ESTIMATING ABOVE GROUND TREES BIOMASS
OF FOREST COVER USING
FIELD MEASUREMENT AND QUICKBIRD IMAGE
IN LORE LINDU NATIONAL PARK-CENTRAL SULAWESI

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2007
STATEMENT

I, Naimatu Solicha, here by stated that this thesis entitled:

Estimating Above Ground Trees Biomass of Forest Cover
Using Field Measurement and Quickbird Image
In Lore Lindu National Park-Central Sulawesi

are results of my work during the period of June February until August 2007 and it has not been published before. The content of the thesis has been examined by the advising committee and the external examiner.

Bogor, August 2007

Naimatu Solicha
ACKNOWLEDGMENT

This thesis was completed with the support of STORMA program. STORMA stands for Stability of Rainforest Margin in Indonesia is an Indonesian-German collaboration research funded by the German Research Foundation (FDG). I would like to give my highly appreciation to FDG-STORMA for the research support and the following people that give a high encouragement and help to finish my thesis:

1. My family for giving the unwavering faith and support me to finish my master degree.
2. Dr. Tania June, Dr. Antonius B.W. and Dr. M. Ardiansyah as my supervisor and co-supervisors for their guidance, help, idea, comment and constructive criticism during my research.
3. Dr. M. Buce Saleh as the external examiner for his positive inputs and ideas.
4. Dr. Surya Tarigan, Dr. Adam Malik and Mr. Wolfram Lorenz as the STORMA coordinators of IPB, Untad and German for their assistance during the implementation of research.
5. Mr. Abdul Rauf and Mr. Heiner as STORMA B1 Sub Program Coordinator for helping to arrange the field observation, discussion and their positive input and idea.
6. My friend in MIT IPB for helping and supporting me in finishing thesis and pass our ups and down during finishing our master degree.
7. Kak Amran and all of STORMA assistants for giving kindness, help, assistance, support me during the field observation in Sulawesi.
8. Adhi Tyan Wijaya for moral support, positive suggestion and his patience accompany and listen to my problems in finishing my master degree.
9. MIT secretariat and all staff for helping me to arrange the administration, technical and facilities.

Hopefully, this thesis could give the positive contribution to forestry research.
Naimatu Solicha was born in Surabaya, East Java Indonesia on October 1st 1982. She was graduated from Brawijaya University, Agricultural Faculty, and Agronomy Department in 2004. She was entered the IPB Graduate School in year 2005. Before entering the Graduate School of Bogor Agricultural University she worked as assistant lecturer in Brawijaya University and as private English tutor.

She was enrolled as private student in Master of Sciences in Information Technology for Natural Resources Management in August 2005. Her final thesis is “Estimating above ground trees biomass and carbon stock of forest cover using Multispectral Satellite images in Lore Lindu National Park-Central Sulawesi”
ABSTRACT

NAIMATU SOLICHA (2007). “Estimating above ground trees biomass of forest cover using field measurement and QuickBird image in Lore Lindu National Park-Central Sulawesi” under supervision of Dr. Tania June, Dr. Antonius B.W and Dr. M. Ardiantsyah

Forests play an important role in global carbon cycling, since they hold a large pool of carbon as well as potential carbon sinks and sources to the atmosphere. Accurate estimation of forest biomass is required for greenhouse gas inventories and terrestrial carbon accounting (Muukkonen and Heiskanen, 2006). The biomass of forest provides estimates of the carbon pools in forest vegetation because about 50% of it is carbon. Direct measurement of biomass on the ground is time consuming (expensive), and repeated measurements, if they occur at all, are generally limited to 10 year interval. The possibility that above ground forest biomass can be determined from space is a promising alternative to ground-based methods. Remote sensing has opened an effective way to estimate forest biomass and carbon. By the combination of data field measurement and allometric equation, the above ground trees biomass is possible to be estimated over the large area.

The objectives of this research are: (1) To estimate the above ground tree biomass and carbon stock of forest cover in Lore Lindu National Park by combination of field data observation, allometric equation and multispectral satellite image; (2) to find the equation model between parameter that determines the biomass estimation.

The method of this research use an approach of estimating the biomass that combines field studies (forest inventory data), analysis of multispectral satellite imagery, allometric equation and statistical analysis. Forest cover type classification was utilized for analyzing the biomass per pixel in each different cover type. The classifications for each cover type by using the region based different spectral value in each observation plot refer to QuickBird Image.

The field data observation and satellite image classification influencing much on the accuracy of trees biomass and carbon stock estimation. The correlation analysis resulted the main regression equation in estimating the tree biomass of tropical forest, biomass=6E-05DBH$^{2.6705}$ and biomass= 0.0065e$^{13.615 NDVI}$. There are 4 forest cover types observed in this research. Forest cover type A is natural forest without timber extraction (closed canopy). Forest cover type B is natural forest with minor extraction. Forest cover type C is natural forest with major timber extraction. Forest cover type D is agroforestry system. Forest cover type A and B has the higher biomass than C and D, it is about 596.41-618.66 ton/ha and 583.94-622.19 ton/ha. Forest cover type C is 446.65-468.50 ton/ha. Forest cover type D has the lowest biomass is about 193.31-214.34 ton/ha. Natural forest has high biomass, because of the tropical vegetation trees
heterogeneity with minimum disturbance. Forest cover D has the lowest trees biomass because its vegetation component as secondary forest with the homogeneity of cacao plantation. The forest biomass for each cover type will be useful for the further equation analysis when using the remote sensing technology for estimating the total biomass.
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I. INTRODUCTION

1.1 Background

Forests play an important role in global carbon cycling, since they hold a large pool of carbon as well as potential carbon sinks and sources to the atmosphere. Accurate estimation of forest biomass is required for greenhouse gas inventories and terrestrial carbon accounting (Muukkonen and Heiskanen, 2006). In addition, forests play a major role in the global carbon cycle (Canadian Council of Forest Minister, 1997) by virtue of the fact that they occupy one third of land surface, but account for two thirds of the net annual photosynthesis (Berlyn and Asthon, 1996).

Lore Lindu National Park, Central Sulawesi, Indonesia is one of the most important protected areas in Indonesia and was declared a “Biosphere Reserve” in 1977. Biosphere reserves were conceived as “experimental sites for sustainable development, research and monitoring on ecosystems and conservation of biodiversity”, and are at the same time meant to “promote well being of local people who live in and around the reserve” (UNESCO, 1995). As the protected forest in Indonesia, Lore Lindu has many trees and animal biodiversity (endemic land birds and most of its endangered mammals). It is home to many of Sulawesi’s unique species and provides water resources to more than 300,000 people living in the area. The forest properties will become an important thing to be explored when dealing with the protection effort of the area, and to know the function of the forest for reserving biomass and the carbon pool to the
Biomass is defined as the total amount of life and inert organic matter above and below expressed in tons of dry matter per unit area. It is a useful measure for assessing changes in forest structure. Changes in forest biomass density are brought about by natural succession; human activities such as silviculture, harvesting and degradation; and natural impact by wildfire and climate change. Biomass density is also useful variable for comparing structural and functional attributes of forest ecosystems across a wide range of environmental conditions (Brown, 1997).

The biomass of forest provides estimates of the carbon pools in forest vegetation because about 50% of it is carbon. The quantity of biomass in forest is a result of the difference between production through photosynthesis and consumption by respiration and harvest processes. Through photosynthesis, plant absorbs carbon dioxide from the atmosphere and stores the carbon in biomass in the form of sugars, starch and cellulose. Biomass estimation will provide the means for calculating the amount carbon dioxide that can be removed from the atmosphere.

The information on biomass is essential to assess the total and the annual capacity of forest vigor. Estimation of aboveground biomass is necessary for studying productivity, carbon cycles, nutrient allocation, and fuel accumulation in terrestrial ecosystem (Ryu et al., 2004). Biomass and carbon content are generally high in tropical forests, reflecting their influence on the global carbon cycle.

The carbon stock indicates the contribution of forest to carbon cycles related to mitigation of climate change. There are global classifications of carbon
stock like carbon in woody biomass, carbon in above ground tree biomass, carbon in below ground tree biomass, and soil carbon. A major proportion of the Carbon and nutrients in terrestrial ecosystems is found in the tree components. There are five approaches that can be used for estimating biomass: destructive sampling, by using existing volume data, based on stand table, geographic information system modeling and combination between field study and remote sensing (Brown, 1997).

To reduce the need for destructive sampling, biomass can be estimated by measuring the tree properties such as stem diameter at specified height, by using allometric equation (Hairiah, Sitompul, Noordwijk and Palm, 2001).

Direct measurement of biomass on the ground is time consuming (expensive), and repeated measurements, if they occur at all, are generally limited to 10 year interval. The possibility that above ground forest biomass might be determines from space is a promising alternative to ground-based methods (Hese et al., 2005 in Houghton, 2005).

Remote sensing has opened an effective way to estimate forest biomass and carbon (Rosenqvist et al., 2003). According to the IPCC GPG (2003) (Intergovernmental Panel on Climate Change, Good Practice Guidance), remote sensing methods are especially suitable for verifying the national carbon pool estimates, particularly the aboveground biomass (Muukkonen and Heinsaken, 2006). Remote sensing takes an important role in the estimation of biomass and carbon stock over large forest area. By combining remote sensing technology and empirical model of allometric equation biomass and carbon stock of forest cover area can be estimated.

Remote sensing images can be used in the estimation of aboveground
biomass by indirect estimation of biomass through some form of quantitative relationship (regression equations) between band ratio indices (NDVI, GVI etc) or other measures such as direct radiance values per pixel or digital numbers per pixel, with direct measures of biomass or with parameters related directly to biomass, e.g. leaf area index (LAI).

The biomass estimation over a large area by using remote sensing and standwise forest inventory data has been conducted in many regions by using the different multispectral imagery. These regions cover arid area, boreal forest and tropical forest. Muukkonen and Heiskanen (2006) used ASTER and MODIS satellite data to estimate biomass of boreal forests in southern Finland. Zheng et al. (2004) used Landsat 7 ETM+ for estimating aboveground biomass of managed landscape in northern Wisconsin, USA. Murdiyarso and Wasrin (1995) estimated carbon release from tropical forests conversion using remote sensing technique. The different satellite data for the biomass estimation will give the different estimation result. Therefore, the different accuracy and equation model derived from the different satellite data will give the important consideration in choosing the appropriate data used.

1.2 Objectives

The objectives of this research are:

- To estimate the above ground tree biomass and carbon stock of forest cover in Lore Lindu National Park by combination of field data observation, allometric equation and multispectral satellite image.

- To find the equation model between parameter that determines the biomass estimation.
1.3 Output

- Correlation and Linear Regression equation model of tree biomass and vegetation index, remote sensing biomass and field biomass
- Normalized Difference Vegetation Index (NDVI) value using QuickBird satellite image
- Per hectare trees biomass derived from different forest cover type and multispectral satellite image classification as the reference to estimate the total biomass and carbon stock in sample plot and whole area
- Total trees biomass and carbon stock of whole study area

1.4 Thesis Outline

To accomplish two preceding objectives, several steps will be taken. Firstly, a literature reviews, presented in Chapter 2. It will be conducted to provide a context for the work performed in this study. The relevance of this work is demonstrated through the examination of several methods in estimating the tree biomass and carbon stock.

The second part of the literature review involves an examination of biomass and carbon stock, the various method and regression model for estimating tree biomass, the use of remote sensing and different satellite images in forestry application especially in estimating its properties.

Methodology is described in Chapter 3, covering the research time, the description of study area, technical method and instrument that will use to collect and analysis the data.

In Chapter 4 results are displayed and discussed covering: field data observation, vegetation analysis, forest cover type classification, correlation
between parameter, model analysis, above ground tree biomass and carbon stock estimation for each forest cover type and whole study area.

Chapter 5 provides the conclusions and recommendations of this study.
II. LITERATURE REVIEW

2.1 Biomass and Carbon Stock

2.1.1 Definition of Biomass

Biomass was the name given to any recent organic matter that had been derived from plants as a result of the photosynthetic conversion process. Biomass is the mass (or weight) of living matter per unit area of ground. It is expressed in weight per unit area (ton or kg/ha). Between different vegetation types, biomass range from around 0.1 ton/ha for desert and 500 ton/ha for tropical rain forest. In the study of carbon budget, biomass is important because it directly represents the amount of carbon stored in living plants.

Aboveground biomass was difficult to quantify over large areas using traditional techniques and executed the relationship between LAI derived from NDVI and estimated aboveground biomass based on plant height. The aboveground biomass of the plant could be easily estimated with some accuracy from allometric relationship of trunk height (FAO 1997 in Thenkabail et al., 2002). Biomass ton per hectare depend on the plant height (regression with model LAI) and planting density.

Half of a tree mass is carbon, so large amounts of carbon are stored in plants and they are the largest carbon store of terrestrial carbon. In most ecosystems, most of carbon is stored below ground, either as roots and decaying biomass or as organic carbon in the soil. The tree carbon calculation used general allometric relationships to estimate aboveground biomass of the tree.
C-stock means the total carbon which stored in the biomass component and nekromass, above and inside soil (soil organic matter, plant root, and microorganism) per unit area of ground.

2.1.2 Biomass Estimation

Biomass, an estimate of the total living or dead organic material expressed as a weight per area (e.g. ton per hectare), has been the greatest interest when aggregated over regional conditions (Schroeder et al., 1997; Fang et al., 1998). For example, at the country scale of resolution, Brown et al. (1999) produced a map of density and pools of all forests in the eastern U.S by converting inventoried wood volume estimates of aboveground and belowground biomass. Combining these estimations with AVHRR satellite data produced map with 4x4 km grid cells: these products are useful, but are too coarse for many forest management purposes except the larger, strategic ones, for example, involving Kyoto report. Instead, spatially explicit estimates of stand or ecosystem biomass are now sought by managers as one component of the carbon cycling budget for a given forest, and as an input to important criteria and indicators of sustainable forestry such as percentage of biomass volume by general forest type (CCFM, 1997). Increasingly, biomass estimation is required at the stand level.

Traditionally, stand biomass estimates are derived by the same process as regional estimation of biomass, by conversion of stem volume estimates from the forest inventory database (Aldred and Alemdag, 1988). In less-well-inventoried areas of the world, biomass estimates may be developed through forest cover type volume tables (Brown and Lugo, 1984). The estimate begins with single tree estimates by species and site types. The appropriate local allometric equations are
developed to partition the estimate into foliar, branch, stem and root biomass estimates, or perhaps into two components: aboveground and belowground woody biomass components (Lavigne, Luther, Franklin and Hunt, 1996). A recent strategy is to develop a large-scale system for biomass estimation. Such an approach assumes that better biomass estimates can be generated by referencing all available information in a multistage approach: the forest inventory, the available satellite and airborne imagery, and data collected in the field in permanent sample plots (Czaplewski, 1999; Fournier et al., 1999).

2.1.3 Methods for Estimating Biomass Density from Existing Data

There are two main approaches for estimating the biomass density of woody formations based on existing data. The first approach is based on the use of existing measured volume estimates (VOB per ha) converted to biomass density (ton/ha) using variety of “tools” (Brown et al. 1989, Brown and Iverson 1992, Brown and Lugo 1992, Gillespie et al. 1992). The second approach directly estimates biomass density using biomass regression equations. These regression equations are mathematical function that relates oven-dry biomass per tree as a function of a single or a combination of tree dimension. They are applied to stand tables or measurements of individual trees in stands or in lines (e.g. windbreaks, live fence posts, home gardens). The advantage of this second method is that it produces biomass estimates without having to make volume estimates, followed by application of expansion factors to account for non-inventoried tree components. The disadvantage is that there is a smaller number of inventories report stand tables to small diameter classes for all species. Thus, not all countries
in the tropics are covered by these estimates. To use either of these methods, the inventory must include all tree species. There is no way to extrapolate from inventories that do not measure all species (Brown, 1997).

2.1.3.1 Approach 1: Biomass Density based on Existing Volume Data

This method is based on existing volume per ha data and is best used for secondary to mature closed forest only, growing in moist to dry climate. It should be used for closed forest only because the original data base for developing this approach was based on closed forest. The primary data needed for this approach is Volume over bark (VOB)/ha, that is inventoried volume over bark of tree bole (Brown, 1997).

General equation

Biomass density can be calculated from VOB/ha by first estimating the biomass of the inventoried volume and then expanding this value to take into account the biomass of the other aboveground components as follows (Brown and Logo 1992).

\[
\text{Above ground biomass density (ton/ha)} = \text{VOB} \times WD \times \text{DEF}
\]

Where:

- \( WD \) = volume weighted average wood density (t/ha of oven-dry biomass per m\(^3\) green volume)
- \( \text{BEF} \) = biomass expansion factor (ratio of aboveground oven-dry biomass of trees to oven-dry biomass of inventoried volume)

Volume Weighted Average Wood Density (WD)

Wood density is defined as the oven-dry mass per unit of green volume (either ton/m\(^3\) or grams/cm\(^3\)). Few data on wood density for trees in tropical Africa and Asia are expressed in units of mass of wood at 12% moisture content per unit of volume. A regression equation was developed by Reyes et al. (1992) to
convert wood density based on oven-dry mass and green volume.

\[ Y = 0.0134 + 0.800 X \ (r^2=0.99) \]

Where:
- \( Y \) = wood density based on oven-dry mass/green volume
- \( X \) = wood density based on 12% moisture content

**Biomass Expansion Factor (BEF)**

Broadleaf forests: Biomass expansion factor is defined as the ratio of total aboveground oven-dry biomass density of trees with a minimum DBH of 10 cm or more to the oven-dry biomass density of the inventoried volume.

\[ BEF = \exp\{3.213-0.506*\ln(BV)\} \text{ for } BV<190 \ t/ha \\
1.74 \text{ for } BV \geq 190 \ t/ha \]

Where:
- \( BV \) = biomass of inventoried volume in t/ha, calculated as the product of VOB/ha (m\(^3\)/ha) and wood density (t/m\(^3\))
  (sample size=56, adjusted \( r^2 = 0.76 \))

**2.1.3.2 Approach 2: Biomass Density based on Stand Tables**

Another estimate of biomass density is derived from the application of biomass regression equations to stand tables. The method basically involves estimating the biomass per average tree of each diameter (diameter of breast height, DBH\(^1\)) class of stand table, multiplying by the number of trees in the class, and summing across all classes (Brown, 1997).

**Biomass Regression Equations**

The biomass regression equations for broadleaf forests were developed from a database that includes trees of many species harvested from forest from all three tropical regions (a total of 371 trees with a DBH ranging from 5 to 148 cm

\(^1\) Diameter breast height (DBH) is a standard method of expressing the trunk diameter of the tree, measuring at 1.3 m above ground
from ten different sources) (Brown, 1997). The biomass regression equations can provide estimates of biomass per tree. The data base was stratified into main climatic zone, regardless of species: dry or where rainfall is considerably less than potential evapotranspiration (e.g. <1500 mm rain/year and dry season for several months), moist or where rainfall approximately balances potential evapotranspiration (e.g. 1500-4000 mm rain/year and a short dry season to no dry season), and wet or where rainfall is in excess of potential evapotranspiration (e.g. >4000 mm rain/year and no dry season). Table 2.1 depicts the regression models for estimating biomass of tropical trees based on rainfall climatic zone, as the research result conducted by Brown, Gillespie and Lugo (1989) in MacDicken (1997).

The linear regression equation approach requires the selection of the regression equation that is best adapted to the conditions in the study area. Linear regression models have been fitted to data in various situations of variable site and ecological conditions globally.

### Table 2.1 Biomass regression equations for biomass estimation of tropical trees.

<table>
<thead>
<tr>
<th>Climate type based on annual rainfall</th>
<th>Equation</th>
<th>( R^2 ) Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry (&lt;1500 mm)</td>
<td>( Y = 34,4703 - 8,0671 \ D + 0.6589D^2 )</td>
<td>0.67</td>
</tr>
<tr>
<td>Moist (1500-4000 mm)</td>
<td>( Y = 38,4908 - 11,7883 \ D + 1.1926D^2 )</td>
<td>0.78</td>
</tr>
<tr>
<td></td>
<td>( Y = \exp[-3,1141 + 0.9719 \ln (D^2H)] )</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td>( Y = \exp[-2,4090 + 0.9522 \ln (D^2HS)] )</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>( H = \exp[1.0701 + 0.5677 \ln D] )</td>
<td>0.61</td>
</tr>
<tr>
<td>Wet (&gt;4000 mm)</td>
<td>( Y = 13,2579 - 4,8945 \ D )</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>( Y = \exp[-3,3012 + 0.9439 \ln (D^2H)] )</td>
<td>0.90</td>
</tr>
<tr>
<td></td>
<td>( H = \exp[1.2017 + 0.5627 \ln D] )</td>
<td>0.74</td>
</tr>
</tbody>
</table>

Where:
- \( Y \) = Biomass/plant (kg)
- \( D \) = Diameter at Breast height (cm)
- \( H \) = Height (m)
- \( S \) = Wood density (ton/m³)
Table 2.2 Estimation of tropical forests biomass using regression equations of biomass as a DBH function.

<table>
<thead>
<tr>
<th>Restrictions: DBH and climate based on annual rainfall</th>
<th>Equation</th>
<th>$R^2$</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>5 &lt; DBH &lt; 40 cm Dry transition to moist (rainfall &gt; 900 mm)</td>
<td>$Y = \exp{-1.996 + 2.32 \times \ln(DBH)}$</td>
<td>0.89</td>
<td>FAO</td>
</tr>
<tr>
<td>3 &lt; DBH &lt; 30 cm Dry (rainfall &lt; 900 mm)</td>
<td>$Y = 10^{-0.535 + \log10(p \times r^2)}$</td>
<td>0.94</td>
<td>FAO</td>
</tr>
<tr>
<td>DBH &lt; 80 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>$Y = \exp{-2.134 + 2.530 \times \ln(DBH)}$</td>
<td>0.97</td>
<td>FAO</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Dry (rainfall &lt; 1 500 mm)</td>
<td>$Y = 34.4703 - 8.0671 \cdot DBH + 0.6589 \times DBH^2$</td>
<td>0.67</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>$Y = \exp{-3.1141 + 0.9719 \times \ln[(DBH^2)H]}$</td>
<td>0.97</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
<tr>
<td>DBH &gt; 5 cm Moist (1 500 &lt; rainfall &lt; 4 000 mm)</td>
<td>$Y = \exp{-2.4090 + 0.9522 \times \ln[(DBH^2)HS]}$</td>
<td>0.99</td>
<td>Winrock (from Brown, Gillespie and Lugo, 1989)</td>
</tr>
</tbody>
</table>

Source: FAO document “Assessing carbon stocks and modeling win-win scenario of carbon sequestration”

Where: $p = 3.1415927$
$r$ = radius (cm)
$DBH$ = diameter at breast height (cm)
$H$ = height (m)
$BA = J \times r^2$
$S$ = wood density (0.61)

The work done by Brown, Gillespie and Lugo (1989) and FAO (1997) on estimation of above ground biomass of tropical forests using regression equations of biomass as a function of DBH is central to the use of this approach. DBH is used in estimating the amount of wood volume is a stand of trees (White 1998 in FAO). Some of the equations reported by Brown, Gillespie and Lugo (1989) have become standard practice because of their wide applicability. Table 2.2 presents a summary of the equations, as found in the specialized literature, including the
restrictions placed on each method.

2.1.3.3 Approach 3: Biomass Estimation from GIS Modeling

The approach for estimating biomass density based on modeling method with GIS (Geographic Information System) technology uses various existing digital data bases and maps of reliable inventories, population, density, climate, vegetation, ecofloristic zones, soils and topography. This method was developed as a means to extrapolate reliable inventory data that is generally limited in area coverage to biomass density estimates at larger scales such as continents (Brown, 1997).

Forest biomass density has been modeled in a multi-stage approach using GIS software packages and a variety of spatial and statistical data base. For estimating forest biomass density using GIS, the present distribution of forest biomass density was assumed to be based on the potential amount that the landscape can support under prevailing environmental conditions, and the cumulative impact of human activities on forests that reduce it biomass density. Many spatial data layers have been developed from existing data bases or were prepared by specialist (FAO, 1993 in Brown 1997). These data layers were entered into a GIS and processed according to specifications of the model.

The first step in this analysis was to estimate a potential biomass density (PBD) for forests. This was accomplished by first developing an index of potential biomass density based on climatic, edaphic and topographic factors. The potential biomass density map was masked with a forest map, produced by reclassifying all the forest classes of the vegetation maps into one forest class. The potential biomass density index (PBI) was calculated according to a simple model.
based on overlaying the following GIS data layers:

\[ PBI = \text{climatic index} + \text{precipitation} + \text{soil (texture, depth, slope)} + \text{topography} \]

Each of these factors was spatially represented by a numerical scale whose values were ranked according to how the particular factor affected forest biomass. The digital maps were overlain according to the above model and the results calibrated and validated using existing forest inventories for mature forests.

The final step was to add the influence of all human activities that result in a reduction of biomass of forests. This step was accomplished by using the biomass estimates from reliable forest inventory data. The first step was to calculate degradations ratios, defined here as biomass density estimations from the inventories (representing all forests of a sub-national unit) divided by the potential biomass for all forest in the same sub-national unit.

2.1.3.4 Approach 4: Biomass Estimation with Field Studies and Remote Sensing

A more comprehensive and reliable approach for estimating biomass change is to combine a new field studies with analysis of high resolution remote sensing imagery. The remote sensing efforts would be used to delineate forests into various distinct biomass strata. Then using statistical design, permanent plots in these forest strata could be established. For estimating biomass directly, stand tables are sufficient with use of the generic biomass regression equations. At least two measurements on permanent plots are needed to estimate biomass change. These measurements should preferably be a minimum of 5 year apart, particularly in forest vulnerable to change (Brown, 1997 and Hairiah et al, 2001).
2.1.4 Carbon Stock

Carbon stock is the amount of carbon which is stored in the biomass component and necromas above and below soil surface (soil organic content, plant root and microorganism) per unit area of land (Hairiah et al., 2003). The unit is in Mg ha$^{-1}$ (mega gram per ha = ton per ha). One of the important functions of the forest is as the terrestrial carbon stock, because carbon is stored in the form of vegetation biomass.

2.1.5 Carbon stock measurement

2.1.5.1 Aboveground C: Allometric relation for trees

A major proportion of the C and nutrients in terrestrial ecosystem is found in the tree component. To reduce the need for destructive sampling, biomass can be estimated from an easily measured property such as stem diameter at a specified height, by using an allometric equation. Such equations exist for many forest types and a small number are species specific (Hairiah et al., 2001). Destructive measurement of trees (cutting down and weighting) to generate allometric equations, which have high precision needs a lot of labor and time, but when it is done it can be applied to other tree species in the same forest area. A substantial number of allometric equations have been developed for various climatic zones, forest types and tree species (Brown, 1997), using a variety of algebraic forms and parameter values.

The calculation of carbon stock as biomass consists of multiplying the total biomass by a conversion factor that represents the average carbon content in biomass. It is not practically possible to separate the different biomass components in order to account for variations in carbon content as a function of
the biomass component. Therefore, the coefficient of 0.55 for the conversion biomass to C, offered by Winrock (1997), is generalized here to conversions from biomass to carbon stock:

$$C = 0.55 \times \text{biomass (total)}$$

This coefficient is widely used internationally, thus it may be applied on a project basis. The results may be displayed in a similar fashion to total biomass.

Carbon stocks of natural forests in Southeast Asia Using GIS, Brown et al., (1993) estimated that in 1980 the Winrock (1997) average C density of tropical forests in Asia was 144 ton C/ha in biomass and 148 ton C/ha in soils (up to 100 cm), which corresponds to total estimates of 42 and 43 Pg C for the whole continent, respectively. It was noted that C densities and pools in vegetation and soil varied widely by eco-floristic zone and country. Actual biomass C densities range from less than 50 to more than 360 ton C/ha with most forests having 100-200 ton C/ha.

A similar study reported an average maximum aboveground biomass C stock in forest lands in tropical Asia of 185 ton C/ha with a range of 25 to more than 300 ton C/ha. Palm et al. (1993), as reported by Houghton (1991), showed that the forests in tropical Asia have C densities between 40-250 ton/ha and 50-120 ton/ha in vegetation and soils, respectively. Southeast Asian forests have an aboveground biomass range of 50-430 ton/ha (25-215 ton C/ha) and >350-400 ton/ha (175-200 ton C/ha) before human incursion (Brown et al., 1991). For national GHG inventories, the IPCC (1997) recommends a biomass density default value of 275 ton/ha (or 138 ton C/ha) for wet forests in Asia.

There are limited data on C densities of natural forests in the specific
Southeast Asian countries. Indonesian forests have been estimated to have a C density ranging from 161-300 ton C/ha in aboveground biomass (Murdiyarso and Wasrin, 1995), 150-254 ton C/ha in above ground biomass and upper 30 cm of soil (Hairiah, et al., 2000) and 390 ton C/ha in above ground biomass and below ground pools (Hairiah and Sitompul, 2000).

2.1.5.2 Below ground C: root biomass

Roots are an important part of the C cycle because they transfer large amounts of C directly into the soil, where it may be stored for long time. Most of below-ground biomass of forest is contained in coarse roots (>2mm diameter), but most of that of annual crops is allocated to fine roots. Similar to the approach for above ground biomass via allometric relations based on stem diameter, the below ground biomass can be estimated from the proximal roots at the stem base. The theoretical basis for this relationship is found in the fractal branching properties of root system (van Noordwijk and Purnomosidhi, 1995).

2.1.5.3 Belowground C: Soil Organic Matter

Soil organic matter content at any point in time is the result of organic inputs and the past rates of decomposition, as determined by inherent properties of the soil and the vegetation or land use system of the site. There are large differences in C storage capacity of soil related to: soil texture, landscape position and degree of drainage, mineralogy and physical disturbance.

2.2 Remote Sensing

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data required by a device that is not in contact with the object, area or phenomenon under investigation.
2.2.1 Remote Sensing Application in Forestry

Application of remote sensing to sustainable forest management are presented in four categories that include classification of forest cover type, estimation of forest structure (inventory mapping), forest change detection and forest modeling. The inventory mapping of forest covers the measurement of cover, age, DBH, height, biomass, volume and growth (Franklin, 2001). Users in many countries adopt the remote sensing in many applications in forestry. These applications include forest cover type characterization, determination of forest stand conditions and forest health, site characterization and fire monitoring (Wynne and Carter, 1997). In India use remote sensing for plantation inventory and monitoring, timber volume estimation, species identification, estimation of biomass and productivity and biodiversity monitoring (Raa et al., 1997).

Table 2.3 listed the most system provide observation from a single sensors in either optical (e.g. Landsat, SPOT, IRS) or microwave (e.g. Radarsat, ERS-1) portion of the spectrum; occasionally a satellite will carry both types of sensor (e.g. ALMAZ). A few systems have thermal detectors or other sensors as part of the package but, in essence, the choice of a platform/sensor package in support of forestry applications has been limited in the past to a few satellites with quite similar characteristic in the optical or microwave portions of the spectrum (Franklin, 2001).
Table 2.3 Characteristic of selected existing and proposed satellite platforms and sensors for forestry.

<table>
<thead>
<tr>
<th>Identification</th>
<th>Sensor</th>
<th>Numb. of band</th>
<th>Spatial Resolution (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Current Operational Satellites (Year 2000)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Landsat-5</td>
<td>TM</td>
<td>7</td>
<td>30-120</td>
</tr>
<tr>
<td></td>
<td>MSS</td>
<td>4</td>
<td>82</td>
</tr>
<tr>
<td>Landsat-7</td>
<td>ETM+</td>
<td>7</td>
<td>15-30</td>
</tr>
<tr>
<td>SPOT-2</td>
<td>HRV</td>
<td>4</td>
<td>10-20</td>
</tr>
<tr>
<td>SPOT-4</td>
<td>HRV</td>
<td>5</td>
<td>10-20</td>
</tr>
<tr>
<td></td>
<td>VI</td>
<td>4</td>
<td>1150</td>
</tr>
<tr>
<td>RESURS-01-3</td>
<td>MSU-KV</td>
<td>5</td>
<td>170-600</td>
</tr>
<tr>
<td>IRS-1B</td>
<td>LISS</td>
<td>4</td>
<td>36-72</td>
</tr>
<tr>
<td>IRS-1C, -1D</td>
<td>LISS, PAN</td>
<td>4, 1</td>
<td>23-70, 5.8</td>
</tr>
<tr>
<td>IRS-P4 (Oceansat)</td>
<td>OCM</td>
<td>8</td>
<td>360</td>
</tr>
<tr>
<td>JERS-1</td>
<td>VNIR, SWIR SAR</td>
<td>8, 1</td>
<td>20, 18</td>
</tr>
<tr>
<td>Almaz</td>
<td>SAR</td>
<td>3</td>
<td>4-40</td>
</tr>
<tr>
<td>Radarsat</td>
<td>SAR</td>
<td>1</td>
<td>9-100</td>
</tr>
<tr>
<td>ERS-1,-2</td>
<td>AMI (SAR) ATSR</td>
<td>1, 4</td>
<td>26, 1000</td>
</tr>
<tr>
<td><strong>Space Imaging</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ISS-15</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
</tr>
<tr>
<td>NOAA-14</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
</tr>
<tr>
<td>NOAA-L</td>
<td>AVHRR</td>
<td>5</td>
<td>1100</td>
</tr>
<tr>
<td><strong>Proposed satellite (launch window 2000-2007)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Earthwatch</td>
<td>Quickbird</td>
<td>5</td>
<td>0.82-3.2</td>
</tr>
<tr>
<td>Orbus-3</td>
<td>Orbus</td>
<td>5</td>
<td>1-4</td>
</tr>
<tr>
<td>Orbus-4</td>
<td>Orbus Hyperspectral</td>
<td>5, 200</td>
<td>1-4, 8</td>
</tr>
<tr>
<td>IRS P5 (Cartosat)</td>
<td>Pan</td>
<td>1</td>
<td>2.5</td>
</tr>
<tr>
<td>IRS P6</td>
<td>LISS, AWiFS</td>
<td>7, 3</td>
<td>6-23.5, 80</td>
</tr>
<tr>
<td>SPOT 5</td>
<td>HRV, VI</td>
<td>5</td>
<td>5-1150</td>
</tr>
<tr>
<td>KVR-100</td>
<td>Camera</td>
<td>1</td>
<td>1.5</td>
</tr>
<tr>
<td>TK350</td>
<td>Camera</td>
<td>1</td>
<td>10</td>
</tr>
<tr>
<td>EO-1</td>
<td>Hyperion LAC, ALI</td>
<td>220, 256, 10</td>
<td>30, 250, 10-30</td>
</tr>
<tr>
<td>WIS</td>
<td>EROS</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>CBERS-2</td>
<td>CCD, IRMSS, WFI</td>
<td>5, 4, 2</td>
<td>20, 80-160, 260</td>
</tr>
<tr>
<td>Resource21</td>
<td>A, B, C, D</td>
<td>5</td>
<td>20</td>
</tr>
<tr>
<td>ADEOS-II</td>
<td>GLI</td>
<td>36</td>
<td>250-1000</td>
</tr>
<tr>
<td>Kompas</td>
<td>CCD</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>ARIES</td>
<td>ARIES-1</td>
<td>97</td>
<td>10-30</td>
</tr>
</tbody>
</table>
### 2.2.2 Remote Sensing for Aboveground Biomass Estimation

Remotely sensed data are understood here as the data generated by sensors from a platform not directly touching or in close proximity to the forest biomass. Therefore, these data comprise images sensed from both aircraft and satellites. Remote-sensing imagery can be extremely useful, particularly where validated or verified with ground measurements and observations (i.e. “ground truth”). Remote-sensing images can be used in the estimation of aboveground biomass in at least three ways (FAO document, 2000)

- Classification of vegetation cover and generation of a vegetation type map. This partitions the spatial variability of vegetation into relatively uniform zones or vegetation classes. These can be very useful in the identification of groups of species and in the spatial interpolation and extrapolation of biomass estimates.
- Indirect estimation of biomass through some form of quantitative relationship (e.g. regression equations) between band ratio indices (NDVI, GVI, etc.) or other measures such as direct radiance values per pixel or...
digital numbers per pixel, with direct measures of biomass or with parameters related directly to biomass, e.g. leaf area index (LAI).

- Partitioning the spatial variability of vegetation cover into relatively uniform zones or classes, which can be used as a sampling framework for the location of ground observations and measurements.

2.2.3 Different Satellite Images in Biomass and C-Stock Estimation

Landsat TM satellite image was used for regional biomass mapping in Madhav National Park-India (Ravan and Roys, 1996). In estimating the biomass, the ground based method was applied. It means that for estimating total above ground biomass (dry weight) natural ecosystem was divided into three components: trees, shrubs and grasses. Ground sampling was carried out by lying sample plots in homogenous vegetation strata. The quantitative measurements of plant parameters in these plots include girth at breast height (for trees) and height of individual plant. The result indicates that there is a significant relationship with spectral responses. These relationships have seasonal dependency in varying phonological conditions. The relationships are strongest in visible bands and middle infrared bands. However, spectral biomass models developed using middle infrared bands would be more reliable as compared to the visible bands as the later spectral regions are less sensitive to atmospheric changes. It was observed that brightness and wetness parameters show very strong relationship with the biomass values. Multiple regression equations using brightness and wetness isolates have been used to predict biomass values. The model used has correlation coefficient of 0.77. Percent error between observed and predicted biomass was 10.5%. The biomass estimated for the entire national park using stratified and
spectral response modeling approaches were compared and showed similarity with the difference of only 4.69%. The result indicates that satellite remote sensing data provide capability of biomass estimation (Ravan and Roys, 1996).

2.2.4 Remote Sensing Estimation of LAI

Leaf Area Index (LAI) is ratio of the total area of all leaves on a plant to the area of ground covered by the plant (m²/m²). LAI is defined as one sided green area per unit ground area in broadleaf canopies and as projected needle leaf area in coniferous canopies. LAI provides a simple measure of plant canopy density. LAI varies from less than 1 in desert to greater than 10 over tropical rain forest. Therefore, changes in LAI can also be indicative of land cover change (Nemani et al., 1996).

LAI describes a fundamental property of the plant canopy in its interaction with the atmosphere. It is an important structural parameter for quantifying the energy and mass exchange characteristic of terrestrial ecosystem such as photosynthesis, respiration, carbon, and nutrient cycle, and rainfall interception (Gong et al. 2003).

In some remote sensing studies, LAI is expressed as a one-sided ration of leaf area to projected ground area; in others, all sided LAI is measured. LAI is an important structural attribute of forest ecosystem because of its potential to be a measure of energy, gas and water exchanges. For example, physiological processes such as photosynthesis, transpiration and evapo-transpiration are functions of LAI (Pierce and Running 1988). Accordingly, LAI and forest cover type are the two critical inputs available from remote sensing that are required to run ecological process models to estimate growth and productivity across the
landscape (Running et al., 1986; Bonan, 1993; Peterson and Waring, 1994). LAI may be estimated at a variety of scales and with many different instrument and techniques (Chen and Cihlar, 1995). In the field, LAI can be estimated using litterfall sampling, sapwood allometric and light interception observation and all of labor-intensive and impractical for larger stands and landscapes (Smith et al., 1991; Fassnacht et al., 1994).

Remote sensing estimation of LAI is based on the knowledge that green leaves interact selectively with solar radiation (Jasinski, 1996). Much of the near-infrared energy is reflected by foliage (Knipling, 1970; Gausman, 1977); much of the visible energy (dominated in the red portion of the spectrum) is absorbed by photosynthesis pigments (Waring et al., 1995). Vegetation indices such as NDVI or the simple ration (SR) can be used to capture the way in which red and near-IR reflectance differ in single measure. The common approach of LAI estimation is empirical and semi-empirical modeling; the same approach discussed above, involving correlation of spectral indices with field estimates and the extension of such estimates over large areas with regression (Curran et al., 1992; Peddle et al., 1999; Wulder et al., 1996) or canopy reflectance model (Huemmrich and Goward, 1997).

### 2.2.5 Vegetation Indices

A vegetation index is a quantitative measure used to measure biomass or vegetative vigor, usually formed from combinations of several spectral bands, whose values are added, divided, or multiplied in order to yield a single value that indicates the amount or vigor of vegetation. The simplest form of vegetation index is a ratio between near infrared and red reflectance. For healthy living vegetation,
this ratio will be high due to the inverse relationship between vegetation brightness in the red and infrared regions of the spectrum.

A vegetation index (VI) was introduced as a simple remote sensing tool for over 25 years. Vegetation indices have been used for many years of increasing importance in the field of remote sensing. VI was a number that is generated by some combinations of remote sensing band and may have some relationship to the amount of vegetation in a given image pixel. Remote sensing devices operated in the green, red and near infrared 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 indices in use are summarized in Table 2.4. 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.

Cohen (1991) suggests that the first true vegetation index was the simple ratio (SR), which is the near-infrared (NIR) to red reflectance ratio described in Birth and McVey (1968)

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

Rouse et al., (1974) developed what is now called the generic Normalized Difference Vegetation Index (NDVI).
Table 2.4 Selected Remote Sensing Vegetation Index (Jensen 2000).

<table>
<thead>
<tr>
<th>Vegetation Index</th>
<th>Equation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Simple Ratio (SR)</td>
<td>( SR = \frac{NIR}{RED} )</td>
</tr>
<tr>
<td>Normalized Difference Vegetation Index (NDVI)</td>
<td>( NDVI = \frac{NIR - red}{NIR + red} )</td>
</tr>
<tr>
<td>Infrared Index (II)</td>
<td>( II = \frac{NIR_{TM4} - MidIR_{TM5}}{NIR_{TM4} + MidIR_{TM5}} )</td>
</tr>
<tr>
<td>Perpendicular Vegetation Index</td>
<td>( PVI = \sqrt{(0.355_{mm4} - 0.149_{mm2})^2 + (0.355_{mm2} - 0.852_{mm4})^2} )</td>
</tr>
<tr>
<td>Greenness Above Bare Soil (GRABS)</td>
<td>( GRABS = G - 0.09178B + 5.58959 )</td>
</tr>
<tr>
<td>Moisture Stress Index (MSI)</td>
<td>( MSI = \frac{MidIR_{TM5}}{NIR_{TM4}} )</td>
</tr>
<tr>
<td>Leaf Relative Water Content Index (LWCI)</td>
<td>( LWCI = \frac{-\log[1 - (NIR_{TM4} - MidIR_{TM5})]}{-\log[1 - NIR_{TM4} - MidIR_{TM5}]} )</td>
</tr>
<tr>
<td>MidIR Index</td>
<td>( MidIR = \frac{MidIR_{TM5}}{NIR_{TM7}} )</td>
</tr>
<tr>
<td>Soil Adjusted Vegetation Index (SAVI) and Modified SAVI (MSAVI)</td>
<td>( SAVI = \frac{(1 + L)(NIR - red)}{NIR + red + L} )</td>
</tr>
<tr>
<td>Atmospherically Resistant Vegetation Index (ARVI)</td>
<td>( ARVI = \left( \frac{p_{air}^{<em>} - p_{rb}^{</em>}}{p_{air}^{<em>} + p_{rb}^{</em>}} \right) )</td>
</tr>
<tr>
<td>Soil and Atmospherically Resistant Vegetation Index (SARVI)</td>
<td>( SARVI = \frac{p_{air}^{<em>} - p_{rb}^{</em>}}{p_{air}^{<em>} + p_{rb}^{</em>} + L} )</td>
</tr>
<tr>
<td>Enhanced Vegetation Index (EVI)</td>
<td>( EVI = \frac{p_{air}^{<em>} - p_{red}^{</em>}}{p_{air}^{<em>} + C_{1}p_{blue}^{</em>} - C_{2}p_{blue}^{*} + L} (1 + L) )</td>
</tr>
</tbody>
</table>

2.2.5.1 Simple Ratio (SR)

Cohen (1991) suggest that the first true vegetation index was the Simple Ratio (SR), which is the near-infrared (NIR) to red reflectance ratio described in Birth and McVey (1968); in Jensen (2000)

\[
SR = \frac{RED}{NIR}
\]
2.2.5.2 Normalized Difference Vegetation Index (NDVI)

NDVI (Normalized Difference Vegetation Index) 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.

The pigment in plant leaves, chlorophyll strongly absorbs visible light (from 0.4 to 0.7 µm) for use in the photosynthesis. The cell structure, on the other hand, strongly reflects near infrared light (from 0.7 to 1.1 µm). The more leaves a plant has, the more these wavelengths of light are affected, respectively.

By comparing visible and infrared light, scientist measures 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 near infrared. Mathematically, NDVI is written as:

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

The actual difference between the reflected sunlight from the red part of the spectrum and the reflected energy in the near infrared gives a qualitative measure for photosynthesis activity. NDVI value range from minus one (-1.0) to plus one (+1.0) and are unitless (Wunderle et al, 2003).

NDVI is a good indicator of the ability for vegetation to absorb photosynthetically active radiation has been widely used by researcher to estimate green biomass, LAI and patterns of productivity. The main advantages of the use of the NDVI for monitoring vegetation are the simplicity of calculation, the high degree of correlation of the NDVI with a variety of vegetation parameters and the
extensive area coverage and high temporal frequency of remote sensing data (Hess T. et al., 1996).

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 is too sparse, background signal (e.g. soil) can change NDVI significantly. Depending on the vegetation coverage, dark soil enhances the NDVI (Wunderle 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.

A few studies have attempted to predict forest biomass using the relationships between reflectance and crown closure, crown size, and species. In Japan, Lee and Nakane (1997) estimated biomass with a variety of vegetation indices obtained from Landsat TM Imagery in predominantly deciduous stands (comprised of Quercus serrata, Catanea crenata and Carpinus laxiflora), pine (Pinus densiflora) forests, and Japanese cedar (Cryptomeria japonica) plantation. The NDVI was best in predicting biomass in the pine stands (R value was 0.85). In the deciduous and cedar plantations, the difference between band 5 and 7 (called the DVI) was the best predictor (R value=-0.83 for cedar, and +0.80 for deciduous stands) (Table 2.5).

Table 2.5 The relationship between Landsat TM-Based DVI (Difference between bands 5 and 7) and biomass in 33 stands of deciduous and cedar plantation in Japan.

<table>
<thead>
<tr>
<th>Stand Type</th>
<th>R Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cedar</td>
<td>-0.83</td>
</tr>
<tr>
<td>Deciduous</td>
<td>+0.80</td>
</tr>
</tbody>
</table>

Source: Adapted from Lee and Nakane (1997)
The sign of the relationship between biomass and DVI changed in the cedar plantations compared to the deciduous stands. The cedar plantation was comprised of stands with the relatively similar age classes. Trees were a uniform diameter and canopy height. The spectral response was more scattered due to the sharp, triangular cedar crown. The DVI was thought to be more sensitive to vegetation density than to leaf moisture content and color. The changes in the relationship among the species were attributed to the influences of different shadowing and leaf biomass.

Biomass distribution in forest ecosystem is a function of vegetation type, its structure and site condition. Ground based sampling in functional homogenous vegetation categories is an approach which has found acceptability in the recent past (Shute and West 1982)

The NDVI has been shown to be useful in estimating vegetation properties, many important external and internal influence restrict its global utility.

2.3 Empirical Modeling

Empirical models are based on statistical analysis of observed data, and these are usually applicable only to the same conditions under which the observations were made. An empirical model is based only on data and is used to predict but not to explain the process of system. An empirical model consists of a function that captures the trend of the data. Data are essential for an empirical model.

Sometimes with a derived model, it might be difficult or impossible to differentiate or integrate a function to perform further analysis. Empirical
modeling (EM) offered both a broad foundational perspective on computing and a novel practical approach to modeling. Central to the EM perspective was an emphasis on the power of the computer to represent state in particular, state that was easily interpretable. Adopting a broad concept of what constituted a computer any reliable, interpretable, state changing device led to a view in which the context for computing (e.g. other devices and users) was significant as the computer itself.

Empirical model application was used to estimate biomass and carbon stock of oil palm (Htut, 2004). Empirical model using correlation analysis was very useful to examine the validation of field data to estimate LAI by using various remote sensing data and various crops. In addition, ground truth data was essential to estimate LAI based on NDVI. Fieldwork should still be undertaken, to get specific information that couldn’t be derived from the images.
III. RESEARCH METHODOLOGY

3.1 Time and Location

This research was conducted from February-August 2007. The study area is located in Lore Lindu, Central Sulawesi, Indonesia. Lore Lindu is one of the National Parks in Central Sulawesi, administratively it is belong to Donggala and Posos Regency, Central Sulawesi. The majority area of Lore Lindu National Park lies within seven districts namely Palolo, Kulawi, Sigi Biromaru, Dolo Lore Utara, Lore Tengah and Lore Selatan. Geographically lays on 119°58’–120° 16’E and 1°8’–1°3’ N.

This research was funded by BMZ and STORMA program. STORMA (Stability of Rainforest Margin in Indonesia) is an Indonesian-German collaborative Research Centre funded by the German Research Foundation (FDG)

Lore Lindu has a tropical climate with high humidity. Temperatures vary only a few degrees over the course of the year. Day time temperatures in lowland areas of the park range from 26-32°C. Highland areas are significantly cooler, as air temperature drops 6°C with every 1,100m rise in height. Rain falls throughout the year, the heaviest periods occurring during the northern monsoon which lasts from November to April. There is no pronounced wet and dry season.

The area has altitude ranges from 200m above sea level on the Gumbasa River to 2,355 m above sea level at the summit of Mount Nokilalaki, in the northeast of the park. This range of altitudes is a contributory factor to the high level of biodiversity that is found throughout the park, as assorted plants and
animals are able to inhabit the different ecological niches that this rugged landscape creates. The average annual rainfall of the park varies between 2000 and 4000 mm depending on location; it is generally heavier in the southern region of the park. This water supply is crucial to surrounding regions. The Sopu-Gumbasa river system irrigates and supplies the densely-populated Palu Valley, one of the country’s driest regions (receiving only 700mm per year due to the rain-shadow effect of the surrounding mountain). Lariang is the other major river system. It is the longest river in Sulawesi (approximately 225km long) and drains 60% of the park, mostly in the south.

![Figure 3.1 Research Study Area.](image)

### 3.2 Data Source

There are two main kinds of data using in this research are remote sensing data and field measurement data.
3.2.1 Remote Sensing Data

The multispectral satellite image data that will be used in this research is QuickBird satellite image.

Table 3.1 Acquisition Date of QuickBird Satellite Image.

<table>
<thead>
<tr>
<th>Image</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>QuickBird</td>
<td>April, 15th 2004</td>
</tr>
</tbody>
</table>

3.2.2 Field Measurement Data

The main measurement data derived from field are LAI (Leaf Area Index), plant height, diameter breast height, and plant density. LAI data from field is important to relate and obtain the equation with vegetation index value with another parameter. Plant height data is not only useful to derive the height equation with LAI in the field, but also to determine the dry weight that reflects the above ground biomass. Plant density is used for calculating the dry weight that reflects the above ground biomass in hectare.

The selection of these trees in multi-species forest poses a challenging sampling design. The selected trees must come from the population of interest, represent the major species in the forest and represent all size classes (Brown, 1997).

3.3 Method

This research was conducted by using the fourth approach as mentioned in literature of estimating the biomass that combines field studies (forest inventory data), analysis of multispectral satellite imagery, allometric equation and statistical analysis. The general procedures are described in Figure 3.2.
Figure 3.2 General procedure of biomass and carbon stock estimation.

3.4 Forest Cover Type Classification

Forest cover type classification is useful for analyzing the biomass per pixel in each different cover type. The habitat description as defined by STORMA (by workshops of 1-9 September 2003) consist of 6 type, these are: Habitat type A, B, C, D, E and F (D, E and F included in D as agro forestry system).

1. Habitat type A: Natural forest with traditional use (rattan extraction) but without timber extraction; closed canopy.

2. Habitat type B: Natural with minor extraction of small trees (used to build small pondoks) not affecting the closure of the upper canopy layer.

3. Habitat type C: Natural forest with major timber extraction indicated by large, artificial gaps in and pronounced decrease of the canopy cover to only 40-60%.

4. Habitat type D: Agro-forestry system (dominated by cacao) with remaining
natural forest trees as shade trees. Canopy closure: 20-50%. Low intensity management.

5. Habitat type E: Agro-forestry system (dominated by cacao) shaded by diverse spectrum of planted trees and trees naturally grown after clear cutting.

6. Habitat type F: Agro-forestry system with a shade tree layer dominated by one tree species (Erythrina)>90% of all shade trees belong to one tree species. Canopy closure: 20-50%

[Note: the intensity of the agro forestry management not really differs between habitat types D, E and F. in all types crops are more or less planted in rows]

The classifications for each cover type by Supervised Classification (Maximum Likelihood) using region or training sample set of plot observation. It based on the different spectral value in each observation plot refer to QuickBird Image (Figure 3.3).

![Flowchart](image)

**Figure 3.3 Forest covers type classification procedure.**
3.5 Vegetation Index

Remote sensing technology using satellite image has a view of large areas of the surface to estimate the vegetation index value. Normalized Difference Vegetation Index was chosen for the vegetation analysis because the different resolution and time acquisition of three available images will contain different aspect that need to be normalized. NDVI of QuickBird Satellite imagery data obtained by the product of the ratio of near infrared and red channels, is formulated as follow

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

3.6 Field Data Measurement

The selected trees must come from the population of interest, represent the major species in the forest and represent all size classes. The method of field sampling applied for collecting field data is quadrate sampling, with 30m x 30m plot size. The scheme for distributing sample over the area of interest, use stratified systematic random sampling. Stratification done for the forest cover becomes A, B, C, D type. A systematic way was chosen to spread the plant in row evenly, and then the trees were measured for each row randomly. Stratification will achieve greater precision provided that the strata have been chosen so that members of the same stratum are as similar as possible in respect of the characteristic of interest.

The diameter breast height was calculated from the girth of the trees and converted to the trees diameter. Trees total height was measured by using vertex that has the function of measuring heights, distance, angle inclination and air temperature. The x and y trees canopy was also measured by using vertex.
Figure 3.4 The sampling scheme for field measurement data.

Leaf Area Index (LAI) was measured by using manual calculation that combine the digital leaf measurement for each leaf area then multiply by the total leaf calculated in the each observation trees the divided by x and y canopy area. The digital camera is utilized for take a picture of leaf to be converted to digital form. Leaf area measurement utilized the Autocad Map Software.

The procedure is described in Figure 3.5. The sequential method to measure LAI manually are: (1) taking a picture of an average trees leaf that represent the leaf of each tree species within observation plot; (2) measure the real length of the trees leaf, real length measurement used for calibration between leaf picture and width length of real leaf; (3) digitize the area of leaf in a software and derive the real leaf area for each leaf area within plot observation; (4) total leaf in each tree species within observation plot was counted manually by using the total leaf for each branch approach; (5) multiply the total leaf with leaf area; (6) the total leaf divided by the canopy area where the trees are projected.
3.7 Calculating Biomass using Allometric Equation (ton/ha)

The empirical model is chosen to estimate biomass and carbon content by using field data. Empirical model were based on statistical analysis of observed data, and these were usually applicable (derived from previous research).

Therefore, the biomass of the tree is estimated with allometric relationship of total height and diameter breast height. Allometric relationship of total height and DBH will be used to measure quantity of biomass (FAO 1997). To calculate biomass ton per hectare the following allometric equation use:

\[
W_{dry} = \exp[-3.1141 + 0.9719\ln(D^2H)] \ldots \ldots \text{(Brown, 1997)}
\]

Where:  
\(W_{dry}\) = total biomass (ton/ha)  
\(D\) = diameter at Breast height (cm)  
\(H\) = height of plant between blocks (m)  
\(P\) = planting density within the blocks
3.8 Calculating Carbon-Stock (ton/ha)

An estimate of carbon stock in plantation is generally based on allometric equations relating as carbon or biomass to plant height.

Equation to calculate carbon stock,

\[ C – \text{Stock} = 0.55 \times \text{Biomass(total)} \ldots (\text{Winrock (1997),}) \]

3.9 Statistical Analysis

3.9.1 Standard deviation

The first and easy method of analyzing different use of image in estimating the tree biomass is by comparing the global statistics of each data set; specifically means and standard deviations as well as the absolute differences between the two data sets [e.g. Bosltad and Stowe 1994, Rieger 1996].

The **standard deviation** (s) is a measure of the spread of its values. It is defined as the square root of the variance (s²)

\[ s = \sqrt{\frac{1}{N - 1} \sum_{i=1}^{N} (x_i - \bar{x})^2}, \]

The standard deviation is the root mean square\(^2\) (RMS) deviation of values from their arithmetic mean. The standard deviation is the most common measure of statistical dispersion, measuring how widely spread the values in a data set is. If the data points are close to the mean, then the standard deviation is small. Conversely, if many data points are far from the mean, then the standard deviation is large. If all the data values are equal, then the standard deviation is zero.

\(^2\) Also known as the **quadratic mean**, is a statistical measure of the magnitude of a varying quantity. It is especially useful when variates are positive and negative
Standard deviation may serve as a measure of uncertainty. In physical science for example, the reported standard deviation of a group of repeated measurements should give the precision of those measurements. When deciding whether measurements agree with a theoretical prediction, the standard deviation of those measurements is of crucial importance: if the mean of the measurements is too far away from the prediction (with the distance measured in standard deviations), then we consider the measurements as contradicting the prediction. This makes sense since they fall outside the range of values that could reasonably be expected to occur if the prediction were correct and the standard deviation appropriately quantified.

3.9.2 Correlation Coefficients

Correlation is a measure of the relation between two or more variables. The measurement scales used should be at least interval scales, but other correlation coefficients are available to handle other types of data. Correlation coefficients can range from -1.00 to +1.00. The value of -1.00 represents a perfect negative correlation while a value of +1.00 represents a perfect positive correlation. A value of 0.00 represents a lack of correlation.

Comparison of two-dimensional data can also be examined by computing the correlation coefficient of the two images. The correlation coefficient ($\rho$) of two images or matrices $A$, $B$ of the same size can be defined as

$$\rho = \frac{\sum_{n_1} \sum_{n_2} A(n_1, n_2)B(n_1, n_2)}{\sqrt{\sum_{n_1} \sum_{n_2} A^2(n_1, n_2)\sum_{n_1} \sum_{n_2} B^2(n_1, n_2)}}$$

Where $\rho$ has a value between 0 to 1 (indicating low to high correlation), $n_1$ is the number of row in the image, $n_2$ is the number of column in the image.
<table>
<thead>
<tr>
<th>Correlation coefficient</th>
<th>Interpretation</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.00 - &lt; 0.20</td>
<td>The relation is very weak (ignorable)</td>
</tr>
<tr>
<td>≥0.20 - &lt; 0.40</td>
<td>The relation is low</td>
</tr>
<tr>
<td>≥0.40 - &lt; 0.70</td>
<td>The relation is moderate/enough</td>
</tr>
<tr>
<td>≥0.70 - &lt; 0.90</td>
<td>The relation is strong/high</td>
</tr>
<tr>
<td>≥0.90 - ≤ 1.00</td>
<td>The relation is very strong/high</td>
</tr>
</tbody>
</table>

Source: JP. Guilford, Fundamental Statistic in Psychology and Education (taken from Somantri and Muhidin, 2006)

3.9.3 Correlation between the parameter

The correlation describes the direction and strength of a straight-line relationship between two variables. Correlation is written as $r$.

- Positive $r$ indicates positive association between the variables, and negative $r$ indicates negative association.
- The correlation $r$ always falls between -1 and 1. Values of $r$ near 0 indicate a very weak straight-line relationship. The strength of the relationship increases as $r$ moves away from 0 toward either -1 or 1. Values of $r$ close to -1 or 1 indicate that the points lie close to a straight line. The extreme values $r = 1$ and $r = -1$ occur only when the points in a scatterplot lie exactly along a straight line.
- Because $r$ uses standard scores, the correlation between $x$ and $y$ does not change when we change the units of measurement of $x$, $y$ or both.
- Correlation ignores the distinction between explanatory and response variables. If we reserve our choice of which variable to call $x$ and which to call $y$, the correlation does not change.
- Correlation measures the strength of only straight-line association between two variables. Correlation does not describe curved relationships between variables, no matter how strong they are.
A scatter plot displays the relationship between two variables. Correlation measures the strength and direction of a straight-line relationship. A regression line summarizes the relationship between two variables, but only in a specific setting.

The regression model is produced from the analysis of correlation between the variables of biomass, DBH, total height, vegetation index and LAI. The objective of regression analysis is to predict the dependent variable (y) about the independent variable (x). The regression analysis use the linear and non linear model to produce the best model that is fit the data field observation.

### 3.10 Resource Requirement

<table>
<thead>
<tr>
<th><strong>Hardware</strong></th>
<th>PC Pentium IV Printer</th>
<th>Software running Printing</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Software</strong></td>
<td>Arc View ER Mapper Microsoft office</td>
<td>Spatial data processing Image processing Non-spatial data entry processing, statistical analysis and reporting</td>
</tr>
<tr>
<td><strong>Equipment</strong></td>
<td>GPS Digital camera Vertex Measuring tape</td>
<td>Position measurement LAI Measurement Plant height and x y canopy measurement DBH measurement</td>
</tr>
</tbody>
</table>

---

3 A regression line is a straight line that describes how a response variable y changes an explanatory variable x takes different values. A regression line often used to predict the value of y for a given value of x. Regression, unlike correlation, requires that we have an explanatory variable and a response variable.
## 3.11 Research Schedule

<table>
<thead>
<tr>
<th>Activity</th>
<th>Month</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2</td>
</tr>
<tr>
<td>Research preparation</td>
<td></td>
</tr>
<tr>
<td>- Literature Review, Design</td>
<td></td>
</tr>
<tr>
<td>project</td>
<td></td>
</tr>
<tr>
<td>- Research proposal</td>
<td></td>
</tr>
<tr>
<td>- Preparation of recommendation</td>
<td></td>
</tr>
<tr>
<td>Letter</td>
<td></td>
</tr>
<tr>
<td>Data Collection</td>
<td></td>
</tr>
<tr>
<td>- Secondary Data collection:</td>
<td></td>
</tr>
<tr>
<td>- Satellite Image</td>
<td></td>
</tr>
<tr>
<td>- Vegetation data</td>
<td></td>
</tr>
<tr>
<td>- Vector and raster data support</td>
<td></td>
</tr>
<tr>
<td>- Data primer collection (ground</td>
<td></td>
</tr>
<tr>
<td>check)</td>
<td></td>
</tr>
<tr>
<td>Data Processing</td>
<td></td>
</tr>
<tr>
<td>Data Analysis</td>
<td></td>
</tr>
<tr>
<td>Research Report</td>
<td></td>
</tr>
<tr>
<td>Seminar</td>
<td></td>
</tr>
</tbody>
</table>
IV. RESULT AND DISCUSSION

The results of this research are based on the expected output. Those are correlation regression equation model and graph of each parameter, total tree biomass and carbon stock estimated value, and total tree biomass and carbon stock for each forest cover type and whole study area.

4.1 Field Data Measurement

Plots observation were based on the forest cover type as defined by STORMA in the second phase (by workshops of 1-9 September 2003) consist of 6 type, these are: Habitat type A, B, C, D, E and F. Forest cover A, B, C and C are natural or primary forest and forest cover type D, E, F are agroforestry system. The plot observation shows that forest cover A has more closed canopy than the other, because there is no timber extraction. Forest cover type B still has close canopy, even with the minor extraction of small trees (diameter<5cm) it has no significant influences on canopy layer. Forest cover C has less trees and canopy layer than A and B due to the timber extraction that reduce trees density inside the plot observation. Forest cover type D, E and F are agro-forestry system that dominated with cacao, most of the plot observation is cacao plantation with shaded trees inside. The total plots observations are 19 plots located in Toro-Kulawi district listed in the Table 4.1.

The habitat types are considered as the parameter in determining the vegetation forest type by using stratified systematic random sampling. The type of D, E and F are included in one type as D type (agro forestry). These habitat type
will represent the different vegetation grow in the different land condition, topography and rainfall rate.

Table 4.1 Plot observation in Toro-Kulawi district.

<table>
<thead>
<tr>
<th>Plot No.</th>
<th>Cover Type</th>
<th>Plot Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>South Kalabui</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>North Kalabui</td>
</tr>
<tr>
<td>3</td>
<td>A</td>
<td>Lonca</td>
</tr>
<tr>
<td>4</td>
<td>A</td>
<td>Kolewuri</td>
</tr>
<tr>
<td>5</td>
<td>B</td>
<td>Lonca</td>
</tr>
<tr>
<td>6</td>
<td>B</td>
<td>Kalabui</td>
</tr>
<tr>
<td>7</td>
<td>B</td>
<td>Kolewuri</td>
</tr>
<tr>
<td>8</td>
<td>C</td>
<td>Komanua</td>
</tr>
<tr>
<td>9</td>
<td>C</td>
<td>Kuku</td>
</tr>
<tr>
<td>10</td>
<td>C</td>
<td>Lonca</td>
</tr>
<tr>
<td>11</td>
<td>D</td>
<td>Penga</td>
</tr>
<tr>
<td>12</td>
<td>D</td>
<td>Ambi</td>
</tr>
<tr>
<td>13</td>
<td>D</td>
<td>Abia</td>
</tr>
<tr>
<td>14</td>
<td>E</td>
<td>Iskandar</td>
</tr>
<tr>
<td>15</td>
<td>E</td>
<td>Ace</td>
</tr>
<tr>
<td>16</td>
<td>E</td>
<td>Abdullah</td>
</tr>
<tr>
<td>17</td>
<td>F</td>
<td>Dada</td>
</tr>
<tr>
<td>18</td>
<td>F</td>
<td>Theodoris</td>
</tr>
<tr>
<td>19</td>
<td>F</td>
<td>Andreas</td>
</tr>
</tbody>
</table>

Figure 4.1 Plot distribution of field data observation.
The habitat types are considered as the parameter in determining the vegetation forest type by using stratified systematic random sampling. The type of D, E and F are included in one type as D type (agro forestry). These habitat type will represent the different vegetation grow in the different land condition, topography and rainfall rate. The plots distribution over the study area represents the different cover type of A, B, C, D, E and F as figured in Figure 4.1.

The observation result of each forest cover type condition was figured in Figure 4.2 and Figure 4.3. Forest covers A, B and C are natural or primary forest and forest cover type D, E and F are agro forestry system. Forest cover A has more closed canopy than the other, because there is no timber extraction. Forest cover B still has closed canopy, even with minor extraction of small trees (diameter<5cm) it has no significant influences on canopy layer. Forest cover C has less trees and canopy layer than A and B due to the timber extraction that reduce trees density inside the plot observation. Forest cover D, E and F are agro-forestry system that dominated with cacao, because most of the plot observation is cacao plantation that combined with shaded trees.
Figure 4.2 Plot observation for cover type A and B.
Figure 4.3 Plot observation for cover type C and D.
4.2 Forest cover type classification using Quick Bird image

The study area of Toro-Kulawi District was chosen for the biomass analysis, because of the consideration about the image data availability that covered this area (Figure 4.4).

This research has only been focused on the above ground trees biomass
estimation and carbon stock estimation of year 2006/2007 by using Quick Bird acquisition 2004 (one of these three the satellite images). The consideration of using Quick Bird satellite images is because it has newest acquisition date and highest resolution so that the point of plot observation easier to be identified than using the other satellite images.

Forest cover type classification was conducted by using Supervised Classification of QuickBird satellite image based on region training that utilizes the spectral value of field plot observation. The image was classified into forest and non forest area. Forest cover type was classified into A, B, C, D and non forest area (Bare land, shrubs, cloud and paddy field) as depicted in Figure 4.5.

![Forest covers type classification of Quick Bird image.](image)

The independent test analysis was conducted to estimate the accuracy of image classification derived from QuickBird. It utilizes the plot observation used in the supervised classification and plot, which is not included as the training set of the classification. The non training area is used to check the accuracy of supervised classification result by plotting those non training area on the supervised classification result. The independent test resulted from QuickBird
image classification show that the image classification accuracy is about 50%.
The classification accuracy matrix test is displayed in appendix.

The inappropriate ground control point (GCP) taken in the study area that
does not cover the plot observation will influence the accuracy of the geometric
correction. In addition, the multispectral of QuickBird satellite image could affect
the variety of spectral value of the classification result that lead to the decreasing
of classification accuracy.

Table 4.2 Percentage of forest and non forested area in study area

<table>
<thead>
<tr>
<th>Area</th>
<th>Type</th>
<th>Total Area (Ha)</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Forested</td>
<td>A</td>
<td>699.04</td>
<td>40</td>
</tr>
<tr>
<td></td>
<td>B</td>
<td>525.02</td>
<td>30</td>
</tr>
<tr>
<td></td>
<td>C</td>
<td>94.53</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>D</td>
<td>119.54</td>
<td>7</td>
</tr>
<tr>
<td>Non-forested</td>
<td>Bareland</td>
<td>28.26</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td>Shrubs</td>
<td>94.41</td>
<td>5</td>
</tr>
<tr>
<td></td>
<td>Paddy field</td>
<td>193.23</td>
<td>11</td>
</tr>
<tr>
<td></td>
<td>Total</td>
<td>1754.03</td>
<td>100</td>
</tr>
</tbody>
</table>

The percentage of forest and non forested area of study area derived from
QuickBird image classification (Table 4.2) show about 82% study area is forested
area, and 18% are non forested area. The dominant forest cover of forested area is
type A about 40% and followed by type B, D, C respectively. Non forested area is
dominated with paddy field about 11% of total area.

4.3 Correlation between the parameters

The strength of correlation, correlation pattern and equation model of
each parameter will be explained by using the regression correlation analysis. The
regression models used to know the correlation pattern in the analysis are: linear,
logarithmic, exponential, polynomial and power as possible regression models.
Those models were chosen in which the “good fit” passes through most of the
plotted observation points, in order to give the best prediction model. The result of regression correlation analysis will show the strength and the type of model between the parameter of trees biomass, DBH, total height, vegetation index and LAI. The equation derived from the regression model type will be used to calculate the dependent variable (y).

### 4.3.1 Biomass and Diameter Breast Height (DBH)

The correlation between the trees biomass and DBH for each cover type was tested independently among all plots observation for each cover type by using regression analysis and ANOVA test. Analysis of variant (ANOVA) result and homogeneity test shows that there no significant different between the parameter of each observation plot for all forest cover type (statistical result in appendix).

![Figure 4.6 Tree biomass and DBH of forest cover type A using polynomial regression.](image)

The independent test analysis used for each plot observation A separately using polynomial regression model (Figure 4.6), the result of the correlation
regression pattern, visually shows that there is no significant different between each plot observation data within forest cover type A. It is mean that the regression model derived from each correlation regression analysis is also allowed to be implemented because DBH highly correlated with the dependent variable of trees biomass.

The plot observation data of B1, B2 and B3 are also compared using independent test. The pattern trend derived from polynomial and power correlation regression of B1, B2 and B3 (Figure 4.7 and Figure 4.8) is visually show that DBH influence on trees biomass is not significantly difference between each observation plot. The correlation between the parameter is equally high about 98%.

![Figure 4.7 Tree biomass and DBH of forest cover type B using polynomial regression.](image)

\[
y_{B1} = 1.1329x^2 - 2.9149x - 73.494 \\
R^2 = 0.9939
\]

\[
y_{B2} = 1.3002x^2 - 26.401x + 197.27 \\
R^2 = 0.9972
\]

\[
y_{B3} = 1.3842x^2 - 26.444x + 160.96 \\
R^2 = 0.9722
\]
The independent power regression trend pattern of forest cover type C (Figure 4.9) for each plot, show that there is no different gap of DBH influence on biomass between the observation plots. The correlation coefficient of the power model is equally high about 90%.

Figure 4.8 Tree biomass and DBH of forest cover type B using power regression.

Figure 4.9 Tree biomass and DBH of forest cover type C using power regression.
Independent test of forest cover type D using polynomial and power regression model (Figure 4.10 and Figure 4.11), visually show that there is no significant different of observation plot data DBH on tree biomass.

\[
y_{1,3,5,7,9} = 1.1654x^2 - 21.351x + 89.158 \\
R^2 = 0.9213
\]

\[
y_{2,4,6,8} = 1.3466x^2 - 26.466x + 128.01 \\
R^2 = 0.8795
\]

Figure 4.10 Tree biomass and DBH of forest cover type D using polynomial regression.

Figure 4.11 Tree biomass and DBH of forest cover type D using power regression.

The independent test resulted from statistical analysis of forest cover A,
B, C and D infer that the plot observation data within each forest cover type is possible to be used to further regression analysis to derive the equation regression model for trees biomass prediction, because there is no significant different among each plot for all forest cover type.

The plot observation data for all point of forest cover type A, B, C and D is used to derived the regression model that the trend line of dispersion plot value are fitted using polynomial, power and linear model. The correlation is about 90% for all forest cover type show the strong correlation between tree biomass and DBH. The equation model derived from each forest cover type is summarized in Table 4.3.

\[
y = 109x - 1597 \\
R^2 = 0.834
\]

\[
y = 1.2888x^2 - 16.508x + 60.506 \\
R^2 = 0.9656
\]

\[
y = 0.0829x^{2.6291} \\
R^2 = 0.9823
\]

![Figure 4.12 Tree biomass and DBH correlation regression model of forest cover type A](image)

The strong correlation of forest cover type B, C and D (Figure 4.13 and Figure 4.14) derived from power regression model.
Figure 4.13 Tree biomass and DBH correlation regression model of forest cover type B.

Figure 4.14 Tree biomass and DBH correlation regression model of forest cover type C.
The regression coefficient of each cover type and general tropical forest is about 90%, it shows a high correlation between biomass and DBH vegetation of tropical rainforest.

Figure 4.15 Tree biomass and DBH correlation regression model of forest cover type D.

Figure 4.16 Tree biomass and DBH correlation regression model of tropical rain forest covering type A, B, C and D.
The correlation coefficient of non linear regression model derived from the analysis is higher than linear regression model. However, the equation model from the linear regression model is still usable, because the correlation coefficient is strong (more than 80%). The curve pattern from non linear regression model (polynomial and power) is highly representing the pattern of biomass that influenced by diameter of each tree in forest cover A, B, C and D.

The high of correlation value of forest cover A, B, C and D between the tree biomass and DBH shows that the diameter breast, the parameter reflecting the trees stem influence much on biomass compared with another growth parameter, as the previous research proved that the stem biomass gives the biggest percentage to the total tree biomass. The trees biomass on *Acacia mangium* (tropical forest tress) 80% of biomass is on stem, 11% on branch, 5% on leaves and 4% on small branch (Wicaksono, 2004). Another result from the biomass in tropical forest trees study of Adinugroho (2002) also resulted the resemble distribution percentage of biomass.

### 4.3.2 Biomass and Total Height

The independent correlation test and ANOVA test was also conducted for trees biomass and tree total height parameter in each forest cover type. Analysis of variant (ANOVA) result shows that there is no significant different between the parameter of each observation plot for all forest cover type (statistical result in appendix).

The power regression pattern of forest cover type A and B visually show that there is significant different between total height influence of the observation plot (Figure 4.17 and Figure 4.18). The correlation between the parameter of each
pattern plot is strong, depicted in correlation coefficient is more than 80% resulted from power regression model.

Figure 4.17 Tree biomass and total height of forest cover type A using power regression.

Figure 4.18 Tree biomass and total height of forest cover type B using power regression.
The pattern of power regression model of forest cover C (Figure 4.19) show that the difference value of total height on tree biomass is different when the total height reach more than 25 m. It is due to the condition of plot observation of forest cover C that has different vegetation density, but the difference is tolerable because the pattern of changing is equally the same.

![Figure 4.19 Tree biomass and total height of forest cover type C using power regression.](image)

\[
y_{C1} = 0.0063x^{3.7457} \\
R^2 = 0.8894 \\
y_{C2} = 0.1615x^{2.4668} \\
R^2 = 0.6312 \\
y_{C3} = 0.1509x^{2.6875} \\
R^2 = 0.8201
\]

Figure 4.19 Tree biomass and total height of forest cover type C using power regression.

![Figure 4.20 Tree biomass and total height of forest cover type D using polynomial regression.](image)

\[
y_{D1} = -0.0276x^2 + 76.26x - 302.15 \\
R^2 = 0.7563 \\
y_{D5} = 0.6605x^2 + 73.085x - 316.09 \\
R^2 = 0.7357 \\
y_{D4} = 2.5675x^2 - 12.876x + 15.241 \\
R^2 = 0.7135 \\
y_{D3} = 0.3641x^2 + 59.397x - 261.65 \\
R^2 = 0.8471 \\
y_{D6} = 1.0147x^2 + 2.8755x - 3.1677 \\
R^2 = 0.9015
\]

Figure 4.20 Tree biomass and total height of forest cover type D using polynomial regression.
The polynomial regression pattern of forest cover D derived from independent analysis, shows that there is no significant different on influencing total height to tree biomass between the observation plot.

The plot observation data for all points of forest cover type A, B, C and D is used to derived the regression model that the trend lines of dispersion plot values are fitted using polynomial, power and linear model. The correlation coefficient of the trees biomass and total height of each cover type is lower than its correlation with the trees diameter, but the correlation is still high range about 70%-90% from non linear model (Figure 4.21 - Figure 4.25). The equation model between tree biomass and total height derived from each forest cover type is summarized in Table 4.3.

\[
y = 0.0354x^{3.1512} \\
R^2 = 0.8875
\]

\[
y = 182.43x - 2055.1 \\
R^2 = 0.4505
\]

\[
y = 7.3733x^2 - 135.75x + 496.5 \\
R^2 = 0.5792
\]

Figure 4.21 Tree biomass and total height correlation regression model of forest cover type A.
Figure 4.22 Tree biomass and total height correlation regression model of forest cover type B.

Figure 4.23 Tree biomass and total height correlation regression model of forest cover type C.
**Figure 4.24** Tree biomass and total height correlation regression model of forest cover type D.

**Figure 4.25** Tree biomass and DBH correlation regression model of tropical rain forest covering type A, B, C and D.
The more strength relation is derived from non linear regression model of forest cover A, B, C and D. The pattern curve of the model is curvilinear. It means that the total trees height will influence significantly on biomass when the trees reach certain total height.

4.3.3 Biomass and LAI

The regression coefficient of trees biomass and leaf area index is not high as another parameter correlation (Figure 4.26). This correlation coefficient of trees biomass and LAI is moderate (enough) more than 50%. The highest percentage of trees biomass is allocated in trees diameter instead of the trees leaf density.

\[
\begin{align*}
y &= 0.0084x^2 + 104.93x - 165.9 \quad R^2 = 0.4272 \\
y &= 21.182x^{1.6241} \quad R^2 = 0.5821 \\
y &= 33.584e^{0.4073x} \quad R^2 = 0.5938
\end{align*}
\]

![Figure 4.26 Trees biomass and LAI correlation.](image)

The correlation between biomass and LAI is related with photosynthesis process. The more increasing of plant age, the photosynthesis rate decreased because of the decreasing of sun radiation, consequently the biomass will be constant (Sitompul and Guritno, 1995).
4.3.4 Biomass and NDVI

The correlation coefficient is more than 50%, means the correlation between trees biomass NDVI is moderate (Figure 4.27). The model of trees biomass and NDVI may still be applied for deriving the forest cover biomass map. This correlation is not as high as another parameter that representing the trees biomass. In applying this model, many things need to be considered first because the different acquisition time and wetness of the captured area will influence much on the vegetation index value.

![Figure 4.27 Biomass and NDVI image correlation of each cover type.](image)

4.3.5 LAI and NDVI

The correlation coefficient derived from NDVI and LAI is moderate for representing the relation among these parameter, it is about 60% from non linear regression model of polynomial, exponential and power regression pattern as depicted in Figure 4.28. This correlation is supposed to be high based on the theory. NDVI value was highly related to LAI (Growrd and Dye; Box et al.,
The tropical rain forest has variety component of vegetation, especially in the primer or natural forest cover type. The vegetation variety also contained in each plot field observation. Every vegetation species has the Leaf Area Index range based on its total area and width canopy cover. It will influence the data variety to derive the correlation coefficient and equation model. In addition, impreciseness of coordinate point of each observation plot will also influence the correlation between the parameter when entered in the statistical analysis.

\[ y = 96.094x^2 - 115.91x + 36.812 \quad R^2 = 0.6729 \]
\[ y = 17.955x^{5.3265} \quad R^2 = 0.677 \]
\[ y = 0.0181e^{7.1392x} \quad R^2 = 0.6754 \]

Figure 4.28 LAI and NDVI image correlation.

4.4 Model analysis

The equation models of trees biomass, DBH and total height derived from each cover type are summarized in the Table 4.3. The detail statistical analysis information can be found in the appendix. The equation model summarize in Table 4.3 most has high correlation between the parameters.

The A, B, C and D forest cover type have different model to estimate the trees biomass. It is based on the specific condition of each cover type. The statistical analysis was done by using many sample data (50-70 trees for each
cover type) within field plot observation. Each model has different regression coefficient that shows the correlation strength of parameters in the model. The highest regression coefficient has the highest correlation; it means that the model is highly recommended. These models can be applied for estimating biomass in the tropical rain forest with the same condition as mentioned in Table 4.3.

Table 4.3 Equation model between the parameters.

<table>
<thead>
<tr>
<th>Type</th>
<th>Vegetation Type Description</th>
<th>Model</th>
<th>( R^2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Natural forest with traditional use (rattan extraction) but without timber extraction; closed canopy</td>
<td>( Y = \log \text{DBH}-1597 )</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 1.2888\text{DBH}^2-16.508\text{DBH}+60.506 )</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0829 \text{DBH}^{1.629} )</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0354 \text{TH}^{1.151} )</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = -1192 + 125 \text{DBH} - 46.4 \text{TH} )</td>
<td>0.84</td>
</tr>
<tr>
<td>B</td>
<td>Natural with minor extraction of small trees not affecting the closure of the upper canopy layer.</td>
<td>( Y = 66.366\text{DBH}-822.57 )</td>
<td>0.83</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 1.2921\text{DBH}^2-17.999\text{DBH}+70.513 )</td>
<td>0.95</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0835\text{DBH}^{2.0342} )</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0483\text{TH}^{1.0581} )</td>
<td>0.85</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 5.3769\text{e}^{0.211\text{TH}} )</td>
<td>0.79</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = -863 + 158 \text{DBH} - 120 \text{TH} )</td>
<td>0.85</td>
</tr>
<tr>
<td>C</td>
<td>Natural forest with major timber extraction indicated by large, artificial gaps in and pronounced decrease of the canopy cover to only 40-60%.</td>
<td>( Y = 0.1079\text{DBH}^{2.5216} )</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0626\text{TH}^{2.9134} )</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = -1223 + 13.4 \text{DBH} + 97.9 \text{TH} )</td>
<td>0.86</td>
</tr>
<tr>
<td>D</td>
<td>Agro forestry system (dominated by cacao) with remaining natural forest trees as shade trees.</td>
<td>( Y = 0.0631\text{DBH}^{2.3524} )</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 1.1716\text{DBH}^2+21.001\text{DBH}-88.968 )</td>
<td>0.91</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.1475\text{TH}^{2.6252} )</td>
<td>0.75</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = -416 + 24.7 \text{DBH} + 40.0 \text{TH} )</td>
<td>0.76</td>
</tr>
<tr>
<td></td>
<td>Natural Forest without timber extraction and minor extraction</td>
<td>( Y = 1.2238\text{DBH}^2-12.183\text{DBH}+8.1704 )</td>
<td>0.97</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0407\text{TH}^{3.1182} )</td>
<td>0.87</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 610.33\text{NDVI}^{2.508} )</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>Tropical Forest containing ABCD cover type</td>
<td>( Y = 6E-05\text{DBH}^{2.6705} )</td>
<td>0.96</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0013\text{DBH}^2-0.0159\text{DBH}+0.0347 )</td>
<td>0.86</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0002\text{TH}^{1.6783} )</td>
<td>0.82</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = -1.13 + 0.0701 \text{DBH} + 0.0364 \text{TH} )</td>
<td>0.67</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 33.584 \text{e}^{0.4073 \text{LAI}} )</td>
<td>0.59</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( Y = 0.0065 \text{e}^{13.615 \text{NDVI}} )</td>
<td>0.54</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( \text{LAI} = 17.955 \text{NDVI}^{5.3265} )</td>
<td>0.67</td>
</tr>
</tbody>
</table>

Prerequirement model under moist climate (1500<rainfall<4000mm/year) and DBH>5 cm

- \( Y \) = Biomass (kg/plant)
- DBH = Diameter at Breast Height (cm)
- TH = Total height (m)
- LAI = Leaf Area Index
- NDVI = Normalized Difference Vegetation Index

To derive biomass in ton/ha= by multiplying biomass with Population in Ha/1000
4.4.1 Comparison between field and biomass model

The difference value between trees biomass resulted from field and model was used to analyst the correlation of DBH and total height that significantly influence on trees biomass.

4.4.1.1 DBH on field and biomass model

The curve pattern of Figure 4.29 - Figure 4.31 show the linear correlation between trees biomass and DBH occurred when the trees diameter reach 60 cm. It means that the diameter will significantly influence the biomass. The increasing of trees biomass in forest cover type A followed by the trees diameter, when trees diameter already reach 60 cm.

![Figure 4.29 DBH on field and model trees biomass comparison of forest cover type A.](image1)

![Figure 4.30 DBH on field and model trees biomass comparison of forest cover type B.](image2)
The correlation trend of cover type A is different from the pattern of cover types B and C. The diameter in forest cover type B and C will significantly influence the trees biomass increasing when the trees diameter reaches 30 cm (Figure 4.30 and Figure 4.31).

The correlation curves of forest cover type D is constant (flat), means that trees diameter give no significant change on trees biomass increasing (Figure 4.32). Forest cover D is a cover type with agro-forestry system that dominated with cacao. The homogeneity of cacao plantation determines this curve regression.
4.4.1.2 Total height on field and model biomass

The regression linear curves of all cover types (A, B, C and D) have a same pattern, which show the significant influence of total height on trees biomass when the total height is more than 15 m (Figure 4.33-Figure 4.36).

**Figure 4.33 Total height on field and model trees biomass comparison for forest type A.**

**Figure 4.34 Total height on field and model trees biomass comparison for forest type B.**
4.5 Biomass and Carbon Stock Estimation

The total trees biomass resulted from every pixel in remote sensing image (Table 4.4) for each cover type was derived from data field observation, allometric equation and Quick Bird multispectral satellite image classification.

Table 4.4 shows that the trees biomass of each forest cover type is different. The biomass range is derived from the standard deviation of biomass estimation between the observation plots. The forest cover type A and B has the higher biomass than C and D, it is about 596.41-618.66 ton/ha and 583.94-622.19 ton/ha. Forest cover type C has 446.65-468.50 ton/ha trees biomass. Forest cover
type D has the lowest biomass is about 193.31-214.34 ton/ha. The three high biomass per hectare is belongs to natural forest A, B and C cover type. Natural forest has heterogeneity of tropical vegetation trees that lead to the high biomass. Forest cover D has the lowest biomass because its vegetation component as secondary forest with the homogeneity of cacao plantation.

### Table 4.4 Field trees biomass estimation in each cover type.

<table>
<thead>
<tr>
<th>Plot</th>
<th>Type</th>
<th>Ton/ha</th>
<th>Ton/ha</th>
<th>Range + (ton/ha)</th>
<th>Range - (ton/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>421.25</td>
<td>607.54</td>
<td>618.66</td>
<td>596.41</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>841.30</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>A</td>
<td>754.23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>A</td>
<td>413.37</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>B</td>
<td>1044.45</td>
<td>603.06</td>
<td>622.19</td>
<td>583.94</td>
</tr>
<tr>
<td>6</td>
<td>B</td>
<td>396.76</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>B</td>
<td>367.98</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>C</td>
<td>687.33</td>
<td>457.58</td>
<td>468.50</td>
<td>446.65</td>
</tr>
<tr>
<td>9</td>
<td>C</td>
<td>252.25</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>C</td>
<td>433.14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>11</td>
<td>D</td>
<td>148.75</td>
<td>203.83</td>
<td>214.34</td>
<td>193.31</td>
</tr>
<tr>
<td>12</td>
<td>D</td>
<td>686.27</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>13</td>
<td>D</td>
<td>67.23</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>D</td>
<td>77.35</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>15</td>
<td>D</td>
<td>256.94</td>
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<td></td>
</tr>
<tr>
<td>16</td>
<td>D</td>
<td>60.30</td>
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</tr>
<tr>
<td>17</td>
<td>D</td>
<td>375.78</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>18</td>
<td>D</td>
<td>73.60</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>19</td>
<td>D</td>
<td>88.23</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

### Table 4.5 Total trees biomass estimation of study area.

<table>
<thead>
<tr>
<th>Type</th>
<th>Total Area (Ha)</th>
<th>Biomass/ha (ton)</th>
<th>Total Biomass (ton)</th>
<th>C-Stock (ton)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>699.035</td>
<td>607.54</td>
<td>424690.17</td>
<td>233579.59</td>
</tr>
<tr>
<td>B</td>
<td>525.021</td>
<td>603.06</td>
<td>316620.47</td>
<td>174141.26</td>
</tr>
<tr>
<td>C</td>
<td>94.533</td>
<td>457.58</td>
<td>43255.99</td>
<td>23790.80</td>
</tr>
<tr>
<td>D</td>
<td>119.541</td>
<td>203.83</td>
<td>24365.71</td>
<td>13401.14</td>
</tr>
<tr>
<td>Total</td>
<td>808932.35</td>
<td></td>
<td>444912.79</td>
<td></td>
</tr>
</tbody>
</table>

The total biomass of study area was calculated by multiplying the area in hectare resulted from Quick Bird image classification with biomass per hectare of each forest cover type. The total trees biomass estimation in the study area is
808932.35 ton, and carbon stock 444912.79 ton.

The forest biomass for each cover type will be useful for the further equation analysis when using the remote sensing technology for estimating the total biomass. The image classification result derive from remote sensing data will determine the accuracy of total biomass estimation.

### 4.5.1 Comparison between research result with other published data

The published data of aboveground biomass in tropical Asian countries (Table 4.6) could be used as the reference comparison for research result of above ground trees biomass. There is no brief explanation about the recent above ground biomass data estimated in Indonesia in certain forest cover type and climate condition, especially for tropical forest in Sulawesi. Hence, this FAO data for tropical Asian countries and another general reported data are used for the comparison analysis of above ground biomass resulted from the research. Forest cover type and general climate are the basic reference for the comparison.

The above ground trees biomass of forest cover type A and B has the higher biomass than C and D, it is about 596.41-618.66 ton/ha and 583.94-622.19 ton/ha. Forest cover type C has 446.65-468.50 ton/ha trees biomass. Forest cover type D has the lowest biomass is about 214.34-193.31 ton/ha.

As reported Brown et al. (1991) that Southeast Asian forest have an aboveground biomass range of 50-430 ton/ha (25-215 ton C/ha) and >350-400 ton/ha (175-200 ton C/ha) before human incursion. Indonesian forests have been estimated to have a C density ranging from 161-300 ton C/ha in aboveground biomass (Murdiyarso and Wasrin, 1995), 390 ton C/ha in above ground biomass and below ground pools (Hairiah and Sitompul, 2000).
<table>
<thead>
<tr>
<th>Country</th>
<th>Forest type</th>
<th>General Climate</th>
<th>Aboveground biomass (t/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Bangladesh</td>
<td>Closed-large crowns</td>
<td>Moist</td>
<td>210</td>
</tr>
<tr>
<td></td>
<td>Closed-small crowns</td>
<td>Moist</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>Disturbed closed</td>
<td>Moist</td>
<td>190</td>
</tr>
<tr>
<td></td>
<td>Disturbed open</td>
<td>Moist</td>
<td>85</td>
</tr>
<tr>
<td></td>
<td>Closed-large crown</td>
<td>Moist</td>
<td>206</td>
</tr>
<tr>
<td></td>
<td>Closed-small crowns</td>
<td>Moist</td>
<td>162</td>
</tr>
<tr>
<td>Cambodia</td>
<td>Dense</td>
<td>Moist</td>
<td>295</td>
</tr>
<tr>
<td></td>
<td>Semi-dense</td>
<td>Moist</td>
<td>370</td>
</tr>
<tr>
<td></td>
<td>Secondary</td>
<td>Moist</td>
<td>190</td>
</tr>
<tr>
<td></td>
<td>Open</td>
<td>Moist</td>
<td>160</td>
</tr>
<tr>
<td></td>
<td>Well to poorly stocked evergreen</td>
<td>Moist</td>
<td>100-155</td>
</tr>
<tr>
<td></td>
<td>Deciduous</td>
<td>Moist</td>
<td>120</td>
</tr>
<tr>
<td>Malaysia-</td>
<td>Superior to moderate hill</td>
<td>Moist</td>
<td>245-310</td>
</tr>
<tr>
<td>Peninsular</td>
<td>Upper hill</td>
<td>Moist</td>
<td>275</td>
</tr>
<tr>
<td></td>
<td>Distributed hill</td>
<td>Moist</td>
<td>200</td>
</tr>
<tr>
<td></td>
<td>Logged hill</td>
<td>Moist</td>
<td>180</td>
</tr>
<tr>
<td></td>
<td>Forest fallow</td>
<td>Moist</td>
<td>140</td>
</tr>
<tr>
<td></td>
<td>Freshwater swamp</td>
<td>Moist</td>
<td>220</td>
</tr>
<tr>
<td></td>
<td>Distributed freshwater Swamp</td>
<td>Moist</td>
<td>285</td>
</tr>
<tr>
<td></td>
<td>Logged freshwater swamp</td>
<td>Moist</td>
<td>185</td>
</tr>
<tr>
<td>Malaysia-</td>
<td>Mixed dipterocarps-dense stocking, flat to undulating terrain</td>
<td>Moist</td>
<td>325-385</td>
</tr>
<tr>
<td>Serawak</td>
<td>Missed dipterocarps-dense stocking, mountainous</td>
<td>Moist</td>
<td>330-405</td>
</tr>
<tr>
<td></td>
<td>Mixed dipterocarps-medium stocking, flat to mountainous</td>
<td>Moist</td>
<td>280-330</td>
</tr>
<tr>
<td>Philippines</td>
<td>Old-growth dipterocarp</td>
<td>Moist</td>
<td>370-520</td>
</tr>
<tr>
<td></td>
<td>Logged-dipterocarp</td>
<td>Moist</td>
<td>300-370</td>
</tr>
<tr>
<td>Sri Lanka</td>
<td>Evergreen-high yield</td>
<td>Moist</td>
<td>435-530</td>
</tr>
<tr>
<td></td>
<td>Evergreen-medium yield</td>
<td>Moist</td>
<td>365-470</td>
</tr>
<tr>
<td></td>
<td>Evergreen-low yield</td>
<td>Moist</td>
<td>190-400</td>
</tr>
<tr>
<td></td>
<td>Evergreen-logged</td>
<td>Moist</td>
<td>255</td>
</tr>
<tr>
<td></td>
<td>Secondary</td>
<td>Moist</td>
<td>280</td>
</tr>
</tbody>
</table>

Source: Brown(1997) on FAO Jurnal of Biomass density estimates for developing country based on existing inventories

The estimated above ground trees biomass resulted from the research, especially from cover type A and B is comparable with reported biomass for tropical forest cover before human incursion and with the condition of evergreen-high yield in another tropical Asian countries. The above ground trees biomass of forest cover type C 446.65-468.50 ton/ha trees biomass. This estimation biomass
value is relatively high if compared with forest cover type C condition (major timber extraction). This condition equal with the disturbed close, logged hill and evergreen logged forest of another tropical Asian countries that range about 180-255 ton/ha.

Forest cover type D has the lowest biomass is range about 193.31-214.34 ton/ha. In fact this estimation value is still higher than the previous research study that resulted 116-176 ton/ha (Tomich et al., 1998) from agro forestry system. It because there are several big trees shading surround the cacao plantation. The comparison is summarized in table Table 4.7.

Table 4.7 The comparison between actual biomass estimation with published data.

<table>
<thead>
<tr>
<th>Forest Cover</th>
<th>Actual Biomass Estimation (ton/ha)</th>
<th>Published Biomass Estimation(ton/ha)</th>
<th>Condition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>596.41-618.66</td>
<td>&gt;350-400</td>
<td>Aboveground biomass of Southeast Asian forest</td>
<td>Brown et al. 1991</td>
</tr>
<tr>
<td>B</td>
<td>583.94-622.19</td>
<td>322-600</td>
<td>Aboveground biomass of Indonesian forests</td>
<td>Murdiyarso and Wasrin, 1995</td>
</tr>
<tr>
<td>C</td>
<td>446.65-468.50</td>
<td>180-255</td>
<td>Logged hill, Disturbed close and evergreen logged of Southeast Asian forest</td>
<td>Brown et al., 1991</td>
</tr>
<tr>
<td>D</td>
<td>193.31-214.34</td>
<td>116-176</td>
<td>Agro forestry</td>
<td>Tomich et al., 1998</td>
</tr>
</tbody>
</table>

The possible errors source that influence the accuracy of trees biomass estimation along the estimation process are field data measurement, image classification and coordinate point taken from GPS.
V. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

1. This research has analyzed the combination of the field data observation, allometric equation, multispectral satellite images classification in estimating the total tree biomass and carbon stock of the study area. The field data observation and satellite image classification influencing much on the accuracy of trees biomass and carbon stock estimation.

2. The forest cover type A and B has the higher biomass than C and D, it is about 596.41-618.66 ton/ha and 583.94-622.19 ton/ha. Forest cover type C is 446.65-468.50 ton/ha. Forest cover type D has the lowest biomass is about 193.31-214.34 ton/ha. Natural forest has high biomass, because of the tropical vegetation trees heterogeneity. Forest cover D has the lowest trees biomass because its vegetation component as secondary forest with the homogeneity of cacao plantation. The percentage of carbon stock is about 55% of tree biomass content. Forest cover type A and B has higher carbon stock than forest cover type C and D.

<table>
<thead>
<tr>
<th>Forest Cover Type</th>
<th>Biomass (ton/ha)</th>
<th>C-Stock (ton/ha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>596.41-618.66</td>
<td>334.15</td>
</tr>
<tr>
<td>B</td>
<td>583.94-622.19</td>
<td>331.68</td>
</tr>
<tr>
<td>C</td>
<td>446.65-468.50</td>
<td>251.66</td>
</tr>
<tr>
<td>D</td>
<td>193.31-214.34</td>
<td>112.10</td>
</tr>
</tbody>
</table>

3. The study area of Toro-Kulawi District, part of Lore Lindu National Park as reserved area has high biomass and carbon stock content.
5.2 **Recommendation**

1. The historical data is needed to be used to compare the tree biomass estimation. The comparison process is difficult because there is no historical data of biomass and carbon stock estimation in study area.

2. The comparison study of among the different multispectral satellite image will give the valuable contribution in forest above ground biomass and carbon stock. This kind of information will give the consideration to the user in choosing the appropriate data source to estimate the above ground biomass.

3. The appropriate ground control point (GCP) is important to be considered when doing the field measurement. The GCP as the geometric correction reference should be taken inside the observation plot or the distinct area such as the intersection of road and river near the observation plot.

4. Different vegetation index is useful to be analyzed to find another equation model between biomass and vegetation index.

5. The correlation equation developed can be used to estimate tree biomass and carbon stock of the whole area of Lore Lindu National Park.
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APPENDIX