapping such as percent cover and standing biomass are not as accurate [Phinn et al., 2008; Knudby and Nordlund, 2011; Lyons et al., 2011; Lyons et al., 2012]. Interestingly, Mumby et al. [1997] obtained quite good accuracy of seagrass standing crop map from relatively homogenous seagrass habitat. His result highlights the fact that mapping seagrass properties at mixed community level was still tricky. Additionally, from insitu spectral measurement, Roelfsema et al. [2006] and Fyfe [2003] found out that seagrass species was effectively separable from remote sensing only up to the depth of three meter. Moreover, even the accuracy of seagrass species map derived using high resolution data, especially in heterogeneous seagrass habitat is still relatively low and inconsistent [Phinn et al., 2008; Lyons et al., 2011]. Depending on the complexity of seagrass species classification scheme being used, the accuracy may vary from low to high [Sagawa et al., 2008; Yang and Yang, 2009].

In this study, we addressed the complexity of mapping continuous LAI at species and at community level. Previous studies showed that mapping at species level was difficult, so we identified the most effective alternative scheme for species composition. We proposed seagrass classification scheme at life-form level instead of at species level scheme due the nature of energy interaction between downwelling irradiiances and seagrass reflecting tissue. Seagrass growing and extending vertically within water column interact uniquely to the downwelling irradiances compared to seagrass living covering the substrate. Our result showed that at homogenous seagrass habitat i.e. $Enhalus acoroides$ bed, the accuracy of mapping improved. However, at mixed life-form seagrass bed, there is no significant
improvement over the accuracy of LAI mapping. Mapping seagrass habitat with mixed life-form was just as difficult as mapping seagrass at community level. Furthermore, we also found out that even at seagrass habitat with similar life-form, the variation due to species characteristic still greatly control the characteristic of EM interaction. It was shown by the low accuracy of $Th,Cr$ class. In short, the most feasible approach of mapping accurate seagrass LAI would be still at homogenous seagrass habitat.

The basic of seagrass LAI mapping is the unique relationship between remote sensing downwelling irradiances, especially visible bands, with seagrass tissue. Ideally, as the condition or the properties of seagrass changing, the value in the corresponding pixel changes as well. This is related with the extent, composition, and biophysical condition of the reflecting seagrass tissue, which in fact, is also controlled by the species characteristics. As a consequence, to be ideal, seagrass LAI mapping should be performed at species basis. However, the change in pixel value might not always due to the change in seagrass properties i.e. species composition and LAI, but might be also due to the additional reflectance caused by water column, sunglint, atmospheric noises, and water depth variation. That is why; several necessary corrections were performed prior to seagrass LAI modeling to isolate seagrass reflectance. The results have showed that inversed bands were better than PC bands and sunglint-free bands for seagrass LAI mapping (Fig. 6 and Tab. 4).

The resulting LAI map was only available at community level since the environmental configuration of seagrass habitat in the study area prevented the use of medium spatial resolution image to properly map seagrass species. Seagrass in the study area is quite narrow and fringing along the shoreline and as a result, at AVNIR-2 and ASTER pixel size, it is highly possible to have many misclassifications during seagrass species mapping. Consequently, it would be possible that the model for $Ea$, will be mistakenly applied on $Th,Cr$ because the pixel is classified as $Ea$. Since at species basis the model is species-specific, when this condition occurs, the error of LAI model would be very high. Nevertheless, seagrass LAI analysis at species level showed us that if the mapping can be performed at species basis and with relatively accurate seagrass species map derived from image at higher spatial and spectral resolution, the accuracy of seagrass LAI map may considerably increase. The source of the error of seagrass LAI model may came from the remote sensing procedure and field data. The characteristics of remote sensing data with specific resolution i.e. spatial, spectral, temporal, and radiometric, are the first source of error. Spatial resolution affects the precision of seagrass information collected by the sensor on each pixel. Therefore, as the pixel size increases, the error is getting higher. In this study, image with 10 m and 15 m spatial resolution data were used. At that data precision, combined with the geometrical error of the image and GPS data to collect the sample, the propagation of error will lead to the decrease in the quality of seagrass LAI model.

At medium spatial resolution data, species mapping is very difficult, and thus mapping seagrass LAI at species level, especially at narrow seagrass bed cannot be performed. However, if the meadow of seagrass is vast with relatively homogenous seagrass composition, medium spatial resolution data may still able to perform at species level LAI mapping. Indeed, higher spatial resolution may deliver better result in term of information accuracy and precision. In fact, higher spatial resolution data is intended to do mapping at higher map scale and lower spatial resolution data is more suitable to do mapping at smaller map scale. Therefore, proportional to the intended usage of the image, the accuracy and precision of
each image is comparable. Using higher spatial resolution data may also introduce higher impact of sunglint, sensor noises, intra-habitat variations, and various energy attenuation due to tidal fluctuation.

The combination of spectral and radiometric resolution of the image is also another source of error. Both images, especially ASTER have very limited number of water penetration band which limit their ability to detect any subtle change or variation in seagrass habitat. Moreover, 8-bit data may also not precise enough to follow small changes in seagrass LAI. Higher coding ability and spectral resolution is definitely needed to precisely and accurately record the variation of seagrass LAI in a complex seagrass system.

Additionally, the delay between the date of image acquisition and field survey may further decrease the accuracy of seagrass model. In the study area, seagrass habitat is well protected and the extent does not change much overtime. Therefore, the delay between image acquisition date and field survey data was not really adversely impact the quality of the model. In area with high seagrass dynamics and disturbance, the delay between image acquisition date and field survey may result in significant decrease in the seagrass LAI model quality.

The process of isolating seagrass reflectance may also exhibit errors. Path radiance removal, sunglint correction and normalization of water column effect would produce residual which kept the R² from getting higher. However, it was still much better than not performing any correction. During water column correction, the quality of bathymetry image highly determines the quality of the outcome image since the rate and intensity of energy attenuation is the direct function of water depth. Furthermore, the combination of bathymetry image and water column attenuation coefficient which was also derived empirically from the image itself may ineffectively alter the pixel value of seagrass. Therefore, in fact, if the quality of bathymetry data can be improved and the attenuation coefficients are calculated directly from optical measurement on seawater, the quality of seagrass LAI model may improve.

LAI data taken in the field also became the source of the error during the quantification of relationship between image value and seagrass LAI. Since seagrass LAI data from the second field survey was estimated from PC, there was an error from the regression which also enters the model. Moreover, the bias of calculation of seagrass PC via photo quadrate technique i.e. ripples, waves, specular reflection, seagrass life-form, highly mixed species, may also increase the amount of potential error in the LAI model. Furthermore, at seagrass habitat where various species are mixed together and interleaved each other, the mapping would be more difficult.

Generally, the better band for seagrass LAI mapping would be green band (Tab. 4). Its sensitivity to chlorophyll content within seagrass tissue, relatively lower atmospheric scattering, and good water penetration ability were the reasons for its superiority over blue and red band. However, at specific purpose such as mapping complex species class consist of various life-form i.e. Ea, Th and Th, Cr, additional information from blue and red band would be highly beneficial. The sensitivity of green and red band to seagrass LAI was also found by Yang et al. [2011]. Therefore, images without blue band i.e. ASTER, SPOT series may still able to deliver good seagrass LAI map. Information contained in each band may be integrated into unique information via PCA transformation. However, the application of PCA is generally better when applied on the original bands. Applying PCA on the original bands was faster and yielded comparable result with those came from inversed bands. Applying PCA transformation on inversed bands may increase the explaining power of the bands in exchange to the more robust processing task.
The results of seagrass LAI mapping have showed that ASTER and AVNIR-2 performance was not significantly different, which means that the descriptive resolution of both images for seagrass LAI mapping is relatively similar and information taken in the field via our proposed mapping unit is able to accommodate the variation of information contained in AVNIR-2 and ASTER pixel. Although AVNIR-2 yielded higher accuracy and lower SE, the accuracy was for 100 m$^2$ instead of 225 m$^2$. Therefore, since the level of precision of ASTER was lower, it was understandable if the SE is higher. Unless good seagrass species map can be produced using higher spatial resolution data, the accuracy differences of LAI map derived from high and medium spatial resolution data may not really significant. At higher spatial resolution data, the error due to GPS or image spatial displacement may adversely impact the quality of LAI model. It is difficult to obtain handheld GPS with the same level of accuracy with the currently available high spatial resolution data i.e. Worldview-2, Geoeye, Quickbird. Therefore, it is hard to precisely and accurately match the coordinate taken in the field with the corresponding pixel in the image. The mismatch between field data with the corresponding pixel value may negate the relationship between seagrass LAI and image pixel value. In addition, as the resolutions increase, the effect of sunglint, sensor noises, intra-habitat variations, and tidal fluctuations is also greater. In short, with higher resolutions data, it is possible to obtain better seagrass LAI model; however, care must be taken to effectively exploit the benefit.

Lastly, the availability of seagrass LAI map would be very important in modeling the amount of carbon being sequestered from the atmosphere by seagrass. Seagrass LAI represents the extent of photosynthesizing tissue as well as chlorophyll concentration, which affect the rate of photosynthesis. As a result, information about seagrass LAI can be used to estimate the NPP [Dierssen et al., 2010]. Furthermore, LAI is highly related with standing crop and carbon stock, and thus it can be used to conservatively estimate the amount of carbon being buried in the carbonate sediment via carbonate dissolution. This process creates huge carbonate pools in the seagrass sediment which trap the sequestered carbon during photosynthesis for millennia. The use of LAI to predict carbon stock is more effective than standing crop because LAI measurement can be done much faster and safer to the environment as it requires minimal harvesting. Faster sampling may increase the number of sample and the cost and time effectiveness of carbon stock mapping. Seagrass PC is also a faster approach to predict carbon stock, however, seagrass PC sensitivity to LAI is highly species-specific, and thus, it is not effective when performing mapping and survey at community basis.

Conclusions
Our results showed that mapping seagrass LAI at community level was feasible at medium resolutions image. Although the accuracy was still not high, it open up the possibility of better mapping in the future when image with enhanced resolutions is widely available and operational. At present, the difficulties of seagrass LAI mapping are mainly due to the sensor, method, and environmental limitation. Sensor characteristics such as spectral, spatial, radiometric and temporal resolution are the first source of error and then followed by the method being used to isolate seagrass reflectance from additional atmospheric and water column reflectance. The addition of several bands at green and red wavelengths at approximately around 500 nm to 650 nm would be beneficial for seagrass shallower than 10 m. For seagrass beyond 10 m, narrow slice of wavelength between 400 nm to 500 nm
in the blue green region would be the best options. Spatial resolution of sub 10 m would be effective for seagrass mapping, however, when using very high spatial resolution data, the mapping will be more complex as it requires better geometric precision field data and the noises might become higher. The process of collecting field data may also become the source of error, both due to spatial displacement or due to the accuracy of collected information. While providing little error of LAI estimation for species such as *Thalassia hemprichii* and *Cymodocea rotundata*, photo quadratic method used in this study underestimate the actual LAI of species which grow vertically such as *Enhalus acoroides*. In addition, if the seagrass is narrow and the bed is mixed with various species interleaved together, it would be difficult for any remote sensing data to properly estimate the LAI. Mapping seagrass LAI with similar life-form and species may improved the accuracy of mapping, however, mapping the LAI of seagrass beds consist of various species, although having similar life-form, was as difficult as mapping seagrass LAI at community level. Therefore, the error is not solely due to the limitation of remote sensing but also due to the environmental restriction of seagrass habitat. Last, the synchronization between input data, method and the nature of seagrass habitat would determine the success of seagrass LAI mapping.

The mild pixel size of AVNIR-2 and ASTER partly generalized the uniqueness of interaction between downwelling irradiances and seagrass with specific species and life-form composition. As a result, the accuracy of seagrass map at community and at species level was not significantly different. The results also indicate that if seagrass species map is available at considerable precision and accuracy, mapping seagrass LAI could be better. However, it also depends on the configuration of seagrass habitat in the area under investigation. Vast seagrass meadows with distinct boundary between species may be able to be mapped via medium resolutions image. Field data is an important component in the success of seagrass LAI mapping. In this study, we managed to select several map-able factors which influence the distribution of seagrass LAI as the mapping unit for stratified random sampling design. Samples taken from each mapping unit was able to bridge and accommodate the detail of information contained in each pixel sizes. It was justified by the relatively similar performance of AVNIR-2 and ASTER during LAI mapping. In addition, we also found out that AVNIR-2 and ASTER has similar seagrass LAI descriptive resolution. The resulting LAI map from the two images showed similar distribution pattern. The main difference would be in the level of precision of the LAI map where AVNIR-2 with higher spatial resolution was able to deliver better level of detail.

Future works of seagrass LAI mapping should incorporate image with better spectral, spatial, and radiometric resolution. If the number of water penetration band could be increased, the selection and the pool of information that can be used to model seagrass LAI will also expand. Since seagrass mapping is a complex task, we require as much information as possible from any available wavelengths to obtain the most effective result.

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