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 Thallasadendron 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>
</tr>
</thead>
<tbody>
<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>
</tr>
</tbody>
</table>

(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 \(10^{10}\) 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 \textit{et al.}, 2001).](image)

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 (EORC 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 lie 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.</td>
</tr>
<tr>
<td></td>
<td>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>
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 be 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 involves 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.
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 xi and target tk in form of (0,1) range
   b. Randomize of weight wij and vjk using (-1,1) value
   c. Initialize of threshold unit activation, x0 = 1 and h0 = 1

2) Feed forward step: predicting T (with Y)
   a. Take training set xi and tk
   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:

\[ y_k = \frac{1}{1 + e^{\sum v_{jk} h_j}} \]  \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 (\( \delta_k \)) to adjust vjk:

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

\[ v_{jk}^{new} = v_{jk}^{old} + \beta \delta_k h_j \]  \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 \( w_{ij} \):

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

\[ w_{ij}^{new} = w_{ij}^{old} + \beta \tau_j v_{jk} \]  \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
- X = 28/30 = 93%
- Y = 15/30 = 50%
- Z = 20/40 = 50%

User Accuracy
- X = 28/57 = 49%
- Y = 15/21 = 71%
- Z = 20/22 = 91%