IDENTIFICATION SEAGRASS CONDITION FROM ALOS AVNIR-2 USING ARTIFICIAL NEURAL NETWORK AT PARI ISLAND

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GRADUATE SCHOOL
BOGOR AGRICULTURAL UNIVERSITY
BOGOR
2011
STATEMENT

I, Amran Firdaus, hereby declare that this thesis entitled

Identification Seagrass Condition from ALOS AVNIR-2
Using Artificial Neural Network at Pari Island

Is a result of my own work under the supervision advisory board and that it has not been published before. The content of the thesis has been examined by the advising the advisory board and external examiner

Bogor, May 2011

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AMRAN FIRDAUS. Identification Seagrass Condition from ALOS AVNIR-2 using Artificial Neural Network at Pari Island. Under the supervision of KUDANG B SEMINAR and ANTONIUS B WIJANARTO.

Seagrass beds have important roles in marine life, but the unavailable of information about the condition of seagrass causes difficulties in managing coastal areas properly. Regularly updated and accurate information on the percentage cover of seagrass is an essential component of the knowledge required to monitor, understand and manage this resource. Artificial Neural Network (ANN) was applied to ALOS AVNIR-2 to identify seagrass condition. Twenty two classification scenarios were done to compare the result of accuracy. There are three class of seagrass condition. Seagrass cover more than 60% indicates the condition of good seagrass. Seagrass cover from 30% to 59.9% indicates the condition of medium seagrass. Seagrass cover below 29.9% indicates the condition of poor seagrass.

Best accuracy was obtained by scenario H by entering combination of blue (0.42 to 0.50 μm) and NIR (0.76 to 0.89 μm) wavelength plus water depth data as input parameters, with a value of 71.43% overall accuracy. However, looking at individual class, Scenario C, which is 58.33% of overall accuracy by using combination of blue (0.42 to 0.50 μm), green (0.52 to 0.60 μm), NIR (0.76 to 0.89 μm) wavelength plus water depth achieved higher producer and user accuracy. Overall, the result of identification seagrass condition from ALOS AVNIR-2 using artificial neural network at Pari Island in 2010 is dominated by poor seagrass, while good seagrass and medium seagrass were found in small area.

Key words: Seagrass condition, ALOS AVNIR-2, ANN classification, overall accuracy, producer accuracy, user accuracy, Pari Island.
AMRAN FIRDAUS. Identification Seagrass Condition from ALOS AVNIR-2 using Artificial Neural Network at Pari Island. Dibimbing oleh KUDANG B SEMINAR dan ANTONIUS B WIJANARTO.

Padang lamun memiliki peran penting dalam kehidupan laut, namun tidak tersedianya informasi tentang kondisi padang lamun menyebabkan kesulitan dalam mengelola kawasan pesisir dengan benar. Memperperbaharui secara teratur dan akurat tentang informasi luas tutupan lamun merupakan hal yang penting dari pengetahuan yang dibutuhkan untuk memantau, memahami dan mengelola sumberdaya ini. Artificial Neural Network (ANN) telah diterapkan pada ALOS- AVNIR 2 untuk mengetahui kondisi lamun. Dua puluh dua skenario klasifikasi dilakukan untuk membandingkan hasil akurasi. Ada tiga kelas kondisi lamun. Tutupan lamun lebih dari 60% menunjukkan kondisi padang lamun baik. Tutupan lamun dari 30% sampai 59,9% menunjukkan kondisi lamun sedang. Tutupan lamun dibawah 29,9% menunjukkan kondisi lamun jelek.

Hasil akurasi terbaik diperoleh oleh skenario H yang memasukan kombinasi panjang gelombang biru (0.42 to 0.50 μm), dan NIR (0.76 to 0.89 μm) ditambah data kedalaman air sebagai parameter masukan, dengan nilai keseluruhan akurasi 71,43%. Namun, melihat kelas individu, Skenario C, dengan nilai akurasi keseluruhan 58,33% yang menggunakan kombinasi panjang gelombang biru (0.42 to 0.50 μm), hijau (0.52 to 0.60 μm), NIR (0.76 to 0.89 μm) ditambah data kedalaman air mencapai nilai lebih tinggi untuk akurasi produser dan pengguna. Secara keseluruhan, hasil identifikasi kondisi lamun dari ALOS AVNIR-2 menggunakan artificial neural network di Pulau Pari tahun 2010 didominasi oleh lamun jelek, sedangkan lamun baik dan sedang ditemukan di sebagian kecil area.

Kata kunci: Kondisi lamun, ALOS AVNIR-2, klasifikasi ANN, akurasi keseluruhan, akurasi produser, akurasi pengguna, Pulau Pari.
AMRAN FIRDAUS. Identification Seagrass Condition from ALOS AVNIR-2 using Artificial Neural Network at Pari Island. Under the supervision of KUDANG B SEMINAR and ANTONIUS B WIJANARTO.

Seagrass ecosystems are important and critical habitat for the survival of marine biota of life, even to advocate one alternative livelihood and income of the community who have long lived in coastal areas. Seagrass meadows produce a variety of goods (finfish and shellfish) and provide ecological services (maintenance of marine biodiversity, regulation of the quality of coastal waters, protection of the coast line) which are directly used or beneficial to humans and condition the economic development of Indonesian coastal zones. On the other hand, seagrass is also sensitive to various human activities such as reclamation, adding the port, making jeti, settlements, surface flow, the waste industry and coastline unstable. Understanding the extent and condition of these seagrass meadows and how they change over time is essential for their management and sustainable use.

Considering to the very extensive area to be studied, for obtaining precise information of Indonesian seagrass coverage, it is favorable to use remote sensing technique as alternative tool. In Indonesia, particularly seagrass identification using satellite imagery is still rarely done. The objective of this research is to identify the seagrass condition from ALOS AVNIR-2 using Artificial Neural Network classification scenario.

Study area in this research is located in Jakarta Province, Seribu Island District, precisely in Pari Island covering Burung Island, Tengah Island, and Kongsi Island. Pari Island has depth range between 0-50 meters, which the physics and chemical parameter of water has a good range where the seagrass can live. Seagrass meadow on Pari Island is the vegetation that lives in shallow waters. Pari Island is also having an important livelihood for almost the entire community surrounding it, which depends on seaweed farming and fishing.

Seagrass cover is a parameter to determined seagrass condition based on declaration of environment minister number 200/2004. There are three classifications of seagrass condition; 1) seagrass more than 60% indicates the condition of good seagrass, 2) seagrass cover from 30% to 59,9% indicates the condition of medium seagrass, and 3) seagrass cover below 29,9% indicates the condition of poor seagrass. Seagrass cover is referred to as the horizontally projected foliage cover of the seagrass canopy, which is recognized as a key information requirement for seagrass monitoring.

This research is performed from September 2010 to March 2011. Satellite imagery of ALOS AVNIR-2 acquisition date is September 18th, 2009, and field survey data in September 2010 is the main data for this study. Water condition data of the year 2009 from MODIS Aqua and Landsat-7 acquisition of the year 2006 are also used as supporting data.
There are three main steps to identifying seagrass condition: image preprocessing, image classification, and accuracy assessment. In this study, geometric correction and atmospheric correction was applied before image classification, including subset and masking image. On image classification stage, some data observation and measurement from field survey directly will be used for ANN classification, and another will used for validation. Forty eight points of field data were divided into two data sets: 26 in the training data set and 22 in the testing. In this research, ANN supervised classification was guided by variety of input data sets including field survey, satellite imagery and expert knowledge to produce seagrass condition map. Twenty two scenario processes were done to compare the result of accuracy.

Field data were used to determine training sites for three levels of seagrass cover classes ( \( \leq 29.9\% \), 30-59.9\%, \( \geq 60\% \) ) in the ANN supervised image classification process. Reflectance signatures for each of the three different seagrass cover classes were extracted from the ALOS AVNIR-2 scene of Pari Island for the calibration field sites, which served as training sites for the image classification process. Characteristic spectral reflectance signatures were defined for each of the target levels of seagrass cover to be mapped.

Classification scenarios were developed to identify the seagrass condition at Pari Island. For this purpose, shallow water habitat was classified into nine classes; sea, sand, lagoon, coral, reef slope, mix habitat (coral, seagrass, seaweed, and sand), poor seagrass, medium seagrass, and good seagrass. The separability of ROIs between good seagrass and other habitat (poor seagrass, lagoon, sea, sand, coral, mix habitat, and reef slope) are 2.0, except between good seagrass and medium seagrass is 1.99. The separability between medium seagrass and other habitat (poor seagrass, lagoon, sea, sand, coral, mix habitat, and reef slope) are 1.93, 2.0, 1.95, and 2.00 achieved between poor seagrass and lagoon, sea, sand, coral, mix habitat, and reef slope respectively. From that value of separability, two lower separability values got between medium seagrass and sand (1.68), and medium seagrass and coral (1.88).

From all of the classification scenarios that have been conducted, the results obtained accuracy varies for each scenario. Half of the accuracy of classification scenarios has value zero, while others were worth an average accuracy of 50%. The best accuracy was achieved by using combination of blue (0.42 to 0.50 \( \mu m \)) and NIR (0.76 to 0.89 \( \mu m \)) wavelength plus water depth, with an overall accuracy of 71.43%. However, looking at individual class, the classification scenario that used blue (0.42 to 0.50 \( \mu m \)), green (0.52 to 0.60 \( \mu m \)), NIR (0.76 to 0.89 \( \mu m \)) wavelength plus water depth achieved higher producer and user accuracy. Even NIR wavelengths are absorbed by water, but in this study this wavelength (0.76 to 0.89 \( \mu m \)) can be used for the habitat classification. It can be caused the water depth which was below 2 meters.

Several factors that affect the accuracy assessment in this study, these include number of input parameter, number of training sample and test point, and accuracy of GPS. Overall, the result of identification seagrass condition from ALOS AVNIR-2 using artificial neural network at Pari Island in 2010 is dominated by poor seagrass, while good seagrass and medium seagrass are found in small area.
Furthermore, to improve the identification seagrass condition, it is important to explore the ability of ANN classification method itself, by changing the settings of the neural network training (training momentum, training rate, etc.). It would be better to use some of the satellite imagery with dissimilar sensor and different spatial resolutions to make a compare fine analysis of the results of classification. This is expected to obtain higher accuracy.

Key words: Seagrass condition, ALOS AVNIR-2, ANN classification, overall accuracy, producer accuracy, user accuracy, Pari Island.
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A thesis submitted for the degree Master of Science in Information Technology for Natural Resources Management Program Study

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CURRICULUM VITAE

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2. Penguji dilibatkan dalam penilaian yang dilakukan oleh pihak terkait.

3. Penilaian harus melibatkan penguji berpengalaman dalam bidang penelitian yang sama.

4. Hasil penilaian harus disampaikan dalam bentuk laporan yang tercakup dalam penilaian.

Hak Cipta Dilindungi Undang-Undang
I. INTRODUCTION

1.1. Background

The large knowledge about the biology and ecology of seagrass gained during the last third of the 20th century has driven increased awareness of the economic value of seagrass to humans. Seagrass feature high rates of primary production. As any other photosynthetic organism, seagrass fix carbon dioxide using the energy provided by light and transform it into organic carbon to sustain seagrass growth and biomass production. High rates of biomass production imply high rates of oxygen production, a byproduct of photosynthesis, which is released to the surrounding waters.

Seagrass ecosystems are important and critical habitat for the survival of marine biota of life, even to advocate one alternative livelihood and income of the community who have long lived in coastal areas. In addition seagrass meadows also have several functions, among which is a trap for sediment, reducing abrasion coast, fisheries production support, as the habitat of various types of biota (flora and fauna) sea coast. On the other hand, seagrass is also sensitive to various human activities such as reclamation, adding the port, making jeti, settlements, surface flow, the waste industry and coastline unstable (Short and Echeverria 1996, Duarte 2002).

In several areas of Indonesia, seagrass coverage and its distribution has been change from time to time. For having so many islands and long coastal areas, it was roughly estimated that approximately 30,000 km2 of seagrass cover Indonesian Archipelago (Kuriandewa et al., 2003). However, reliable data of such information is inadequately available, since former and recent seagrass researches rarely measured the extent of seagrass intentionally; they mainly focused on the biology of seagrass and its associated biota (Hutomo, Kiswara and Azkab 1988).

Pari Island has depth range between 0-50 meters, which the physics and chemical parameter of water has a good range where the seagrass can live. Pari Island stand on coral reef flat with others islands on it, namely the Burung Island, Tikus Island, Tengah Island, and Island Kongsi. On the reef flat, there found some
lagoon, and three complete tropical ecosystems such as mangroves, seagrass beds, and coral, including the diversity of biological resources (fish, crustaceans, mollusca, echinoderms, and seaweed) were quite abundant until the early 1980's (Wouthuyzen et al., 2008). Therefore, Pari Island was set as an observation station marine science (particularly coastal areas) since 1970. In addition, Pari Island is also having an important livelihood for almost the entire community surrounding it, which depends on seaweed farming and fishing. The study conducted in 2008 by Wouthuyzen about the overall status evaluating ecosystems and living resources in Pari Island showed that the biological resources in the cluster Pari Island experienced a drastic decrease in symptoms. If it occurs continuously, it can be expected to further decline of biological resources at Pari Island, which impact on decreasing the catch of fishermen and people's income Pari Island.

Remote sensing for identification of seagrass has many advantages when compared to conventional survey methods, which may include spatial only a narrow area. Mapping of seagrass properties from remote sensing and/or field data has been conducted in other tropical, sub-tropical and temperate environments. ALOS AVNIR-2 is a visible and near-infrared radiometer for observing land and coastal zones and provides better spatial resolution. It will be useful for monitoring the condition of coastal resources such as mangrove forests, seagrass meadows, coral reefs, coastal line change, and water quality. Seagrass extent was mostly measured using rough estimation technique. Considering to the very extensive area to be studied, for obtaining precise information of Indonesian seagrass coverage, it is favorable to use remote sensing technique as alternative tool.

Research on mapping and monitoring of shallow-water ecosystems have been carried out using satellite image data (McKenzie et al. 2001). But in Indonesia, particularly the seagrass identification using satellite imagery is still rarely done, only a few locations that have been done, including the east coast Bintan Island in Riau Islands, Lembeh Strait and North Minahasa in North Sulawesi, Sanur Beach in Bali, Gili Lawang and Gili Sulat in Lombok Island, and Kotania and Pelitajaya Bay in West Seram, Maluku.
Over the years, a number of classifications have been applied to produce maps of the seagrass beds for a range of scientific and management purposes. The most commonly used classification methods in remote sensing are statistical classification algorithms such as the minimum distance and the maximum likelihood. Although widely used, conventional statistical classification techniques may not always be appropriate for mapping from remotely data. These methods have their restrictions, related particularly to distributional assumptions and to limitations on the input data types (Foody 1999).

The Artificial Neural Network (ANN) has seen a lot of interest from past few years. It has been successfully applied to a wide range of domains such as finance, medicine, engineering, geology and physics. Kaul et al., (2005), stated that many authors reported better accuracy when classifying spectral images with an ANN approach than with a statistical method such as maximum likelihood. Neural networks, with their ability to learn by example make them very flexible and powerful. However, a more important contribution of the ANNs is their ability to incorporate additional data in the classification process. A limited amount of research has been conducted on the application of neural networks to identify seagrass condition. Respond to this matter and to provide descriptive information for proposed management of seagrass ecosystem, identification of seagrass condition was carried out in Pari Island using remote sensing technique and ANN classification.

1.2. Objectives

The objective of this research is to identify the seagrass condition from ALOS AVNIR-2 using Artificial Neural Network classification scenario.

1.3. Scope of Study

1. Location: Pari Island is located at the position 106° 34’ 0” – 106° 38’ 0” East Longitude and 05° 52’ 50” – 05° 54’ 50” South Latitude, Jakarta province.

2. Data analysis in this study focus only seagrass condition based on declaration of minister environment no 200/2004.
1.4. Problem Statement

The reason why choose seagrass is due to an important role in marine life, but the unavailable of information about the condition of seagrass causes difficulties in managing coastal areas properly. Seagrass meadows produce a variety of goods (finfish and shellfish) and provide ecological services (maintenance of marine biodiversity, regulation of the quality of coastal waters, protection of the coast line) which are directly used or beneficial to humans and condition the economic development of Indonesian coastal zones. Understanding the extent and condition of these seagrass meadows and how they change over time is essential for their management and sustained use. Regularly updated and accurate information on the percentage cover of seagrass is an essential component of the knowledge required to monitor, understand and manage this resource.

1.5. Research Output

The output of this research is information about the condition of seagrass in Pari Island – Seribu Island, which can be used as a reference for managing coastal areas as a whole.
II. LITERATURE REVIEW

2.1. Seagrass

Seagrass are marine flowering plants (angiosperms); thus they live and complete their entire life cycle submerged in seawater (including underwater flowering, pollination, distribution of seeds and germination into new plants). Seagrass also propagate vegetative by elongating their rhizomes; a whole meadow may be one single clone resulting from one seedling. Both sexual reproduction and vegetative growth are critical to the propagation and maintenance of seagrass meadows (Hemminga and Duarte 2000).

Seagrasses have had many traditional uses (Terrados and Borum, 2004). They have been used for filling mattresses (with the thought that they attract fewer lice and mites than hay or other terrestrial mattress fillings), roof covering, house insulation and garden fertilizers (after excess salts were washed off). Seagrass habitats also provide shelter and attract numerous species of breeding animals. Fish use the seagrass shoots as a protective nursery where they, and their fry, hide from predators. Likewise, commercially important prawns settle in the seagrass meadows at their post-larval stage and remain there until they become adults (Watson et al., 1993).

Seagrass can be found all over the world except in the polar region. In Indonesia, there are only about 7 genus and 12 species belonging to the family of 2, namely: Hydrocharitacea and Potamogetonaceae. Types of communities that make up the single seagrass beds, among others: Thalassia hemprichii, Enhalus acoroides, Halophila ovalis, Cymodoceae serulata, and Thallasiadendron ciliatum from some type of seagass, have any of Thallasodendron ciliatum limited, while Halophila spinulosa recorded in the area of Jakarta, Anyer, Baluran, Irian Jaya, Lombok and Belitung. Similarly, new Halophila decipiens is found in Jakarta Bay, Bay of Moti-Moti and Kepulaun Aru (Den Hartog, 1970; Azkab, 1999; Bengen 2001).
Seagrass Cover

Seagrass cover is referred to as the horizontally projected foliage cover of the seagrass canopy, which is recognized as a key information requirement for seagrass monitoring (McKenzie et al., 2001). Seagrass cover describes the fraction of sea floor covered by seagrass and thereby provides a measure of seagrass abundance at specific water depths. Depending on sampling strategy, seagrass cover may reflect the patchiness of seagrass stands or the cover of seagrass within the patches – or both aspects. Measurements of cover have a long tradition in terrestrial plant community ecology and are also becoming widely used in aquatic systems.

Method description: The study area can be either coarsely defined as a corridor through which the diver swims, or be more precisely defined as quadrates of a given size. Percent cover of seagrass is usually estimated visually by a diver as the fraction of the bottom area covered by seagrass. The cover can be estimated directly in percent or assessed according to a cover scale. When stones constitute part of the bottom substratum it is important to define whether seagrass cover is assessed relative to the total bottom area or relative to the sandy and silty substratum where seagrass can grow.

Seagrass cover is parameter to determined seagrass condition based on declaration of environment minister number 200/2004 (Table 2.1). There are three classification of seagrass condition; 1) seagrass more than 60% indicates the condition of good seagrass, 2) seagrass cover from 30% to 59,9% indicates the condition of medium seagrass, and 3) seagrass cover below 29,9% indicates the condition of poor seagrass.

<table>
<thead>
<tr>
<th>Cover (%)</th>
<th>Condition</th>
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<tr>
<td>≥ 60</td>
<td>Good</td>
</tr>
<tr>
<td>30 - 59,9</td>
<td>Medium</td>
</tr>
<tr>
<td>≤ 29,9</td>
<td>Poor</td>
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Table 2.1 Classification of Seagrass

(Minister of Environment 200/2004)
2.2. Remote Sensing

Remote Sensing is the science and art of acquiring information (spectral, spatial, and temporal) about material objects, area, or phenomenon, without coming into physical contact with the objects, or area, or phenomenon under investigation (Lillesand and Kiefer, 1994). Without direct contact, some means of transferring information through space must be utilized. In remote sensing, information transfer is accomplished by use of electromagnetic radiation (EMR). The radiance recorded by a remote sensing instrument contains a number of components when water masses are being imaged (Figure 2.1). EMR is a form of energy that reveals its presence by the observable effects it produces when it strikes the matter. EMR is considered to span the spectrum of wavelengths from 10-10 mm to cosmic rays up to 1010 mm, the broadcast wavelengths, which extend from 0.30-15 mm.

Figure 2.1. The pathways of light over and in a shallow water system.
(Dekker et al., 2001).

Now, the satellite imageries from different kind of sensor are commercially available. By using an image processing system it is possible to analyze remotely sensed data and extract meaningful information from the imagery. Besides the knowledge of image processing techniques, a fundamental understanding of capabilities of certain sensor system is required. Remote sensing
technology that has a capability to give data on natural resources and its environment over a large region within relative short time is strongly needed in a multidisciplinary activity related to natural resources (Wasrin and Setiabudi, 1998).

2.3. Advance Land Observing Satellite (ALOS)

ALOS is the satellite which sophisticated with accumulated technology by development and use of Japanese Earth Resources Satellite-1 (JERS -1) and Advanced Earth Observing Satellite (ADEOS). ALOS is an Advanced Earth Observing Satellite launched from Tanegashima Space Centre on January 24th, 2006. ALOS works the observation operation in the sun-synchronous orbit at the cycle of the 46 days. Top its performance, ALOS has been equipped by three remote sensing sensor instruments which are: 1) Panchromatic Remote-sensing Instrument for Stereo Mapping (PRISM), it is a panchromatic sensor, provides 2.5m spatial resolution images. It has three optical system; forward look, nadir look, and backward look, so it can be high-frequency and acquire highly precise topography data; 2) Advanced Visible Near- Infrared Radiometer-2 (AVNIR-2), it is a multi-spectrum sensor with four bands in visible to near infra red, and provides 10 m spatial resolution images; 3) Phased Array L-band Synthetic Aperture Radar (PALSAR), it is an active microwave sensor using L-band frequency to achieve cloud-free and day-and-night land observation. It has three observation mode; Fine, ScanSAR, and Polarimetric, provides 10m to 100m spatial resolution images (EAOR JAXA).

2.3.1. Advance Visible and Near Infrared Radiometric Type 2

ALOS Satellite with sensor AVNIR-2 has 3 visible spectrums i.e. band1 (blue), band2 (green) and band3 (red) which have the ability of penetration into water column, also it has a near infra-red (band4) which has the ability of differentiate object. AVNIR-2 is a visible and near-infrared radiometer for observing land and coastal zones and provides better spatial resolution. It will be useful for monitoring the condition of coastal resources such as mangrove forests, seagrass meadows, coral reefs, coastal line change, and water quality (EORC JAXA).
AVNIR-2 is a successor to AVNIR that was on board the Advanced Earth Observing Satellite (ADEOS), which was launched in August 1996. Its instantaneous field-of-view (IFOV) is the main improvement over AVNIR. AVNIR-2 also provides 10m spatial resolution images, an improvement over the 16m resolution of AVNIR in the multi-spectral region. Improved CCD detectors (AVNIR has 5,000 pixels per CCD; AVNIR-2 7,000 pixels per CCD) and electronics enable this higher resolution. A cross-track pointing functions for prompt observation of disaster areas is another improvement. The pointing angle of AVNIR-2 is +44 and -44 degree. Table 2.2 and Table 2.3 show the characteristics and product processing definition of ALOS AVNIR-2.

Table 2.2 AVNIR-2 Characteristics

<table>
<thead>
<tr>
<th>Number of Bands</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelength</td>
<td>Band 1: 0.42 to 0.50 micrometers</td>
</tr>
<tr>
<td></td>
<td>Band 2: 0.52 to 0.60 micrometers</td>
</tr>
<tr>
<td></td>
<td>Band 3: 0.61 to 0.69 micrometers</td>
</tr>
<tr>
<td></td>
<td>Band 4: 0.76 to 0.89 micrometers</td>
</tr>
<tr>
<td>Spatial Resolution</td>
<td>10 m (at Nadir)</td>
</tr>
<tr>
<td>Swath Width</td>
<td>70km (at Nadir)</td>
</tr>
<tr>
<td>S/N</td>
<td>&gt;200</td>
</tr>
<tr>
<td>MTF</td>
<td>Band 1 through 3: &gt;0.25</td>
</tr>
<tr>
<td></td>
<td>Band 4: &gt;0.20</td>
</tr>
<tr>
<td>Number of Detectors</td>
<td>7000/band</td>
</tr>
<tr>
<td>Pointing Angle</td>
<td>-44 to +44 degree</td>
</tr>
<tr>
<td>Bit Length</td>
<td>8 bits</td>
</tr>
</tbody>
</table>

Table 2.3 Product Processing Definition

<table>
<thead>
<tr>
<th>Level</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A</td>
<td>This is AVNIR-2 raw data, which is clipped out of L0 data, decompressed and processed with tie generation. Radiometric calibration and geometric correction coefficients are added for level 1B processing</td>
</tr>
<tr>
<td>1B1</td>
<td>This level applies radiometric calibration and adds absolute calibration coefficient to level 1A data. Geometric correction coefficient is also added for level 1B2 processing</td>
</tr>
<tr>
<td>1B2</td>
<td>This level applies geometric correction on level 1B1 data. Following correction option applicable. R: Geo-reference data</td>
</tr>
<tr>
<td></td>
<td>G: Layering data on map. Geo-coded data</td>
</tr>
<tr>
<td></td>
<td>D: DEM correction (only in the Japanese region)</td>
</tr>
</tbody>
</table>

(http://www.eorc.jaxa.jp/ALOS/en/about/avnir2.htm)
2.4. Remote Sensing Application for Seagrass Identification

Satellite remote sensing technology changed dramatically at the end of the 1990s. Sensors with increased spatial resolution will better suit the discrimination of small and patchy, or narrow, linear seagrass beds that commonly occur in small estuaries but they may not improve the accuracy of mapping large seagrass meadows (e.g. Mumby and Edwards, 2002; Malthus and Karpouzli, 2003). However, because of the wide range of satellite sensors now available, imagery can be selected to match the scale and objective of almost any seagrass mapping project.

Remote sensing of aquatic environments (seagrass, sand, macro-algae, mud, and coral reefs) requires sensors with greater sensor signal-to-noise ratio than those applied in terrestrial environments. Coupled with this factor is the number of quantization levels to which the sensor can record, referred to as the radiometric resolution of the sensor. This must be high enough to allow a range of brightness levels over which a classification can be performed and sensitive enough to be able to detect the lower reflectance of the deeper seagrass beds (Dekker et al., 2001). Seagrasses may grow with sparse cover and can be spectrally confused with other benthic features such as areas of macro-algae, detritus, and corals. The small size and/or linear shape and patchy nature of many seagrass meadows means that in many cases high spatial resolution is also required to accurately determine their distribution and abundance.

Remote sensing for identification of seagrass has many advantages when compared to conventional survey methods, which may include spatial only a narrow area. Remote sensing technology has advantages, namely: 1). Able to record data and information widely and repeated. Multitemporal can be use for detecting changes in community structure and health of an ecosystem such as coral reefs and seagrass (Mumby et al. 2004). 2). Have the many bands / channels, which can be used to analyze various purposes by using specificity of each band. 3). It can used to reach difficult areas visited by humans / ship. 4). easily analyzed using a computer because the data in digital form. 5). the price of information is relatively less expensive (Mumby et al. 1999).
Identification of the aquatic environment can be defined as ‘the gathering of data and information on the status of the water’. The purpose of identification varies from assessing status, detecting changes and providing early warning to detecting reasons for changes or evaluating effects of e.g. an environmental policy. Identification may be conducted at different scales ranging from local over regional to global scales and may involve a variety of indicators. Depending on the purpose and scales of identification, different identification strategies and indicator can be recommended (see Philips and McRoy 1990, Bortone 2000 (part II), Short and Coles 2001). The choice of method for identifies seagrass beds depend on the objectives of identifying. When the objective is to catalogue the presence/absence of seagrass or coarsely assess the area distribution, the choice is for macro-scale maps of low resolution. By contrast, when objective is to provide detailed data on distribution and change in seagrass areas or to estimates the biomass, the best choice is high-resolution map.

2.5. Artificial Neural Network

An artificial neural network consists of a collection of processing elements that are highly interconnected and transform a set of inputs to a set of desired outputs. The result of the transformation is determined by the characteristics of the elements and the weights associated with the interconnections among them. By modifying the connections between the nodes the network is able to adapt to the desired outputs (Fox, 1990 and Frank, 1994). A neural network would be capable of analyzing the data from the network, even if the data is incomplete or distorted. Similarly, the network would possess the ability to conduct an analysis with data in a non-linear fashion. Both of these characteristics are important in a networked environment where the information which is received is subject to the random failings of the system.

The network properties include connectivity (topology), type of connections, the order of connections, and weight range. The topology of a neural network refers to its framework as well as its interconnection scheme (Figure 2.2). The framework is often specified by the number of layers and the number of nodes per layer. Three types of layers include (Fu, 1994):
• The input layer: The nodes, which encode the instance presented to the network for processing

• The hidden layer: The nodes, which are not directly observable and hence hidden. They provide nonlinearities for the network.

• The Output layer: The nodes, which encode possible concept (or value) to be assigned to the instance under consideration. For example each input unit represents a class of object.

The behavior of a NN (Neural Network) depends on both the weights and the input-output function (transfer function) that is specified for the units. The ANN use variety of activation functions such as linear, logistic, hyperbolic tangent or exponential functions etc. Some of the activation functions are explained below. This function typically falls into one of three categories: linear, threshold, and sigmoid.

For linear units, the output activity is proportional to the total weighted output. For threshold units, the output are set at one of two levels, depending on whether the total input is greater than or less than some threshold value. For sigmoid units, the output varies continuously but not linearly as the input changes. Sigmoid units bear a greater resemblance to real neurons than do linear or threshold units, but all three must be considered rough approximations. Logistics function and hyperbolic tangent functions are the most common forms of sigmoid functions used in ANN. It is advantageous to use because the relationship between the value of the function at a point and the value of the derivative at a point reduces computational burden during training. If the output range is between 0 and 1 then it is called a binary sigmoid function or logistic function.

The learning rule is one of the most important attributes to specify for a neural network (Fu, 1994). Backpropagation is learning algorithm using multilayer feedforward network with a different function in artificial neural. The general multilayer feedforward network is fully interconnected hierarchy consisting of an input layer, one or more hidden layer and output layer. During the learning phase, input patterns are presented to the network in some sequences. Figure 2.2 describes the process inside the feedforward backpropagation algorithm network.
Figure 22. Backpropagation Neural Network

- \( x_i \): input variable of node \( i \) in input layer
- \( h_j \): output of node \( j \) in hidden layer
- \( Y_k \): output of node \( k \) in output layer (predicted value of node \( k \))
- \( W_{ij} \): weight connecting node \( i \) in input layer and node \( j \) in hidden layer
- \( V_{jk} \): weight connecting node \( j \) in hidden layer and node \( k \) in output layer

Basic learning algorithm of backpropagation modifies the interconnection Weight on the network so that signal error is minimum (closer to zero). Backpropagation learning algorithm can be done step by step as follows (Petterson, 1996):

1) Initialization:
   a. Normalization of input data \( x_i \) and target \( t_k \) in form of (0,1) range
   b. Randomize of weight \( W_{ij} \) and \( V_{jk} \) using (-1,1) value
   c. Initialize of threshold unit activation, \( x_0 = 1 \) and \( h_0 = 1 \)

2) Feed forward step: predicting \( T \) (with \( Y \))
   a. Take training set \( x_i \) and \( t_k \)
   b. Active of input layer-hidden layer unit with:

   \[
   h_j = \frac{1}{1 + e^{-\sum W_{ij}x_i}} \]

   (II-1)
c. Active of hidden layer-output layer units with:

\[ y_k = \frac{1}{1 + e^{\sum j h_j}} \]  \hspace{1cm} (II-2)

3) Minimize error of weight with vjk and wij adjustment. This process is called backward step.

a. Computing error of the nodes in output layer (δk) to adjust vjk:

\[ \delta_k = y_k (1 - t_k)(t_k - y_k) \]  \hspace{1cm} (II-3)

\[ v_{jk}^{new} = v_{jk}^{old} + \beta \delta_k \cdot h_j \]  \hspace{1cm} (II-4)

Where:

\[ \beta \]: constant of momentum

\[ t_k \]: predicting value

b. Compute error of nodes in input layer (\( \tau_j \)) to adjust weights \( w_{ij} \):

\[ \tau_j = h_j (1 - h_j) \sum_k \delta_k \cdot v_{jk} \]  \hspace{1cm} (II-5)

\[ w_{ij}^{new} = w_{ij}^{old} + \beta \tau_j \cdot v_{jk} \]  \hspace{1cm} (II-6)

4) Move to the next training set, and repeat step 2. Learning process is stopped if \( y_k \) are close enough to \( t_k \). The termination can be based on the error \( E \). For instance, learning process is stopped when \( E < 0.0001 \)

\[ E_{tot} = \frac{1}{P} \sum_{p=1}^{P} E_{p} \]  \hspace{1cm} (II-7)

Where:

\( T_{kp} \): target value of p-th data from training set node k

\( y_{kp} \): prediction value of p-th data from training set node k

The network can be used to predict \( t \) by inputting values of \( x \) after being trained.

2.6 Accuracy Assessment

The most common accuracy assessment of classified remotely sensed data is error matrix, sometimes known as confusion matrix. There are three types of accuracy can be generated from error matrix; overall accuracy, producer accuracy
and user accuracy. Overall accuracy represents the number of correctly classified pixels. The producer accuracy indicates the probability that a sampled point on the map is that particular class. The user accuracy indicates the probability that a certain reference class has also been labeled that class indicates (Janssen and Huurneman 2001).

Error matrices are very effective representations of map accuracy, because of the individual accuracies of each map category are plainly described along with both errors of inclusion (commission error) and error of exclusion (omission errors) present in the map and the error matrices can be used to compute overall accuracy, producer’s and user accuracies, kappa coefficient. A commission error occurs when an area is included in an incorrect category. An omission error occurs when an area is excluded from the category to which it belongs. Overall accuracy is simply the sum of the major diagonal (i.e., the correctly classified pixels or samples) divided by the total number of pixels or samples in the error matrix. This value is the most commonly reported accuracy assessment statistic. Individual category accuracies instead of just the overall classification accuracy are represented by producer’s and user accuracies.

An examination of the error matrix suggests at least two methods for determining individual category accuracies. The most common and accepted method is to divide the number of correctly classified samples of category X by the number of category X samples in the reference data (column total for category X). An alternate method is to divide the number of correctly classified samples of category X by the total number of samples classified as category X (row total for category X). It is important to understand that these two methods can result in very different assessments of the accuracy of category X. It is also important to understand the interpretation of each value. The mathematical example is shown in table 2.4 below (Congalton and Green 1999).
Table 2.4 Example of an Error Matrix

<table>
<thead>
<tr>
<th>Classified Data</th>
<th>Reference</th>
<th>Data</th>
<th>Row Total</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X</td>
<td>Y</td>
<td>Z</td>
</tr>
<tr>
<td>X</td>
<td>28</td>
<td>14</td>
<td>15</td>
</tr>
<tr>
<td>Y</td>
<td>1</td>
<td>15</td>
<td>5</td>
</tr>
<tr>
<td>Z</td>
<td>1</td>
<td>1</td>
<td>20</td>
</tr>
<tr>
<td>Column Total</td>
<td>30</td>
<td>30</td>
<td>40</td>
</tr>
</tbody>
</table>

Sum of the mayor diagonal = 63

Overall Accuracy = $63/100 = 63\%$

Producer Accuracy

<table>
<thead>
<tr>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>X = 28/30 = 93%</td>
<td>X = 28/57 = 49%</td>
</tr>
<tr>
<td>Y = 15/30 = 50%</td>
<td>Y = 15/21 = 71%</td>
</tr>
<tr>
<td>Z = 20/40 = 50%</td>
<td>Z = 20/22 = 91%</td>
</tr>
</tbody>
</table>
III. METHODOLOGY

3.1 Time and Location

Research is performed from September 2010 to March 2011. Step of data collection, processing, analysis, and was done in campus Master of Science in Information Technology for Natural Resources Management of Bogor Agricultural University and National Coordinating Agency for Surveys and Mapping.

Seagrass conditions studied are located in Jakarta Province, Seribu Island District, precisely in Pari Island. Geographically, it is situated between 05° 50' - 05° 52' South and 106° 34' - 106° 38' East. Study area in this research show in figure 3.1 below, covering Burung Island, Tengah Island, and Kongsi Island.

![Figure 3.1. Study Area](image-url)
3.2. Material and Tools

The main data is satellite imagery and supporting data are digital map and in-situ measurement data that obtained from survey. Whereas, the tools are equipment, hardware and software, these are used for capturing, processing, and analyzing the data.

3.2.1. Data Source

The principle supporting data for this study include the following discussed matters:

1. Water condition data in 2009, data is acquisition from MODIS Aqua.
2. Satellite imagery of ALOS AVNIR-2 acquisition date September 18th, 2009, covering Pari Island and its surrounding. This spatial data provided by National Coordinating Agency for Surveys and Mapping (Bakosurtanal).
3. Landsat-7 acquisition year 2006, this satellite imagery provides by Research Centre for Oceanography.
4. Field survey data, data is collected from visual observation and measurement in the field directly in September 2010.

3.2.2. Required Tools

Several hardware and software’s and equipments that required in order carrying out the whole research activities are:

1. Hardware consists of Notebook Intel ® Centrino Duo 1.83GHz, and colour printer.
2. Software used are ENVI Image Processing, ESRI ArcView Spatial Analysis, and MS Office 2007.

3.3. Research Step

There are three main steps to identifying seagrass condition. Firstly, image pre-processing, secondly image classification, and last step is accuracy assessment. In this study, geometric correction and atmospheric correction was
applied before image classification, including subset and masking image. On image classification stage, some data observation and measurement from field survey directly were used for ANN classification, and another was used for validation. Forty eight points of field data were divided into two data sets: 26 in the training data set and 22 in the testing. Determination site observations and field data capture technique is determined by random sampling at area (10m x 10m), adjusted with spatial resolution of ALOS AVNIR-2 satellite imagery. The research approach for seagrass identification in this study is shown in Figure 3.2.

Figure 3.2. The research approach
3.3.1. Image Preprocessing

In the context of digital analysis of remotely sensed data, preprocessing refer to those operations that are preliminary to the main analysis. Typically preprocessing operations could include (1) radiometric preprocessing to adjust digital values for the effect of hazy atmosphere and/or (2) geometric preprocessing to bring an image into registration with a map or another image. In this study, operation subset image that cover only study area, and masking land objects that will not be classified was included as part of preprocessing process.

3.3.2. Image Classification

ALOS digital image processing was carried out using Environment for Visualizing Images (ENVI) version 4.4. In this research, ANN supervised classification was guided by variety of input data sets including field survey, satellite imagery and expert knowledge to produce seagrass condition map. Twenty two scenario processes would be done to compare the result of accuracy as shown in Table 3.1.

The starting point of image classification is the different spectral characteristics of the different materials on the Earth’s surface. Digital image classification is the process of assigning pixels to classes. Usually each pixel is treated as individual unit composed of values in several spectral bands. By comparing pixels to one another and to those of known identity, it is possible to assemble group of similar pixels into classes that match the informational categories of interest to users of remotely sensed data. Field data were used to determine training sites for three levels of seagrass cover classes (≤ 29.9%, 30-59.9%, ≥ 60%) in the ANN supervised image classification process. Reflectance signatures for each of the three different seagrass cover classes were extracted from the ALOS AVNIR-2 scene of Pari Island for the calibration field sites, which served as training sites for the image classification process. Characteristic spectral reflectance signatures were defined for each of the target levels of seagrass cover to be mapped.
Table 3.1. Scenario Input Classification

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Input</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>4 Original Band (Band 1, 2, 3, and 4) and water depth</td>
</tr>
<tr>
<td>B</td>
<td>3 Original Band (Band 1, 2, and 3) and water depth</td>
</tr>
<tr>
<td>C</td>
<td>3 Original Band (Band 1, 2, and 4) and water depth</td>
</tr>
<tr>
<td>D</td>
<td>3 Original Band (Band 1, 3, and 4) and water depth</td>
</tr>
<tr>
<td>E</td>
<td>3 Original Band (Band 2, 3, and 4) and water depth</td>
</tr>
<tr>
<td>F</td>
<td>2 Original Band (Band 1 and 2) and water depth</td>
</tr>
<tr>
<td>G</td>
<td>2 Original Band (Band 1 and 3) and water depth</td>
</tr>
<tr>
<td>H</td>
<td>2 Original Band (Band 1 and 4) and water depth</td>
</tr>
<tr>
<td>I</td>
<td>2 Original Band (Band 2 and 3) and water depth</td>
</tr>
<tr>
<td>J</td>
<td>2 Original Band (Band 2 and 4) and water depth</td>
</tr>
<tr>
<td>K</td>
<td>2 Original Band (Band 3 and 4) and water depth</td>
</tr>
<tr>
<td>L</td>
<td>4 Original Band (Band 1, 2, 3, and 4)</td>
</tr>
<tr>
<td>M</td>
<td>3 Original Band (Band 1, 2, and 3)</td>
</tr>
<tr>
<td>N</td>
<td>3 Original Band (Band 1, 2, and 4)</td>
</tr>
<tr>
<td>O</td>
<td>3 Original Band (Band 1, 3, and 4)</td>
</tr>
<tr>
<td>P</td>
<td>3 Original Band (Band 2, 3, and 4)</td>
</tr>
<tr>
<td>Q</td>
<td>2 Original Band (Band 1 and 2)</td>
</tr>
<tr>
<td>R</td>
<td>2 Original Band (Band 1 and 3)</td>
</tr>
<tr>
<td>S</td>
<td>2 Original Band (Band 1 and 4)</td>
</tr>
<tr>
<td>T</td>
<td>2 Original Band (Band 2 and 3)</td>
</tr>
<tr>
<td>U</td>
<td>2 Original Band (Band 2 and 4)</td>
</tr>
<tr>
<td>V</td>
<td>2 Original Band (Band 3 and 4)</td>
</tr>
</tbody>
</table>

The most important aspect in neural network is the training phase, because the weights and the network characteristics are defined to be used to another dataset. Before dataset used in training phase, it should be normalized in range of 0 to 1, and then renormalized it after this phase. Dataset also has to be splitting by randomize for the training and validation. Figure 3.3 show the multilayer feedforward backpropagation neural network process that used in this research.

The number of nodes in the input layer depends on upon the number of corresponding neural network. In this case 5 nodes for processing element of inputs will be used to defined 3 possible output training pattern (i.e. seagrass condition). There are three classes for seagrass condition; good, medium, and poor. The three output pattern corresponds to the five inputs to generate the relationship in form of weight in the ANN system.
Figure 3.3. Structure of Backpropagation Neural Network

The backpropagation learning is inclusive of supervise, which determines the output from the input by using the training set. The training of Artificial Neural Network has the following step based on ENVI help 4.4:

- **Training Threshold Contribution field**, enter a value from 0 to 1.0. The training threshold contribution determines the size of the contribution of the internal weight with respect to the activation level of the node. It is used to adjust the changes to a node's internal weight. The training algorithm interactively adjusts the weights between nodes and optionally the node thresholds to minimize the error between the output layer and the desired response. Setting the Training Threshold Contribution to zero does not adjust the node's internal weights. Adjustments of the nodes internal weights could lead to better classifications but too many weights could also lead to poor generalizations.

- **Training Rate field**, enter a value from 0 to 1.0. The training rate determines the magnitude of the adjustment of the weights. A higher rate will speed up the training, but will also increase the risk of oscillations or non-convergence of the training result.
• Training Momentum field, enter a value from 0 to 1.0. Entering a momentum rate greater than zero allows you to set a higher training rate without oscillations. A higher momentum rate trains with larger steps than a lower momentum rate. Its effect is to encourage weight changes along the current direction.

• Training RMS Exit Criteria field, enter the value of RMS error at which the training should stop. If the RMS error, as shown in the plot during training, falls below the entered value, the training will stop, even if the number of iterations has not been met. The classification will then be executed.

• Training Iteration. The maximum iteration will decide at the practice.

The classification step of BPNN:

- Input layer of units, which are activated by the input image data. The input image pixel values are linearly scaled to a value between 0.0 and 1.0 for input to the neural network with the minimum and maximum image channel.

- Hidden layer is in between input layer and output layer. Calculate the input layer-hidden layer unit with Equation (II-4) and hidden layer-output layer units with Equation (II-5).

- The output layer of units represents the output classes. In this study the seagrass condition has 3 classes such as good (C1), medium (C2), and poor (C3).

- Target is used for comparator the output. The target was obtained from training area. Learning process is stopped if prediction values are close enough to the target value by calculating the error with equation (II-10).

<table>
<thead>
<tr>
<th>Table 3.2. Neural Network Parameter</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>Training Threshold Contribution</td>
</tr>
<tr>
<td>Training Momentum</td>
</tr>
<tr>
<td>Training of Hidden Layer</td>
</tr>
<tr>
<td>Training Rate</td>
</tr>
<tr>
<td>Training RMS Exit Criteria</td>
</tr>
<tr>
<td>Number of Iteration</td>
</tr>
</tbody>
</table>
Table 3.2 shown neural network parameter used in this study, and considering time consuming for all scenarios input have to be test, number iteration set to maximum 20000.

3.3.3. Accuracy Assessment

After the classification has been completed, it is important to estimate the accuracy of the result. The most common way to express classification accuracy is the preparation of a so-called error matrix also known as confusion matrix or contingency matrix. The columns of the matrix represent the verification data, while the rows indicate the classified image. The elements of the matrix are the number of pixels assigned to a class by the classification procedure, in relationship with the identification through the verification data. Several descriptive and analytical statistical techniques are based on the accuracy matrix.

The most common way to express the accuracy of such images/maps is by a statement of the percentage of the map area that has been correctly classified when compared with reference data or "ground truth." This statement is usually derived from a tally of the correctness of the classification generated by sampling the classified data, and expressed in the form of an error matrix. In this kind of tally, the reference data (usually represented by the columns of the matrix) are compared to the classified data (usually represented by the rows). The major diagonal indicates the agreement between these two data sets. Overall accuracy for a particular classified image/map is then calculated by dividing the sum of the entries that form the major diagonal (i.e., the number of correct classifications) by the total number of samples taken.
IV. RESULT AND DISCUSSIONS

4.1. General Condition

Pari Island waters are territorial waters that are surrounded by cliffs that are protected from exposure to the open sea. This area has a water depth of 0 meters to 50 meters, with the shallow waters around the islands. Seagrass meadow on Pari Island is the vegetation that lives in shallow waters. From the bathymetric data obtained, it was found that the seagrass vegetation found in the data collection is at a depth of 2 meters below the waters with a high brightness. Seagrass in the island region is a region which rays are protected from exposure to the high seas so that current flows in the region tend to be low even almost non-existent (calm water), scattered seagrass vegetation in the region near the island down to the bluff area.

A preliminary study in this research is recognizing water condition in study area on September 2009 that used as reference for next remote sensing process. Water clarity and Dissolved and Detritus Organic Matter from MODIS satellite Imagery used as parameter to identify water condition (Figure 3.1). The aim of this step is to avoid misinterpretation of the object for next image processing. The diffuse attenuation coefficient at 490 nm (K490) is an indicator of water clarity. K490 expresses how deeply visible light in the blue to green region of the spectrum penetrates in the water column. The value of K490 represents the rate at which light intensity at 490 nm is attenuated with depth. On September 2009, water clarity value is 0.04 (figure 4.1) which means water relatively clear, because that light can penetrate in water column until 25 meters depth (0.04/1 meter).

Dissolved organic matter and particulate organic matter (or particulate organic carbon, POC, defined below) is distinguished as the fractions of organic matter in water samples that are either passed through or retained by a filter (nominally a glass fiber filter with 0.7 um pore size). Colored (also called chromophoric) dissolved organic matter (CDOM) is optically detectable, i.e., it absorbs light, most strongly in the blue to UV range. In sufficient
concentrations, CDOM will thus provide color to the water in which it is dissolved. High concentrations of CDOM in ocean waters interfere with accurate estimation of chlorophyll $a$ concentration in remotely-sensed data. Figure 4.1 show the value of DOM is 0.009 gram/m$^3$. It mean that water have low dissolved organic matter. From the value of water clarity and DOM, generally it can be stated that water condition in Pari Island is good in September 2009.

4.2. Image Preprocessing

An ALOS image (Figure 1), acquired on 18 September 2009, which is used in this study is the result of image sensors AVNIR recording consisting of 4 channel / wavelength range. Channels 1, 2, and 3 respectively is the wavelength range of blue (0.42 to 0.50 μm), green (0.52 to 0.60 μm), red (0.61 to 0.69 μm), while channel 4 is the near infrared (0.76 to 0.89 μm) wavelength range. The image used has a level 1B2, which was corrected in a systematic radiometric and geometric. However, radiometric corrections remain to be done again because of the shadow areas of digital value more than 0 (zero). From the histogram it can be seen a minimum value of the digital image. This minimum value was used as a deduction for the entire coverage of the image digital values. The result of

Figure 4.1 Water Clarity and Detrital Organic Matter in 2009
histogram adjustment for radiometric correction is presented in table 4.1. After performed histogram adjustment the minimum brightness value will be zero.

Table 4.1 Statistic before and after radiometric correction

<table>
<thead>
<tr>
<th>Basic Statistics</th>
<th>Before</th>
<th>After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>Max</td>
<td>Min</td>
</tr>
<tr>
<td>Band 1</td>
<td>131</td>
<td>219</td>
</tr>
<tr>
<td>Band 2</td>
<td>85</td>
<td>224</td>
</tr>
<tr>
<td>Band 3</td>
<td>53</td>
<td>184</td>
</tr>
<tr>
<td>Band 4</td>
<td>12</td>
<td>30</td>
</tr>
</tbody>
</table>

Afterward, even this image already geometrically corrected, ALOS image 2009 corrected again with Landsat-7 ETM satellite imagery 2006 which have geometric corrected by theodolite water pass leveling, and registered to the UTM Zone 48S, WGS84 coordinate system. Geometric correction intended to reduce errors by position or location based on reference data that are considered true. In order to correct geometric image, measuring the position of objects on the ground are easily recognized among the ends of the pier, jeti, street intersection and assumed that will not change for a long time. Eight control point used in this image, because Pari Islands have flat topografi area. This Geometric correction uses polynomial of control point type with linear order and nearest neighbor resampling. For medium resolution image on flat areas, the polynomials models are sufficient. Total Root Mean Square (RMS) error in this geometric correction is 0.457151. This value describes how consistent the transformation is between the different control points. The smaller RMS value indicated that accuracy of geometric correction has improved. Overall, RMS error of less than 0.5 pixels was achieved for each transformation.

After the radiometric and geometric have already done, it is better to subset image that cover only study area. In these instances it is beneficial to reduce the size of the image file to include only the area of interest (Figure 4.2). This not only eliminates the extraneous data in the file, but it speed up processing due the smaller amount of data to process. Subset images made to focus research on areas of study and object of each pseudo color composite image and each spectral channel.
Figure 4.2 Subset of remote sensed data to focus at region of interest.

To avoid any interference from the influence of other objects, then the image will be used for identification of seagrass condition, carried out restriction area (cropping) or masking. Masking is mainly done to remove the clouds and land objects that will not be classified. Masking method can be performed using Boolean logic in the software and can also be done with manual digitization processes. Separation of land and water objects intended for the spectral value used in the classification process is not affected by the spectral value of the land. To separate the land and waters will be determined boundary pixel value of land and water (the value of landmarks). Values above the threshold (the value of landmarks) will be considered null or no to that will appear is below the threshold value.

4.2.1. Field Survey

The field survey was carried out in four days (21, 22, 23 and 24 of September 2010), one year after the acquisition of the ALOS image, but in the same season based on visual observation. There are 48 (forty eight) sample point area is recorded in the field by handheld Global Positioning System, mostly in seagrass habitat (Figure 4.3). At each point, the percentage seagrass cover and water depth was determined.
4.2.2. Region of Interest (ROIs)

Regions of interest (ROIs) are portions of images, either selected graphically or selected by other means, such as thresholding. Typical uses of ROIs include extracting statistics for classification, masking, and other functions. You can use any combination of polygons, points, or vectors as an ROI. ROI separability is an option to compute the spectral separability between selected ROI pairs for a given input file. Both the Jeffries-Matusita and Transformed Divergence separability measures are reported. These values range from 0 to 2.0 and indicate how well the selected ROI pairs are statistically separate. Values greater than 1.9 indicate that the ROI pairs have good separability. For ROI pairs with lower separability values, you should attempt to improve the separability by editing the ROIs or by selecting new ROIs. For ROI pairs with very low separability values (less than 1), you might want to combine them into a single ROI (J.A. Richards, 1999). The result of ROIs separability can be seen in appendix B.
In appendix B, it can be seen the separability of ROIs between good seagrass and other habitat (poor seagrass, lagoon, sea, sand, coral, mix habitat, and reef slope) are 2.0, except between good seagrass and medium seagrass is 1.99. The separability between medium seagrass and other habitat (poor seagrass, lagoon, sea, sand, coral, mix habitat, and reef slope) are 1.93, 2.0, 2.0, 1.68, 1.88, 1.96 and 2.0 respectively. Value 2.00, 2.00, 2.00, 1.97, 1.95, and 2.00 are achieved between poor seagrass and lagoon, sea, sand, coral, mix habitat, and reef slope respectively. From that value of separability, two lower separability values got between medium seagrass and sand (1.68), and medium seagrass and coral (1.88). It can be stated, that not all the ROIs can well separability by this selected point.

4.3. Image Classification

A classification scenario was developed to identify the seagrass condition at Pari Island. For this purpose, shallow water habitat was classified into nine classes; sea, sand, lagoon, coral, reef slope, mix habitat (coral, seagrass, seaweed, and sand), poor seagrass, medium seagrass, and good seagrass. Those classes are derived from field observation and considering by the spatial resolution of ALOS data. The data set training areas are represented by each habitat type selected based on the ground reference points collected from the field supported by the local knowledge of the area. The image classification and mapping process were done through supervised neural network classification.

During the classification process, RMS value and number of iteration evaluated. It can be seen from plot of neural network (figure 4.4), that graph begun stable from iteration 10000 during the classification which RMS value approximately 0.65. Based on this plot, iteration 10000 was applied to all the scenario input classification.
Figure 4.4. Plot of Neural Network Classification

Figure 4.5 ANN Habitat Classifications in Pari Island in 2010 (Scenario A)

Result of habitat classification as shown in figure 4.5, poor seagrass indicated by the blue color almost dominates the entire study. Mix habitat (seaweed, coral, and seagrass) seen as yellow and sand (white color) also dominant in Pari Island in 2010. Good seagrass (red) and medium seagrass (green) are found only in small area. This habitat classification map presented by
inputting all original band (band 1, 2, 3, and 4) and water depth (Scenario A) into ANN classification, which number of iteration is 10000.

### 4.4. Accuracy Assessment

After all scenario classification was done, the next step was to assess its accuracy. The result of calculation accuracy can be seen from the overall accuracy (OA), producer accuracy (PA) and user accuracy (UA). The overall accuracy is the proportion of ground control points correctly classified. This gives an idea of the level of accuracy for the whole map. The user and producer accuracies are calculated for each individual class of habitat which is particularly useful because types of habitat are often differently captured by remote sensors. The user accuracy is the probability that a classified pixel actually represents that class on the field. The producer accuracy is the probability that any of the pixels of one class has been correctly classified.

For the accuracy assessment, twenty two ground truth points were used which have not been used in the image classification. Table 4.2 presented the result of accuracy assessment from all scenario classifications. In this study, the accuracy assessments focus only on seagrass habitat, which categorized in 3 types, which are good seagrass, medium seagrass, and poor seagrass.

Table 4.2 Accuracy Assessment (with Parameter Training Neural Network; Threshold Contribution of 0.9, Momentum 0.9, Hidden Layer 1, Rate 0.2, and Iteration of 10000)

<table>
<thead>
<tr>
<th>(+) Water Depth</th>
<th>Scenario</th>
<th>Input</th>
<th>Overall Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Band 1, 2, 3, 4</td>
<td>53.33</td>
<td></td>
</tr>
<tr>
<td>B</td>
<td>Band 1, 2, 3</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>C</td>
<td>Band 1, 2, 4</td>
<td>58.33</td>
<td></td>
</tr>
<tr>
<td>D</td>
<td>Band 1, 3, 4</td>
<td>58.33</td>
<td></td>
</tr>
<tr>
<td>E</td>
<td>Band 2, 3, 4</td>
<td>58.33</td>
<td></td>
</tr>
<tr>
<td>F</td>
<td>Band 1, 2</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>G</td>
<td>Band 1, 3</td>
<td>50</td>
<td></td>
</tr>
<tr>
<td>H</td>
<td>Band 1, 4</td>
<td>71.43</td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>Band 2, 3</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>J</td>
<td>Band 2, 4</td>
<td>25</td>
<td></td>
</tr>
<tr>
<td>K</td>
<td>Band 3, 4</td>
<td>51.14</td>
<td></td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>(-) Water Depth</th>
<th>Scenario</th>
<th>Input</th>
<th>Overall Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>L</td>
<td>Band 1, 2, 3, 4</td>
<td>41.67</td>
<td></td>
</tr>
<tr>
<td>M</td>
<td>Band 1, 2, 3</td>
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<td></td>
</tr>
<tr>
<td>N</td>
<td>Band 1, 2, 4</td>
<td>33.33</td>
<td></td>
</tr>
<tr>
<td>O</td>
<td>Band 1, 3, 4</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>P</td>
<td>Band 2, 3, 4</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Q</td>
<td>Band 1, 2</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>R</td>
<td>Band 1, 3</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>S</td>
<td>Band 1, 4</td>
<td>46.29</td>
<td></td>
</tr>
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<td>T</td>
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<td>0</td>
<td></td>
</tr>
<tr>
<td>U</td>
<td>Band 2, 4</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>V</td>
<td>Band 3, 4</td>
<td>0</td>
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</tr>
</tbody>
</table>
From all of the classification scenarios that have been conducted, the results obtained accuracy varies for each scenario. Half of the accuracy of classification scenarios has value zero, while others were worth an average accuracy of 50%. Most of the classifications scenarios that have a value of zero occur when only enter original bands as input parameter (without water depth data.) Best accuracy results occurred in scenario H, with a value of 71.43% overall accuracy (Table 4.4), by enter two original band (band 1 and band 4) plus water depth data as input parameter.

Pasqualini et al. (2004) reported in his research that the comparison of overall accuracy between SPOT 5 (2.5 m) and SPOT 5 (10 m) is between 73% to 96 % for mapping seagrass in four classes; sand, photophilous algae on rock, patchy seagrass beds and continuous seagrass beds at the Laganas Bay (Mediterranean Sea). By considering more specifically the division of classes seagrass in this study, the accuracy obtained by using ALOS satellite imagery (71.43%) close to accuracy of the results obtained by using the SPOT 5 satellite imagery.

Table 4.4 Matrix of overall accuracy (Scenario H)

<table>
<thead>
<tr>
<th>Class/Ground Truth (Pixels)</th>
<th>Good</th>
<th>Medium</th>
<th>Poor</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>0</td>
<td>1</td>
<td>0</td>
<td>1</td>
</tr>
<tr>
<td>Poor</td>
<td>2</td>
<td>2</td>
<td>9</td>
<td>13</td>
</tr>
<tr>
<td>Total</td>
<td>2</td>
<td>3</td>
<td>9</td>
<td>14</td>
</tr>
</tbody>
</table>

Overall accuracy = (0+1+9)/14 = 71.43 %

It also needs to analyze the results of individual accuracy of each class of object. For comparison was shown several scenarios that have a value above 55% overall accuracy, as seen in table 4.5, 4.6, 4.7, and 4.8, the scenario C (by input; band1, 2, 4, and water depth), with 58.33% of overall accuracy having value of producer accuracy (PA) and user accuracy (UA) is better than the other scenarios, even with scenarios H (OA = 71.42%). From the fourth accuracy table, only scenario C that has no accuracy value of zero. The other scenario will not be discussed because they have value of accuracy assessment is poor.
Table 4.6 shows (scenario C) that good seagrass had the highest user accuracy (100%) while poor seagrass had the highest producer results (100%). Medium seagrass and poor seagrass were fairly accurately mapped with a user accuracy of 50% and 56% respectively. As well as when compared with the scenarios D and E scenarios that have the same overall accuracy value, c scenario is better in terms of accuracy of the producer accuracy and user accuracy. From producer accuracy side (Table 4.6), it can be seen that bad accuracy value was found in good seagrass (25%), and medium seagrass (33%), this may be caused by the fact that bottom type are least difference compare to other habitats. Another reason may be due to inadequate number of sample point and (6 points for good seagrass, and 8 points for medium seagrass)

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0/2</td>
<td>0/0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>1/3</td>
<td>1/1</td>
<td>33</td>
<td>100</td>
</tr>
<tr>
<td>Poor</td>
<td>9/9</td>
<td>9/13</td>
<td>100</td>
<td>69</td>
</tr>
</tbody>
</table>

Table 4.7 Producer and User Accuracy (Scenario D)

<table>
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<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0/3</td>
<td>0/0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>1/3</td>
<td>1/2</td>
<td>33</td>
<td>50</td>
</tr>
<tr>
<td>Poor</td>
<td>6/6</td>
<td>6/10</td>
<td>100</td>
<td>60</td>
</tr>
</tbody>
</table>

Table 4.8 Producer and User Accuracy (Scenario E)

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Good</td>
<td>0/3</td>
<td>0/0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Medium</td>
<td>1/3</td>
<td>1/2</td>
<td>33</td>
<td>50</td>
</tr>
<tr>
<td>Poor</td>
<td>6/6</td>
<td>6/10</td>
<td>100</td>
<td>60</td>
</tr>
</tbody>
</table>
Overall, scenarios that use original band plus water depth as input parameter in ANN classification was produce better accuracy than in scenario that use only original bands as input. One of the actively contributes to a result of accuracy is number of input data, the more number of inputs used for ANN classification, the results obtained accuracy will get better. Limitation of sample point is another factor that influences the level of accuracy, its only 26 sample points for training and 22 for test used in this study. An additional part could be affect the accuracy is the difference position between imagery and GPS, which caused the displacement location of the object being observed.

By some processes that have been done, it can be said that in order to identify the condition of seagrass from ALOS AVNIR-2 satellite imagery using Artificial Neural Network Classification, the fairly good result has been achieved. Although there are some values that bad accuracy on some classification scenario that is caused by at least the input parameters used. From the analysis results of accuracy, among all the input parameters that most influence the level of accuracy are: band 1 and band 2, band 4, and water depth data. That indicate wavelength of blue (0.42 to 0.50 μm) and green (0.52 to 0.60 μm) is effective for identifying the condition of seagrass. Even NIR wavelengths are absorbed by water, but in this study this wavelength (0.76 to 0.89 μm) can be used to habitat classification. It can be caused that water depth in study is below 2 meter.

The optimal wavelengths for the discrimination of seagrass species (530–580 nm) and some other important regions of spectral separation (520–530 nm, 580–600 nm) conveniently lie within the range of wavelengths that are least attenuated by coastal waters (Fyfe 2003), NIR reflectance could be very useful for mapping intertidal seagrass exposed at low tide or for detecting floating mats of leaves and algae, but these wavelengths are rapidly attenuated by water.

Seagrass maps generated from the classification ANN with input parameter 3 Original Band (Band 1, 2, and 4) and water depth can be seen in Figure 4.5, the study area is dominated by the poor seagrass (blue color), while good seagrass (red color) and medium seagrass (green) are found in few areas in the north Pari Island.
Figure 4.6 Seagrass map in Pari Island by Scenario C (Band 1, 2, 4, and water depth) of ANN Classification.
V. CONCLUSION AND RECOMMENDATIONS

5.1 Conclusion

Detecting shallow water habitats from remote sensing images is faced with a lot of challenges as the signal received at the sensor is a mixture of responses from the atmospheric path between the sensor and the seafloor as well as the water column overlying the habitat. Nevertheless, some conclusions that can be used as a reference of this study in relation to the identification of seagrass conditions are as follows.

- Shallow water habitats were classified into nine classes: sea, sand, lagoon, coral, reef slope, mixed habitat (coral, seagrass, seaweed, and sand), poor seagrass, medium seagrass, and good seagrass.
- Artificial Neural Network (ANN) has been applied to ALOS AVNIR-2 to identify seagrass conditions. Twenty-two classification scenarios were used to obtain optimum results. It has been found that the best accuracy that can be achieved by using a combination of blue (0.42 to 0.50 μm) and NIR (0.76 to 0.89 μm) wavelength plus water depth, with an overall accuracy of 71.43%. However, looking at individual classes, the classification scenario that used blue (0.42 to 0.50 μm), green (0.52 to 0.60 μm), and NIR (0.76 to 0.89 μm) wavelength plus water depth achieved higher producer and user accuracy.

Several factors that affect the accuracy assessment in this study are the number of input parameters, the number of training samples and test points, and the accuracy of GPS. Overall, the result of identifying seagrass conditions from ALOS AVNIR-2 using artificial neural networks at Pari Island in 2010 is dominated by poor seagrass, with good seagrass and medium seagrass found in small areas.
5.2. Recommendation

Further research is needed to consider those aspects that will affect the classification process, such as the possibility of GPS error, the selection of sample data should also be considered a spatial resolution of satellite imagery to be used. More important it’s still necessary to explore the ability of ANN classification method itself, by changing the settings of the neural network training (training momentum, training rate, etc.). It would be better to use some of the satellite imagery with dissimilar sensor and different spatial resolution to make a comparison of the results of classification, so that the accuracy obtained is more comprehensive.
VI. REFERENCES


Appendix A. Summary of ALOS AVNIR-2

Odi_ProductManagementNo="A1005115"
Odi_ProductManagementBranchNo="001"
Sccs_SceneID="ALAV2A194453720"
Sccs_SceneShift="0"
Pds_ProductID="O1B2G_U"
Pds_ResamplingMethod="CC"
Pds_UTM_ZoneNo="48"
Pds_MapDirection="MapNorth"
Pds_PixelSpacing="10"
Pds_OrbitDataPrecision="Precision"
Pds_AttitudeDataPrecision="OnSitePrecision"

Img_FrameSceneCenterLatitude="-5.975"
Img_FrameSceneCenterLongitude="106.568"
Img_FrameSceneLeftTopLatitude="-5.598"
Img_FrameSceneLeftTopLongitude="106.185"
Img_FrameSceneRightTopLatitude="-5.596"
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Img_FrameSceneLeftBottomLatitude="-6.353"
Img_FrameSceneLeftBottomLongitude="106.187"
Img_FrameSceneRightBottomLatitude="-6.351"
Img_FrameSceneRightBottomLongitude="106.951"

Img_SunAngleElevation="67.12"
Img_SunAngleAzimuth="70.65"

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Img_SaturationLevelOfBand2="1.50"
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Pdi_L1ProductFileName04="IMG-02-ALAV2A194453720-O1B2G_U"
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Lbi_ProcessLevel="1B2"
Lbi_ProcessFacility="HEOC"
Lbi_ObservationDate="20090918"
Appendix B. Result of ROIs separability for training sample.

Input File: hslmask24
ROI Name: (Jeffries-Matusita, Transformed Divergence)

<table>
<thead>
<tr>
<th>ROIs Name</th>
<th>Good</th>
<th></th>
<th>ROIs Name</th>
<th>Medium</th>
<th></th>
<th>ROIs Name</th>
<th>Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Medium</td>
<td>2.00</td>
<td></td>
<td>Good</td>
<td>2.00</td>
<td></td>
<td>Good</td>
<td>1.99</td>
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<tr>
<td>Poor</td>
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| ROIs Name | Coral | | ROIs Name | Mix Habitat | | ROIs Name | Reef Slope |
|-----------|-------|---|-----------|-------------|---|--------|
| Good      | 2.00  | | Good      | 2.00       | | Good     | 2.00 |
| Poor      | 1.88  | | Poor      | 1.96       | | Poor     | 2.00 |
| Medium    | 1.97  | | Medium    | 1.95       | | Medium   | 2.00 |
| Lagoon    | 2.00  | | Lagoon    | 2.00       | | Lagoon   | 2.00 |
| Sea       | 2.00  | | Sea       | 2.00       | | Sea      | 2.00 |
| Sand      | 2.00  | | Sand      | 2.00       | | Sand     | 2.00 |
| Mix Habitat | 1.96 | | Coral     | 1.96       | | Coral    | 2.00 |
| Reef Slope | 1.96 | | Reef Slope | 2.00       | | Mix Habitat | 2.00 |

| ROIs Name | Reef Slope | | ROIs Name | Mix Habitat | | ROIs Name | Reef Slope |
|-----------|------------|---|-----------|-------------|---|--------|
| Good      | 2.00       | | Good      | 2.00       | | Good     | 2.00 |
| Poor      | 1.96       | | Poor      | 2.00       | | Poor     | 2.00 |
| Medium    | 1.95       | | Medium    | 2.00       | | Medium   | 2.00 |
| Lagoon    | 2.00       | | Lagoon    | 2.00       | | Lagoon   | 2.00 |
| Sea       | 2.00       | | Sea       | 2.00       | | Sea      | 2.00 |
| Sand      | 2.00       | | Sand      | 2.00       | | Sand     | 2.00 |
| Mix Habitat | 2.00     | | Coral     | 1.96       | | Coral    | 2.00 |
| Reef Slope | 2.00      | | Reef Slope | 2.00       | | Mix Habitat | 2.00 |