FOLIAGE BIOMASS ESTIMATION IN TROPICAL LOGGED OVER FOREST EAST KALIMANTAN, INDONESIA

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FOLIAGE BIOMASS ESTIMATION IN TROPICAL LOGGED OVER FOREST EAST KALIMANTAN, INDONESIA

THESIS

by

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Dedicated to

My husband and my daughter, for their patience, support, and waiting for my success

Abstract

Evidence indicates that annual loss of forest cover in Indonesia is the highest compared to other countries in South East Asia. Especially in the study area, the Labanan forest logging concession in Eastern Kalimantan, the forest disturbance is caused by the planned and unplanned logging done by the forest concessionaires and/or illegal loggers. The forest biomass provides estimates of the carbon pools because approximately 50% of it is carbon. The net carbon accumulation by the stand is represented by Net Primary Production (NPP) and is determined by daily difference between gross photosynthesis and respiration. Because foliage contains chlorophyll and it is closely related to the photosynthetic activities, so that foliage is the essential component needed in the carbon (biomass) production, besides foliage itself is a component of forest biomass. Consequently, it is very important to monitor the fluctuation of foliage biomass as consequences of the forest cover loss.

The general objective of this study is to combine the inventory and remotely sense data to find out the most accurate method of the foliage biomass estimation in the tropical logged over forest. The destructive method was applied to generate the regression equation of the foliage biomass and this equation was used to estimate the foliage biomass in the plots. The foliage biomass in each plot was then linked with the remotely sensed data derived from Landsat-7 ETM+.

The study revealed two possible models to estimate the foliage biomass; these are exponential and 3rd degree polynomial. These models showed highly correlation between DBH with the foliage biomass with R^2 equal to 0.82 and 0.91 for exponential and 3rd degree polynomial, respectively. In addition, there is a significant relationship between canopy cover and foliage biomass ($R^2 = 0.75$). On the other hand, this study was not able to find out a significant relationship between the vegetation indices (AVI, NDVI, ARVI, MSAVI2) and principal components with foliage biomass.

These low correlations are likely due to several reasons, such as error of the foliage biomass model application, saturation of the vegetation indices, and also spatial and spectral resolution of the Landsat-7 ETM+ image. This study concluded that DBH and canopy cover can be used as a predictor of the foliage biomass in the study area. On the other hand, the vegetation indices and principal component analysis can not be used due to their non significant result.

Key words: forest, carbon, foliage, biomass, photosynthetic, estimation, monitor, vegetation indices, principal components.

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Table of contents

List of figures

List of tables

1. Introduction

1.1. Biomass Issue Related to the Climate Change

Climate change resulting from increasing Earth's surface temperature has become a global concern. The main cause of climate change is the anthropogenic increase in greenhouse gas concentrations in the Earth's atmosphere. Carbon dioxide (CO_2) is the principal greenhouse gas. Its concentration in the atmosphere is the result of a cycle between different carbon pools: CO_2 is the product of the oxidation of carbon from these pools. Forests are important carbon pools which continuously exchange $CO_2$with the atmosphere, due to both natural processes and human action (FAO, 2003). Carbon is found in several pools in the forest: (FAO, 2002)

- The vegetation: living plant biomass consisting of wood and non-wood materials.
- Dead wood and litter: dead plant biomass, made up of plant debris.
- Soil organic matter, the humus. Humus originates from litter decomposition. Organic soil carbon represents an extremely important pool.

The role of tropical forests in global biogeochemical cycles has heightened interest in estimating the biomass density of tropical forests. The biomass of forests provides estimates of the carbon pools in forest vegetation because about 50% of it is carbon. Moreover, above ground productivity derived from biomass assessment can be useful in quantifying above ground carbon sequestration by the forest at any particular time interval (Brown, 1997).

The United Nations Framework Convention on Climate Change (UNFCCC) has created several instruments for reducing greenhouse gas concentrations in the atmosphere. They aim at encouraging investments in "clean" development activities which limit greenhouse gas emissions or fix carbon in the earth's ecosystems. Some of these instruments are still under development and not yet operational. One of them, the "Clean Development Mechanism" (CDM), is both a development instrument and a method allowing industrialized countries to reduce emissions at the lowest possible cost. (FAO, 2003). The CDM has a dual objective**:** (FAO, 2002)

- To help developing countries achieve sustainable development, and contribute to the ultimate objective of the Convention. Emissions in developing countries, which are presently low, might soon exceed those of developed countries, if measures are not taken to introduce reduced-emission technologies. The principle is to encourage investment flow and the transfer of technologies from the developed countries to the developing countries, to help them in their development trajectory while minimizing their greenhouse gas emissions.
- To help the developed countries fulfill their commitments to limit or reduce missions.

Over 130 nations have ratified UNFCCC which means that these nations need to make national greenhouse gas emission inventories. Changes in land cover, use, and management of forests produce sources and sinks of carbon dioxide to and from the biosphere. To estimate the magnitude of these sources and sinks requires reliable estimates of the biomass density of the forests undergoing change (Brown, 1997).

As a tropical country, Indonesia is covered mostly by forests. Of its total area 181,157,000 ha, 58% is covered by forest (FAO, 2000) and has high potential biomass 533 t/ha (Brown, 1997). In contrast, the total annual reduction of forest cover is the greatest in Indonesia compared to other countries in South East Asia. Moreover, new evidence from Indonesia indicates that annual loss of 1.8 million hectares per year, an increase of 500,000 ha over the present estimate (FAO, 2000). Therefore, estimation of biomass is necessary to monitor vegetation cover change, especially in the study area which is prone to the human disturbance either by the planned harvesting done by the forest concessionaires or unplanned logging by the forest concessionaires or illegal logger.

The net carbon accumulation by stand is represented by Net Primary Production (NPP) and is determined by the daily difference between gross photosynthesis and respiration, which both take place in the leaves. Photosynthesis response is regulated by canopy conductance to CO_2, leaf maintenance, respiration and daily metrological condition, including air pressure, air temperature and solar irradiance (Kimball et al., 1999). In addition, photosynthesis activity requires solar radiation in the 0.4-0.7 µm range (also known as photosynthetically active radiation or PAR). A green leaf is composed of chlorophyll and non photosynthetic components (e.g. other pigments in the leaf, primary/secondary/tertiary veins, and cell walls) (Zhang et al., 2005).

Because foliage contains chlorophyll and it is closely related to the photosynthetic activities, so that foliage is the essential component needed in the carbon (biomass) production, besides foliage itself is a component of forest biomass. Consequently, it is very important to monitor the fluctuation of foliage biomass as consequences of the forest cover loss.

1.2. Total above ground and foliage biomass estimation methods

Araujo et al.(1999) defined biomass as the quantity, expressed in mass unit, of the vegetal material content per unit area in a forest. In general, the estimated biomass components are vertical above ground biomass or standing alive, composed of trees and shrubs (not considering the roots), dead aboveground biomass, composed of litter and fallen trunks and the belowground biomass, composed of roots On the other hand, Brown (1997) defined biomass as the total amount of above ground living organic matter in trees expressed as oven-dry tons per unit area. These components generally account for the greatest fraction of total biomass in a forest and they do not pose many logistical problems in its estimation. The later definition is used in this study.

The biomass estimations vary in their procedure, complexity and time demand depending on the specific aim of estimation operation. There are three general methods to generate the equation to estimate biomass, i.e. non destructive methods, sub sampling method and complete harvesting

method. The first method is done by means of sampling without destruction or felling the trees as applied by Vann et al. (1998); Verwijs and Telenius (1999); Montes et al. (2000) and Adhikari (2005). The second method requires tree felling, weighing and drying of a small sample (Gier, 1999), and the last method using complete harvesting of randomly selected plots or individual trees within plots, by Brown (1997); Araujo (1999); Hashimoto et al. (2000); Nelson et al. (1999); Ketterings et al. (2001); Nascimento and Laurancea (2002); Zianis and Mencuccini (2004)

The main dendrometric characteristics that determine the biomass equation are DBH and height, as well as wood density. The linear and non linear relationships have been built (Araujo, 1999), but the most commonly used mathematical model biomass studies is the form of power function:

$$M = aD^b \tag{1.2.1}$$

Where a and b are the scaling coefficients, M is total biomass above ground tree dry biomass and D is diameter at breast height (DBH) (Zianis and Mencuccini, 2004).

Carvalho (2003); Hoffmann (2002); Zhang et al. (2004); King (2005); Porte (2002) used the tree component method to develop the biomass equation, namely foliage, branch and stem biomass. According to Carvalho (2003), the prediction for the tree components can be summed to the prediction from total tree regression. The tree biomass equation is a function of the independent variables from i^{th} component equation.

Compared to stem biomass, the prediction of crown-related biomass (foliage and branches) is more difficult to make because of its complex structure and irregular distribution. To date, estimating foliage and branch biomass (as n important component of the forest productivity) remains one of the least understood aspects of forest growth and yield, although some studies on crown biomass distribution have been published (Zhang et al., 2004). Furthermore, the foliage biomass is directly related to the photosynthesis activities, since a green leaf is composed of chlorophyll. Moreover, the foliage biomass can be used to model the net photosynthesis (Martin and Aber, 1997) and also as an essential element in forest modelling (Hoffmann and Usoltev, 2002).

The possible dendrometric characteristic that are used to determine foliage biomass are diameter outside bark at the base of the live crown (Zhang et al., 2004), (Grote, 2002); DBH (Naidu et al., 1998), (Riano et al., 2004) and (Hoffmann and Usoltev, 2002). Each predictor chosen is based on different reasons, for instance Zhang et al (2004) reported that diameter outside bark at the live crown serves as better predictor for foliage biomass since its values is not monotonic increasing function like DBH. In contrast, it is understandable to use DBH as predictors for the stem biomass because it is a convenient and accurate measure of stem size. However, foliage biomass of individual trees does not increase steadily with age as does stem. But, Hoffmann and Usoltev (2002) reported that DBH is the most economical and precise parameters to predict the broadleaf and needle leaves compare to diameter at base of the crown, age and mean diameter increment. In this study, DBH was used and its performance was tested to estimate the foliage biomass because this parameter is the most common used in forest inventory. Consequently the foliage biomass equation proposed can easily be applied as long as the DBH data is available in the study area.

1.3. Remotely sensed data

The advance of remote sensing data and also the technique of generating information from it are interesting to explore. This study incorporated several vegetation indices and also image transformation linked with the up-to date research of biomass estimation.

1.3.1. Vegetation Indices

A vegetation index (VI) is a dimensionless, radiation-based measurement computed from some spectral combination of remotely sensed data. It is used to infer vegetation properties by isolating the contribution of vegetation from other materials (e.g. soil or water). Vegetation indices take the advantage of large difference in vegetation reflectance between the visible (VIS) and near-infrared (NIR) parts of the spectrum. Plants absorb VIS radiation and reflect strongly in the NIR. Typical indices use the ratio or difference of VIS and NIR reflectance.

The most commonly used VI is the Normalized Difference Vegetation Index (NDVI). Refer to the equation this index is computed from the different between NIR and Red (R) radiance reflected from the surface and transmitted through the atmosphere.

$$NDVI = (NIR - R)/(NIR + R) \quad (1.3.1)$$

This difference is sensitive to the presence of vegetation, since green vegetation usually decreases the signal in the R due to chlorophyll absorption and increase the signal in the NIR. The NDVI was shown to be related to canopy photosynthesis (Kaufman and Tanré, 1992). The effect of scattering and absorption by atmospheric aerosol, gases and undetected clouds reduce significantly the sensitivity of NDVI. The conceptual approach for the development of the atmospherically resistance index was proposed by Kaufman and Tanré (1992), this approach is based on the spectral characteristics of vegetation, soil and the atmospheric affect. They claimed that Atmospherically Resistant Vegetation Index (ARVI) is four times less sensitive to the atmospheric effect than the NDVI by adding Blue (B) reflectance.

$$ARVI = (NIR - 2R + B)/(NIR + 2R - B) \quad (1.3.2)$$

To improve the vegetation sensitivity by reducing the soil effect, Hueté (1988) proposed Soil-Adjusted Vegetation Index (SAVI) and it was modified by Qi et al. (1994) by induction of L (adjustment factor) function used in SAVI.

$$MSAVI2 = ((2NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - 2R)})/2 \quad (1.3.3)$$

The Modified Soil Adjusted Vegetation Index (MSAVI) showed increasing the dynamic range of vegetation signal and minimizing the soil background influence, resulting in greater vegetation sensitivity as defined by a “vegetation signal” to “soil noise” ratio.

Another VI that is claimed to be sensitive to the vegetation signal is Advance Vegetation Index (AVI). AVI is more sensitive to the vegetation quantity as compared to NDVI (Rikimaru, 2002). AVI can be directly generated from the Forest Canopy Density Mapper (FCD). The basic equation to obtain this index is :

B1~B7: TM Band 1~7 data

B43=B4-B3 after normalization of the data range.

CASE-a : B43 < 0, AVI= 0

CASE-b : B43 > 0, AVI= ((B4+1) x (256-B3) x B43)1/3

However, although each indices have their own advantages, they all have limitations particularly NDVI, they become stagnant approaching a saturation phase after a certain canopy covers, biomass density or LAI (Qi et al., 1994; Myneni and Asrar, 1994; Rondeaux et al., 1996; Gemmell and McDonald, 2002; Gitelson et al, 2002; Hueté et al., 2002). Consequently, they are insensitive to subtle change of forest parameters.

1.3.2. Image Transformation

Principal Component Analysis (PCA) is a transformation technique used to reduce the dimensionality of the original data set. The purpose of this procedure is to compress all of the information contained in an original *n*-band data set into fewer than *n* "new bands". The new bands are then used instead of the original data. Principal component image data values are simply linear combinations of the original data values multiplied by the appropriate transformation coefficients. These coefficients are statistical quantities know as *eigenvectors* or *principal components*. They are derived from the variance/covariance matrix of the original image data (Lillesand, *et al.*, 2004). Hence, principal component image is as result of the linear combination of the original data and the eigenvector on a pixel-by-pixel basis throughout the image. It should be noted in the Figure1.3.1 that data along the direction of the first component (axis I) have a greater variance or dynamic range than data plotted against either of the original axes (band A and B).The data along the second principal component direction have less variance. This is a characteristic for all the principal component images. In general, the first principal component (PC1) includes the largest percentage of the total scene succeeding components image (PC2, PC3 ….PCn) and each contain a decreasing percentage of scene variance.

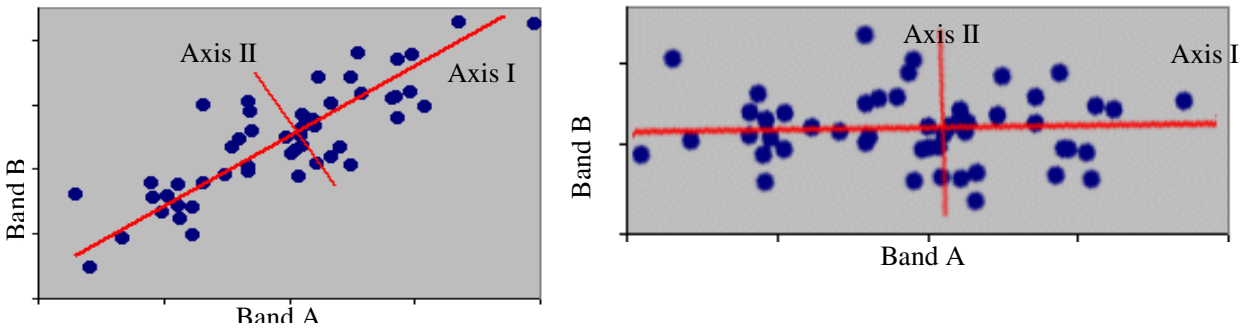


Figure 1.3.1 Rotated coordinates axes used in principal component analyses

1.3.3. Application of remotely sensed data to estimate biomass

A large number of studies have evaluated the possibility of using remotely sensed data to estimate biomass. A variety of vegetation indices have been developed using broad-band remotely sensed data based on the spectral features of green vegetation. The advantages of using remotely sensed data include the ability to obtain the measurement from every location covering large areas at relatively low cost. Lee and Nakane (1997); Steininger (2000); Foody et al.(2003); Okuda et al. (2004); Zheng et al. (2004); Lu et al. (2004) and Rahman et al. (2005) explored the ability of remotely sensed data especially from Landsat TM images by evaluating the relationship between the vegetation indices and the total above ground biomass (TAGB) content.

Lee and Nakane (1997) using topographic corrected Landsat TM found a significant relationship between NDVI with biomass of pine forest type (R^2 = 0.85), while Steininger (2000) found significant relationships between middle-infrared reflectance with volume and TAGB. In addition, Zheng et al. (2004) found that MSAVI to be strongly correlated with TAGB for pine forest and near infra red reflectance as well. In contrast, Lu et al. (2004) found that single band TM5 and linear transformed indices such as PC1 (the first component in a principal component analysis), KT1 (brightness of the tasselled cap transform), and albedo are strongly correlated with TAGB, somewhat independent of biophysical environments. Furthermore, he concluded that indices which use TM4 and TM3, such as ARVI and NDVI are weakly correlated with TAGB. However, vegetation indices using band TM5 data improve correlations with TAGB in forests that are characterized by a complex stand structure. Forest stand structure and associated canopy shadow affect the forest stand parameters and TM spectral response relationships. The low correlation was also found by Okuda et al. (2004) who concluded that TAGB is poorly correlated with Landsat TM reflectance and also with NDVI.

Rahman et al. (2005) used dummy variables to generate the relationship between TAGB and the reflectance of Landsat TM. They found that visible band (TM 2) contain the highest information of forest TAGB and this result differed from Steininger (2000) who found that TM 5 is highly correlated. Before applying dummy variables for the regression, all TM band showed the low correlation with TAGB, but after the dummy variables were applied the correlation increased dramatically. And finally they found that the strongest predictor for TAGB was TM 2. So far Rahman et al. (2005) in their paper could not explain why their result differed from Steininger (2000). This difference may be caused by the different land covers. Rahman et al. (2005) derived their data from 9 different land covers such as primary forest, secondary forest, bamboo, shrub, plantation, teak, acacia, rubber and non vegetated while Steininger (2000) collected the data from tropical secondary forest. This probably caused the different reflectance captured by sensor. Moreover, Steininger (2000) found that this correlation was likely caused by the canopy that dominated by a planophile distribution of broadleaf of *Cecropia spp* that causes increase in canopy shading and decreases in middle infra red.

Foody et al.(2003) found that the relationship between predicted and measured TAGB derived from vegetation indices differ markedly in both strength and direction among sites (Brazil, Thailand, and Malaysia). As it was stated by Gemmell and McDonald (2000) that the relationship between spectral indices and forest parameters can be site and scene dependent, which will limit their general

applicability. Moreover, the general form of the indices response to changes in cover could be explained by shadowing effect linked to the heterogeneous nature of forest.

1.4. Problem statement

From many publications, there are a lot of biomass equations developed based on different method, different species and different site. Before these equations can be used, we have to verify whether these are applicable to the area of interest, because different species and different sites result in different growth performance. If the validation involves felling tree of a sufficient number, more than 25 of representative trees, it might be better to generate a new equation for the area concerned (Gier, 2003).

Even though Indonesia is covered mostly by forest, however biomass studies are rarely conducted. So far, from the scientific publication there are only two biomass studies found in Indonesia i.e. Ketterings et al. (2001) who studied biomass in Sepunggur, Sumatra and Hashimoto et al.(2000) in Kalimantan. Both studies used different approaches. The first study was based on the DBH and the total dry weight and the second was based on age, site condition and dominant species to estimate the biomass. These two equations can not be applied in the study area because the first equation is derived from the samples located in different island that is likely not suitable for the study area, while the second equation using the predictors that are difficult to measure and can not meet the objective of this study.

Although many studies have investigated the ability of remotely sensed data to estimate the biomass of forests, including tropical forests, many problems have been encountered. The key concern here is that while there are case studies that demonstrate the accurate estimation of forest biomass from remotely sensed data, the methods used may not generally accurate in space and time. It means that a relationship derived for the accurate prediction of biomass at one site or time period may not yield accurate predictions when applied to image of another site and/or acquired at another time (Foody et al., 2003).

The issue of canopy cover and the density of the green vegetation (foliage) is the most importance issue related to spectral reflectance. Forest canopy structure controls the reflected light (Williams et al., 2003b). Furthermore, rays leaving the canopy to the sensor provide information on the radiance/reflectance of the canopy (Gemmell and McDonald, 2000). In addition, because light is captured primarily by leaf tissue of trees canopies, the quantity of leaf tissue (its biomass), the arrangement of the leave within the crown and the leaf biomass distribution throughout the tree affect light interception (Mourelle et al., 2001).

Therefore, to address the biomass estimation problem, this study measured the component of tree biomass i.e. foliage biomass in the study area, explore the ability of using remotely sensed data and establish a relationship between foliage biomass and different vegetation indices.

Figure 1.4.1 Top of the canopy in tropical forest

Based on the limitations that exist, this study will incorporate the following assumptions:

- The growth of the trees from 2003-2005 does not significantly differ within plots.
- Reflectance of each species is not significantly different.
- Reflectance captured by the sensor is mainly coming from foliage and background.

1.5. Research objectives

The general objective of this study is to combine the forest inventory and remotely sensed data to find out the most accurate method of foliage biomass estimation in the tropical logged over forest. The destructive method was applied to generate the regression equation and this equation was used to estimate the foliage biomass in the plots. The foliage biomass in each plot was then linked to data derived from remotely sensed data. This general objective is supported by these specific objectives, i.e.:

a. To develop an equation of foliage biomass of tropical logged over forest
b. To determine the relationship between forest canopy cover with the foliage biomass.
c. To establish a relationship between foliage biomass and vegetation indices
d. To examine the ability of Principal Component Analyses technique to generate information about foliage biomass

1.6. Research questions

a. Is there a significant relationship between foliage biomass and DBH?
b. Is canopy cover (CC) capable to estimate foliage biomass?
c. Which vegetation indices (NDVI, ARVI, MSAVI2 and AVI) best estimate foliage biomass?
d. Is PCA technique capable of generating information about foliage biomass?

1.7. Hypothesis

The foliage biomass has a stronger relationship with the vegetation indices, canopy cover and principal components compare to that of the total above ground biomass

1.8. Research approach

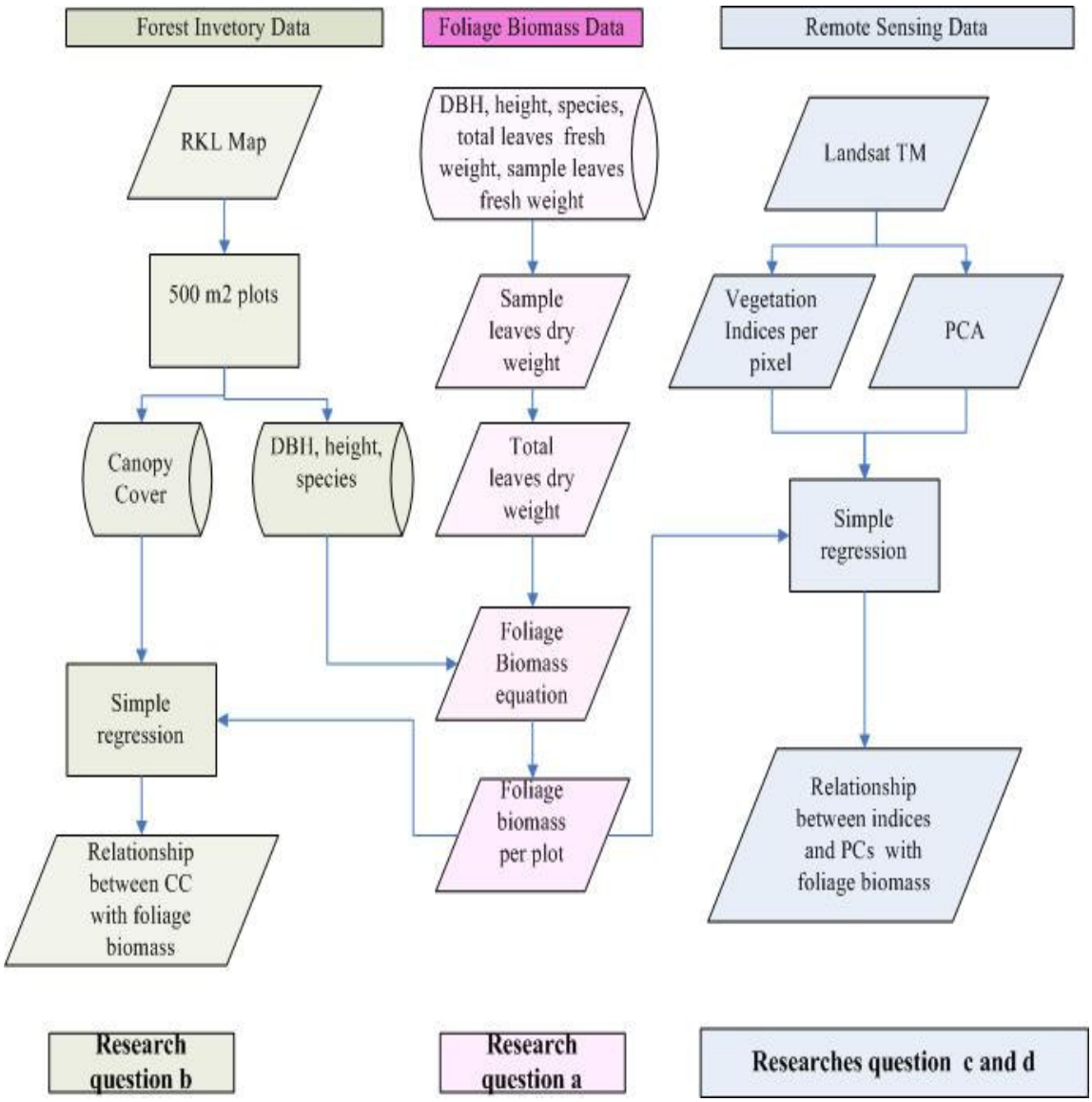


Figure 1.8.1Research approach

2. Methods

2.1. Study area

To achieve the objectives of the research, the study require the following conditions:

- Tropical logged over forest
- Accessible
- Availability of recently remote sensing data
- Availability of others secondary data such as map, tree map, species dominant etc.
- Availability of supporting staff in the field

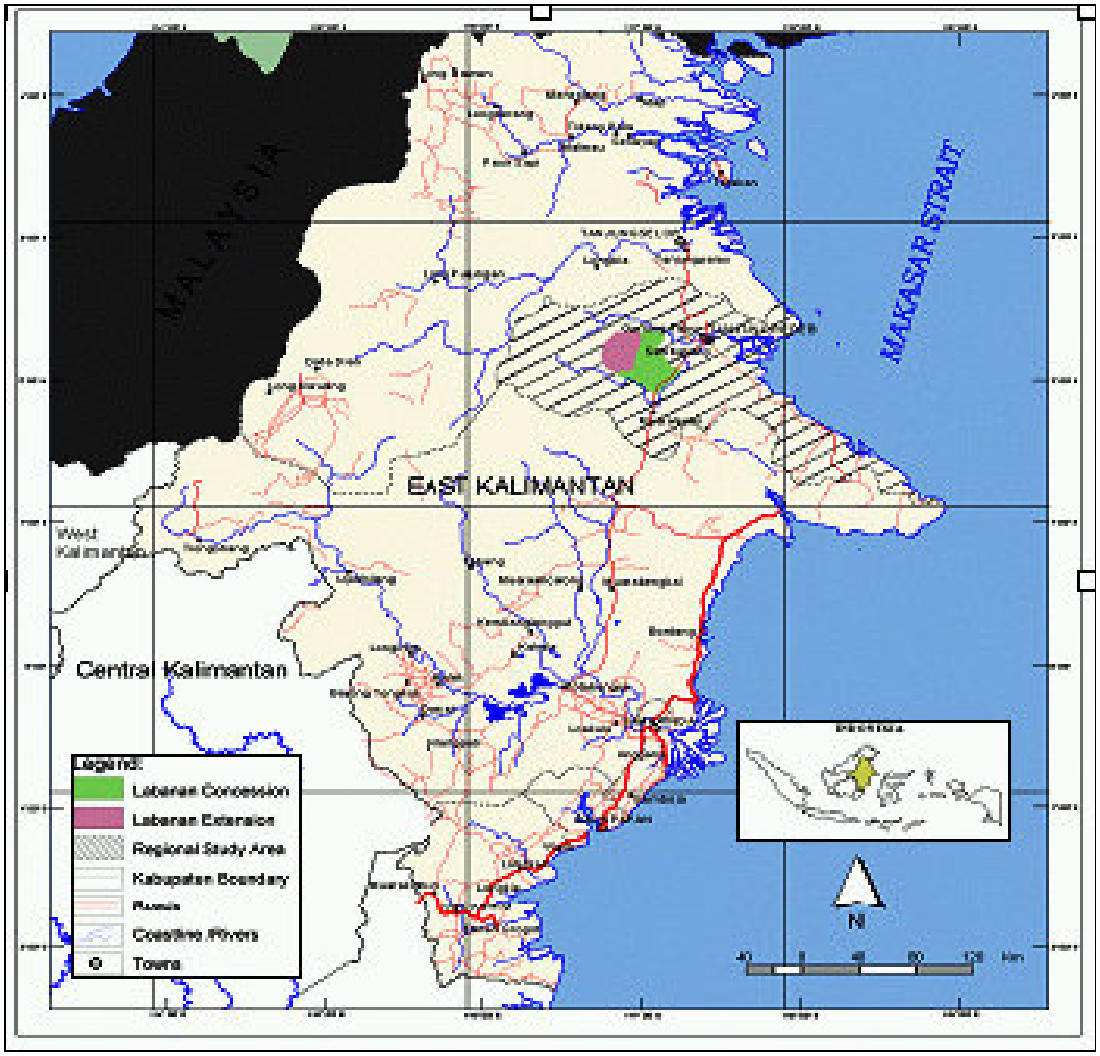


Figure 2.1.1 Study area in East Kalimantan

Based on the above requirements the study was conducted in Labanan concession area, located in Berau district, East Kalimantan, Kalimantan Island, Indonesia. This area is managed by PT. Inhutani I, a government owned Concession Company. The boundary of the study area lies between the latitude of $2^0$10' N to $1^0$45' N and longitude of 116°55' and 117°20' E (Fauzi, 2001).

There is several forest research projects carried out either by local or intergovernmental-collaboration institutions. From 1989 until 1996, the STREK (Silvicultural Techniques for the Regeneration of logged over forest in East Kalimantan) was carried out. The focus of the project was on the development of silvicultural and management rules leading to sustained productivity of the forest in East Kalimantan. The project carried out under the authority of MoF through Forestry Research and Development Agency and PT. Inhutani I with the assistance of CIRAD (Centre de Cooperation Internationale en Recherche Agronomique pour le Développement: centre of international cooperation in agronomic research for development). From 1996 to 2003, the Berau Forest Management Project (BFMP) has been carried out under cooperation between MoF and European Union. The focus of the project is on development, research and promoting a replicable example of sustainable forest management at operational level. To support that project, Ministry of Forestry and Estate stated Labanan FMU as a special status area under decree No. 866/Kpts-II/1999 (Kuswandari, 2004)

The total area of FMU is 83,240 ha and it is divided into deferent function by regional and district plans as written in Table 2.1.

Table 2.1.1Forest function

No.	Function	Area (ha)
1.	**Forest Land Use Plan (*TGHK*)**	
	Limited production forest	26,997
	Production Forest	26,997
	Non Forest Area (*Areal Penggunaan Lain*)	1,676
2.	**Provincial Landuse Planning (*RTRWP*)**	
	Forest Area (*Kawasan Budidaya Kehutanan*)	81,564
	Non Forest Area (*Kawasan Budidaya Non Kehutanan*)	1,676

(Kuswandari, 2004)

Labanan concession area is divided into seven five-year working plan areas or *Rencana Karya Lima Tahun* (RKL). Furthermore, each RKL is divided into five annual working plan areas or Rencana Karya Tahunan (RKT). A former company which held this concession, PT Inhutani I, started logging activities in 1976 until early 2003 when there was an agreement between District Government of Berau, PT Inhutani I, and a local company on joint cooperation of the concession area. They established a shared company called PT Hutan Sanggam Labanan Lestari on 4 February 2003 (Wijaya, 2005) . The map and the description of RKL can be seen in Figure 2.1.2 and Table 2.1.2. In each RKL, selective cutting and planting system (TPTI) has been done in order to accomplish the sustainable forest management. The schedule and activities of TPTI is written in Table 2.1.3.

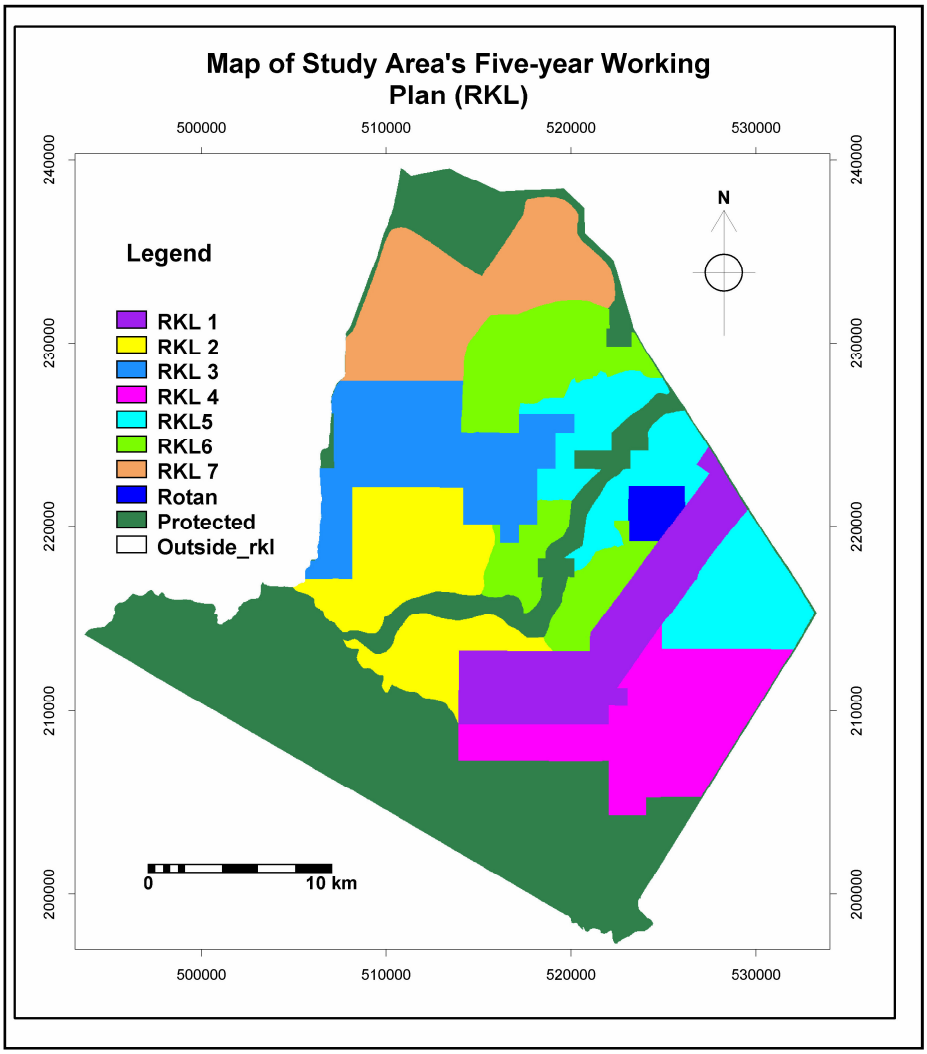


Figure 2.1.2Five-year working plan compartments

Table 2.1.2Five Year Working Plan in Labanan concession

RKL	Area (ha)	Year of logging	Age after logging	Remarks
1	6,749	1976-1980	25-29	
2	7,502	1981-1985	20-24	
3	7,720	1986-1990	15-19	
4	7,597	1991-1995	10-14	
5	8,182	1996-2000	5-9	
6	7,579	2001-2005	2, 3, 4	no more logging in 2004
7	7,610	2006-2010	-	

RKL = five-year working plan
(Source : Modified from Zaitunah (2004)

Table 2.1.3 Series of activities and schedule of selective cutting and planting system (TPTI)

No	Stage of TPTI activities	Time of implementation (year)	Explanation
1	Organization of working area	Et - 3	Includes boundary demarcation for logging compartments.
2	Stand inventory before logging.	Et - 2	Includes 100% pre-harvest inventory in logging compartments (only DBH >10 cm measured).
3	Opening up of forest area.	Et - 1	Construction of logging roads in logging compartments.
4	Logging.	Et	Felling of selected marked trees and extraction of logs.
5	Liberation.	Et + 1	Enhancement of natural regeneration by creating more openings for light to reach the upcoming seedlings. This is achieved by climber cutting and other silvicultural operations
6	Inventory of residual stand.	Et + 1	Includes 100% post-harvest inventory in logged over compartments to estimate the standing stock left behind after logging is completed. Only the commercial species with DBH > 20 cm are recorded.
7	Procurement of planting stock.	Et + 2	Estimation of seedlings needed for enrichment planting and its collection generally from forest and grow in nursery.
8	Enrichment planting.	Et + 2	Enrichment planting in areas where there is less chance for establishment of natural regeneration.
9	First stage tending.	Et + 3	
10	Advanced tending: Liberation Thinning	Et + 4 Et + 9 Et + 14 Et + 19	Thinning is aimed to reduce competition between future crop (crop for next rotation) and unwanted species. The trees, which compete with the future crop, are killed by cambium cutting and poisoning.
11	Forest protection and research.	Continually	

(Note: Et denotes the year when the logging takes place).

Forest type of Labanan is often called *lowland mixed dipterocarp* forest because of the dominance in the canopy and the emergent stratum of the family of the *Dipterocarpaceae*. The most common genera within this family are *Shorea, Dipterocarpus*, and *Vatica.* Common species are *Shorea parvifolia*, *Dipterocarpus acutangulus, Shorea pinanga* and *Shorea hopeifolia* (Dahal, 2002). The analyses of data from STREK plots indicated that the net recoverable re-growth of commercial tree species after logging in Labanan is 0.73 m^3 per year, significantly less than 1 m^3per year (Tyrie, 1999)

The study area is situated inland of coastal swamps and consists of undulating to rolling plains, with isolated masses of high hills and mountains. This variation in topography is a consequence of folding and uplift of rocks, resulting from tension in the earth crust. The Labanan landscape can be classified into:

- Flat land, these are floodplains adjacent to the river Siduung, Kelai and Segah,
- Sloping land, these are undulating to rolling and hillocky plains, which are dominant landforms in Labanan,
- Steep land, medium to high gradient hills with steep to extremely steep topography, and
- Complex landforms, limestone associated landscapes, consisting of undulating plains

Sedimentary rock (sandstone, clay stone, siltstone) is the dominant parent material. Limestone deposits are trending east to west-northwest. Fluvial sediments are found in alluvial plains. Acid metamorphic rock (schist) is found in the southern part of the concession (Mantel, 1999)

The rainfall pattern shows typical features of a tropical zone with highly intensive and local concentrated rains. According to the annual rainfall classes, the area is moist condition (annual rainfall 1500 - 3000 mm). The rainfall regime contains two seasons; the dry season stretches normally from June to October, although mean values remain relatively high (above 100 mm) during dry period and the wet season from November to May (BFMP, 1999).

2.2. Remotely sensed data

Remote sensing data will be used in this study because of its advantages that include the ability to obtain measurements from every location in the forest, the speed with which remotely sensed data can be collected and processed, the relatively low cost of many remote sensing data types and the ability to collect data easily in areas that are difficult to access on the ground.

2.2.1. Pre-processing

Landsat-7 ETM+, acquired on May 31, 2003 of path 117 and row 59 was used. This image was already geo referenced; its coordinate system is WGS 84, UTM Zone 50N. Three main pre-processing steps involving geometric and atmospheric radiometric corrections were applied.

Geometric correction
Using coordinate measured using GPS as ground control point (GCP) and first order polynomial to register and then re-sampled the image using nearest neighbourhood.

Atmospheric correction
This was done to remove the atmospheric effect due to absorption and scattering. The correction used ATCOR 2 in Erdas 8.7.

Radiometric correction
To remove any bias due to the sensor parameter, the digital number will be converted into the radiance value and then to the surface reflectance in order to calculate the spectral vegetation indices.

Conversion to radiance from DN value will use the equation: (NASA, 2004)

$$L_\lambda = \text{"}gain\text{"} * Q_{cal} + offset \qquad (2.2.1)$$

$$L_\lambda = \left((L\max_\lambda - L\min_\lambda)/(Qcal\max - Qcal\min)\right) * (Qcal - Qcal\min) + L\min_\lambda$$

Where,
L = spectral radiance of the sensor aperture in watt/(m^2 *steradian*µm)
Gain = the rescaled gain in watt/(m^2 *steradian*µm)

Offset = the rescaled bias in watt/(m^2 *steradian*µm)
$L\max_\lambda$ = the spectral radiance that is scaled to Qcal max in watt/(m^2 *steradian*µm)
$L\min_\lambda$ = the spectral radiance that is scaled to Qcal min in watt/(m^2 *steradian*µm)
Qcal max = the maximum quantized calibrated pixel value (corresponding to $L\max_\lambda$) in DN
Qcal min = the minimum quantized calibrated pixel value (corresponding to $L\min_\lambda$) in DN
Qcal = the quantized calibrated pixel value in DN.

The gain and offset, and sun elevation angle were obtained from the TM image header file. Conversion from radiance to the surface reflectance will use the equation: (NASA, 2004)

$$\rho = \frac{\pi L_\lambda d^2}{E_o \cos\Theta_o} \qquad (2.2.2)$$

Where:
ρ = reflectance of the object
L_λ = the spectral radiance measured by the sensor in watt/(m^2 *steradian*µm)
Θ_o = solar zenith angle in degree
E_o = solar irradiance at mean earth-sun distance in watt/(m^2 *µm)
d = Earth-Sun distance in astronomical units

2.2.2. Vegetation indices and Principal Components calculation

Although the indices were sensitive to forest cover, the indices were also significantly affected by variation in a number of extraneous factors, including background reflectance, stand structure and crown leaf area index and also the atmosphere (Gemmell and McDonald, 2000). In this study, indices that potentially capable of reducing such influences were tested. These indices were AVI, NDVI, ARVI and MSAVI2. The PC's were also tested in order to find the most informative bands within TM bands.

The calculation to generate the vegetation indices was done after conversion of DN value to surface reflectance. The study incorporated with tree individual bands of Landsat-7 ETM+ (BLUE, RED and NIR), excluding green, mid IR and the thermal band. All the analyses were done in Erdas 8.7 Imagine except the generation of AVI by FCD Mapper soft ware. Similar to the reflectance calculation the indices calculation were done using model builder in Erdas 8.7. After the calculation of the indices per pixel, then using a window 3x3 calculated the mean value of the centre of the pixel where the coordinate of the samples were located (Lu et al., 2004). These values then were linked to the foliage biomass value of the plots using ArcMap.

2.3. Field data collection

There were two types of field data collection. First, data related to the development of the foliage biomass and second, forest inventory data that will be used to build the relationship between foliage biomass with remotely sense data. Field data collection used several tools such as global positioning system (GPS), compass, clinometer, caliper, diameter measuring tape, hemispherical camera, chainsaw and weighing scale.

2.3.1. Foliage biomass data

Foliage biomass data were taken by felling the trees outside the concession area with the same forest type (Appendix 8). Five species of trees were chosen as representation of the dominant family *Dipterocarpaceae* and genera *Shorea* and *Vatica*. These species are Keruing (*Dipterocarpus acutangulus*), Red meranti (*Shorea parvifolia*), Tengkawang (*Shorea pinanga*), Majoh (*Shorea johorensis*) and Resak (*Vatica rassak*). Stewart and Dunson (1992) recommended that at least 12 trees per species should be felled to provide data for regression analyses, while Ketterings et al. (2001) used 29; Nelson et al. (1999) 17 and more than 25 trees (Gier, 2003). However, in this study, total of 35 trees were felled stratified by diameter classes, i.e. 10-15, 15-20, 20-25, 25-30, 30-35, 35-40, 40-45,45-50 cm, 75 cm and 89 cm. These diameter ranges were selected in order to represent DBH of the actual condition of diameter distribution.

In this study, the dendrometric variable used to estimate the foliage biomass was the DBH as used by Naidu et al (1998) and Hoffmann and Usoltev (2002). Measurement of the DBH was done using calliper before the sample tree was felled. After the tree was felled the measurement of the total height and crown height were done. All the leaves were separated. The Total fresh weight of leaves was measured using weighing scale. Two samples (20-50 gram) of leaves were taken. Each sample was then dried to constant weight at a temperature of 105^{o} C, to get the sample dry weight. This dry weight was then used to estimate the total dry foliage biomass of a single tree (kg).

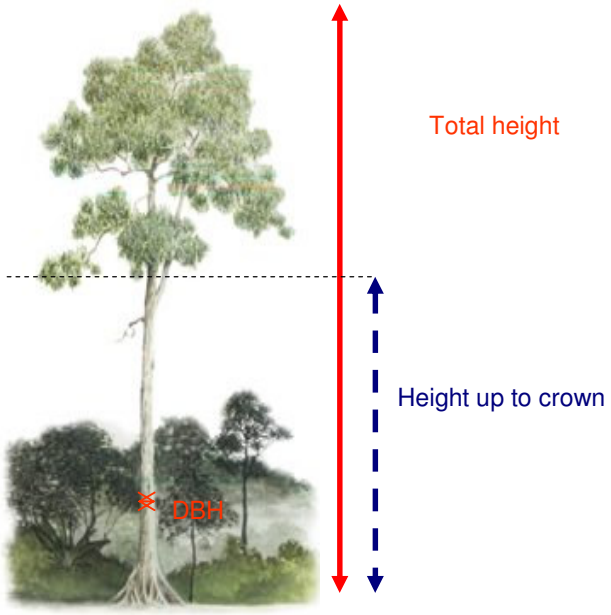


Figure 2.3.1Tree height measurement

2.3.2. Forest Inventory data

Stratified random sampling was designed to collect different variables because the population is not homogeneous as a result of applying the different logging period of each RKLs. The advantage of using this method is that the estimates of the population will be more precise than that given by a simple random sample of the same size (Freese, 1984). Therefore, the RKLs were considered as different strata. The coordinate sample plots were selected randomly within each stratum. The coordinate points were derived using Hawth's analyses tools version 3.19. As the time and resources available determines the sample and method (Freese, 1984), total of 90 plots were established in the field .

Plots were designed in a circular shape. This shape was chosen because it was easy and quick to implement in the field. The sampling plot was 500 m^2 with radius ranging between 12.62 m to 15.78 m, depending on the terrain slope. This radius gave a diameter approximately 25 m for the plot, compatible with the spatial resolution of Landsat-7 ETM+. The coordinate of the plots were taken using GPS and by calculating the azimuth and distance from reference location.

In each plot, all trees with diameter at breast height (DBH) greater than or equal to 10 cm were recorded using diameter tape. The parameters measured were species name, DBH, average tree height and also the canopy cover. DBH was measured at 1.3 m above ground using measuring tape. Trees with buttresses were measured 30 cm above the upper part of the buttress.

The canopy covers were measured using hemispherical camera. A camera with fisheye lens was set beneath forest canopy at 1.5 m height above ground at the centre of the plot. Levelling was

used to orient and level the camera properly. The photos numbers were recorded. The photos of the canopy closure were printed and scanned to make the digital format.

2.4. Data analyses

Raw data was graphed to provide visual assessment of the relationship between foliage biomass and the independent variables (DBH). Least square regression and weighted linear regression with backward elimination techniques were used to develop exponential and polynomial models. The statistic analyses were done using SPSS 12.0.1, MSExcel and also Regdat and PolyReg program.

The proposed models can be determined as equations:

1. Polynomial : $Y = b_0 + b_1 X + b_2 X^2 + b_3 X^3$
2. Exponential : $Y = b_0 e^{b_1 X}$

Where:

Y	= foliage biomass (kg)	b	= constant
X	= DBH (cm)	e	= 2.718.

After finding the best equation of foliage biomass, this equation then was used to predict the foliage biomass of the plots from the inventory data. Based on the inventory data, amongst 90 plots collected, 50 plots consist of trees with the diameter more than 50 cm. Since the equation could not be extrapolated beyond the range DBH used as input to prepare the equation, the calculation of the foliage biomass was done only in the plots consist of the trees in range of diameter of 10 cm to 50 cm. The foliage biomass was expressed in kg/plots (kg/500m^2).

The canopy covers were analysed using visual interpretation and also Gap Light Analyzer (GLA) Version 2.0. The canopy covers were derived from the % of canopy openness. % Canopy Openness is the percentage of open sky seen from beneath a forest canopy. This measure is computed from the hemispherical photograph only, and does not take into account the influence of the surrounding topography (Fraser, 1999). The canopy covers equal 100% - % canopy openness.

The relationship between the canopy cover and vegetation indices with the foliage biomass content were analysed using simple regression analyses.

Then, the test of the difference between some correlation coefficients (Snedecor and Cochran, 1989) was done to examine whether foliage biomass has stronger correlation with the canopy cover, indices and PCs compared to that of the TAGB with the canopy cover, indices and PCs, the hypotheses tested were:

Ho : There are no significant differences between correlation of foliage biomass with CC, vegetation indices and PCs and that of TAGB with CC, vegetation indices and PCs ($r_1 = r_2 = r_3$)

Ha : There are significant differences between correlation of foliage biomass with CC, vegetation indices and PCs and that of TAGB with CC, vegetation indices and PCs ($r_1 \neq r_2 \neq r_3$)

Where:

R_1 = correlation between foliage biomass derived from 3rd degree polynomial with CC, vegetation indices and PCs

R_2 = correlation between foliage biomass derived from exponential model with CC, vegetation indices and PCs

R_3 = correlation between TAGB with CC, vegetation indices and PCs

TAGB was calculated by applying equation developed by Brown (1997). The equation used was Y = Exp{-2.134+2.530*ln(DBH)}. This equation was for broadleaf tropical moist forest suitable to the study area which has the same zone (Appanah, 1998). This equation was used because, for the moment, this was the best available one that was constructed using more than 100 weighted trees (Chave et al., 2004).

3. Results

3.1. Foliage Biomass Equation

During the analyses two outliers were found, i.e. trees with DBH 75 cm and 89 cm. These outliers were removed from the data in order to get the better equation. The first outlier was caused by applying a different method of measurement for the tree with DBH 75 cm. The sub sampling was applied for this tree, but because the software did not work properly and field condition did not favour such measurement, the estimation of the total biomass could not be done. Another outlier was a tree with DBH 89 cm. When this tree was felled by the logger, the canopy structure did not represent the full canopy and also many lianas was found surrounding canopy. Finally, only 33 samples of trees were used.

Using least square regression analysis, the exponential model show a high correlation between DBH and foliage biomass (Regression, foliage biomass (Y) = EXP {3.11+ 0.06 *ln (DBH)}, R^2 = 0.82, p = 0.05) as in Figure 3.1.1.

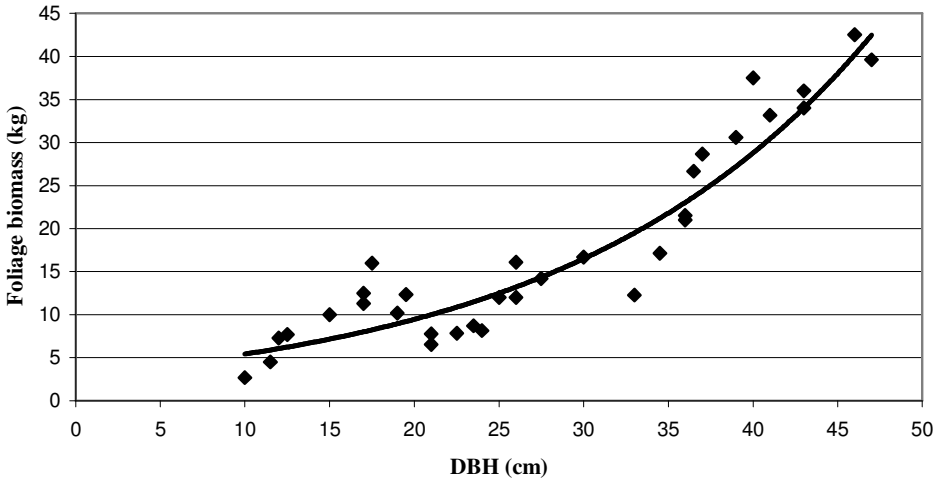


Figure 3.1.1Exponential fit line

The polynomial model was derived by weighed linear regression analysis using backward elimination technique. It was found that (DBH) and $(DBH)^2$ were not significant at p = 0.05. However, $(DBH)^3$ is significantly correlated with foliage biomass (regression, foliage biomass (Y) = 6.64+ 0.0004 $(DBH)^3$, R^2 = 0.91, p < 0.05) as in Figure 3.1.2 and Appendix 2.

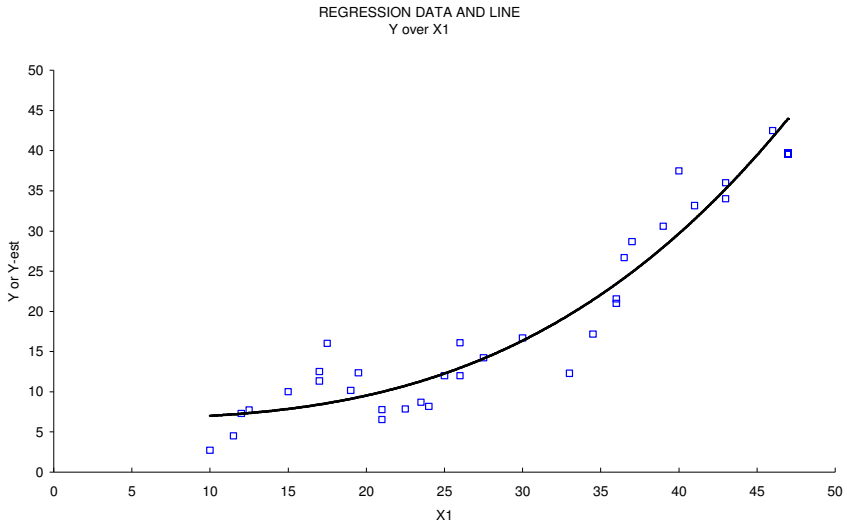


Figure 3.1.2 Regression Curve derived using backward elimination, X1 = DBH (cm), Y = dry foliage (kg)

Both foliage biomass equations were used to estimate the foliage biomass of the selected plots that consist of DBH within the range of 10-50 cm. After the calculation, it was found that the distribution of foliage biomass was not normally distributed. Thus, data were transformed by means of logarithmic transformation. The TAGB data were also be transformed to make their data were normally distributed before they were used in regression analyses.

3.2. Forest Parameters

The t-test for two mean differences using probability level (α) 0.05 showed that some forest parameters on five-year logging blocks (RKLs) were not significantly different, especially for canopy cover, though they were logged in different time period (Appendix 5). The figure 3.2.1 showed that canopy cover, basal area and number of species ranged from 63 to 68%, 29 to 42 m^2/ha and 16 to 21 respectively.

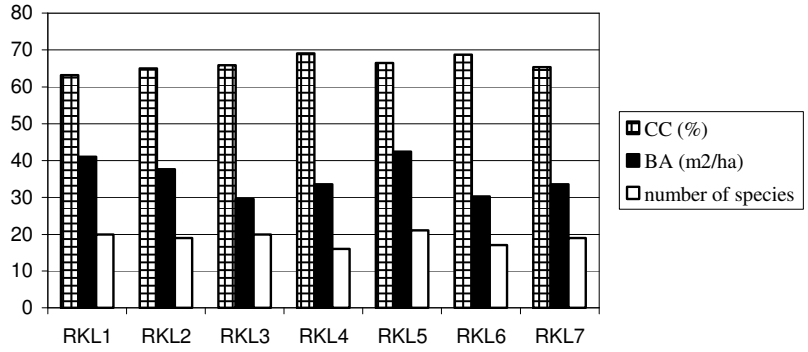


Figure 3.2.1Forest parameters in the different logging time

The total number of species was 124 and the most dominant one was *Shorea sp.* 7.62% (Appendix 4). It was found that most of the trees had diameter less than 50 cm and only 5.32 % which had diameter greater than 50 cm. Trees with diameter greater than 50 cm were distributed in 50 plots of the total 90 plots.

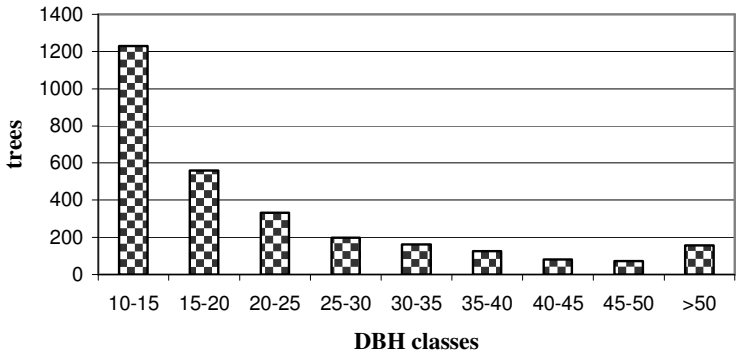
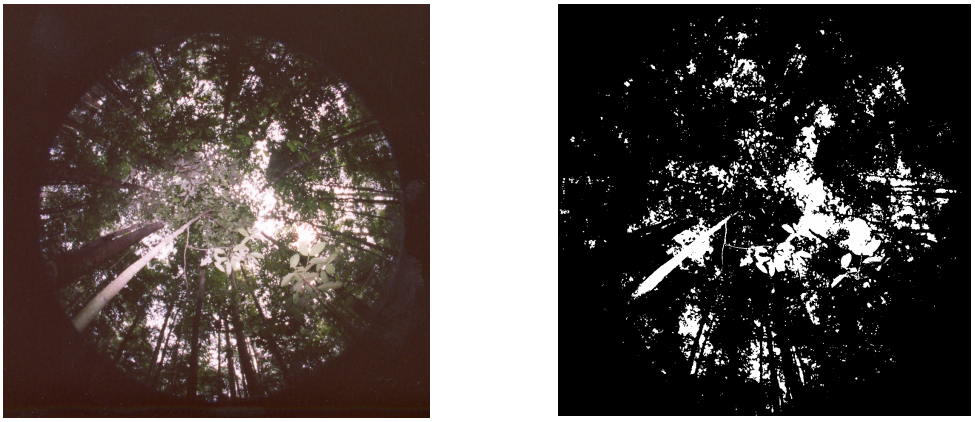


Figure 3.2.2DBH distribution found in the study area

3.3. Canopy Covers and Biomass

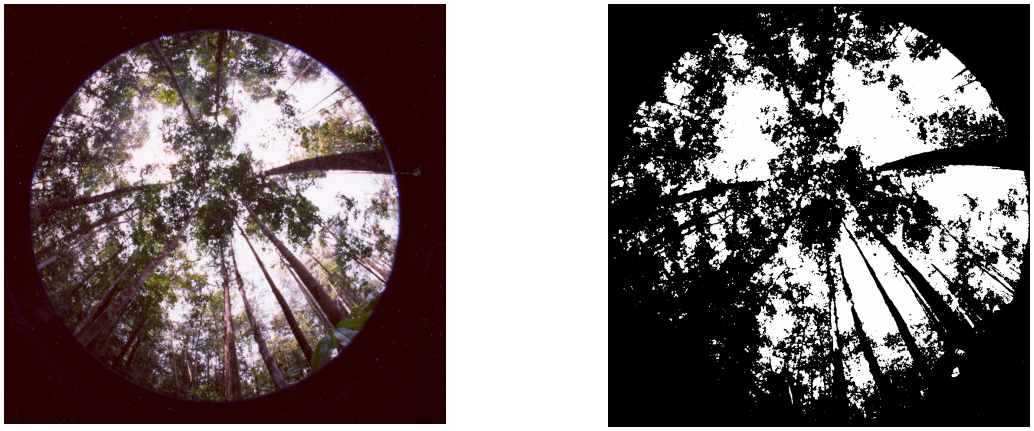
During the analyses of canopy covers using Gap Light Analyzer (GLA), it was realised that the procedure produced relative value of the canopy openness on the basis of the given threshold. As the threshold values are subjective and depended on personal perception, the result will be different from user to user. In addition, the soft ware was only able to differentiate between the dark and bright object. The stem and foliage of the tree such as *Koompassia malaccensis* that reflect light appear bright then the software recognises them as the openness (Figure 3.3.1). The problem of subjectivity also occurred during visual interpretation. The difference between both methods was in their precisions. In visual interpretation the precision was 5 %, while in the GLA it was 0.01 %.



(a) (b)

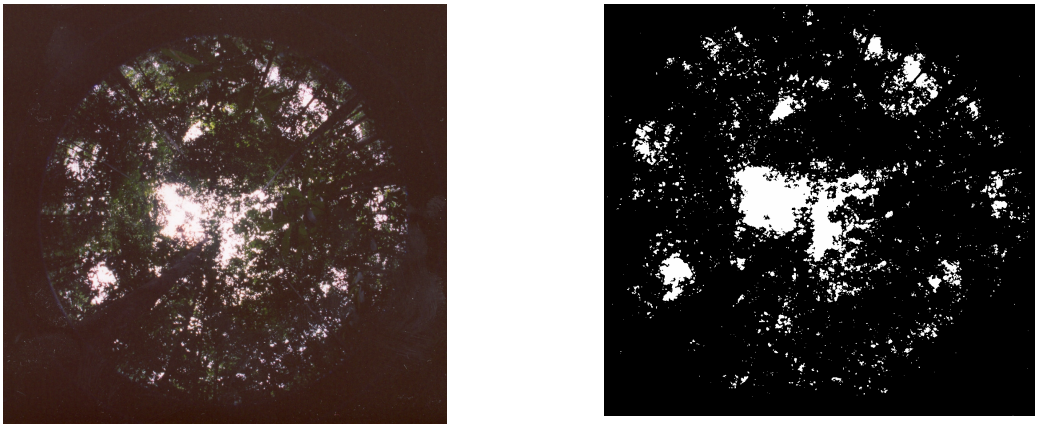
Figure 3.3.1 Hemispherical photo of bright stem and foliage of *Koompassia malaccensis* (a) and analysed photo (b)

Figure 3.3.2 and Figure 3.3.3 were the examples of sparse and dense canopy analysed by GLA. Each photo represented the canopy cover of each plot.



(a) (b)

Figure 3.3.2 Hemispherical photo of sparse vegetation (a) analysed photo (b)



(a) (b)

Figure 3.3.3 Hemispherical photo of dense vegetation (a) analysed photo (b)

Comparing the two analyses methods, it was found that there was a positive correlation between CC from visual interpretation (CC_{Visual}) and CC from GLA (CC_{GLA}) (regression, $CC_{Visual} = 0.9213*CC_{GLA}+10.525$, $R^2 = 0.81$, $p = 0.05$). An increase in CC_{GLA} was followed by 0.92 increases in CC_{GLA} as in Figure 3.3.4. CC derived from GLA was assumed to be correct since it was more precise than that from visual interpretation.

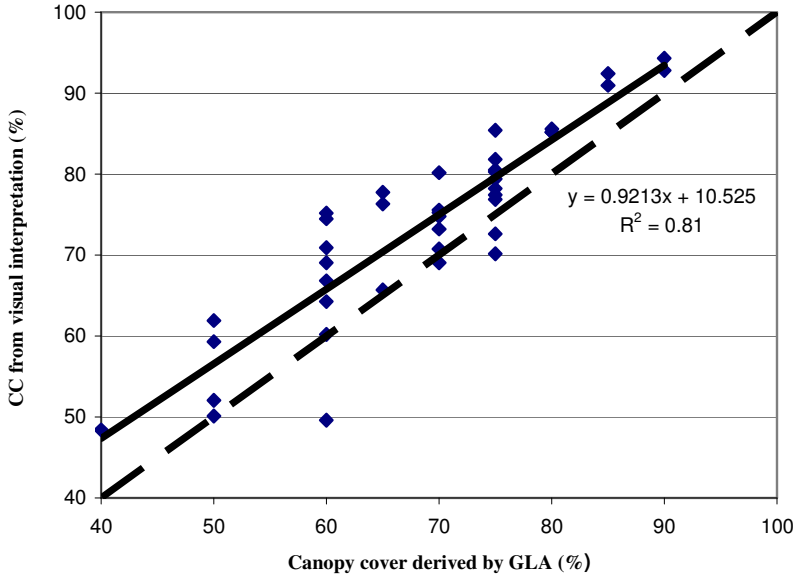
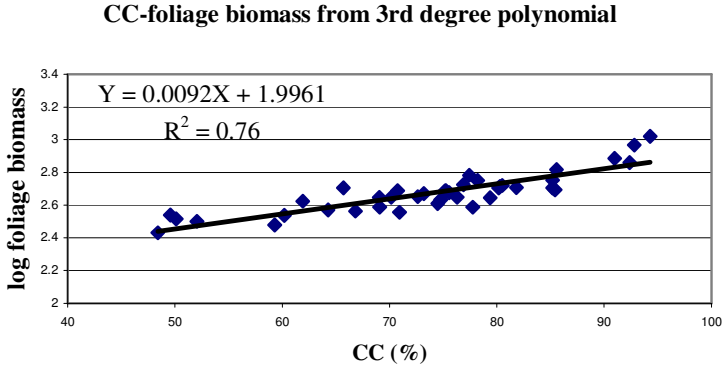


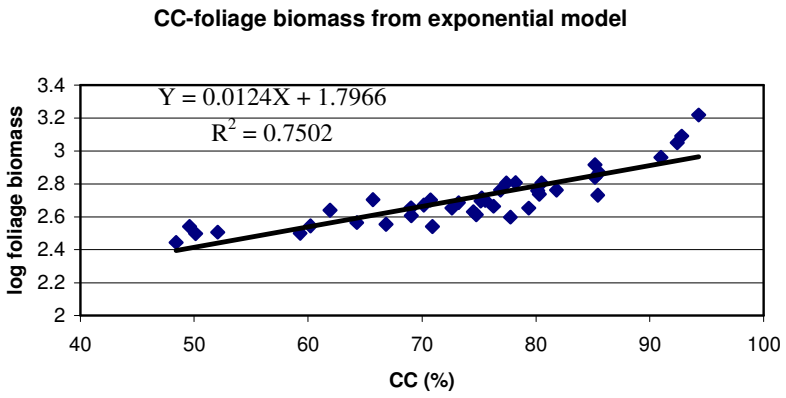
Figure 3.3.4 Comparison of canopy cover derived from visual interpretation and GLA

Further analyses then were done in order to find out the correlation between the foliage biomass derived from each model (exponential and 3rd degree polynomial) and TAGB with CC_{GLA}. It was found that there were high correlations between CC_{GLA} with the log foliage biomass derived from 3rd degree polynomial (regression, log foliage biomass (Y) = 0.0092X + 1.9961, $R^2 = 0.76$, $p < 0.05$) and log foliage biomass derived from exponential model (regression, log foliage biomass (Y) = 0.0124X + 1.7966, $R^2 = 0.75$, $p < 0.05$). On the other hand, such correlation was not found with log TAGB (regression, log foliage biomass (Y) = 0.0105X + 3.3749, $R^2 = 0.44$, $p < 0.05$) as in Figure 3.3.5(c).

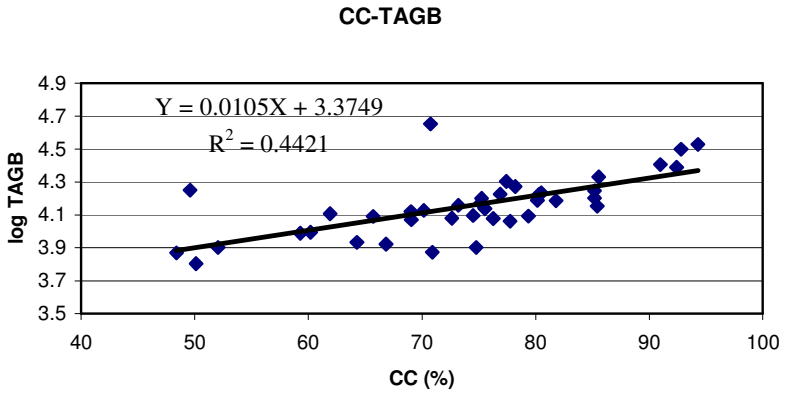


(a)

Figure 3.3.5 Correlation between CC with log foliage biomass from 3rd degree polynomial (a) from exponential model (b) and log TAGB (c)



(b)



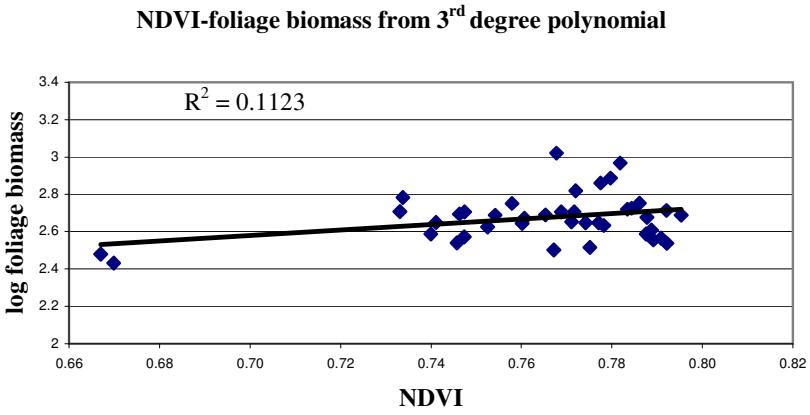
(c)

Figure 3.3.5 (continued)

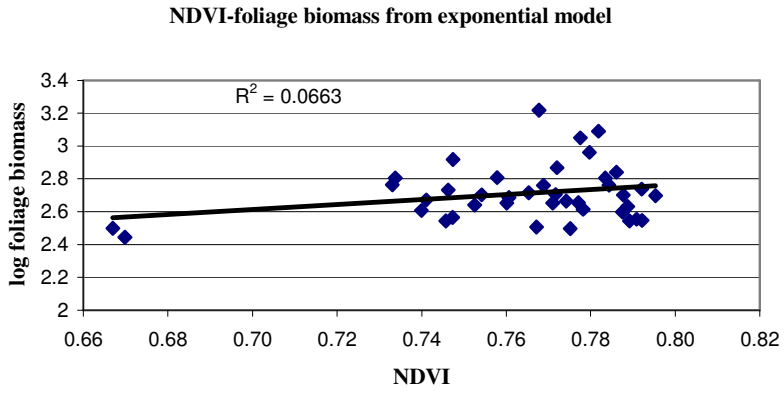
Figure 3.3.5 showed that an increase in the CC_{GLA} resulted in increase of log foliage biomass as much as 0.0092 (a), 0.0124 (b) and increase log TAGB 0.0105 (c). This implies that the foliage biomass and TAGB can be derived from the hemispherical photos, where crown covers can be easily estimated.

Moreover, test of the difference between three correlation revealed that these correlations were significantly different (χ^2test, χ^2= 6035.5, df = 2, $p \approx 0$). It means that foliage biomass derived from 3rd degree polynomial and from exponential model had stronger relationships with CC_{GLA} than that of TAGB with CC_{GLA} (Appendix 7).

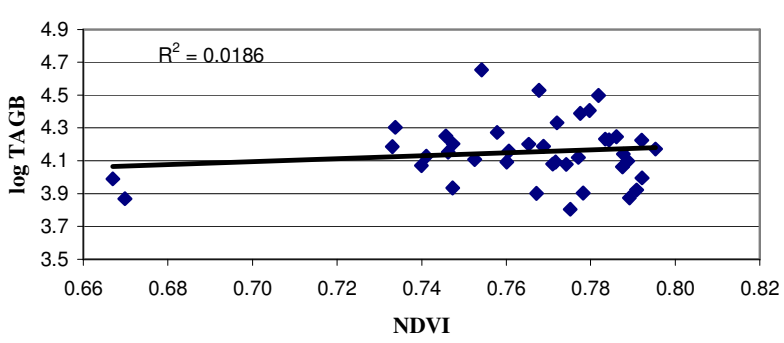
3.4. Vegetation Indices and Foliage Biomass



(a)



(b)



(c)

Figure 3.4.1 Correlation between NDVI with log foliage biomass from 3rd degree polynomial (a) from exponential model (b) and log TAGB(c)

Our analyses revealed that there were low correlations between NDVI with log foliage biomass derived from 3rd degree polynomial (Pearson correlation, r = 0.335, p = 0.1), log foliage biomass from exponential model (Pearson correlation, r = 0.257, p = 0.1), and also log TAGB (Pearson correlation, r = 0.136, p = 0.4). Using the same analyses, the low correlations were found also in other indices (Table 3.4.1)

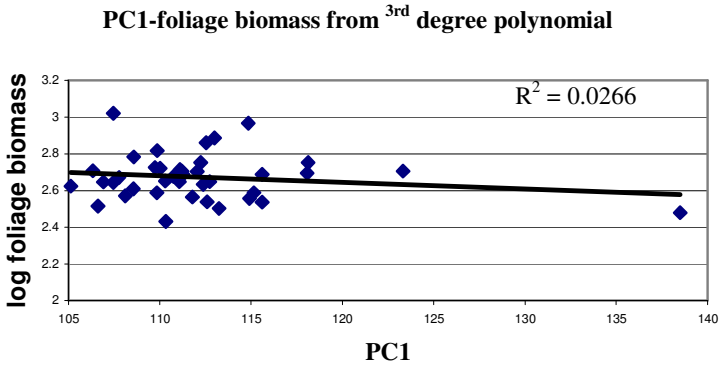
Table 3.4.1Correlation analyses of log foliage and log TAGB with the indices

Indices		log foliage biomass from 3rd degree polynomial	log foliage biomass from exponential model	log TAGB
NDVI	: Pearson correlation (r)	0.335	0.257	0.136
	: p (2-tailed)	0.1	0.1	0.4
ARVI	: Pearson correlation (r)	0.284	0.238	0.150
	: p (2-tailed)	0.12	0.14	0.36
MSAVI2	: Pearson correlation (r)	0.154	0.131	-0.016
	: p (2-tailed)	0.48	0.42	0.92
AVI	: Pearson correlation (r)	0.07	0.055	0.053
	: p (2-tailed)	0.84	0.74	0.71

Since it was found that there were low correlations between the whole indices with log foliage biomass and log TAGB, the further analysis could not be done to prove the hypotheses. It could not be concluded that there are significant differences between the correlation of foliage biomass with vegetation indices and that of TAGB with vegetation indices.

3.5. Principal Component and foliage biomass

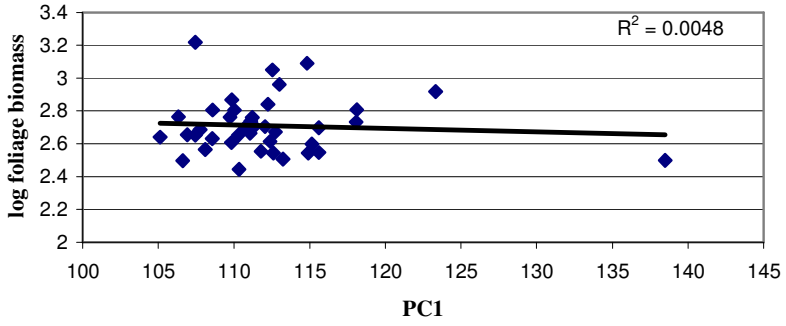
Statistical analyses revealed that there were low correlations between PC1 with log foliage biomass derived from 3rd degree polynomial (correlation, r = -0.163, p = 0.34), from exponential model (correlation, r = -0.069, p = 0.67), and also log TAGB (correlation, r = 0.066, p = 0.69).



(a)

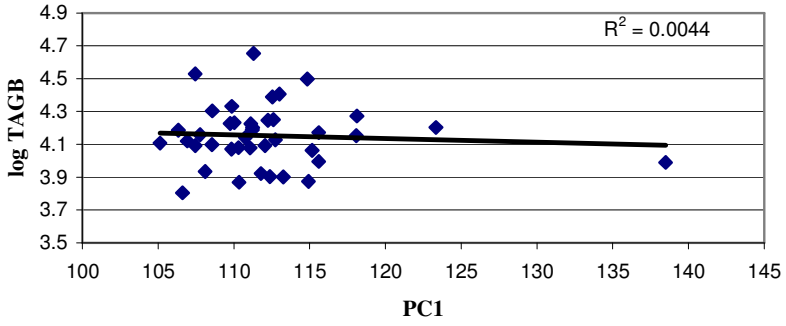
Figure 3.5.1Correlation between PC1 with log foliage biomass from 3rd degree polynomial (a) from exponential model (b) and log TAGB (c)

PC1-foliage biomass from exponential model



(b)

PC1-TAGB



(c)

Figure 3.5.1 (continued)

The low correlation were also found between PC2 and PC3 with log foliage biomass and log TAGB (Table 3.5.1)

Table 3.5.1 Correlation of log foliage and log TAGB with principal components

Indices		log foliage biomass from 3rd degree polynomial	log foliage biomass from exponential model	log TAGB
PC1	: Pearson correlation (r)	-0.163	-0.069	0.066
	p (2-tailed)	0.34	0.67	0.69
PC2	: Pearson correlation (r)	0.158	0.136	-0.004
	: p (2-tailed)	0.50	0.40	1.00
PC3	: Pearson correlation (r)	0.239	-0.195	-0.095
	: p (2-tailed)	0.21	0.23	0.57

Due to low correlations between the whole PCs with log foliage biomass and log TAGB, the further analysis could not be done to prove the hypotheses. So that, it could not be concluded that there are significant differences between the correlation of foliage biomass with PCs and that of TAGB with PCs.

4. Discussion

4.1. Foliage Biomass Equation

The foliage biomass in the form of exponential model is in agreement with the foliage biomass equations produced by Naidu et al. (1998), Bartelink (1998), Ketterings et al. (2001), Hoffmann and Usoltev (2002), Williams et al.(2003a) and Grote (2002).

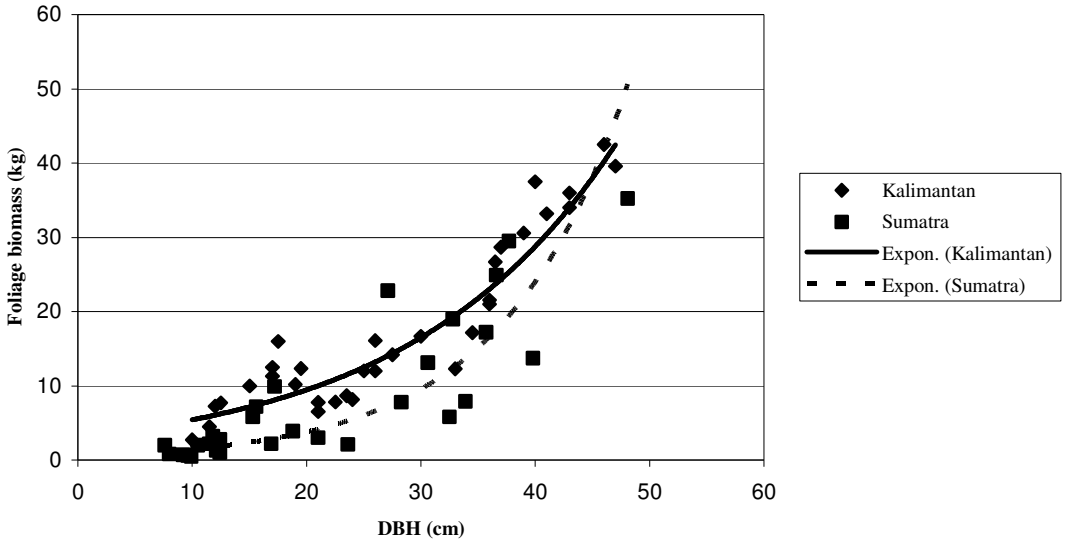


Figure 4.1.1 Comparison between foliage biomass Kalimantan and Sumatra (Ketterings et al., 2001)

The foliage biomass produced by Ketterings et al. (2001) was derived using 29 harvested individual trees in secondary forest stands in Sepunggur, Jambi province Sumatra. These 29 trees were from different species. Blazier et al. (2004) found the difference of above ground dry mass (branch and foliage) between two loblolly pine (*Pinus taeda* L.) of North Carolina Coastal and local Oklahoma/Arkansas. This may explain why the Sumatra's equation was slightly different with the Kalimantan's equation. However, both data showed the same pattern. If these data were combined they will result in a new equation but with lower R^2 (0.66) as in Figure 4.1.2. It suggests that there is a possibility to derive the new equation based on these combined data in order to increase its applicability, since the data derived from the various species from different site condition.

However, this exponential model has disadvantage that the precision of the relationship between the foliage biomass and DBH cannot be established. The coefficient of determination refer to the logarithmic equation and not the equation (Gier, 2003)

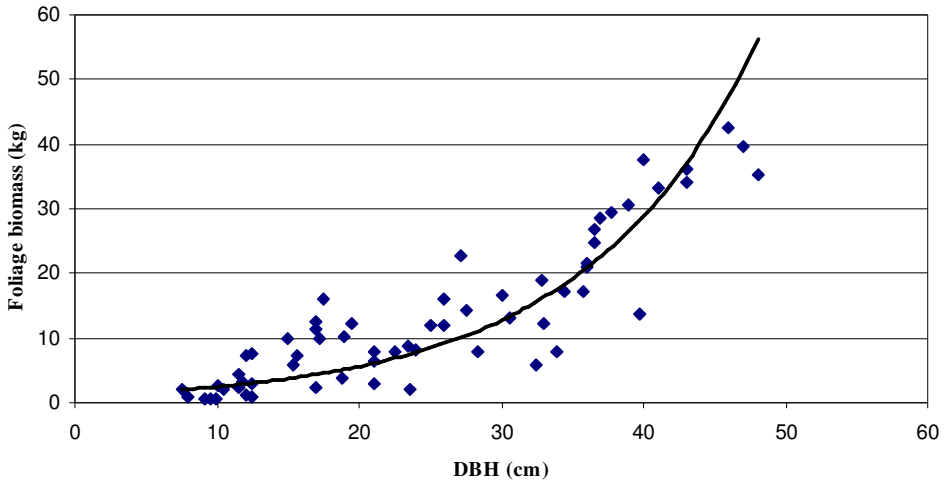


Figure 4.1.2Foliage biomass using data from Kalimantan and Sumatra (Ketterings et al., 2001)

The foliage biomass in the form of 3rd degree polynomial confirms the findings of Gier (2003) and Adhikari (2005) who reported significant relationship between DBH and woody biomass. However, this model have disadvantage that the shape may be biologically unreasonable (Ketterings et al., 2001). While the exponential curve represents the way in which some organisms grow at certain stages (Snedecor and Cochran, 1989). Because of the limitation of the data, at this moment, we can not make a concrete conclusion as to which model is better.

Although the R^2 was high, it was not free from error. Only 82 % and 91 % of the variance was explained by exponential and 3rd degree polynomial model, respectively, while the rest was error. There were several errors detected. First was the measurement of stem diameter. The diameter was measured at approximately 130 cm or at breast height. In the field it was not possible to measure in this exact height since the operators were not of the same height. In addition, measurement was done using caliper. However, since the stem is not uniformly cylindrical, the diameter measured was prone to error, although the measurements were done twice per individual trees, perpendicular to each other.

Secondly, when individual tree was felled, the surrounding trees were also affected. Their crowns were broken and sometimes they felled also. It was difficult to differentiate the crowns of the sampled trees from the others, especially if these from the same species. This condition explains why the sub sampling method was difficult to apply in the study area.

Thirdly, the capacity of weighing scale was 25 kg and the fresh weight exceeded 100 kg. Consequently 4 or more measurements were done. In addition, the sample weight was taken by 1 kg weighing scale with precision of 10 gram while the sample was approximately only 20-50 gram. These small measurements were difficult in the field.

These three errors are called the measurement error (Cunia, 1986). Other errors that probably affect foliage biomass model are error due to sampling error and statistical modeling. Sampling error is error due to sample tree selection resulted from sampling design by which the sample tree are selected, by the number of the sample and by inherent variation between the foliage biomass of various tress (Cunia, 1986). In this study the number of the sample trees was small (35) and consisted of only 5 tree species within the certain diameter range (Appendix 1). These probably were not enough to represent the actual value of foliage biomass in the field that consists of approximately 124 trees species (Appendix 4) with the various diameter range (Figure 3.2.2).

In addition, statistical model used in the data analysis and estimation were exponential and polynomial. Between these two models we cannot conclude yet which is the best one since the limitation of the data. As stated by (Cunia, 1986), for any given data, the analysis may resulted in different biomass model.

Since some errors were detected during the model derivation, the validation is still needed in order to make the model more accurate and applicable. These can be done by taking more samples of individual trees with higher diameter classes from similar species. This is to accommodate conditions in the field that consists of diameter higher than those used in the equation. Another possibility is by sampling trees from different genera or species that exist in the field with representative diameter range.

4.2. Canopy covers and biomass

Our result revealed a positive significant relationship between canopy cover (CC) with log foliage biomass. From this relationship, 75 % of the variance is explained by the model. It implies that the more the canopy percentage the more the foliage biomass is. This result confirms Zhang et al. (2004) and Ilomaki et al. (2003) findings where they concluded that the distribution of foliage was influenced by crown length and foliage biomass increases with crown length. In addition, Bartelink (1998) reported the exponential correlation between crown projection area (m^2) with crown biomass.

From this relationship, it implies that individual trees with more leaves horizontally distributed are prone to have higher CC than those that are vertically distributed. Consequently, their foliage biomass will appear higher as well. In this study, canopy covers only represent the foliage in the dimension of area, whereas the foliage biomass represents the mass dimension. According to Frazer et al. (2005), canopy are shaped by all components of stand structure including live tree-size and age distribution, stem density, species composition, crown widths and depths, leaf area and density, growth form and spatial arrangement of individual boles. It implies that the correlation between CC and foliage biomass are specific, because if it is generated from broadleaf species it can not be applicable in needle leaf, because both of them have different canopy structure. Broadleaf is more horizontally distributed (wider crown) than needle leaf. In stand level, the layers of the stand also influence the foliage biomass and its distribution. Stands with multi layers (different species composition, and different age) will be different from that with single layer (monoculture, uniform, even age) in term of their foliage biomass content although both of them

have the same CC. Since forest stand in the study area consists of more than one layer, then the correlation can not be applied directly in the single layer forest stand.

The relationship between CC and TAGB confirms the result of Gier (2003) who found significant relationship between CC with volume. Canopy cover was estimated using Panchromatic, 1:5000 scale aerial photo of the open woodland in The Netherlands. He concluded that CC was the second best independent variable correlated with plot volume (r = 0.5716) after the high of the tallest tree (r = 0.6497).

This finding suggests that it is possible to estimate the foliage biomass and TAGB in the study area using CC in order to reduce the labor-intensive ground survey in collecting DBH data. But before this finding can be applied, validation has to be made. Since the relationship was derived from the small samples (40) and it did not cover the whole possible CC value in the field. Figure 4.3.1 shows that the CC data were concentrated in the range of 65-85%.

It seems that all the plots mostly covered by the vegetation with canopy cover range from 49.6-94.3% (Figure 3.2.1). Related to remotely sensed data, reflectance of the surface captured by the sensor was mainly the reflectance of the forest cover. The dense canopy cover influenced the performance of the vegetation indices, since the vegetation used the visible band and NIR. The visible bands have tendencies to be absorbed while the NIR is reflected by the green vegetation.

4.3. Vegetation Indices and Biomass

The results revealed that there were low correlations between all vegetation indices and PC tested with the foliage biomass and TAGB as well.

4.3.1. Normalized Difference Vegetation Index (NDVI)

The low correlation between NDVI with the foliage biomass and TAGB was in agreement with Lu et al. (2004), Foody et al.(2003) and Okuda et al. (2001) . Lu et al. (2004) revealed that indices which use a combination of TM3 and TM4 such as ARVI and NDVI were poorly correlated with the forest parameters, such as TAGB. Moreover, the poorly correlated NDVI was also found by Zarco-Tejada et al. (2004) and (2005) when detecting the chlorophyll a and b content using hyper spectral data. They concluded that the traditional indices such as NDVI normally show low correlation with leaf biochemical. In addition, NDVI yielded coefficient of determination equal to 0 ($R^2 \approx 0$) on aggregated pixel and 0.36 on pure pixels.

One of the possible causes of this low correlation can be attributed to the condition in the field. All of the plots selected were covered by forest canopy in the range of 49.6 %-94.3%. As reported by Gemmell and McDonald (2002), Qi et al. (1994) and Gitelson et al. (2002), NDVI was quite linear when high covers (> 50%) were reached, it became insensitive to cover change. Moreover, Hueté et al. (2002) found that NDVI asymptotically saturate in high biomass region. In addition, Myneni and Asrar (1994) and Rondeaux et al. (1996) also reported that NDVI was saturated in the canopy leaf area index > 2. Rondeaux et al. (1996) confirmed that NDVI will give poor information about

vegetation canopy when the soil background is unknown. The issue of saturated NDVI is not only reported for forest canopy but also in mature corn field (Chen et al., 2005).

The low correlation was also attributed to the inability of data with spectral resolution of Landsat-7 ETM+ to account for the variability of forest biophysical features that relate to biomass. Therefore, using multi spectral satellite images acquired only within visible, near-infrared, and shortwave infrared wavelengths (0.4–2.5 mm) was probably insufficient to detect local changes in TAGB (Okuda et al., 2004). On the other hand, Okuda et al. (2004) managed to find significant correlations between canopy height, derived from aerial photo with TAGB in Pasoh forest reserve in Malaysia. It is obvious that compared to Landsat TM image, aerial photo has higher spatial resolution, consequently it can be used to detect the forest parameters more accurately than Landsat TM image. Landsat TM image cannot detect the local variation in TAGB since it cannot provide structural information on the vegetation surface.

Forest structure also affected the performance of the index as reported by (Lee and Nakane, 1997). Lee and Nakane (1997) managed to find a significant relationship between NDVI with the TAGB of pine (*Pinus densiflora*) but the low correlation with broadleaf (*Quercus serrata, Castanea crenata* and *Carpinus laxiflora*) stands. It is likely that the low correlation is due to the structural variation of the forest. Pine forest is composed of relatively similar age classes and generally it is fully stocked by uniform canopy heights and crown types, while broadleaf, especially in tropical forest consists of multiple layers, multi species and non uniform canopy height and type.

4.3.2. Atmospherically Resistant Vegetation Index (ARVI)

It was found that there was low correlation with the foliage biomass and TAGB in the dense CC. This results was in agreement with Kaufman and Tanré (1992) and Myneni and Asrar (1994). Kaufman and Tanré (1992) revealed that ARVI has similar dynamics range to NDVI. It implies that similar to NDVI, ARVI saturates when certain canopy cover is reached. Moreover, Myneni and Asrar (1994) reported that ARVI was saturated after canopy leaf area index > 2 that is likely the cause of the low correlation with the foliage biomass and TAGB. Our result also confirms to the finding of Lu et al. (2004) who reported low correlation between ARVI with TAGB.

Figure 4.3.1 showed that ARVI exceeds NDVI in the whole canopy covers. On the other hand Kaufman and Tanré (1992), did not find such phenomenon. ARVI exceed NDVI after the vegetation fraction reached 80%. Table 4.3.1 showed that the blue reflectance was higher than that of red. This condition was different with the result from Kaufman and Tanré (1992) who used MODIS which has different wavelength with Landsat-7 ETM+. This probably explains why ARVI was always higher than NDVI even in the vegetation fraction < 80%. The minimum value of reflectance blue was higher than the maximum value of red reflectance. Based on the equation 1.3.2, ARVI exceed the value of 1 probably because of the high value of blue reflectance. It was obvious that the red and blue reflectance were mostly absorbed by the green vegetation since most areas were vegetated. However, red was likely to be more absorbed than blue.

Table 4.3.1 Relation between reflectance blue channel, red channel and NIR channel of subset image covering the study area

Reflectance	Minimum	Maximum	Mean	Std. Deviation
Blue	**.083**	.092	.08653	.002634
Red	.027	**.041**	.03183	.002674
NIR	.196	.280	.24549	.016438

4.3.3. Modified Soil Adjusted Vegetation Index (MSAVI)

Our analyses revealed low correlations between MSAVI2 with the foliage biomass and TAGB. The low correlation between MSAVI2 and TAGB confirms the findings of Lu et al. (2004) who reported that MSAVI2 was poorly correlated with TAGB. However, Zheng et al.(2004) found a strong correlation between MSAVI2 and TAGB. This strong correlation may be due to the composition of the forest where their data was derived. Zheng et al.(2004) conducted their study in an even age forest structure in northern Wisconsin USA. This is likely the managed forest because several silvicultural techniques such as clear cutting, thinning and prescribed burning have been applied. It is likely that the difference result is caused by the different in complexity of the forest structure between our study area and the study area of Zheng et al.(2004).

Similar to NDVI, the issue of saturation was also found. MSAVI2 was saturated when large cover value (LAI > 2) was reached (Rondeaux et al., 1996). Because of the inventory data were derived from relatively dense vegetation, it is likely that MSAVI2 can not be as a good predictor of the foliage biomass and TAGB in the study area.

4.3.4. Advance Vegetation Index (AVI)

Rikimaru (2002) reported that if the forest canopy density is high then AVI will be high. The high forest canopy density means that there is a lot of vegetation cover; consequently its biomass is also high. But he also reported that AVI saturated after a certain canopy density. Our study showed low correlations between AVI with foliage biomass and TAGB as well. It is likely that, AVI is in the saturation stage.

Because of this situation, AVI can not perform better than NDVI as stated by Rikimaru (2002). He indicated that AVI was more sensitive to the quantity of vegetation compared to NDVI. In contrast, this study revealed that correlation between foliage biomass with AVI ($r = 0.055$) was lower than that of NDVI ($r = 0.257$)

4.3.5. Principal components

Our analyses revealed low correlation of the three PCs with the foliage biomass and TAGB. However, the findings of Lu et al. (2004) did not show such low correlation. Lu et al. (2004) concluded that PC1 is the most strongly correlated with forest stand parameters compare to PC2 and PC3. Despite showing strong correlation these linearly transformed images provided higher

correlation coefficients than other categories of vegetation indices such as NDVI, ARVI and MSAVI2.

This difference is likely due to the difference in the forest structure. Lu et al. (2004) conducted their research in Brazilian Amazon Basin which is dominated by successional vegetation, most often between 10 and 25 years; 8 and 17 years and less than 15 years whereas in this study the succesional vegetation varies from 0 to 29 years (Table 2.1.1). This succession is distributed within the five year working plan compartments (RKL). Despite this different succession stage, the Brazilian Amazon Basin consists of three different land uses, namely swidden agriculture, agroforestry, and pasture management, whereas Labanan is mainly dominated by logged over forest which is densely covered by canopy.

4.3.6. General discussion

Our analyses of the indices and also PCs in relation to the foliage biomass showed low correlation for all indices and PCs. These low correlations are likely due to several reasons, such as:

1. The error during the foliage biomass construction as discussed in Chapter 4.1 and the application of the model. The error of the application was caused by which regression function was estimated from trees that were not member of the population (Cunia, 1986). Although the samples trees were from the same forest type, these were not belong to the population where the models were applied. In term of the number of species and the diameter range, it was not enough to represent the population.
2. The accuracy of the GPS and the error due to image registration were subject to the low correlation. In order to accommodate the error, the indices and PCs values in each plot were calculated using a window 3x3 to generate their mean value. It means that one plot (500 m^2) have value generated from 8100 m^2 pixel. The issue of mix pixel therefore arises and the indices and PCs could not perform best in such condition.
3. The species composition of the study area is so varied. In each plot, the average number of species is 19. According to Rondeaux et al. (1996) the optical reflectance is affected by plant type (species). Related to the spatial and spectral resolution of Landsat TM, it is too broad to generalize such variation.
4. The CC values are in the stage where most of the indices are saturated. In this stage, the spatial and spectral resolution of Landsat TM can not detect the small difference of the foliage biomass and TAGB as well.

In order to increase the significance and correlation of the indices and PCs with the foliage the next possible steps are:

1. Validation of the foliage biomass equation, as discussed in Chapter 4.1. Considering field condition, there are many possibilities to fell the sample trees. During field work, we found logging activities in the study area. From the informal discussion with the labourers, this area will be utilized as coal mining area. After the selective logging it is likely clear cutting or mining activities will follow. Thus, for this moment, it is possible to cut the trees by following these logging activities.

2. Using the better spatial and spectral resolution of the image such as Quickbird, IKONOS and hyperspectral images. With higher spatial resolution such as Quickbird and IKONOS the variation of forest parameters in the plot will be clearly detected as reported by Greenberg et al. (2005). They managed to identify forest parameters such as shadow area, crown area, DBH, tree density and estimate the biomass using IKONOS imagery data. In addition, hyperspectral remote sensing offers possibilities of investigating vegetation indices based on narrow bands in the whole electromagnetic spectrum (350-2500 nm) (Mutanga and Skidmore, 2004). Mutanga and Skidmore (2004) confirmed that red edge reflectance (680-750 nm) contains information that best estimate biomass at full canopy covers. This finding offers the opportunities to solve the problem of index saturation as found in this study. Regarding the complexity of the canopy covers in the study area, Sims and Gamon (2002a), found that leaf surface reflectance was the most important factor. They managed to find the indices which were designed to eliminate the effect of leaf surface reflectance. These modified indices were highly correlated with the chlorophyll contents across all leaf types. Moreover, Sims and Gamon (2002b) managed to derive a new Canopy Structure Index (CSI) that combines the low absorption water bands with the simple ratio vegetation index (SR) to produce an index with a wider range of sensitivity to photosynthetic tissue area at all canopy thickness. This new findings will allow us to explore the ability of these indices to estimate the forest parameters such as canopy thickness, canopy water content and also leaf pigment content.
3. Taking more samples of forest inventory. From Figure 4.3.1 it seems that NDVI, ARVI and MSAVI2 showed the same pattern. It suggests that these indices were in the saturation phase. The wide range of CC provides independent variation in the surface reflectance and thus allowing us to demonstrate that the issue of saturated indices is due to the CC and to show the better correlation of the VI proposed with the foliage biomass. Consequently, this significant correlation can be used to estimate the foliage biomass in the study area or others that have the same forest structure.

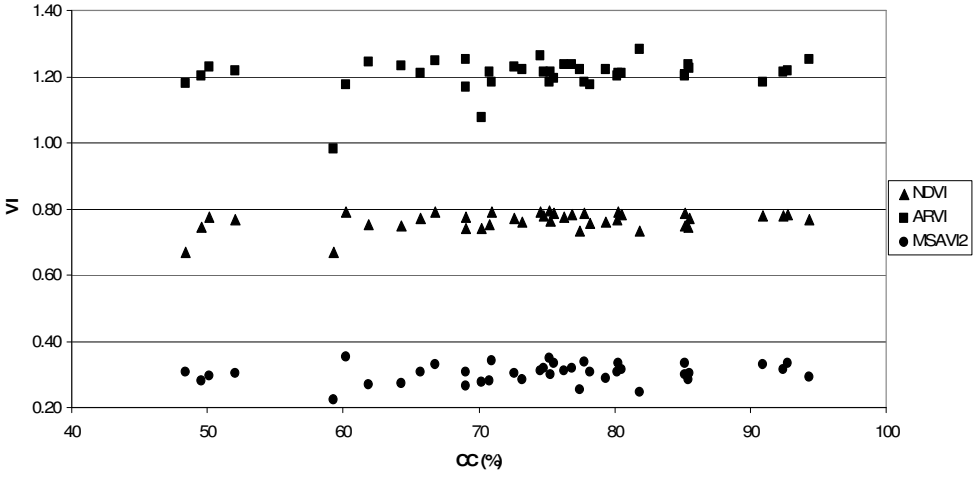


Figure 4.3.1 Comparison between vegetation indices' performances in the different CC condition

The findings of this study suggest that the estimation of foliage biomass can be done by applying the equation proposed which using DBH as predictor. Another finding is foliage biomass and TAGB can be estimated from canopy cover data if canopy covers are systematically measured by means of hemispherical photographs. This approach eliminates the need for labour-intensive ground surveys to measure DBH. Thus, to monitor the alteration of the foliage biomass regarding the transformation of forest structure caused by legal or illegal logging in the study area, we can utilize hemispherical photograph to capture the canopy openness in the systematically well designed sample plots. Instead of employing 3 labourers who will use approximately 30 minutes to measure DBH, 2 persons can be employed and equipped with a hemispherical photographs which will take approximately 5 minutes to capture the canopy openness per plots. Then the calculation of the CC can be done using GLA in a more sophisticated way in the office. However, in order to be more accurate, it requires more samples to validate this correlation. As it is suggested in point 3 above, additional samples are needed. The sample should also include the wide range of CC, from the low to the densely vegetated.

Thus, the advantages that can be derived from these findings to the study area are:

1. To estimate and monitor the foliage biomass by applying the equation proposed. These activities can utilize the forest inventory data before and after logging of PT. Hutan Sanggam Labanan Lestari.
2. To estimate and monitor the foliage biomass and TAGB by utilising hemispherical photographs to generate canopy cover which are measured in systematic method.

5. Conclusions and Recommendations

5.1. Conclusions

a. Relationship between foliage biomass and DBH
There is a significant relationship between the foliage biomass and DBH; the two possible relationships are exponential and 3rd degree polynomial (R^2 = 0.82 and 0.91). Among these two models, we can not conclude yet which one is the most accurate due to data limitation.

b. Capability of canopy covers to estimate foliage biomass
Canopy covers can be used to estimate foliage biomass in the study area, since it was found a highly correlation between CC and the foliage biomass (R^2 = 0.75).

c. Vegetation indices best estimate foliage biomass
Vegetation indices tested in this study could not represent as the best predictor for the foliage biomass, since the analyses found low correlation between these indices with the foliage biomass in the relatively dense vegetation.

d. PCA technique to generate information about foliage biomass
Principle components cannot perform well, since the correlation appeared low. The foliage biomass content cannot be detected using PCA technique.

These studies proved that foliage biomass have a stronger relationship with canopy cover than that of total above ground biomass.

5.2. Recomendations

a. Validation of the foliage biomass equation should be conducted to make this model applicable. There are many possibilities to fell the samples trees by following the logging activities.

b. Using the better spatial and spectral resolution of the image such as Quickbird, IKONOS and hyperspectral images will allow us to clearly detect variation of forest parameters and offer possibilities of investigating vegetation indices based on narrow bands to solve the problem of index saturation as it is found in this study.

c. Taking more samples of forest inventory from the wide range of CC will provide independent variation in the surface reflectance and allow us to overcome the issue of saturation.

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7. Appendices

Appendix 1 Foliage biomass data

Number Tree	Species	DBH (cm)	Dry Leaves (kg)
1	Tengkawang	75.00	12.49
2	Kruing	17.50	16.00
3	Tengkawang	30.00	16.68
4	Red Meranti	17.00	11.32
5	Majau	36.50	26.68
6	Red Meranti	12.00	7.28
7	Red Meranti	22.50	7.84
8	Red Meranti	27.50	14.20
9	Kruing	12.50	7.70
10	Tengkawang	11.50	4.50
11	Tengkawang	15.00	10.00
12	Red Meranti	34.50	17.16
13	Resak	23.50	8.70
14	Resak	10.00	2.70
15	Red Meranti	43.00	34.00
16	Resak	39.00	30.60
17	Resak	19.50	12.34
18	Red Meranti	47.00	39.60
19	Kruing	21.00	6.55
20	Kruing	26.00	16.10
21	Kruing	43.00	36.00
22	Kruing	33.00	12.28
23	Kruing	37.00	28.67
24	Kruing	46.00	42.50
25	Resak	41.00	33.17
26	Red Meranti	36.00	21.00
27	Tengkawang	40.00	37.50
28	Tengkawang	89.00	10.92
29	Tengkawang	36.00	21.53
30	Tengkawang	21.00	7.78
31	Tengkawang	26.00	12.01
32	Resak	25.00	12.00
33	Resak	24.00	8.17
34	Resak	19.00	10.17
35	Resak	17.00	12.50

Appendix 2 Weighted linear regression as calculated using Regdat and Polyreg

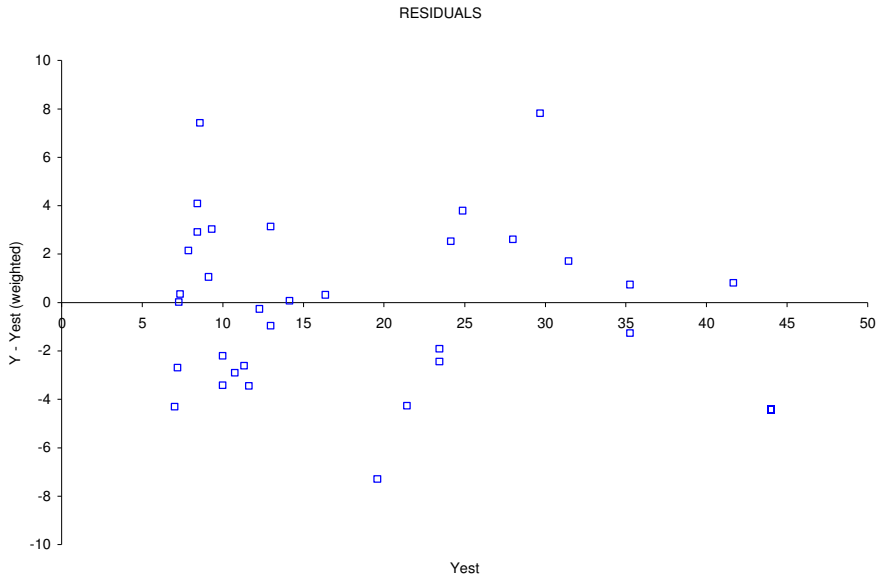
```
WEIGHTED LINEAR REGRESSION
==========================

DATE         : 12-13-2005 (mm-dd-yyyy)
TIME         : 09:46:58
PROGRAM FILE : polyreg.exe
DATA FILE    : __regdat.prn
NAME OBJECT  : DHB-DRY LEAVES
# DATA SETS  :  33

MODEL: Y=B0+B1*X1+B2*X2+B3*X3

Y   = DRY LEAVES (KG)
X 1 = DBH (CM)
X 2 = DBH^2
X 3 = DBH^3

WEIGHT =( 1/X10 )^2

COEFFICIENTS
B 0 =  3.6674935840D+00
B 1 =  3.8619552749D-01
B 2 = -1.4856070963D-02
B 3 =  5.3401345956D-04

ANALYSIS OF VARIANCE
           SS          df       MS
REG.   3.77511D+03     3   1.25837D+03
RES.   3.69508D+02    29   1.27417D+01
TOT.   4.14462D+03    32   1.29519D+02

VAR. RATIO (F) = 9.8760D+01

RES.MEAN SQUARE= 3.5695D+00

MEAN X1        = 2.7561D+01
MEAN Y         = 1.7734D+01

FURNIVAL INDEX = 3.5695D+00

COVARIANCE MATRIX
             B 0            B 1            B 2            B 3
B 0     1.0824D+02    -1.3121D+01     4.7819D-01    -5.3721D-03
B 1    -1.3121D+01     1.6483D+00    -6.1656D-02     7.0602D-04
B 2     4.7819D-01    -6.1656D-02     2.3592D-03    -2.7508D-05
B 3    -5.3721D-03     7.0602D-04    -2.7508D-05     3.2566D-07

MULTIPLE CORRELATIONS
R^2 = 9.1090D-01
R   = 9.5443D-01

CORRELATION MATRIX
            B 0            B 1            B 2            B 3
B 0     1.0000D+00    -9.8231D-01     9.4629D-01    -9.0485D-01
B 1    -9.8231D-01     1.0000D+00    -9.8871D-01     9.6364D-01
B 2     9.4629D-01    -9.8870D-01     1.0000D+00    -9.9243D-01
B 3    -9.0485D-01     9.6364D-01    -9.9242D-01     1.0000D+00

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----
B 0    1.0404D+01    3.5251D-01    -
B 1    1.2839D+00    3.0081D-01    -
```

```
B 2    4.8572D-02   -3.0586D-01    -
B 3    5.7066D-04    9.3578D-01    -
Non-significant variable  X1 will be removed

WEIGHTED LINEAR REGRESSION
==========================

DATE         : 12-13-2005 (mm-dd-yyyy)
TIME         : 09:46:58
PROGRAM FILE : polyreg.exe
DATA FILE    : __regdat.prn
NAME OBJECT  : DHB-DRY LEAVES
# DATA SETS  :  33

MODEL: Y=B0+B1*X1+B2*X2

Y   = DRY LEAVES (KG)
X 1 = DBH^2
X 2 = DBH^3

WEIGHT =( 1/X10 )^2

COEFFICIENTS
B 0 =  6.7416593844D+00
B 1 = -4.1043876789D-04
B 2 =  3.6859639612D-04

ANALYSIS OF VARIANCE
           SS         df       MS
REG.   3.77395D+03     2   1.88698D+03
RES.   3.70661D+02    30   1.23554D+01
TOT.   4.14462D+03    32   1.29519D+02

VAR. RATIO (F) = 1.5273D+02

RES.MEAN SQUARE= 3.5150D+00

MEAN X1        = 2.7561D+01
MEAN Y         = 1.7734D+01

FURNIVAL INDEX = 3.5150D+00

COVARIANCE MATRIX
             B 0            B 1            B 2
B 0     3.6802D+00    -1.2214D-02     2.4034D-04
B 1    -1.2214D-02     5.1388D-05    -1.0662D-06
B 2     2.4034D-04    -1.0662D-06     2.2545D-08

MULTIPLE CORRELATIONS
R^2 = 9.1062D-01
R   = 9.5429D-01

CORRELATION MATRIX
            B 0            B 1            B 2
B 0     1.0000D+00    -8.8818D-01     8.3439D-01
B 1    -8.8818D-01     1.0000D+00    -9.9054D-01
B 2     8.3439D-01    -9.9054D-01     1.0000D+00

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----
B 0    1.9184D+00    3.5142D+00   >1%
B 1    7.1685D-03   -5.7256D-02    -
B 2    1.5015D-04    2.4548D+00   >5%

Non-significant variable  X1 will be removed
```

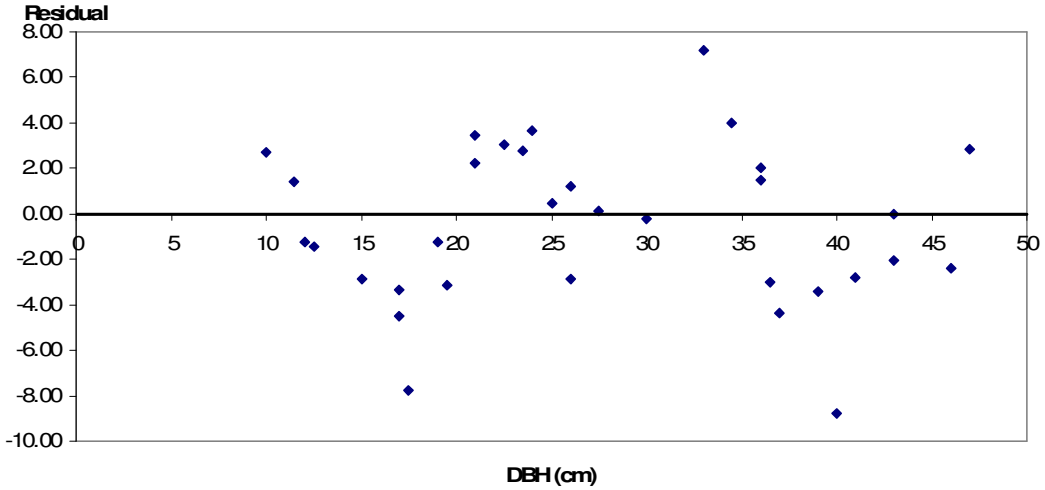
```
WEIGHTED LINEAR REGRESSION
==========================

DATE         : 12-13-2005 (mm-dd-yyyy)
TIME         : 09:46:58
PROGRAM FILE : polyreg.exe
DATA FILE    : __regdat.prn
NAME OBJECT  : DHB-DRY LEAVES
# DATA SETS  :  33

MODEL: Y=B0+B1*X1

Y   = DRY LEAVES (KG)
X 1 = DBH^3

WEIGHT =( 1/X10 )^2

COEFFICIENTS
B 0 =  6.6441032592D+00
B 1 =  3.6008071723D-04

ANALYSIS OF VARIANCE
           SS         df       MS
REG.   3.77391D+03     1   3.77391D+03
RES.   3.70702D+02    31   1.19581D+01
TOT.   4.14462D+03    32   1.29519D+02

VAR. RATIO (F) = 3.1559D+02

RES.MEAN SQUARE= 3.4581D+00

MEAN X1        = 2.7561D+01
MEAN Y         = 1.7734D+01

FURNIVAL INDEX = 3.4581D+00

COVARIANCE MATRIX
             B 0            B 1
B 0     7.5205D-01    -1.2653D-05
B 1    -1.2653D-05     4.1084D-10

MULTIPLE CORRELATIONS
R^2 = 9.1061D-01
R   = 9.5428D-01

CORRELATION MATRIX
            B 0            B 1
B 0     1.0000D+00    -7.1983D-01
B 1    -7.1983D-01     1.0000D+00

SIGNIFICANCE COEFFICIENTS
Coeff. St.Error          t       significance
-----  --------          -       -----
B 0    8.6721D-01    7.6615D+00   >0.1%
B 1    2.0269D-05    1.7765D+01   >0.1%
```

Appendix 3 Residual plots of the foliage biomass equation

The residual plots of polynomial model



The residual plots of exponential model



Appendix 4 Species distribution found in the study area

No.	Species Name	Number	%
1	*Shorea spp*	223	7.62
2	*Syzygium*	172	5.88
3	*Madhuca*	165	5.64
4	*Xanthophyllum*	148	5.06
5	*Knema*	132	4.51
6	*Dacryodes*	111	3.79
7	*Vatica*	111	3.79
8	*Alseodaphne*	105	3.59
9	*Dialium*	104	3.55
10	*Diospyros*	98	3.35
11	*Aporosa*	83	2.84
12	*Polyalthia*	79	2.70
13	*Palaquium*	76	2.60
14	*Drypetes*	66	2.26
15	*Barringtonia*	54	1.85
16	*Dipterocarpus*	54	1.85
17	*Myrisyica*	50	1.71
18	*Baccaurea*	48	1.64
19	*Gluta sp.*	46	1.57
20	*Hopea*	46	1.57
21	*Aglaia*	43	1.47
22	*Nephelium*	42	1.44
23	*Lithocarpus*	39	1.33
24	*Artocarpus*	38	1.30
25	*Mallotus*	38	1.30
26	*Caethocarpus*	31	1.06
27	*Canarium*	27	0.92
28	*Macaranga gigantea*	27	0.92
29	*Pentace*	27	0.92
30	*Allantospermum*	24	0.82
31	*Dillenia*	24	0.82
32	*Santiria*	23	0.79
33	*Calophyllum*	21	0.72
34	*Eusideroxylon zwagerii*	21	0.72
35	*Scapium*	20	0.68
36	*Durio*	19	0.65
37	*Garcinia*	18	0.62
38	*Gironniera*	18	0.62
39	*Koompassia malaccensis*	17	0.58
40	*Semecarpus*	17	0.58
41	*Porterandia*	16	0.55
42	*Archidendron*	15	0.51
43	*Teijsmanniodendron*	15	0.51
44	*Beilschmiedia*	14	0.48
45	*Elateriospermum tapos*	14	0.48
46	*Actinodaphne*	13	0.44
47	*Cyonanthes*	13	0.44
48	*Antidesma*	12	0.41
49	*Gironniera nervosa*	12	0.41
50	*Cynometra*	11	0.38

Appendix 4. (continued)

No.	Species Name	Number	%
51	Gluta renghas	11	0.38
52	Mangifera	11	0.38
53	Mezzettia	11	0.38
54	Sindora	11	0.38
55	Elaeocarpus	10	0.34
56	Glochidion	10	0.34
57	Gonystylus bancanus	10	0.34
58	Heritiera	10	0.34
59	Nauclea	10	0.34
60	Ardisia	9	0.31
61	Gluta wallichii	8	0.27
62	Koilodepas	8	0.27
63	Artocarpus lanceifolia	7	0.24
64	Dialium procerum	7	0.24
65	Macaranga hypoleuca	7	0.24
66	Lophopetalum	6	0.21
67	Ochanostachys amentacea	6	0.21
68	Pometia pinnata	6	0.21
69	Cratoxylon	5	0.17
70	Dyera costulata	5	0.17
71	Magnolia	5	0.17
72	Parashorea smythiesii	5	0.17
73	Stemonurus	5	0.17
74	Anisoptera	4	0.14
75	Croton	4	0.14
76	Ficus	4	0.14
77	Pertusadina	4	0.14
78	Pimilodendron	4	0.14
79	Artocarpus elasticus	3	0.10
80	Blumeodendron	3	0.10
81	Cotylelobium	3	0.10
82	Cryptocarya	3	0.10
83	Dialium induum	3	0.10
84	Kayea borneensis	3	0.10
85	Koompassia excelsa	3	0.10
86	Litsea	3	0.10
87	Microcos	3	0.10
88	Rhodamnia	3	0.10
89	Seranai	3	0.10
90	Vitex sp.	3	0.10
91	Alstonia scholaris	2	0.07
92	Artocarpus anisophyllus	2	0.07
93	Cynometra ramiflora	2	0.07
94	Durio oxleyanus	2	0.07
95	Eudia aromatica	2	0.07
96	Fahrenheitia pendula	2	0.07
97	Kayea	2	0.07
98	Mesua	2	0.07
99	Parinari	2	0.07
100	Parinari oblongifolia	2	0.07

Appendix 4. (continued)

No.	Species Name	Number	%
101	*Parkia speciosa*	2	0.07
102	*Payena*	2	0.07
103	*Pterospermum*	2	0.07
104	*Anthocephalus chinensis*	1	0.03
105	*Castanopsis*	1	0.03
106	*Dialium platicephalum*	1	0.03
107	*Ficus elata*	1	0.03
108	*Heritiera accuminata*	1	0.03
109	*Heritiera simplisipholia*	1	0.03
110	*Hibnocarpus*	1	0.03
111	*Hopea dryobalanoides*	1	0.03
112	*Hopea pachycarpa*	1	0.03
113	*Irvingia malayana*	1	0.03
114	*Lepisanthes*	1	0.03
115	*Mammea*	1	0.03
116	*Moltinuanthes*	1	0.03
117	*Palaquium rostratum*	1	0.03
118	*Parkia sp*	1	0.03
119	*Polyalthia sumatrana*	1	0.03
120	*Pternandra*	1	0.03
121	*Santiria laepidata*	1	0.03
122	*Santiria tomentosa*	1	0.03
123	*Sindora wallichii*	1	0.03
124	*Sterandia*	1	0.03

Appendix 5. p Value of comparison of forest parameters between RKLs

p Value of comparison in canopy covers between RKLs

	RKL1	RKL2	RKL3	RKL4	RKL5	RKL6	RKL7
RKL1							
RKL2	0.650						
RKL3	0.542	0.818					
RKL4	0.131	0.205	0.347				
RKL5	0.449	0.679	0.861	0.481			
RKL6	0.240	0.352	0.502	0.930	0.609		
RKL7	0.591	0.910	0.903	0.254	0.761	0.415	

p Value of comparison in basal area between RKLs

	RKL1	RKL2	RKL3	RKL4	RKL5	RKL6	RKL7
RKL1							
RKL2	0.617						
RKL3	0.022	0.193					
RKL4	0.241	0.575	0.453				
RKL5	0.780	0.429	0.030	0.111			
RKL6	0.013	0.168	0.809	0.475	0.001		
RKL7	0.107	0.492	0.242	0.991	0.024	0.263	

p Value of comparison in number of species between RKLs

	RKL1	RKL2	RKL3	RKL4	RKL5	RKL6	RKL7
RKL1							
RKL2	0.610						
RKL3	0.835	0.782					
RKL4	0.060	0.032	0.062				
RKL5	0.726	0.323	0.551	0.023			
RKL6	0.062	0.033	0.074	0.320	0.019		
RKL7	0.513	0.800	0.656	0.051	0.263	0.061	

Appendix 6 Canopy cover, indices, PCs and biomass data

no_plot	CC_visual	CC_GLA	NDVI	ARVI	MSAVI2	PC1	PC2	PC3	AVI	log_3rd	log_exp	log_TAGB
1	60	49.59	0.75	1.20	0.28	112.59	18.04	-49.00	21.78	2.54	2.54	4.25
2	70	69.06	0.74	1.17	0.27	109.83	15.95	-47.67	0.00	2.59	2.61	4.07
3	50	59.3	0.67	0.98	0.22	138.50	10.98	-38.53	0.00	2.48	2.50	3.99
4	75	70.18	0.74	1.08	0.28	112.73	17.64	-49.13	11.44	2.65	2.67	4.13
7	70	70.76	0.75	1.21	0.28	111.28	18.40	-46.25	47.56	2.69	2.70	4.65
9	75	85.42	0.75	1.24	0.29	118.07	18.94	-47.10	12.00	2.69	2.73	4.15
12	50	61.91	0.75	1.24	0.27	105.12	15.97	-46.98	0.00	2.62	2.64	4.11
13	75	77.43	0.73	1.22	0.25	108.58	14.71	-46.98	0.00	2.78	2.80	4.30
15	80	85.56	0.77	1.22	0.30	109.86	20.93	-49.30	32.33	2.82	2.87	4.33
18	75	81.82	0.73	1.28	0.25	106.33	13.06	-45.53	0.00	2.71	2.76	4.19
21	70	80.18	0.77	1.20	0.31	111.21	21.25	-49.49	0.00	2.71	2.76	4.19
25	80	85.19	0.75	1.20	0.30	123.33	20.62	-48.09	9.11	2.71	2.92	4.20
26	75	79.38	0.76	1.22	0.29	107.45	19.06	-49.95	15.22	2.64	2.65	4.09
28	60	64.27	0.75	1.23	0.27	108.10	17.05	-48.61	0.00	2.57	2.57	3.93
29	70	75.26	0.77	1.21	0.30	111.22	20.37	-48.52	23.33	2.69	2.72	4.20
30	70	74.78	0.78	1.21	0.32	112.38	22.98	-49.31	50.78	2.63	2.61	3.90
31	50	52.06	0.77	1.22	0.30	113.25	20.61	-47.54	8.44	2.50	2.51	3.90
36	85	92.4	0.78	1.21	0.32	112.55	22.82	-48.64	55.22	2.86	3.05	4.39
38	85	90.97	0.78	1.18	0.33	113.01	24.95	-50.69	97.78	2.89	2.96	4.41
41	70	75.55	0.79	1.19	0.33	110.75	25.44	-50.28	75.22	2.68	2.70	4.14
42	80	85.2	0.79	1.20	0.33	112.24	25.46	-50.46	45.00	2.75	2.84	4.25
43	60	69.04	0.78	1.25	0.30	106.92	20.69	-50.15	77.56	2.65	2.65	4.12
46	75	72.63	0.77	1.23	0.30	110.30	20.27	-49.06	27.00	2.65	2.65	4.08
47	40	48.4	0.67	1.18	0.31	110.34	21.89	-50.72	64.11	2.43	2.44	3.87
49	65	76.29	0.77	1.24	0.31	111.07	21.95	-48.46	89.11	2.65	2.66	4.08
50	75	80.5	0.78	1.21	0.32	110.02	22.55	-48.46	31.89	2.72	2.81	4.23
52	60	66.83	0.79	1.25	0.33	111.79	24.63	-48.30	33.56	2.56	2.55	3.92
57	75	76.88	0.78	1.24	0.32	109.74	22.44	-49.31	51.44	2.73	2.76	4.23
59	60	70.92	0.79	1.18	0.34	114.91	26.60	-48.59	57.00	2.56	2.54	3.87
62	60	74.5	0.79	1.26	0.31	108.55	21.76	-46.31	78.44	2.61	2.63	4.10
65	65	77.76	0.79	1.18	0.34	115.15	25.97	-49.06	52.11	2.59	2.60	4.06
66	60	75.18	0.80	1.18	0.35	115.60	28.01	-48.94	100.22	2.69	2.70	4.17
68	50	50.12	0.78	1.23	0.29	106.61	19.83	-46.57	97.33	2.52	2.50	3.80
72	60	60.2	0.79	1.17	0.35	115.60	28.15	-50.96	50.33	2.54	2.55	3.99
73	75	78.2	0.76	1.18	0.31	118.12	21.87	-50.19	18.00	2.75	2.81	4.27
75	75	80.3	0.79	1.21	0.33	111.11	24.99	-49.18	50.89	2.71	2.74	4.22
80	90	94.3	0.77	1.25	0.29	107.45	19.67	-48.32	2.67	3.02	3.22	4.53
81	90	92.8	0.78	1.22	0.33	114.84	25.82	-49.23	51.78	2.97	3.09	4.50
89	65	65.7	0.77	1.21	0.31	112.04	21.28	-47.88	35.11	2.71	2.70	4.09
90	70	73.2	0.76	1.22	0.29	107.76	18.48	-48.71	11.44	2.67	2.69	4.16

Note :

no_plot	: number of plot	PC1	: Principal component 1
CC_visual	: canopy cover from visual interpretation	PC2	: Principal component 2
CC_GLA	: canopy cover from GLA	PC3	: Principal component 3
NDVI	: Normalized Different Vegetation Index	AVI	: Advance Vegetation Index
ARVI	: Atmospheric Resistant Vegetation Index	log_3rd	: Log foliage biomass from 3rd degree polynomial
MSAVI2	: Modified Soil Adjusted Vegetation Index	log_exp	: Log foliage biomass from exponential model
		log_TAGB	: Log total above ground biomass

Appendix 7.Test of the difference between three correlation coefficients

Canopy cover

Ho : $r_1 = r_2 = r_3$

Ha : $r_1 \neq r_2 \neq r_3$

$$\chi^2 = \sum (n_i - 3) z_i^2 - \left[\sum (n_i - 3) z_i\right]^2 / \sum (n_i - 3)$$

Model	n	n_i-3	R^2	r_i	z_i	Weighted z	Weighted Squar
						$(n_i-3)z_i$	$(n_i-3)z^2$
Foliage biomass 3rd degree	40	37	0.75	0.866	1.315	48.655	2367.31
Foliage biomass exponential	40	37	0.75	0.866	1.315	48.655	2367.31
TAGB	40	37	0.44	0.663	1.035	38.295	1466.51
Total	120	111				135.605	6201.13

$$\chi^2 = 6201.3 - 135.605^2 / 111 = 6035.5$$

df = 2

Chi-square table, $p \approx 0$

Ho is rejected

Appendix 8. Samples distribution