THESIS

MANGROVE CLASSIFICATION ON ASTER VNIR USING VEGETATION INDICES AND NEURAL NETWORK
STUDY CASE : BERAU DELTA - EAST KALIMANTAN

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This thesis submitted to
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STATEMENT

I, Hapsari Maharani, hereby stated that this thesis entitled:

**Mangrove Classification on ASTER VNIR using Vegetation Indices and Neural Network, Study Case: Berau Delta - East Kalimantan**

Is the result of my own work during the period of June until September 2008 and that it has not been published before. The advisory committee and the external examiner have examined the content of this thesis.

Bogor, September 2008

Hapsari Maharani

ABSTRACT

ASTER with its VNIR sensor have the capability for mapping vegetation. With the resolution of 15m x 15m, this image should be able to classify mangrove is more details than Landsat TM with resolution of 30m x 30m. Based on this, algorithms was applied to explore the capability of this image for classifying mangrove. These are Standard Back Propagation Neural Network and some vegetation indices (DVI, NDVI, SR, and the modified of these algorithm by using Natural Color Composite : NCC-DVI, NCC-NDVI, NCC-SR). While, as study area, Berau Delta, East Kalimantan is chosen because there are still many species of mangroves.

Each algorithm show different results, but almost all of them capable to classify mangrove into zone level, except modification of vegetation index algorithms. Standard Back Propagation Neural Network is not quite good for classifying mangrove, because it can generate pixels into lower number of classes. While, DVI, NDVI, and SR can classify mangrove into 4 class. Its rather low than Maximum Likelihood Supervised classification and ISODATA Unsupervised classification which produced 5 class. But, when modified vegetation index applied, it a different results. They can detect Nypa fruticans class clearly than other species. Even, by using NCC-NDVI and NCC-SR class Nypa still can differentiate into detailer condition.

The specific condition of the area of study where high frequency of rain, may cause the amount of water content in the vegetation become increase. Since gives influence in low value of NIR reflectance and high reflectance of RED channel, the modified algorithm of vegetation indices using NCC applied, and show result better than standard algorithm of vegetation indices.

Key words: Mangrove, ASTER VNIR, Vegetation Indices, Neural network
<table>
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<tr>
<th>Research Title</th>
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I. INTRODUCTION

1.1 Background

It is well-known that the mangrove ecosystem plays important roles in coastal regions by its functions, which include supplying food and fuel wood for humans and natural protection against erosion. Moreover, mangrove ecosystem has become one of the key factors in considering the global warming issue and thus mangrove ecosystem is becoming increasingly important. However, mangrove mapping is quite a complex undertaking because of its distribution conditions, generally in high association.

Currently, various satellite data are available to assist mangrove area estimate throughout the world. They are Landsat TM, SPOT, ASTER, Quick Bird, etc. In this research, ASTER with VNIR sensor chooses for studied the effectiveness in mapping and classification of mangrove. It is reported as an example of applying satellite data for mangrove management in Berau Delta, East Kalimantan.

Many method and approach used in vegetation classification, especially in mangrove. Generally, it is by selecting certain classification algorithm, like vegetation index algorithm, but it also other algorithms, such as $k$ nearest neighbours, Expert System and Neural Networks (NN) (Walthall et.al., 2004).

In this research some vegetation indices algorithm and non vegetation indices were selected to explore their capability for mangrove classification in ASTER VNIR. They are Different Vegetation Index (DVI), Normalized Difference Vegetation Index (NDVI), and Ratio Vegetation Index (RVI). Other
algorithm which also used are modification of each vegetation indices selected with Natural Color Composite. And the last are Maximum likelihood and Standard Back Propagation Neural Networks.

To find out which one the best algorithm for mangrove classification in estuary area become important, because it will help mapping mangrove indirectly (real ground mapping is almost impossible applied). Beside, hopely by using appropriate algorithm, it can reduce the bias effect of extraneous factors, such as soil and atmosphere easily.

1.2 Objectives

The main objectives of this research are:

1. To know the limitation of ASTER VNIR capabilities for mangrove classification, based on histogram of each bands.

2. To know capability of Standard Back Propagation Neural Network for mangrove classification in ASTER VNIR.

3. To explore the selected vegetation indices algorithms (DVI, IPVI, and NDVI), also the modification of these algorithms using Natural Color Composite for mangrove classification in ASTER VNIR.
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. Rhizophora zone
c. Rhizophora / Bruguiera 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)](image1)

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).
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 absorbtion (low reflectance) by chlorophyll and the low absorbtion (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 carried 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 Phoenix poludosa.
2.3 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 it self 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 absorption 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 (NDVI)</td>
<td>(\text{NDVI} = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}})</td>
</tr>
<tr>
<td>Perpendicular Vegetation Index (PVI)</td>
<td>(PVI = \sqrt{(0.335_{\text{nm}4} - 0.149_{\text{nm}2})^2 + (0.355_{\text{nm}2} - 0.852_{\text{nm}4})^2})</td>
</tr>
<tr>
<td>Greeness 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>{T/M5}}{\text{NIR}</em>{T/M4}})</td>
</tr>
<tr>
<td>Leaf Relative Water Content Index (LWCI)</td>
<td>(\text{LWCI} = -\log\left[1-(\text{NIR}<em>{T/M4} - \text{MidIR}</em>{T/M5})\right] / -\log\left[1-\text{NIR}<em>{T/M4}-\text{MidIR}</em>{T/M5}\right])</td>
</tr>
<tr>
<td>MidIR index</td>
<td>(\text{MidIR} = \frac{\text{MidIR}<em>{T/M5}}{\text{NIR}</em>{T/M7}})</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} = \frac{[\left(P<em>_{\text{nir}} - P</em><em>{\text{red}}\right) / (P*</em>{\text{nir}} + C_1P<em>_{\text{blue}} - C_2P</em>_{\text{blue}} + L)]}{1+L})</td>
</tr>
<tr>
<td>Infrared Index (II)</td>
<td>(\text{II} = (\text{NIR}<em>{T/M4} - \text{MidIR}</em>{T/M5}) / (\text{NIR}<em>{T/M4} + \text{MidIR}</em>{T/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{Red} + \text{NIR}})</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, scientist 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.

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

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 algorithm 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 Percepton). 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 $\delta$ 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.

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 2.3 Parameters of ANN Classifier

<table>
<thead>
<tr>
<th>Learning rate</th>
<th>Hidden layer = 100</th>
</tr>
</thead>
<tbody>
<tr>
<td>Learning rule</td>
<td>Output layer = 0.01</td>
</tr>
<tr>
<td>Variable selection model</td>
<td>Adaptive gradient</td>
</tr>
<tr>
<td>Training and testing</td>
<td>Multiple regression</td>
</tr>
<tr>
<td></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 realize 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 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 uni-
modal (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.
III. METHODOLOGY

3.1 Area Description

Berau Delta, East Kalimantan is located between 1° 54’ 27’’ N – 2° 28’ 36’’N Lat and 117° 55’ 13’’E – 118° 26’ 12’’E Lon. Berau Delta is on estuary area which is composed by sediment material from Berau rivers and Maluku strait.

Berau Delta is one of the anthropogenic area of mangrove in Indonesia. It has similar condition with Mahakam delta about 10 years ago. But, during last four year, Berau delta have little changed. Some area was opened become ponds, and rural settlement. It is easy to detect with remote sensing data of ASTER VNIR 2004 (June 15th, 2004) compared with ASTER VNIR 2008 (June 22nd, 2008) on Figure 3.1

Field survey observation 2005, by BAKOSURTANAL reported that Berau river as small river, reaching 150 km inland, and the catchments basin has low anthropogenic pressure compared to other rivers of the region, so it has relatively low sediment delivery. This enables the presence of large diversity of marine and coastal habitat such as mangroves.

ASTER VNIR captured in 2008 show that in the middle of area Berau delta was managed to became ponds. Some of logging road at the southern of this area were also opened for mining transportation activities, and at the upland of Delta were built to be rural settlement. This condition gives effect into some ecosystem in delta, such as mangrove ecosystem and rivers ecosystem. The crucial impact is disturbed of their biodiversity, not in a long time the population of bird, monkey,
or crocodiles as a native fauna will decrease. In other side, the population of mangrove species itself also decrease because illegal loging.

![ASTER VNIR 2004](image1) ![ASTER VNIR 2008](image2)

Figure 3.1 Landuse Change in Berau Delta at Last Four Years (2004 -2008)

Based on the last field survey observation on middle of June 2008, the human activity in this delta is not too high. It can be indicated by the area of mangrove which is still higher than the thropogenic area. Although, the change of Berau Delta is still not significant, but it can indicate the sustainable of mangrove ecosystem on this area which is threatened.

3.2 Data and General Method

3.2.1 Data

a. Satellite Imagery Data

The multispectral image used in this study is an ASTER image of 2008, which was capture in June 22\textsuperscript{nd}, 2008 with three spectral bands VNIR (Figure 3.2). Band 1 green (520 – 600nm), band 2 red (630 – 690nm), and band 3N near infrared (760 – 860nm). The spatial resolution (expressed as pixel size) is 15 m x 15 m.
b. Field Data and Observation

The image has been checked on the field at middle of June 2008, the result show that the condition of mangrove have been changed, but it is not significant. Field data were taken by observation in rivers track from upland of delta until near the shore line. Transect methods cannot applied because the mangrove condition is very dense. Selection of location to be check is based on the domination of mangrove species. The reports of BAKOSURTANAL survey on 2005, 2006, and 2007, state that there are any specific condition of mangrove zonation in this delta. *Nypa fruticans* is dominated almost the half of the delta area. And the other are woods mangroves, such as *Rhizophora* sp. *Bruguiera* sp, and *Avicenia* sp. They are in the mixing and association condition, so its difficult to separate each other by visual interpretation.

Field observation have some objectives. It is for predicting the level of mangrove class, based on real condition of distribution each species. ASTER
VNIR 15m x 15m still may classify mangrove into level zone, not in species. It is based on two factors, pixel checking and labeling class of mangrove.

- **Pixel checking**
  
  Pixel checking done by selecting area about 1 km which known have specific mangrove condition (As an example is Nypa area on Figure 3.3). Here, used 1 km area for avoid mistakes in position of pixel (pixel sliding when data of GPS tracking overlay into image). In 1 km area representative 67 pixels of ASTER. These group of pixels can used as training area selection in supervised classification, which representative one specific condition of mangrove class.

- **Labeling Class of Mangrove**
  
  The area where selected as training area have specific coverage canopy by certain mangrove species. This is usefully to know the dominant species of mangrove in the area, based on their reflectance. This way is very help in judge the class of mangrove when the condition is not homogen, such as *Rhizophora sp* mixing, *Avicenia sp* mixing, or *Bruguiera sp* mixing. The dominant canopy coverage by one or some species used to labeling the name of class. As an example is show in Figure 3.4.

![Figure 3.3 Example of Pixel Checking by Selected Area (About 1 Km) that have Specific Condition and Representative for Training Area](image-url)
Figure 3.4. Example Labeling Class of Mangrove Based on Dominant Canopy Coverage

3.2.2 General Method

In general, the methods of this research can be seen in figure 3.5. ASTER with VNIR band has been separated from other 11 band of ASTER. Band 3B (backward) as part of visible band cannot be used, because it produce by different sensor of ASTER satellite. Band 3B looks backwards at an angle of 27.6 degree, so it not really vertically down. This band usually use to produce digital elevation model. Band composite that used in this research is False Color Composite 3N-2-1. While, the steps of each methods in this research explained below.
a. **ASTER Image pre processing**

Image processing is the first step in this research work. There are two main procedure, geometric correction and atmospheric correction. Geometric correction was done based on the vector to image registration. The vector data was used is hydrology map of Berau Delta, from BAKOSURTANAL. While, atmospheric correction done by dark pixels correction. Digital number (DN) of each band should be minus by minimum value of DN it self. Image with real digital number change into radiance unit, by adding with scale factor and multiply with offset. The equation is:

\[ R = \text{DN} \times \text{scale factor} + \text{offset} \]

Where R is reflectance value in radiance, DN is Digital Number of each band ASTER VNIR, and Scale factor and offset of each band show in table 3.1 below.
Table 3.1 Scale Factor and Offset of ASTER VNIR Bands

<table>
<thead>
<tr>
<th>Band</th>
<th>Scale Factor</th>
<th>Offset</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.676</td>
<td>-0.676</td>
</tr>
<tr>
<td>2</td>
<td>0.708</td>
<td>-0.708</td>
</tr>
<tr>
<td>3N</td>
<td>0.862</td>
<td>-0.862</td>
</tr>
</tbody>
</table>

b. Water Masking

Masking water and other object such as cloud and sediment by using formula editor to slicing the area only focus in land and vegetation. The aim is to reduce false in analysis, and therefore, the process of classification become easier. To mask water and other object, here using band 3N expressed NIR channel. Because assumption that NIR channel is more sensitive for object with high water content. Figure 3.6 show the result of image masking.

![Figure 3.6 ASTER VNIR Image Masking Water and Cloud](image)

Figure 3.6 ASTER VNIR Image Masking Water and Cloud
c. Predicting Class of Mangrove by Histogram

After the area of research mask in water and other object, histogram of ASTER VNIR bands compared each other to predict amount class of mangrove. This is shown in a number of peaks. The band, which has more peak than the other used as reference to derived number of mangrove class (the number of peak means number of mangrove class). While, the other band which have less number of peak will be neglected (Figure 3.7).

Based on the histogram of each bands, known that band 1 can derived into 12 class peaks, band 2 into 13 class peaks, and band 3N into 11 class peaks. This means that the number peaks of band 2 (Red channel) were used as reference for classifying mangrove.

Figure 3.7. Histogram of Each Band Represented Class of Mangrove Vegetation
d. **ISODATA Unsupervised and Labeling Class by using Field Data**

Unsupervised classification was done before each class has a name. The range of pixels value divide into 13 classes based on peaks of band 2. Afterwards, field data used for labeling the class was derived. It possibly, the number of class from field is quite different with the result from unsupervised classification. The factors that influence this condition will be analyzed and field data will be synchronized with the image classes.

e. **Classification Using Neural Network Supervised Classifier**

Before beginning the iteration, some parameters should be defined: input, output, and hidden layer. It also needs initialization process to standardized input into neural network value.

- Input nodes are band 1, band 2, band 3N
- Hidden layers = 1 learning rates
- Output nodes are amount of class from unsupervised classification
- Initialization:
  
  Normalize input data band 1, band 2, band 3N value (0 -255) and target (tk) into range [0..1]. Then, gives random values between -1 to 1 for all $W_{ij}$ and $V_{jk}$

  The iteration will start with feed forward step to predict target (tk). Target is not the real output value, but it calculate to get specific value for each class. Feed forward step itself divide into two step calculation. First, is calculate hidden nodes ($Z_1, Z_2, Z_3$) and the second is calculate target output.

  The next step is backward step. In this step will compute error of the nodes in output layer, and adjust weight $V_{jk}$ by using constant value of learning rate
(0.3). The result of this calculation used to compute error of the nodes in input layer, and adjust weight $W_{ij}$. (In this step also using constant value of learning rate 0.3).

The iteration will stop if output $Y$ are close enough to target. The termination can be based on the error value. For instance, iteration process is stopped when error less than 0.0001 (this number is must be defined in ENVI 4.2 before iteration process). After being trained, the network can be used to predict certain classes by inputting value of each band. The general step show in figure 3.3.

![Figure 3.3 Model of Standard Back Propagation Neural Network](image)

**f. Classification Using Maximum Likelihood Supervised Classifier**

To produce mangrove map, supervised classification was used. A maximum likelihood supervised classification was carried out using training areas chosen according to the unsupervised classification which have been labeled. Afterwards,
the raw result of the supervised classification was checked during visual interpretation of the satellite image and field data.

**g. Classification using vegetation indices classifier**

There are two types of vegetation indices applied in this research. First is standard vegetation index algorithms such as DVI, NDVI, and SR. While, second is algorithms using Natural Color Composites (NCC). Three standard vegetation indices have been selected from 14 vegetation indices algorithms. They are selected to derive a map of mangrove because can be used in ASTER VNIR, and closely with NDVI, where generally used in many vegetation mapping and classification.

While, the modification algorithm using NCC applied by building synthetic layer green and blue on the image, before applying the vegetation indices algorithms (Figure 3.4). The equations of each layer become change (Table 3.2), also the algorithms of each standard vegetation index.

![Table 3.2 ASTER VNIR Natural Color Composite algorithm and real channel](image)

<table>
<thead>
<tr>
<th>RGB Layer</th>
<th>ASTER VNIR - NCC</th>
<th>ASTER VNIR Channel</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red</td>
<td>Red channel</td>
<td>Red channel</td>
</tr>
<tr>
<td>Green</td>
<td>( \frac{2}{3} \times \text{Green channel} + \frac{1}{3} \times \text{NIR channel} )</td>
<td>Green channel</td>
</tr>
<tr>
<td>Blue</td>
<td>( \frac{2}{3} \times \text{Green channel} - \frac{1}{3} \times \text{NIR channel} )</td>
<td>NIR channel</td>
</tr>
</tbody>
</table>

**a. NCC-DVI**

The standard algorithm of DVI

\[
DVI = \text{NIR} - \text{RED} \tag{1}
\]
NIR input change become blue layer of NCC

\[ ((2/3 \times \text{Green channel}) - (1/3 \times \text{NIR channel})) \times \text{Red channel} \]  

(2)

b. NCC-NDVI

The standard algorithm of NDVI

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

(1)

NIR input change become blue layer of NCC

\[ \text{NCC-NDVI} / ((2/3*\text{Green channel})- (1/3*\text{NIR channel})+\text{Red channel}) \]  

(2)

c. NCC-SR

The standard algorithm of SR

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

(1)

NIR input change become blue layer of NCC

\[ ((2/3 \times \text{Green channel}) - (1/3 \times \text{NIR channel}))/ \text{Red channel} \]  

(2)

Each algorithm of vegetation indices will applied into image. Its not based on unsupervised classification, but specific treatment.
h. Result Analysis Using Map and Histogram

The results of each classification methods in this research are shown in map and histogram. The focus of analysis are the number of mangrove classes that can be derived from each algorithm and the capability to mapping mangrove into certain level of class itself (zone, density, or species). One algorithms will not compared each other, but explored the capability for mangrove classification using ASTER VNIR data were explored.

i. Data Validation

For validation, need to build new training areas of each class of mangrove were used to validate each map where produced. These training areas are different with Region of Interest (ROI) for maximum likelihood supervised classification and neural network. The validation of map as a result of each algorithm applied, checked with confusion matrix. Based on this matrix can predict the accuracy of each class.
IV. RESULT AND DISCUSSION

4.1 Synchronized ISODATA Unsupervised Classification with Field Data

The number of peak from ASTER VNIR bands express the capability of this image to detect class of object on the field. Based on histogram of each band on Chapter III, band 2 have more peaks than the other. It is quite different with the normal condition of reflectance vegetation, because amount of water in the atmosphere and leaf is high. When, observation was done on middle of June 2008 (the same date with ASTER image captured) the frequency of rain at Berau delta is often, almost every day, even more than a times in one day. So, leaf water content becomes increase. The reflectance of NIR was low, while, Red was higher than normal. Because the NIR wavelength absorbed by water.

The impact, when ASTER VNIR image was analyzed, there were only few pixels which have high value of Band 3, because not all of mangrove vegetation have same capability to keep high amount of water in their leaf. The value of Band 3 will high, if the mangrove leaf fast in past the water. In reality, the type of leaf and canopy gives high influenced. Nypa with long leaf and almost vertically, will past the water faster than Avicenia and Rhizophora. This means that the pixels which still have high value in Band 3 are pixels of class Nypa.

While, the condition of band 2 which more sensitive, it is easy to know because the frequency of pixels are more various. This means that, these pixels not only express class of Nypa, but also other kind of mangrove conditions. Based on this, band 2 was used to derived classes in ISODATA unsupervised. There are totally 13 classes, and 5
classes of them are mangrove. The other 7 class are kind of land, and sediment. The last one class is expressed pond.

![ISODATA Unsupervised map and histogram of each class](image)

Figure 4.1 ISODATA Unsupervised map and histogram of each class

Field data as a result of observation and ground checking gives information in certain area that is include into class of ISODATA unsupervised. When the information is overlaid on the image, class 1 represents Avicenia mixing with Nypa or Rhizophora mixing with Nypa, class 2 is Rhizophora mixing with Bruguiera, class 3 is Nypa
homogen, and class 4 is young Nypa mixing with young Rhizophora or Nypa with un
health condition. These data show in Table 4.1 below.

Table 4.1 Synchronized Class of ISODATA and Field Data Observation

<table>
<thead>
<tr>
<th>Class of ISODATA</th>
<th>Field Data Observation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Class 1</td>
<td>Avicenia mixing with Nypa, or Rhizophora mixing with Nypa</td>
</tr>
<tr>
<td>Class 2</td>
<td>Rhizophora mixing with Bruguiera</td>
</tr>
<tr>
<td>Class 3</td>
<td>Nypa homogen</td>
</tr>
<tr>
<td>Class 4</td>
<td>Young Nypa mixing with young Rhizophora, or Nypa with un health condition</td>
</tr>
<tr>
<td>Class 5</td>
<td>Mangroves that was burn or destroyed</td>
</tr>
</tbody>
</table>

From ISODATA unsupervised classification, mangrove can split into five class, while field observation have more than four class (7 class). This means that the capability of ASTER VNIR for classifying mangrove is limited. As an example, Avicenia mixing with Nypa or Rhizophora mixing with Nypa, still group into one class (Class 1). The same condition with Class 4, where young Nypa mixing with young Rhizophora cannot split with Nypa which un health condition.

It maybe other factors that influence the capability of ASTER VNIR for mapping mangrove, there is a density of mangroves. In Class 1, Avicenia mixing with Nypa cannot be separated from Rhizophora mixing with Nypa, because both classes almost have the same density condition. On the map, yellow color on the near shoreline is class of Avicenia mixing with Nypa, While at the upland of delta, the yellow color express
class of Rhizophora mixing with Nypa. From field observation, both of them almost have similar density. In figure 4.2, the photographs captured from the field, for both mixing conditions are shown.

Figure 4.2  Result of field observation, Avicenia mixing with Nypa (left) and Rhizophora mixing with Nypa (right) and the corresponding ASTER image.

Class 4 cannot be seen on map clearly because the area is quite narrow. But, there are two conditions based on field observation that can include into this class. The first is condition of mixing young Rhizophora with young Nypa, and the second is un health Nypa. Area growth by young Rhizophora and young Nypa are not really covered by their canopy, it let the soil reflectance influenced the value of pixels. While, Nypa with un healthy condition, it have bright color look like dry leaf although the density is high
(Figure 4.3). This means that the age of mangrove and healthy condition become important factor in mangrove classification. The young age and un health condition of mangrove cause the reflectance higher and in reality they read as same object on the ASTER VNIR image.

The widest area on the field also on the image is class 2. It is mixing between Rhizophora and Bruguiera. While, Class 3, Nypa is the second widest area.

![Figure 4.3 Young Rhizophora mixing with young Nypa (left), and Nypa with un health condition (right) and the corresponding ASTER image.](image-url)

Both kind of the area have similar character in their reflectance. Rhizophora mixing with Bruguiera have very high density compared with the other mixing of mangrove, because the character of each vegetation canopy is wide and type of their leaf is small. This means
that they can reflecting light better, with low diffuse. Bruguiera and Rhizophora are kind of woods mangrove, they have big stem and dense leaf when they adult. While, Nypa have difference character of leaf and canopy. The area of canopy becomes wide because the types of their leaf are almost vertical, but dense. So, the light that reflected by their leaves almost the same with wide canopy of Rhizophora and Bruguiera. But, its is just can judge in specific condition, where these vegetation have very high density. The result of field observation of both class show in Figure 4.4

Figure 4.4. Rhizophora mixing with Bruguiera (left) and Nypa (right) and the corresponding ASTER image.

Class 5 with green color express condition of mangrove that was burned and destroy by humans. Its about 13.622 m² or 6.349% of total area. The condition of this
area is look like opened land. The reflectance value are quite different and cannot used to identify certain class or species of mangroves. So, on the next discussion, this class will not explained detail. The photograph which capture from the field, represent of Class 5 show in Figure 4.5.

Figure 4.5 Condition of mangrove (burn and destroy) on Class 5, and the corresponding ASTER image

Graph on Figure 4.1 as a result of ISODATA Classifier show that almost all of classes split in same percentage. Class 1 about 11%, Class 2 about 12%, Class 3 about 14%, Class 4 about 13%, and Class 5 is about 6% more. The condition was caused by the ISODATA classifier capability to devise the range of pixels value almost into the same class (based on the class which judge by user).
This means that, by using ISODATA classifier, all class objects that want to detect can be separated easily. But, it is possible that there are any other classes inside class was define. The class object which easy to detect is Nypa on Class 3. On the homogen condition like this, ISODATA Classifier still accurate to used. But, when the condition of vegetation is not homogen, it really needs to be check on the field. While Class 1 and Class 4 which have almost same percentage, in fact they cannot be defined as one specific class of mangrove, because more specific, based on the field observation it should be defined into two classes. So, that this is the reason supervised classification should be done.
4.2 Maximum Likelihood Supervised Classification

4.2.1 Map and Histogram

Maximum likelihood choose as one of the classifier in this research because it has specific objective. Although it not include on the title of the thesis, but it need to test the capability of Standard Back Propagation Neural Network Classifier, by comparing them in capability to produced class. The result of this classifier reported that it can split mangrove into six class, five class appropriate with ISODATA classifier, and one class that detect as object non vegetation (class 6). Class 6 will not include into discussion, because these objects are pond, sediment, and land.

The Figure 4.6 show that Class 4 is quite higher than the other (35% more). This class represent young Nypa mixing with young Rhizophora or Nypa with un health condition. Both condition cannot be separated by using maximum likelihood classifier because the pixel value are almost the same. If it is forced to derive separate classes, the accuracy become low and difficult to identify on the map.

In this research, maximum likelihood was capable to produce accurate map of mangrove. It is because the basic of this method to make pattern in pixels reading is absolutely depend on the training area. If the training area have good distribution in pixel selection, the distance between the mean of each class will be narrow. Then, it can reach the pixels which select to grouping into one class or certain class quite far from the mean. This means that more number of pixels which can include into this class.
The training area was chosen for class 4 have narrow distance mean. This means that, they can reach pixel value are quite represent same reflectance, and cannot spit these into difference class. This condition, can be used as a reason that the capability of ASTER VNIR for mapping mangrove by using maximum likelihood methods limited on level zone.

Class 1 also has same condition with class 4, where two kind of mangrove mixing condition cannot split into difference class. The value of pixels only can group into one class. While, for the homogeny condition like class of Nypa (class 3), and high density of
Rhizophora mixing with Bruguiera (class 2) maximum likelihood more easy to split them from other class.

The resulting classification using maximum likelihood might be expected to be more accurate than the other supervised classifier, even than those produced by either the parallelepiped or $k$-means classifier, it suggest by Mather (2004). Its because on this classifier using training area that being used to provide estimates of the shapes of the distribution of the membership of each class in the p-dimensional feature space as well as the location of the center point of each class.

4.2.2 Validation

The confusion matrix is two dimensional matrix, where the row express reference, and the column is interpretation result. The value in bold is true value of each class. If the matrix is read, there are any different condition between interpretation result and reference. This difference can analyze in each class.

If class 1 test, there are number of pixels on the map that include into class 2, class 3, class 4, and also class 5 and class 6 on the reference. But, its not much, because number of pixel which still read true as class 1 is higher than the other, its about 186731 pixels or more than 56% from total of pixels on class 1. the same condition with class 2, class 3, class 4, class 5 and class 6. Although any pixels read as another class, but the true pixels is quite high. All condition of pixels can produce overall accuracy, 95.512%. Mather (2004), reported the good accuracy for classification is more than 75%, so this result can accepted, because assumed that the error is not highly significant.
<table>
<thead>
<tr>
<th>Class 1</th>
<th>Class 2</th>
<th>Class 3</th>
<th>Class 4</th>
<th>Class 5</th>
<th>Class 6</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>186731</td>
<td>4167</td>
<td>341</td>
<td>3611</td>
<td>7017</td>
<td>4262</td>
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<td>11496</td>
<td>288</td>
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<td>1330881</td>
<td>226351</td>
<td>434951</td>
<td>3472759</td>
</tr>
</tbody>
</table>

On class 2, many pixels of Rhizophora mixing with Bruguiera (886562) read as young Nypa mixing with young Rhizophora or Nypa un health (class 4) on the reference. In other side, on class 4, many pixels read as class 2 (35147). This condition can be happen, because the selection of training area give the result that mean value of each class is almost the same. So, the selection pixels to grouping in their class also have resemble value. It may the pixels on class 2 where include into class 4 are pixels that express Rhizophora and Bruguiera in young age or not too dense. While other class on the matrix are not significant change, so it can neglectfully.
4.3 Neural Network Classification

4.3.1 Map and Histogram

Comparison of result map between Neural Network and Maximum likelihood show that by using Neural Network the number class of mangrove become decreased. There are many pixels generalized into other class.

Two class which cannot identify are Rhizophora mixing with Bruguiera and class Nypa. The both of class have different reasons so they cannot differentiate on image. The group of pixels which should be include in class Rhizophora mixing with Bruguiera, detect as class Nypa un health and destroyed mangrove. While, pixels of Nypa homogen include into class 6, where not analyze in this research (Class 6 is labeled as pond and sediment).

The generalization of these pixels because of the capability of classifier is limited. Neural network cannot identify the pattern of that’s class, as a consequence of vegetation distribution pattern as continuous data.

Pattern in this case This means that the composition of digital number of each band. On image classification this range build based on the algorithm of the classifier. As an example, maximum likelihood able to differentiate class object based on normal distribution. This classifier will grouping the pixels which still tolerant with the limitation range that algorithm’s build. The same condition with Neural Network, the pattern of digital number will build based on training area of each object. Training area of class 1 has certain value were derived from mean, the same condition with class 2, class 3, class 4, class 5 and class 6. This value called as expected output. The expected output it self composed from value of band 1, band 2, and band 3. Well, the neural network will be
easy to differentiate object if composition of band 1, band 2, and band 3 of each object is quite different (called as different pattern).

This means that even the selection of training area (manually) is quite good, but if the pattern is not significant, neural network still cannot identify that’s pixels as unique class. Here, vegetation is one kind of object that difficult to separately by neural network, because the composition of band 1, band 2, and band 3 of each class is resemble.

The capability of neural network to generalized object vegetation, also support by the weighting value and resolution of the image. Weighting value caused the limitation between object become diffuse. So, in the last result the some different object will detect as one object. While, the resolution of the image will influenced the resemble of reflectance value. In this research, ASTER VNIR with resolution 15m x 15m, proved cannot differentiate mangrove detail by using neural network classifier.

Class 2 as mixing of Rhizophora and Bruguiera, have certain pattern between both class at the nearest of class 2, there are class 3 and class 4. Its simple to know on Figure 4.8. Pattern of DN class 2 read as unknown pattern on intermediate two known pattern. The main factor that influence the result of neural network classification is weighting. Because the weighting made input that not really significant different become diffuse. On the output layer, it will produced one specific value, that’s labeled as actual output value. While, training area which build have certain training pattern that can produced expected output value. The actual output value will allocate into certain class of object based on lower difference between expected output and actual output (called as error). More specific, if there are two condition that have same difference between expected and actual output, it will chose the value which near to 1.
Specific pixels that should be allocate into class 2, become include into class 3 or 4 because the difference more closely into that’s class. That’s the reason, pixels on class 2 generalized into class 3 or 4.
If learning pattern of DN band 1 on class 2 analyzed, this pattern can include into class 4, but cannot include into class 3. While on band 2 and 3N, the pattern of DN in class 2 easy to include into class 3 and 4. This means that, the number of pixels which become member of class 4 is quite more than class 3.

While, pixels of Nypa homogen have pattern inside the class 6, which not discuss in this research. This known from the range of DN value inside the range of DN Class 6, for all bands. The same condition with generalization on class 2 become class 3 and 4, almost all of these pixels include into class 6. When a value of actual output choose a class to be allocated, it will choose class 6 because the difference more closely into this class than the other.

![Figure 4.8 Range of DN in Class 4, Class 3, and Class 2 on Band 1, Band 2, and Band 3N](image)

![Figure 4.9 Range of DN in Class of Nypa and 6 on Band 1, Band 2, and Band 3N](image)
While, class 1, class 3 and class 4 are quite good in pixels classification. Its because the training pattern of them are easy to detect by neural network classifier, so that it can be separated easily.

4.3.2 Validation

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Confusion matrix of Neural Network above, support the condition of map and histogram that resulted. Both classes that have specific condition (class 2 and class Nypa) can be easily known by reading the matrix. On column class 2 pixels which detect as class 4 is more than class 3. Its support the condition, that training pattern of class 2 on band 1 only can include into class 4, at the other bands it can include in class 3 and class 4. While, almost of all pixels class Nypa include into class 6.

The classes of mangrove from neural network classification is quite different with maximum likelihood classification. One class that significantly cannot separately by using this classifier is Nypa homogen. On the maximum likelihood result, this class is clearly different with another class, because the reflectance value read as unique pattern. While, by using neural network, Nypa homogen surely cannot separately become unique class. that’s the reason, total class of mangrove that can detect by using this algorithm only four class.
4.4 Vegetation Indices

4.4.1 Difference Vegetation Index (DVI)

Applied subtraction formula on the image will change value of each pixels, also the pattern of DN. When this image classified, it show different map compared with supervised classification. On ISODATA unsupervised classification that was explored at the beginning of Chapter IV, band 2 used to judge the number of class because of various peaks. While, by using DVI the number of class judge based on the histogram of digital number.
The number of peaks on the DVI histogram cannot be calculated easily because it is very dense and various. So, to derive the class of mangrove needs to select certain dominant group of peaks on this histogram which have a lot of member of pixels. While, peaks that have a few member of pixels will be neglectfully.

The result of map and histogram represent on Figure 4.10. There are four class result from DVI classification. Rhizophora mixing with Bruguiera (Class 2 on maximum likelihood) cannot detect as unique class by using this algorithm, because the pixels include into other class, there is class 4. That’s condition because of the value of NIR reflectance of Rhizophora and Bruguiera is quite low, as an impact of high amount of water on the vegetation. Its can proved by the histogram of band 3N is quite low than band 2 (Chapter III). When the value of band 3N substracted with value of band 2 (algorithm of DVI), the difference value become small. Its almost have the same condition with class 4, where mangrove have been burn and destroy by humans. On class 4, the reflectance band 2 is more high because the effect of soil reflectance, while reflectance of band 3N moderately because some vegetation still have leafs, although its not dense.

Class 1 and class 3 almost have same population of pixels. The ISODATA classifier capable to differentiate both condition because, although they are same vegetation. Its because both of them have similar capability to pass the water. So that’s factor cannot influenced the value of subtraction. It is the same with Class 4, Nypa homogen, they leafs which long and vertical pass the water easily, so its not catch much
in the leaves, the subtraction of band 3N and band 2 still give the specific range which can separate with other object value.
4.4.2 Normalized Difference Vegetation Index (NDVI)

The peaks of NDVI histogram (that represent on the Appendix) are smooth because this algorithm can be normalized and the pattern can be studied. There are four dominant peaks on the histogram of NDVI used to derived class on this classification. The result show that class 2 have highest number of pixels frequency, than the other.

![Figure 4.11 Map and Histogram derived from NDVI Classifier](image)

This means that NDVI algorithm cannot detect all kinds of mangrove class on the field. It was only four classes. Mixing between young Nypa and young Rhizophora or
Nypa unhealthy condition cannot be detected clearly. The pixels of this class include into class 2 as an effect of normalization.

Object on Class 2 have high density, while on mixing young Rhizophora and young Nypa is moderately until high. By using NDVI algorithm that value will normalized, so the range of value become narrow. ISODATA classifier cannot split this class, and only detect into one class. Pixels of mixing young Rhizophora and young Nypa labeled into class 2, not on the contrary, its because the population pixels in class 2 are more than this class.

The NDVI can split class 1 and class 3 even the value become normalize. The main factor is character of the canopy of each class is quite different. Nypa homogen on class 3 can reflect the light more than the mixing condition. Its because the canopy coverage is more wide compared with mixing condition. On the mixing condition with other kind of mangrove, leaf of Nypa caused the reflectance become diffused. When NDVI algorithm applied may cause some condition of mangrove mixing become generalized. This condition also can answer the condition pixels on mixing young Rhizophora and young Nypa become include into class 2.
4.4.3 Simple Ratio (SR)

The simple ratio algorithm is a simplest algorithm on vegetation index. Its only by calculate the ratio between NIR and RED channel, or Band 3N and Band 2. Although it just a simple algorithm, but it also can defined class of mangrove on ASTER VNIR. While, the result of this algorithm classification is show on Figure 4.12.

Figure 4.12  Map and Histogram derived from SR Classifier
The highest percentage of amount pixels on the map is class 2, Nypa homogen, about 40.518%. Based on field data that overlay on the map to labeling class, class 2 is not pure Nypa. Many pixels that should be labeled as Avicenia mixing with Nypa include into this class. This is as consequence the division algorithms.

Vegetation Nypa have high reflectance on band 3N and low on band 2. If value of band 3N devide with value of band 2, will get the result smaller value but still not less than 0. This means that there is impossible to get null value, but may the value very low, less than 1.

NIR used as indicator of reflectance light by biomass, while red used as indicator of absorb light by biomass. In health vegetation, NIR become high and red become low. This condition can used to identify pixels to be labeled into certain class. Nypa on the class 2, have high value of digital number on band 3N as indicator of their reflectance. The low value of band 2 also found in the pixel Nypa. This means that class 2 is indicate that condition of vegetation is quite health. Well, pixels of Avicenia mixing with Nypa that include into class 2, means also represented that mixing Avicenia and Nypa or Rhizophora and Nypa on the field have health condition.

Class 3 more express the condition of unhealthy Nypa. This is have been prove by checking pixels on the position of this vegetation on the image compared with field observation. While, mixing between young Rhizophora and young Nypa, not include into this class.

Applying SR algorithm on the ASTER VNIR for mapping vegetation, usefull to detect the healty condition of vegetation. More specific, this simple algorithm have no
capability to detect zonation of mixing mangrove or association, but good in detect the healthy condition of mangrove, based on reflectance of their biomass.
V. CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The pure capability of ASTER VNIR in classify mangrove Berau Delta, resulted 5 class on level zone, not in species. This is based on histogram of band 2 which have more various peaks than other bands. Where class 1 represent avicenia mixing with Nypa or Rhizophora mixing with Nypa, class 2 is Rhizophora mixing with Bruguiera, class 3 is Nypa homogen, and class 4 is young Nypa mixing with young Rhizophora or Nypa with un health condition. While class 5 is condition of mangrove that have been burn and destroy by humans.

The capability of Standard Back Propagation Neural Network for classify mangrove is quite low. The result of classification proved that this method cannot separate class mangrove become detailer, but it precisely generates them into lower number of class. It is because DN of ASTER VNIR that represent reflectance signal of mangroves, read as continuous data, not as discrete data.

Other methods that used to explored capability of ASTER VNIR in classify mangrove is using vegetation indices. Standard algorithm of vegetation indices which selected in this research are DVI, NDVI, and SR. DVI algorithm capable to classify mangrove into four class. The class of mixing Rhizophora and Bruguiera cannot detect, because amount of water on the vegetation make the different value of NIR and RED very low, so this pixels become generate into other class. NDVI also can classify mangrove into four class, class of young rhizophora with young Nypa cannot differenciate with class avicenia mixing with Nypa. Effect normal of the algorithm caused many DN number of these pixels
generate become one class. SR which applied to classify mangrove show the result that it can separate mangrove into four class. Class 1 that represent avicenia mixing with Nypa or Rhizophora mixing with Nypa, cannot detected because the pixels of this class generate into class Nypa as consequence of division formula. But, this can used to identify that Avicenia and Nypa in condition mix are in health condition.

The modification of standard vegetation indices algorithm also applied in this research. Here using NCC to build synthetic NIR. In general, the result is quite different with the standard algorithm, because only Nypa that can detect by using these algorithm. More specific, NCC-DVI able to detect Nypa in mixing condition or homogen. NCC-NDVI can split Nypa homogen become 3 sub class detailer. While, NCC-SR can split Nypa homogen into 2 sub class. The modification of standard vegetation indices algorithms by using NCC for mapping vegetation, especially mangrove is quite good applied in specific condition. Where, there are amount of water in the vegetation influenced reflectance of NIR become low.
5.2 Recommendation

1. Application of Neural network classifier for classifying mangrove is not supported, especially if this algorithm applied on satellite image with the resolution 15m x 15m or lower. Because it can generate pixels become few number of classes. Moreover, its still need research that applied Neural network for classifying mangrove on higher resolution imagery, such as IKONOS or QuickBird.

2. NCC-DVI, NCC-NDVI, and NCC-SR algorithms can used for Nypa mapping and detection, especially in the condition were area has high water amount, such as cases of Berau Delta.
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APPENDIX

Histogram of each Vegetation Index used for derived class on ISODATA unsupervised

DVI

NCC-DVI

NDVI

NCC-NDVI

SR

NCC-SR
PATTERN OF TRAINING AREA FOR NEURAL NETWORK

band 1
class 6 1 148
class 5 137 218
class 4 30 102
class 3 14 61
class 2 121 218
class 1 82 218

band 2
class 6 3 179
class 5 3 109
class 4 3 50
class 3 10 50
class 2 3 29
class 1 3 179

band 3
class 6 3 172
class 5 3 172
class 4 3 89
class 3 3 55
class 2 3 66
class 1 3 172
## CONFUSION MATRIX OF STANDARD BACK PROPAGATION NEURAL NETWORK

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### Ground Truth (Percent)

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**Kappa statistic:** 0.940

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</tr>
<tr>
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<td>2.068%</td>
<td>1.752%</td>
<td>90.509%</td>
<td>2.022%</td>
<td>0.165%</td>
<td>3.404%</td>
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</tr>
<tr>
<td>class 2</td>
<td>0.032%</td>
<td>3.961%</td>
<td>0.477%</td>
<td>94.214%</td>
<td>0.020%</td>
<td>1.296%</td>
<td></td>
</tr>
<tr>
<td>class 3</td>
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<td>1.323%</td>
<td>0.070%</td>
<td>0.039%</td>
<td>97.847%</td>
<td>0.012%</td>
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</tr>
<tr>
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<td>0.356%</td>
<td>3.219%</td>
<td>4.952%</td>
<td>0.022%</td>
<td>91.308%</td>
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</tr>
</tbody>
</table>

**Producer’s Accuracy**

<table>
<thead>
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<th>Classified File</th>
<th>Reference File</th>
<th>class 6</th>
<th>class 4</th>
<th>class 1</th>
<th>class 2</th>
<th>class 3</th>
<th>class 5</th>
</tr>
</thead>
<tbody>
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<td>0.186%</td>
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<td>0.032%</td>
<td>0.669%</td>
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<td>96.456%</td>
<td>1.622%</td>
<td>3.920%</td>
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<td>0.271%</td>
<td>90.535%</td>
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<td>0.000%</td>
<td>3.100%</td>
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<td>0.045%</td>
<td>5.079%</td>
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<td>97.749%</td>
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<td>3.534%</td>
<td>1.265%</td>
<td>0.013%</td>
<td>91.370%</td>
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