II. LITERATURE REVIEW

2.1 Mangrove vegetation

Mangrove describe as plant community that colonize the muddy shores of sheltered coast and river estuaries (Soepadmo, 1998). It dominant in tidal saline estuaries of tropical and subtropical (Twilley, 1998).

Being specific highly productive ecosystems and harbouring a large diversity of species adapted to these particular habitats, they are considered of almost ecological importance. Moreover, they provide a number of direct and indirect services, ranging from protection against coastal erosion (Pearce, 1999).

Santos et al (1997) mentioned that there are any factors that can influence mangrove distribution. Three main factors are beach physiographic, sea waves, and inundate periods. Beach physiographic will influence the composition, species distribution, and area of mangrove forest. On slightly beach, the variability of mangrove ecosystem is higher than steep beach. It is because there are wide place for mangrove growth. While, sea waves and inundate play as seed transportation.

The species distribution of mangrove can be mono-species or mix-species in one area. But it often builds parallel line on beach. Some aspect that caused this mangrove zonation is still in debate by many researchers. Walter and Steiner (1936) approved that level of inundation, salinity, and natural factors become the most important factors. Meanwhile, Chapman (1976) predicted that the main factor that influence mangrove zonation is the amount day of sea rise and
subsided. Johnson and Frodin (1983) suggest one important factor, which also caused the zone of mangrove, that is bio-interaction.

Information about mangrove zonation will be helpful to predict the kind of mangrove species distribution, especially in the accuracy of mangrove mapping. Moreover, it also needs to make decision for coastal management.

Macnae (1966), devide zone of mangrove from beach to land as figure 2.1 follow:

a. Avicennia / Sonneratia zone 

b. Rhizopora zone 

c. Rhizopora / Bruguiiera zone 

d. Bruguiera zone 

e. Nypa zone 

2.2 ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) 

The ASTER instrument, provided by Japan's Ministry of International Trade and Industry and built by NEC, Mitsubishi Electronics Company and Fujitsu, Ltd., measures cloud properties, vegetation index, surface mineralogy, soil properties, surface temperature, and surface topography for selected regions of the Earth.

The ASTER instrument on board the Terra spacecraft does not "see" in color. Every image is obtained in a gray scale from black to white based on brightness of radiation at a precise wavelength between 0.52 and 11.65 microns (ASTER haven’t blue channel). These electronic cameras only collect digital
signal levels that are displayed as gray scale images from black to white, but they can obtain many images at the same time in different parts of the spectrum.

ASTER have three group of spectral bands. They are VNIR (Visible and NearInfrared), SWIR and TIR. Each of them have different resolution. VNIR is about 15 meter, SWIR is 30 meter, and TIR is 90 meter.

![Figure 2.1 Zone of Mangrove from Beach to Land by Macnae (1966)](image)

**Figure 2.1** Zone of Mangrove from Beach to Land by Macnae (1966)

![Figure 2.2 . ASTER Spectral Bands](image)

**Figure 2.2 . ASTER Spectral Bands**

### 2.2.1 Reflectance Characteristics of ASTER VNIR

ASTER is one of sensor which has wavelength VNIR and detailer resolution than Landsat TM (ASTER VNIR has resolution 15 meter). This characteristic can differentiates vegetation from other land surfaces (figure 2.3).
Figure 2.3 Different Reflectance Signal of Vegetation and Dry Soil (Land)

ASTER VNIR have four band channel, green channel, red channel, NIR channel and NIR channel backward. The principles application for each bands is given in table 2.1. below.

Table 2.1 Principle Application for Each Band of ASTER VNIR

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength</th>
<th>Nominal Spectral Location</th>
<th>Principle Application</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>520 – 600 nm</td>
<td>Green</td>
<td>Design to measure green reflectance peak of vegetation, vegetation discrimination and vigor assessment. Also usefull for cultural feature identification.</td>
</tr>
<tr>
<td>2</td>
<td>630 – 690 nm</td>
<td>Red</td>
<td>Designed to sense a chlorophyll absorption region help in plant species differentiation. Also usefull for cultural feature identification.</td>
</tr>
<tr>
<td>3N</td>
<td>760 – 860 nm</td>
<td>Near Infrared</td>
<td>Useful for determining vegetation types, vigor and biomass content, for delineating water bodies and soil moisture discrimination.</td>
</tr>
<tr>
<td>3B</td>
<td>760 – 860 nm</td>
<td>Near Infrared</td>
<td>Used for generate contour map</td>
</tr>
</tbody>
</table>
Reflectance signal of mangrove depend on pigment concentration and optical properties of leaves. Nevertheless, not all of satellite sensors easy to detect these factors. Need high resolution sensor capability to get exact result.

William and Norris (2001) reported that the limited number of spectral band of Landsat TM with resolution 30 meter, in which each band only covers a broad wavelength region of several tens of nanometers, offers a clear example of how opportunities to exploit spectral responses linked to the physico-chemical properties of plants are lost. Same cases with other satellite sensors, the broad spectral information of Landsat TM cannot be used to resolve several key absorption pits as well as reflectance characteristics including the red edge.

William and Norris (2001) added, the unique feature of plant spectral responses between the wavelength of 690 nm and 720 nm can be used to extract important physico-chemical characteristics of plants including chlorophyll contents. Base on this, the wavelength VNIR shown high information content for vegetation detection, because spectral of NIR 760 – 860 nm and VIS-red 630-690 nm.

As regards spectral resolution, one of the earliest digital remote sensing analysis procedures develop to identify a vegetation contribution in an image was the ratio vegetation index, created by dividing NIR by red reflectance. The basic of this relationship is the strong red light absorbttion (low reflectance) by chlorophyll and the low absorbttion (high reflectance and transmittance) in the NIR by the green leaves. Dense green vegetation has a high ratio while a soil has a low value, thus yielding a contrast between the two surfaces (Shanahan et.al.
Spectral reflectance increases with wavelength and is a function of soil moisture (Stark et al. 2000).

NIR reflectance is different in each species due to its independence on factors such as architecture of the canopy, cell structure and leaf inclination. Jackson and Pinter (1986) found that an erectophile canopy generally disperses more radiation in the lower layers than does a planophile canopy, consequently minimizing NIR reflectance. On other hand, reflectance in the visible range is less specific on the species since it is mainly influenced by pigment content and composition (Gitelson et al. 2002).

### 2.2.2 Mangrove Classification using ASTER

For classifying mangrove species, analysis of Band 1 to Band 9 spectra of ASTER was carry out for Can Gio Mangrove biosphere, in Vietnam. Mangrove’s digital number (DN) values in SWIR are generally lower than non-mangrove vegetation such as wild grass and rice paddy. Different mangrove species such as *Avicennia alba*, *Rhizophora apiculata* and *Phoenix paludosa* have different specific DN values. These spectral variations enable us to separate mangroves and classify mangrove species. In particular, different spectral pattern was observed in different mangroves (Hirose, 2006).

Thus, mangrove forests can be separated from non-mangrove woods using ASTER data. After delineating mangrove forests from non-mangrove areas, DN values were examined for different mangrove species such as *Avicenia alba*, *Rhizopora sp* and *Phonic paludosa*. 
Vegetation Index

The identification of vegetation is of major interest, since leaves and needles constitute photosynthetic areas and a principal link between the biosphere and the atmosphere. Vegetation also has a distinctive spectral signature that is characterized by low reflectance in visible region of the solar optical spectrum as well as high reflectance in infrared spectrum. The combination of these two spectral regions can allow to classify vegetation and to determine the quantity of photosynthetic biomass by using vegetation density (Pinty and Verstraete, 1992).

Pinty and Verstraete (1992) added, that different combinations between visible and NIR bands have been used to develop various vegetation index based on image that the National Oceanic and Atmospheric Administration (NOAA) has obtained through its advanced very high resolution radiometer (AVHRR).

Vegetation index itself define as combination of several spectral values that are mathematically recombined to yield a single value indicating the amount or vigor of vegetation within pixel (Campbell, 1996). Most index have used reflectances from visible and infrared bands or radiances in the form of ratios or linear combinations.
A vegetation index was introduced as a simple remote sensing tool for over 25 years. Vegetation index have been used for many years of increasing importance in the field of remote sensing. Vegetation index was a number that is generated by some combination of remote sensing band and may have some relationship to the amount of vegetation in given image pixel. Remote sensing devices operated in the green, red, and NIR regions of the electromagnetic spectrum, they act as sensitive discriminators of variations in radiation output that measure both absorbtion and reflectance effects associated with vegetation.

There are more than 20 vegetation index in use are summarized in Table 2.1. many are functionally equivalent (redundant) in information content (Perry and Lautenschlager, 1984), while some provide unique biophysical information (Qi et.al. 1995). It is useful to review the historical development of the main indices and provide information about recent advances in index development.

2.4.1 Simple Ratio Vegetation Index (SR or RVI)

In remote sensing applications and research, many indices have been develop during the last three decades (Bannari et.al., 1995). Among these indices, the Simple Ratio (SR) or Ratio Vegetation Index (RVI) and the Normalized Difference Vegetation Index (NDVI) have been widely employed for exploiting the spectral signature of vegetation, and beside they did not include any internal factors. It is useful to review the historical development of the main indices and provide information about recent advances in index development.
Cohen (1991) suggest that the first true vegetation index was the simple ratio (SR), which is the NIR to red reflectance ratio described in Birth and McVey (1968).

\[
SR = \frac{\text{NIR}}{\text{Red}}
\]

Table 2.2 Selected Remote Sensing Vegetation Index (Jensen 2000)

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Algorithms</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Ratio (SR)</td>
<td>( SR = \frac{\text{NIR}}{\text{Red}} )</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index</td>
<td>( \text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} )</td>
</tr>
<tr>
<td>Perpendicular Vegetation Index (PVI)</td>
<td>( \text{PVI} = \sqrt{(0.335_{m4} - 0.149_{m5})^2 + (0.355_{m2} - 0.852_{m4})^2} )</td>
</tr>
<tr>
<td>Greenness Above Bare Soil (GRABS)</td>
<td>( \text{GRABS} = G - 0.09178B + 5.58959 )</td>
</tr>
<tr>
<td>Moisture Stress Index (MSI)</td>
<td>( \text{MSI} = \frac{\text{MidIR}<em>{TM5}}{\text{NIR}</em>{TM4}} )</td>
</tr>
<tr>
<td>Leaf Relative Water Content Index (LWCI)</td>
<td>( \text{LWCI} = -\log\left[1-(\text{NIR}<em>{m4} - \text{MidIR}</em>{m5})/\log[1-\text{NIR}<em>{m4} - \text{MidIR}</em>{m5}] \right] )</td>
</tr>
<tr>
<td>MidIR index</td>
<td>( \text{MidIR} = \frac{\text{MidIR}<em>{TM5}}{\text{NIR}</em>{TM7}} )</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI)</td>
<td>( \text{SAVI} = (1 + L)(\text{NIR} - \text{Red})/\text{NIR} + \text{Red} + L )</td>
</tr>
<tr>
<td>Atmospherically Resistant Vegetation Index (ARVI)</td>
<td>( \text{ARVI} = \frac{(P<em>_{\text{nir}} - P</em><em>{\text{rh}})}{(P*</em>{\text{nir}} + P*_{\text{rh}})} )</td>
</tr>
<tr>
<td>Enhanced Vegetation Index</td>
<td>( \text{EVI} = \left<a href="1+L">\frac{(P<em>_{\text{nir}} - P</em><em>{\text{red}})}{(P*</em>{\text{nir}} + C_1P<em>_{\text{blue}} - C_2P</em>_{\text{blue}} + L)}\right</a> )</td>
</tr>
<tr>
<td>Infrared Index (II)</td>
<td>( \text{II} = \frac{(\text{NIR}<em>{m4} - \text{MidIR}</em>{m5})}{(\text{NIR}<em>{m4} + \text{MidIR}</em>{m5})} )</td>
</tr>
<tr>
<td>Soil and Atmospherically Resistant Vegetation Index (SARVI)</td>
<td>( \text{SARVI} = \frac{(P<em>_{\text{nir}} - P</em><em>{\text{rh}})}{(P*</em>{\text{nir}} + P*_{\text{rh}} + L)} )</td>
</tr>
<tr>
<td>Difference Vegetation Index (DVI)</td>
<td>( \text{DVI} = \text{NIR} - \text{Red} )</td>
</tr>
<tr>
<td>Infrared Percentage Vegetation Index (IPVI)</td>
<td>( \text{IPVI} = \frac{\text{NIR}}{\text{NIR} + \text{Red}} )</td>
</tr>
</tbody>
</table>
2.4.2 Normalized Difference Vegetation Index (NDVI)

Rouse et al., (1974) developed what is now called the generic Normalized Difference Vegetation Index (NDVI). NDVI is one of the ratio indices that respond to changes in amount of green biomass, chlorophyll content and canopy water stress. The healthy and dense vegetation show a large NDVI. Areas covered with clouds, water and snow, yield negative index value while areas covered with rock and bare soil result in vegetation indices near zero.

By comparing the visible and NIR light, scientists measure the relative amount of vegetation. Healthy and dense vegetation absorbs most of the visible light that hits it. Unhealthy and sparse vegetation reflects more visible light and less NIR. Mathematically NDVI is written as follow.

\[
\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}}
\]

NDVI value range from minus one (-1.0) to plus one (+1.0) and are unitless (Wunderly et al., 2003).

Environmental factors such as soil geomorphology and vegetation all influence NDVI values should be taken into account. NDVI can be effective in predicting surface properties when vegetation canopy is not too dense or too sparse. If a canopy too sparse, background signal e.g. soil can change NDVI significantly. Depending on the vegetation coverage, dark soil enhance the NDVI (Wunderly et al., 2003). If the canopy too dense NDVI saturates because red reflectance does not change much, but NIR reflectance still increase when the canopy become denser.
2.4.3 Difference Vegetation Index (DVI)

Difference Vegetation index is a vegetation index obtained by subtracting the red reflectance from the NIR reflectance. The algorithm of DVI is show below.

\[ \text{DVI} = \text{NIR} - \text{Red} \]

DVI is proportional to NDVI. Here, DVI is simpler than NDVI but is prone to measurement errors in the NIR and red because it is not normalized by their sum. DVI also sensitive to the amount of the vegetation, and it has the ability to distinguish the soil and vegetation. But, DVI doesn’t give proper information when the reflected wavelengths are being effected due to topography, atmosphere and shadows.

2.4 Natural Color Composite on ASTER

Simulated natural color makes the imagery easy to understand by a wide range of users. Natural-color images are created from blue, green, and red light. Most satellite sensors do not collect data in the blue spectral band of the electromagnetic spectrum. Even when a blue band is available, the blue light, as seen from space, is scattered by atmospheric moisture (the reason for blue skies) creating a very noisy blue band, particularly in humid areas (Mather, 2004).

Terralook, USGS (2008) wrote that most satellite sensors collect near-infrared (NIR) data, which is sensitive to the health of vegetation. In response to the lack of a blue band and the availability of an information-rich NIR band, most satellite images are viewed using some combination of visible and infrared data.
ASTER images use the bands derived from the red, green, and NIR bands to derived the algorithm described below for a simulated natural-color image.

Red = Red
Green = 2/3 Green + 1/3 NIR
Blue = 2/3 Green – 1/3 NIR

The synthetic green band is enhanced through the addition of information from the vegetation-sensitive NIR band. The synthetic blue is created from the spectrally-most-similar green band with the vegetation information suppressed.

2.5 Standard Back Propagation Neural Network (SBP)

There are different algorithms used to classify remote sensing images. The most often used of these, such as the maximum likelihood algorithm, require data with normal distribution. Among the algorithms that do not hypothesize on data distribution are the $k$ nearest neighbours and neural networks (NN) (Walthall et al., 2004).

Artificial NN can be used to develop empirically based on agricultural models. The NN structure is based on the human brain’s biological neural processes. Interrelationship of correlated variables that symbolically represent the interconnected processing neurons or nodes of the human brain are used to develop models (Kaul et al. 2005). Neural Networks are a structure of neurons joined by nodes that transmit information to another neurons, which give a result through mathematical functions. In general, an NN requires three layers, there are input, hidden layer, and output. The input and output layers contain nodes that
correspond to input and output variables, respectively (Hilera and Martinez, 2000).

The Standard Back Propagation (SBP) architecture provided by PREDICT was used to perform classification. SBP is a method for training MLP (Multy Layer Perceptron). This is a method for assigning responsibility for mismatches to each of the processing elements in the network, this is achieved by propagating the gradient of the objective function back through the network to the hidden units. Based on the degree of responsibility, the weight of each individual processing element are modify iteratively to improve the objective function. Input are supplied to the network and each input is given a weight, W. this weight is combined with other weights at the hidden layer node and a new weight is calculated. Weight modifications are made at all nodes then sent back between the first and second layers, until it reach the designed output error rate. An error rate is set to help evaluate the actual value against the predicted value. One node is assigned to each input data. Two parameters, momentum and leaning rates also affect the network.

When the pattern is presented to the input layer, it is evaluated by the hidden layer nodes, which pass on their output to the input layer. This can be thought of as the forward phase. Next step is calculate \( \delta \) (delta) on the output received from this layer. The delta rule helps minimize the error on a gradient.

Each training of the output nodes using gradient descent which is basically getting error down the slope i.e. descending the gradient of the curve. This is the backward phase. Thus the \( \delta \)'s have propagated from the output layer nodes to the
hidden layer nodes. Hence the name is back propagation. The SBP is mathematically defined as:

\[ \Delta W_{ij} = \eta \delta_j \sigma_i \]

If unit \( j \) is an output unit, then \( \delta_j = f'_j(\text{net}_j)(t_j - O_j) \)

If unit \( j \) is a hidden unit, then \( \delta_j = f'_j(\text{net}_j) \sum_k \delta_k W_{jk} \)

Where:

\( \eta \) = learning parameter – specifies the step width of gradient descent
\( \delta_j = t_j - O_j \) = difference between teaching value \( t_j \) and an output \( O_j \) of an output unit which is propagated back.

\( f'_j(\text{net}_j) \) indicates function of which in this case would be define by the delta rule. This algorithm update the weights every training pattern.

Figure 2.5 General Model of Standard Back Propagation neural Network

A least squares objective function is minimized in a feed forward step followed by an error back propagation step during which the output and middle
layer weights are adjusted to reduce the size of error. This process is continued in an interactive fashion for each observation in the data set until some desired degree of error minimization or convergence is reached.

The following parameters were used with the PREDICT classifier:

<table>
<thead>
<tr>
<th>Learning rate</th>
<th>Hidden layer = 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output layer</td>
<td>0.01</td>
</tr>
<tr>
<td>Learning rule</td>
<td>Adaptive gradient</td>
</tr>
<tr>
<td>Variable selection model</td>
<td>Multiple regression</td>
</tr>
<tr>
<td>Training and testing</td>
<td>10-fold cross validation</td>
</tr>
</tbody>
</table>

ANNs present a promising mode to improve classification of remotely sensed images. Many authors reported better accuracy when classifying spectral images with an ANN approach than with a statistical method such as maximum likelihood. However, a more important contribution of the ANNs is their ability to incorporate additional data into the classification process (Kaul et.al. 2005).

2.4 Maximum Likelihood Supervised Classification

It is important to realized that the maximum likelihood method is based on the assumption that the frequency distribution of the class membership can be approximated by the multivariate normal probability distribution. This might be appear to be an undue restriction for, as an eminent statistician once remarked, there is no such thing as a normal distribution. In practice, however, it is generally
accepted that the assumption of normality holds reasonably well, and that the procedure described above is not too sensitive to small departures from the assumption provided that the actual frequency distribution of each class is unimodal (i.e. has one peak frequency). A clustering procedure (unsupervised classification) could be used to check the training sample data for each class to see if that class is multi-modal, for the clustering method is really a technique for finding multiple modes.