Estimation of Forest Biomass and its Error

A case in Kalimantan, Indonesia

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by

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Abstract

The forest ecosystem is an important carbon sink and source containing majority of the above ground terrestrial organic carbon. The condition of East Kalimantan's forest is declining due to fire or logging activities. Sustainable management strategies are necessary to make this forest as carbon sink rather than source. To assess the forest's carbon source potential, dry biomass is quantified since 50% of it is carbon. This study aims to identify biomass equation that best estimate the tree-based above-ground biomass using Furnival's Index as main criterion and to estimate the above-ground biomass of the entire study area. Destructive sampling was done to collect biomass data of sample trees and use these as dependent variable in the least squares analysis. Five different regression models were developed and compared: a power function model with multiplicative error, a polynomial model, a so-called combined variable model, a square-root transformed model and a power function model with additive error. Forest landscape biomass was estimated using Cunia's (1986b) $\hat{w}$ estimator. An empirical relationship of forest plot biomass and ETM+ spectral data was sought for RS-based estimation purposes. Results indicate that power function models best describe the relationship of above-ground biomass and DBH. Furthermore, the power function model with additive error term has a fit which is comparable to the power function with multiplicative error term. This model form is promising for biomass assessment as it does not involve transformation of variable, and the predicted values are not biased. The forest above-ground biomass estimate, considering the errors from first phase sample plots and second phase sample trees, was found to be 328 ± 29.7 tons/ ha (95% confidence interval). The uncertainty of the estimate is 17.4 tons/ha due to first-phase sample plots and 12.3 tons/ha due to second-phase sample trees. Without quantifying the second phase error, the precision of the biomass estimate is underestimated by 41.27%. The above-ground biomass estimate for the entire study area is 14 587 502 ± 1 321 712.8 tons (95% confidence interval). Linear regression results indicate there is insufficient evidence that a linear relationship exist between above-ground biomass and vegetation index/band ratio. This suggests that the vegetation indices and band ratios derived from medium spatial resolution image data is not sufficient to capture the forest characteristics vital to biomass assessment. The use of alternative imaging technology that can capture both vertical and horizontal (spatial) forest characteristics is recommended.

Keywords: *carbon, forest, biomass, bias, error, biomass equation, vegetation index, band ratio, estimation*

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1. Introduction

1.1. Background

1.1.1. Carbon and global climate change

Greenhouse gases play an important role on Earth's climate. These include water vapour, carbon dioxide, methane, nitrous oxide, and ozone. When sunlight reaches the surface of the Earth, some are absorbed and warm the Earth. In turn, the Earth emits long wave radiation towards the atmosphere, a fraction of which is absorbed by the greenhouse gases. The Greenhouse gases then emits long wave radiation both towards space and back to the Earth. The energy emitted downward further warms the surface of the Earth. The process of absorbing long wave radiation by the greenhouse gases and emitting it back resulting to more warming of the Earth's surface is called "greenhouse effect". When the concentration of greenhouse gasses in the atmosphere increased, temperature at the Earth's surface is expected to rise.

Climate models developed in the 90's have shown that global surface air temperature may increase by 1.4 ^{o}C to 5.8^{o}C at the end of the century (IPCC, 2001; Rahmstorf and Ganopolski, 1999). Recent IPCC (2007) report predicted increase in temperature with more precision at 1.8 ^{o}C to 4 ^{o}C at the end of the century. Petit et al. (1999) linked increase in surface air temperature level to increase in the concentration of CO_2 in the atmosphere.

Carbon dioxide (CO_2) is one of the more abundant greenhouse gases and a primary agent of global warming. It constitutes 72% of the total anthropogenic greenhouse gases, causing between 9-26% of the greenhouse effect (Kiehl and Trenberth, 1997). IPCC (2007) reported that the amount of carbon dioxide in the atmosphere has increased from 280 ppm in the pre-industrial era (1750) to 379 ppm in 2005, and is increasing by 1.5 ppm per year. Dramatic rise of CO_2 concentration is attributed largely to human activities. Over the last 20 years, majority of the emission is attributed to burning of fossil fuel, while 10-30% is attributed to land use change and deforestation (IPCC, 2001). Increase in CO_2 concentration, along with other greenhouse gases (GHG), raised concerns over global warming and climate changes. IPCC (2001) report concluded that climate has changed over the past century.

Report from the recent conference of climate scientists in Paris concluded that human activities are to be blamed for the observed climate change (IPCC, 2007). On this basis, efforts to lower down the concentration of GHG's are focused, among others, on limiting influx of carbon dioxide to the atmosphere (United Nations, 1992; United Nations, 1998).

Concerns over potential global climate change have reached international level since the first "World Climate Conference" was organized by World Meteorological Organization (WMO) in 1979. In response, WMO and the United Nations Environment Programme (UNEP) established the Intergovernmental Panel on Climate Change (IPCC) in 1988. Four years later, an international environmental treaty, called United Nations Framework Convention on Climate Change (UNFCCC), was formulated aiming at reducing global greenhouse gas emissions. Article 4 of the UNFCCC requires preventing and minimizing climate change by "*limiting anthropogenic emissions of greenhouse and protecting and enhancing greenhouse gas sinks and reservoirs*" (United Nations, 1992). While UNFCCC did not specifically mention limits for GHG emissions, the Kyoto Protocol, implemented in 2005, stipulates that for the commitment period of 2008-2012, GHG emissions by industrial countries (listed in Annex I) should be reduced by 5% of the 1990 levels. At the same time, net GHG emission by sources and sink, including uncertainty of estimates, must be clearly reported (IPCC, 2003; Olsson and Ardo, 2002; Patenaude et al., 2005; Pfaff et al., 2000; United Nations, 1998).

1.1.2. Forest biomass and assessment

Forest ecosystem plays very important role in the global carbon cycle. It stores about 80% of all above-ground and 40% of all below-ground terrestrial organic carbon (IPCC, 2001). During productive season, CO_2 from the atmosphere is taken up by vegetation and stored as plant biomass (Losi et al., 2003; Phat et al., 2004). For this reason, the UNFCC and its Kyoto Protocol recognized the role of forests in carbon sequestration. Specifically, Article 3.3 and 3.4 of the Kyoto Protocol pointed out forest as potential carbon storage (Brown, 2002; United Nations, 1998).

When the vegetation decomposes, they release carbon back to the atmosphere. Disturbances in the forest due to natural and human influences lead to more carbon released into the atmosphere than the amount used by vegetation during photosynthesis (Brown, 2002). Sustainable management strategies are, therefore, necessary to make the forest a carbon storage rather than source. However, the state

of tropical forests continues to deteriorate. Land conversion is the main reason for 93.4% of the annual net forest loss, while conversion to plantation forest explains the remaining 6.6%. Land conversion resulted from forest mismanagement, such as, illegal forest practices and lack of sound policies and regulations for sustainable forestry (FAO, 2001).

FAO (2004a) defined biomass as "*organic material both above-ground and below-ground, and both living and dead, e.g., trees, crops, grasses, tree litter, roots etc.*". Above-ground biomass consists of all living biomass above the soil including stem, stump, branches, bark, seeds, and foliage. Below-ground biomass consists of all living roots excluding fine roots (less than 2mm in diameter). In forest biomass studies, two biomass units are used, fresh weight (Araujo, et al., 1999) and dry weight (Aboal et al., 2005; Ketterings et al., 2001; Montagu et al, 2005; Saint-Andre et al., 2005). For carbon sequestration application, the dry weight is more relevant because 50% of it is carbon (Losi et al., 2003; Montagnini and Porras, 1998; Montagu et al., 2005). Many biomass assessment studies conducted are focused on above-ground forest biomass (Aboal et al., 2005; Brown, 1997; Kraenzel et al., 2003; Laclau, 2003; Losi et al., 2003; Segura and Kanninen, 2005) because it accounts for the majority of the total accumulated biomass in the forest ecosystem. This study also focuses on the assessment of above-ground forest dry biomass.

Biomass assessment is important for many purposes (Parresol, 1999; Zheng et al., 2004). It is aimed at two major objectives: (1) for resource use and (2) for environmental management. It is important to determine how much fuel wood or timber is available for use. Thus, one needs to know how much biomass is available at one given time. In environmental management, biomass quantification is important to assess the productivity and sustainability of the forest. Biomass is also an important indicator in carbon sequestration. For this purpose, one needs to know how much biomass is lost or accumulated over time. Consequently, the amount of carbon sequestered can be inferred from the biomass change since 50% of the forest dry biomass is carbon (Losi et al., 2003). The Kyoto protocol requires transparent reporting of forest removal and accumulation (biomass change). This implies the use of precise procedure to quantify forest biomass and its uncertainty.

Lu (2006) mentioned three approaches to biomass assessment. These are field measurement, remote sensing, and GIS-based approach. The field measurement is considered to be accurate (Lu, 2006) but proves to be very costly and time consuming (de Gier, 2003). In any of these approaches, ground data is important for

validation. In the case of remote sensing, ground data is needed to develop the biomass predictive model. This means, it is always necessary to a field measurement of biomass for predictive modelling or validation purposes. Typically, the procedure is to randomly select sample trees, measure the tree variables (such as *DBH* or tree height) and the tree biomass, then develop biomass equation using these measurements. The developed biomass equation is used to estimate the tree-based biomass. While measuring the sample tree variables is easy and straightforward, measuring the sample tree biomass is difficult because the trees are large and heavy.

Two methods of measuring sample tree biomass are available: (1) destructive and (2) non-destructive. The conventional destructive method is done by felling the sample tree and then weighing it. Direct weighing can only be done for small trees, but for larger trees, partitioning is necessary so that the partitions can fit into the weighing scale. In cases where the tree is large, volume of the stem is measured. Sub-samples are collected, and its fresh weight, dry weight, and volume are measured. The dry weight of the tree (biomass) is calculated based from the ratio of fresh weight (or volume) to the dry weight. This procedure requires considerable amount of labour and cost, and the use of ratio is biased (Cochran, 1963).

A new destructive method proposed by Valentine et al (1983) and later adapted by de Gier (2003) uses the principle of randomized branch sampling and importance sampling. In the randomized branch sampling, a “path” is determined starting from the butt and ending at the terminal bud. The segments (nodes) comprising the “path” is selected with probability proportional to size (pps). Unconditional probability of selection for each section is calculated. Along the path, points, where a change of taper occurs, are located. The inflated area of points measured along the path is calculated by dividing the diameter squared by its unconditional probability. The calculated inflated area is used to calculate the volume of the segment, say by Smalian’s formula. The unbiased woody tree volume is the sum of these segment volumes (de Gier, 2003).

After the path is selected, importance sampling comes in to randomly locate the sample disk. The whole path is viewed as consisting of infinitely many thin disks, of which one is selected with probability proportional to its diameter squared. To determine the location of sample disk, the tree woody volume is multiplied with a random number and the segment where this volume is reached is identified. The exact location of the sample disk within the identified segment is determined by interpolation. The weight per unit thickness of the disk is determined and divided by

the unconditional probability assigned to the segment from where it is removed. Multiplying this value with the estimated tree woody volume, and dividing it by the square of the disk diameter gives the woody fresh weight. The woody dry weight is calculated in the same manner as the fresh weight. (de Gier, 2003). The determination of path reduces much of the work as those tree segments not included in the path are not measured. Furthermore, there is no need to weigh the whole tree; hence, it is efficient in terms of time and cost. However, the procedure uses considerable amount of computation that decent computing equipment (e.g. HP LX200 palmtop computer or iPaq equipment) is necessary.

The non-destructive method does not require the trees to be felled. Measurement can be done by climbing the tree and measuring its various parts and computing the total volume. Tree density which can be found from literature is used to convert the measured volume into biomass estimate (see Aboal et al., 2005). This procedure takes even more time and cost to perform. Another procedure is to taking two photographs of the tree at orthogonal angles. Then the scale of the photograph is calculated so that the volume of each tree components (stem, branch, foliage) can be calculated. Density of the different tree components is calculated and used to convert the volumes into biomass (Montes et al, 2000). However, the calculated biomass from these procedures can not be validated unless the sample tree is felled and weighed.

Once sample tree variables and biomass data are obtained, and the biomass equation is developed, it is then applied to each tree in the sample plots to obtain the plot biomass. The forest biomass is then estimated by the corresponding sampling design formula for the mean and total estimator or by predictive modelling using remotely sensed spectral data.

1.1.3. Review of biomass equations

Many studies were conducted to develop biomass equation that relates dry biomass of forest trees to its biophysical variables (e.g. diameter-at-breast height (*DBH*), tree height) (Aboal, 2005; Araujo, 1999; Arevalo, 2007; Brown, 1997; Cole and Ewel, 2006; de Gier, 1989, 1999, 2003; Ketterings et al, 2001; Overman, 1994; Zianis and Mencuccini, 2004). The parameters of the biomass equation are typically estimated using linear least squares regression. There are some assumptions that should be met when performing this estimation procedure. The residuals must be distributed normally, independently and with constant variance (Furnival, 1961). The

assumption of constant variance is crucial in linear regression as it affects the validity of hypothesis testing. Typically, biomass data exhibits heteroscedasticity, that is, the error variance is not constant across all observations. This problem can be dealt with either by (1) transformation, such as taking the logarithm of the variables, or (2) by using weights to stabilize the variance. However, the use of transformation leads to another problem discussed below.

The most common biomass equation is a power function with multiplicative error term

$$B = a * (DBH)^b \varepsilon \cdot \tag{1}$$

For example, Ter-Mikaelian and Korzukhin (1997) reviewed biomass equations for 65 tree species of North America, all of the form in equation 1. The popularity of this power function stems from the good fit exhibited by the model using single and easily measurable variable (*DBH*). Power function in (1) is actually not a linear model. It is linearized by taking the logarithm of both the left and right hand side of the equation, giving the linear function

$$\ln B = \ln a + b * \ln(DBH) + \ln \varepsilon \cdot \tag{2}$$

Log-transformation generally solves the problem of heteroscedasticity. Linear least-squares regression is then performed on transformed variables. This procedure is very common because of two reasons: linear function is easy to deal with and statistical theory is established (Smith, 1993). However, the transformation introduces a new problem: the detransformed predicted values are biased (Miller, 1984; Smith, 1993; Sprugel, 1983; Wiant and Harner, 1979). Detransformed estimate of the above model gives the geometric mean of the actual values, which is always less than the arithmetic mean (Miller, 1984; Smith, 1993; Parresol, 1999).

Consider the power function in (1) to have an additive error term (instead of the multiplicative error term), the resulting model can not be linearized by logarithmic transformation. Consequently, parameters of this model form can not be estimated using ordinary least-squares without bias. Hence, linear regression is not appropriate to estimate the parameter for this model (Smith, 1993). A non-linear least squares approach can be used instead. Non-linear estimation uses an iterative process of estimating the values of the parameters such that the sum of the square residuals becomes minimum (Meeter, 1966). Because, non-linear estimation approach does

not involve transformation, the parameter estimates and the predicted values do not suffer from transformation bias. It has been used to estimate parameters of biomass equation by Arevalo (2007) and Saint-Andre et al (2005).

Taking a fractional power transformation of the dependent variable can also be used to linearize curvilinear models. When detransformed, the model becomes

$$B = (a + bDBH + \varepsilon)^N \quad . \tag{3}$$

A simple case is when N=2, called square-root transformation. Snowdown (1985) as cited by Parresol (1999) showed that square-root transformation can be used instead of log transformation when the curvilinearity of the variable is low. This transformation still introduces bias into the prediction of dependent variable. Fortunately, Miller (1984) showed that by adding $\hat{\sigma}^2$ to the prediction of the de-transformed fitted linear model, a low-biased estimator is obtained.

Another biomass equation model based on one explanatory variable is the polynomial model (Cunia, 1986a; Brown, 1997; de Gier, 2003). Generally, it is represented by the equation

$$B = \sum_{i=0}^{m} a_i * (DBH)^i + \varepsilon \cdot \tag{4}$$

Polynomial models can fit quite well on curvilinear relation of biomass and tree variables while maintaining linear combination of explanatory variables. Commonly employed are second and third degree polynomial models.

Other studies tried to combine different variables (e.g. DBH, height, density) into the biomass equation to look at how much gain in variability explained can be achieved. A typical example is $B=a+b(D^2H)$, where D is DBH and H is total tree height. This is used develop standard volume/biomass table. Overman et al (1994) compared different models such as those including total height and wood density. Segura and Kanninen (2005) used *DBH* and commercial height as explanatory variables. In most cases, combined variables and other more complex models are not recommended, either due to small gain in variation explained or for practical reasons (Overman et al, 1994; Segura and Kanninen, 2005). The papers of Jarayaman (1999), Montagu et

al. (2005), Overman (1994), and Segura and Kanninen (2005) list some commonly used biomass models.

There are many biomass equations developed for tropical forests. Most are based on data collected from the Brazilian Amazon forest. One general biomass equation was developed by Brown (1997). It is applicable for moist tropical forest.

1.1.4. Sources of error in biomass estimation

Many sources of error can affect the estimation of forest biomass (Figure 1.1). The first set of errors is the sampling errors in the first-phase and second-phase sampling. When the same sampling procedure is repeated many times over the same forest area, different set of sample plots (or trees) is selected. This result to different set of estimates obtained. At the first phase, selection of sample plots from aerial photographs or satellite image introduces uncertainty on the biomass estimate. In the second stage, selection of trees that are measured to develop biomass equation also contribute uncertainty of the biomass estimate. The size of the sampling error is affected by sampling scheme, sample size, estimation procedure and inherent variability of the variable of interest (Cunia, 1986b, Cunia, 1986c).

The second source of error pertains to the measurement of the tree variables, such as, *DBH*, height or weight measured by diameter tape or caliper, measuring tape, and weighing scale, respectively. Measurement error occurs due to various reasons, including instrument error, recording error, and error due to the nature of the object being measured (e.g. presence of buttress, or irregular girth shape) (Chave et al., 2004). Measurement error has a random and systematic component. The random part is expected to be zero as the number of samples increases. However, the systematic part does not average to zero. Its effect on the estimates becomes more critical as the sample size increases (Cunia, 1986b). In practice, systematic error should be avoided by all means while random error is limited in its variability.

The next source of error is in the choice of model that describes the relation of biomass and tree variables (Chave et al, 2004; Cunia, 1986b, Jenkins, 2003). Several biomass equations of different model forms can be found from the literature. When different model forms are used for the same data set, one would expect to get different parameter estimates.

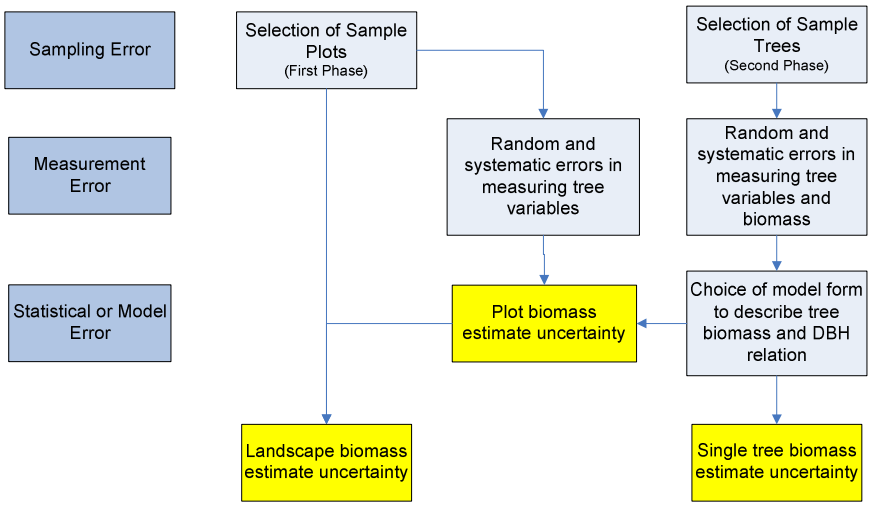


Figure 1.1. Sources of error in forest biomass estimation

Several attempts have been made to quantify the effect of the mentioned errors to the estimates. Cunia (1986b; 1986c) outlined procedures to quantify the combined effect of sampling error and regression error on the estimate of biomass for different sampling techniques. Chave et al (2004) studied how sampling, measurement, and statistical error propagate in the estimation of above-ground biomass in Central Panama. Studies like these support the requirements under Article 3.3 of the Kyoto Protocol.

1.1.5. Remote sensing-based biomass assessment

The conventional method of biomass assessment relies heavily on field measurements. However this approach is time consuming, labour intensive, and difficult to implement in remote areas (de Gier, 2003; Lu, 2004). For small scale studies, the conventional method seems sufficient; however, the more challenging issue of carbon sequestration requires area of wider spatial scale. The use of remote sensing technique is the most practical and cost effective alternative to acquiring data over larger area. Furthermore, it provides spatial information crucial to characterize the spatial distribution of biomass density. Remote sensing technology also offers synoptic view, and periodic measurement of the area of interest.

Remote sensing technique has been used extensively for vegetation mapping and monitoring. It has also been used to investigate land cover change and landscape patterns (Kasischke et al., 1997). In the forestry sector, it has been applied to

measure forest biophysical variables such as crown cover, LAI, and stand volume (Brown et al., 2000; Hall et al., 2006). The role of remote sensing for forest biomass assessment has also been recognized (Patenaude, 2005) and several studies had been conducted for this purpose (Chen et al., 2004; Foody et al., 2001; 2003; Lu et al., 2004; Rahman, 2005; Zheng et al., 2004). Techniques including the use of linear and non-linear regression, K-nearest neighbour, and neural network were used to measure the degree of relation between biomass and spectral data (Lu, 2006).

Preferably, remotely sensed data combined with field measurement (ground data) is used for biomass assessment (Foody et al., 2003; Lu et al., 2004). The field measurement is used either to develop a predictive model for biomass or to validate the outcome from remotely sensed data. Once the predictive model is developed and validated, it can be used to assess biomass on areas of wider scale that are not covered by ground data. In the process, what is impractical with ground observation becomes economically feasible with remote sensing analysis. Two major concern need to be addressed: (1) how to improve the quality of the ground data to produce a more precise predictive model or to better validate the output of remote sensing analysis, and (2) how to extract information from the remotely sensed data that best correlate with biomass.

1.2. Problem statement

A challenge in biomass assessment of tropical rainforest is cost and accuracy (de Gier, 2003). Developing biomass equation is a laborious process. It requires a crew of two or three people to fell and weigh the sample tree. But once established, it can easily be used to estimate forest biomass. There are published equations for forest biomass assessment (Aboal, 2005; Araujo, 1999; Arevalo, 2007; Brown, 1997; Cole and Ewel, 2006; Ketterings et al, 2001; Overman, 1994). It may appear appealing to use one of these equations; however, it is extremely important that they are verified as to applicability to the forest area to be measured. Geographic location, land cover type, and forest management practices tend to affect the relationship of biomass and tree variables (de Gier, 2003).Oftentimes, the sample size and tree diameter range used to construct the equation is limited (Brown, 2002). Thus, validating the biomass equation is extremely important to avoid biased estimate (de Gier, 2003).

In remote sensing-based biomass assessment, biomass equation is indispensable to estimate plot biomass that will be correlated with spectral data. The reason for this goes back to the labour, time and cost involved in field measurement. Common to

many remote sensing-based biomass assessment is to use readily available biomass equations. In most cases, these biomass equations are developed using sample tree data collected from other geographic location but are not validated for the new area of interest. One should realize that the quality of the biomass equation to be used in predictive modelling is important for remote sensing-based biomass assessment.

For the tropical forest of Indonesia, few biomass equations are available. One existing equation found in Brown (1997) is applicable for moist tropical forest. It is based on log-transformation of above-ground biomass and *DBH*. The sample trees used for its development were from Cambodia, Indonesia and Brazil collected by different authors at different time periods. This equation, however, has not been validated for Kalimantan. Quantifying the uncertainty of estimates derived from this model proved to be difficult.

Another equation was developed by Ketterings et al. (2001). It uses *DBH* as explanatory variable. However, it was based on data collected from Sumatra, where the forest condition is most likely different from Kalimantan, thus should be validated. Hashimotio et al (2000) developed a logistic biomass curve for Kalimantan. It is used to estimate biomass accumulation of fallow forest. They considered stand age as explanatory variable, which is not measure in the rainforest. Moreover, fallow forest is entirely a different ecological condition compared to the rainforest this study is focusing with.

Tree-based biomass estimate is calculated by applying the biomass equation to the individual trees of randomly selected plots. The biomass estimate foe all trees in each plot is aggregated to obtain the plot biomass estimate. Forest landscape biomass and its variability is estimated according to the estimation procedure specific to the sampling design used (Cunia, 1986b). In this procedure, only the uncertainty of estimate due to the first phase samples is accounted for, neglecting the effect of the second phase samples (regression error) on the precision of the overall above-ground biomass estimate. At present, no information is available to assess the effect of regression error to above-ground tropical rainforest biomass estimate. However, for the forest inventory in the US investigated by Cunia (1986c), this was found to contribute 62.43% of the total variation. This study aims to give an insight on the magnitude of regression error effect on the above-ground biomass of tropical rainforest in Kalimantan. Thus, quantifying the two sources of biomass estimate uncertainty provides a better picture of the quantity of above-ground biomass in the forest inventory crucial to the objectives of the UNFCC and the Kyoto Protocol.

1.3. Research objectives

1. Compare the precision of tree-based above-ground biomass estimate using power, polynomial, combined variable, and square-root transformed models and select the best-fit biomass equation.
2. Quantify the combined effect of sampling error and regression error on the above-ground biomass estimate in a selected tropical rainforest area.
3. Using the best fit biomass equation in a forest inventory, identify vegetation index/ band ratio that best correlates with above-ground forest biomass.

1.4. Research questions

1. Which model form – power, polynomial, combined variable and square root transformed variable – gives the most precise biomass estimate?
2. How much in the above-ground biomass estimate uncertainty is attributed to sampling error in the first phase and regression error in the second phase?
3. What vegetation index/ band ratio best relate to above-ground biomass, and what is the resulting forest biomass estimate?

1.5. Research hypothesis

1. Because of intrinsic non-linearity of allometric relation of forest tree variables, power function model provides more precise above-ground biomass estimate compared to other model forms.
2. Regression equation, as applied to large number and varying sizes of trees, accrues significant level of uncertainty of total above-ground biomass estimate for mixed tropical forest.
3. Spectral vegetation index or band ratio is linearly related to varying amount of forest above-ground biomass.

1.6. Research approach

The research activities to be done are summarized in the figure below. Details of each step are discussed in the methods chapter.

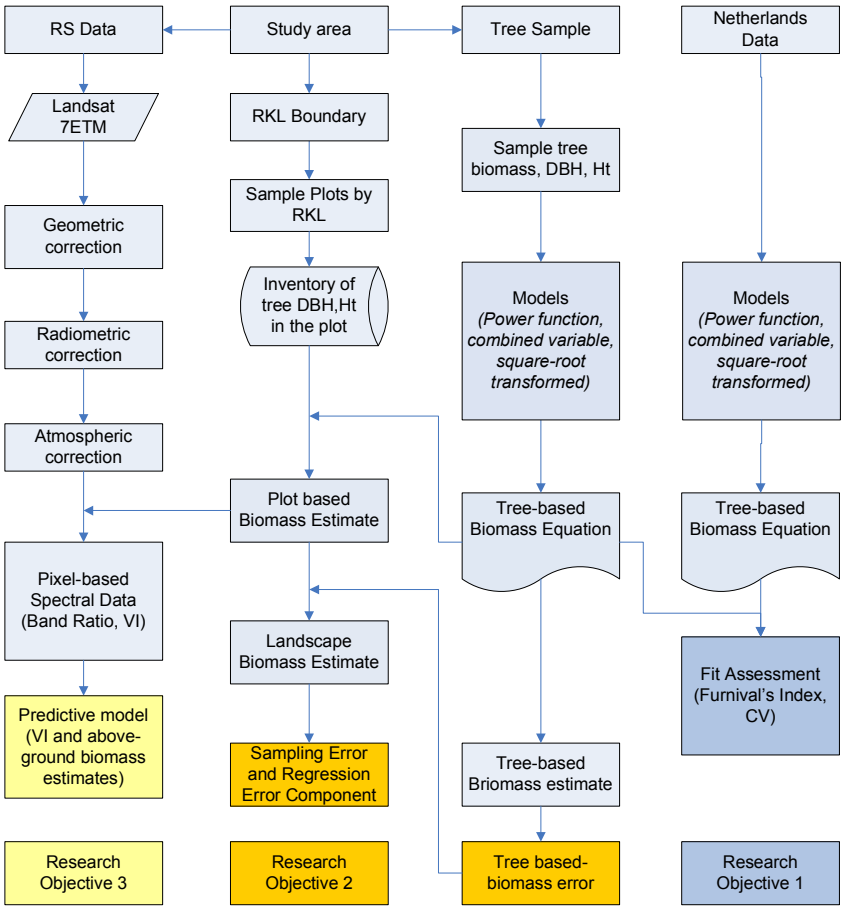


Figure 1.2. Flow diagram of the research approach

2. Methods

2.1. Site selection

Pre-requite to the research is selection of study area. Several criteria were designed to select the study area.

- The study area should be representative of a natural forest.
- The study area should be accessible by foot or by car.
- The study area should have recent remote sensing data, maps and other secondary data available for use in this study.
- Support staff or labour should be available during the field measurement.

2.2. Location, vegetation and forest management

The study area is located within the forest concession area of PT Hutan Labanan Sanggam Lestari (formerly PT Inhutani I Labanan). It lies 30 km South West of Tanjung Redeb, the capital of the Regency, Berau District, East Kalimantan Province, Indonesia. Geographically, the forest concession area is located 1^0 45' N through 2° 10' N latitude, and 116° 55' E through 117° 20' E longitude covering an area of 83,240 ha.

Kalimantan area is typical of tropical forest enjoying considerable amount of precipitation averaging 1949 mm on annual basis and warm temperature between 21^0 C and 34^0 C (BFMP, 1999). The natural vegetation in the study area is mainly dominated by mixed Dipterocarp forest (BFMP, 2001). Most of the commercial trees commonly found belong to *Dipterocarpacea* family such as *Shorea sp, Dipterocarpus sp,Palaquium sp,Gluta sp,and Vatica sp*. Succession by pioneer species is common in the logged-over area, particularly by *Macaranga sp* (*Macaranga gigantea and Macaranga hypoleuca*). *Nauclea sp, Porterandia sp, Glochidion sp* and *Gironniera sp* are found as well (BFMP, 2001).

The forest concession is managed by PT Hutansanggam Labanan Lestari (previously PT Inhutani I), a state owned company, who implemented selective logging since

1976. The whole concession area is divided into seven five-year working plan areas, called *Rencana Karya Lima Tahun (RKL)*. Each RKL is selectively logged for five years following Indonesian Selective Cutting and Planting (TPTI) harvest rate of 8 trees per hectare (van Gardingen, 1998).

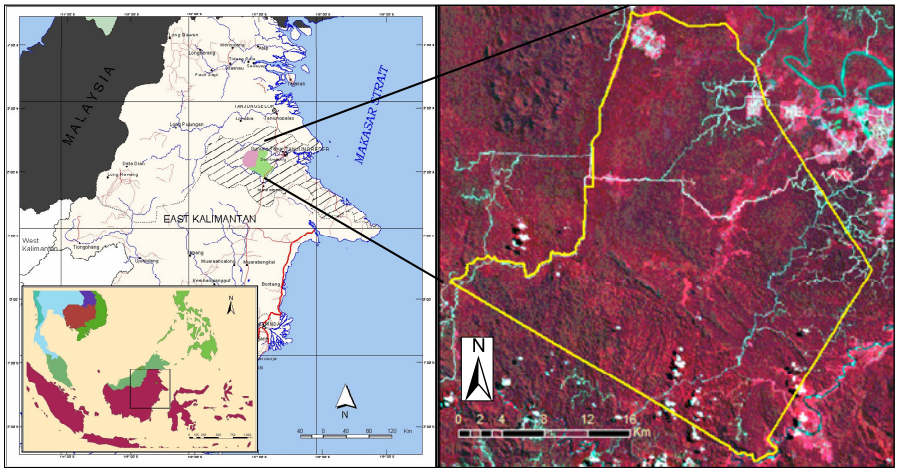


Figure 2.1. Map showing the study area.

2.3. Approach in biomass estimation

Forest biomass estimation involved two phases: selection of sample plots wherein tree variables are measured; and selection of sample trees where tree variables and biomass data are measured (Cunia, 1986b; 1986c; de Gier, 1989; 2003). In the first phase, all trees within the plot are measured, such as, *DBH*, basal area, tree height, crown diameter and crown height, but not tree biomass. In the second phase, the same tree variables are also measured for the sample trees selected; and in addition, tree biomass data. Destructive measurement of the tree biomass involves many steps described in Section 2.4.

The biomass data in the second phase are used to construct biomass equation. The biomass equation developed is applied to each tree in a plot of the first phase. The result is aggregated to obtain biomass estimate of that plot. This process is repeated for each plot to obtain biomass estimate of all plots in the first phase. Using the plot biomass, and depending on the sampling design used, total biomass of the entire forest landscape is estimated.

In the case of using remotely sensed data, such as satellite imagery, the strategy is to obtain plot biomass (as described above) and relate it to spectral data. The plot size needs to be comparable with the pixel size of the image data. A regression model using spectral data as explanatory variable and plot biomass as response variable is developed. The functional relation is used to estimate the biomass of the forest area corresponding to the pixel in the image data. The outcome is a forest above-ground biomass distribution map. In addition, the total above-ground biomass for the entire forest landscape is obtained by aggregating the per pixel biomass estimate. Figure 2.2 summarized the image-based approach to biomass estimation.

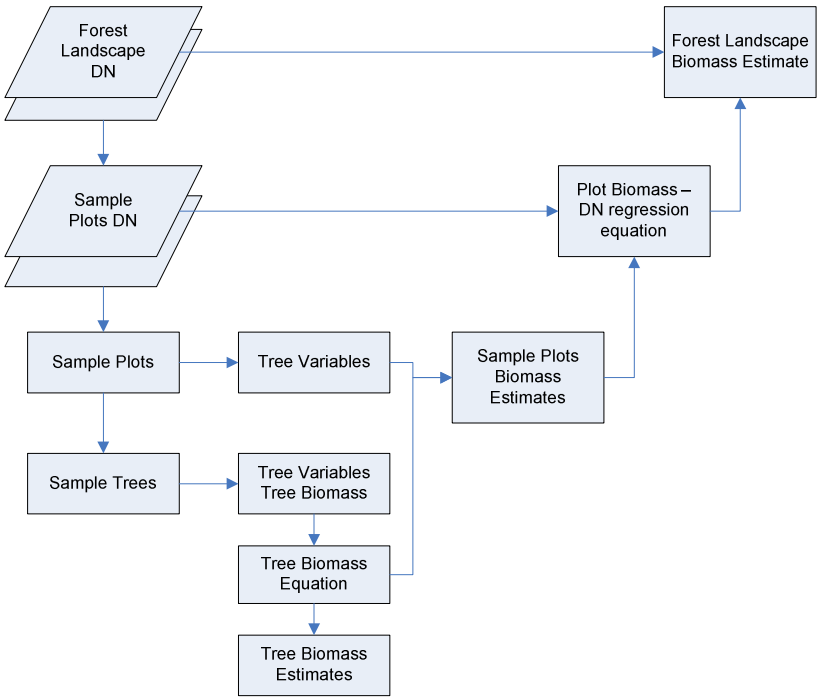


Figure 2.2.Two phase sampling design for biomass assessment.
(Source: de Gier, 2003)

2.4. Data collection

2.4.1. Sample plots

A total of 143 circular plots of 500 m^2 area were measured, of which, 25 were enumerated in 2003, 17 in 2004, 68 in 2005 and 33 in 2006. Circular plot was

preferable because it is easy to implement in the field, and determination of trees inside the plot is less problematic than square plots. The size of the circular plot is approximately 25 m in diameter, comparable with the spatial resolution of Landsat ETM+. The plots were determined using stratified sampling scheme with RKLs as strata. The sample plots were allocated, but not proportionally, as follows: 12 in RKL1, 31 in RKL3, 16 in RKL4, 29 in RKL5, 35 in RKL6, and 20 in RKL7. Unfortunately, no plots were visited in RKL2; hence, this was excluded from the population. Local names, *DBH* and height of trees at least 10 cm *DBH* were recorded (Araujo et al., 1999; Brown, 1997; 2000; Foody et al., 2003). Species or genera names were also verified from PROSEA (Soerianegara and Lemmens, 1993; Lemmens et al, 1995; Sosef et al., 1998). Trees with DBH<10 were not measured since they normally contribute small amount of biomass. Visit of the area suggests that the forest condition has not changed much. Since 2003, logging operation has been stopped and no tree cutting was permitted. The data collected in the sample plots is necessary in determining the mean above-ground biomass per hectare estimate and the total above-ground biomass estimate of the study area. It is also important in determining the precision of the estimates to be determined.

2.4.2. Sample trees

The sample tree data was collection in September, 2006. During the course of the fieldwork, forty trees were destructively measured. Because there was no portable computer to aid in the calculations required for subsampling procedure of de Gier (2003), the conventional method was employed. The tree sizes selected were based on an even distribution in the diameter-at-breast height (*DBH*) classes of 5 cm class width, starting from *DBH*=5 cm up to *DBH* of 70 cm. A number of sample trees smaller than 10 cm *DBH* were also included to fine tune the trend line at smaller *DBH*. Each of the different *DBH* classes needs to have trees that represent it since above-ground biomass is exponentially related to the *DBH*. More sample trees are actually desired in constructing biomass equations; however, the time available for fieldwork limits the number of trees that can be measured. The sample trees were located from areas within 5 km outside the Labanan concession boundary because of the management's "no tree cutting" policy.

Prior to tree cutting, *DBH* was measured using diameter tape. *DBH* is the stem diameter at 1.3 meter above the ground (FAO, 2004b). For trees with enlargement or buttress, the diameter was measured at 30 cm above the main enlargement (FAO, 2004b). Extra care was taken to ensure that the tape runs around the trunk

horizontally. Local names were recorded and genera were verified from the report of Gunawan and Rathert (1999), and PROSEA (Soerianegara and Lemmens, 1993; Lemmens et al, 1995; Sosef et al., 1998). Height of the tree was measured with a measuring tape after cutting the tree. The sample tree was segregated into factions: leaves, twigs (diameter less than 3.2 cm), small branches (diameter between 6.4 cm and 3.2 cm), large branches (diameter greater than 6.4 cm) and stem (Ketterings et al. (2001). The segregation is important because of the systematic difference in moisture content along the length of the tree. The stump height and diameter were measured to get an estimate of its volume and dry weight as described in Section 2.4. Araujo et al. (1999) used 20 cm as cut off between direct weighing and volume estimation. Considering the limited capacity of the weighing scale used and to reduce the partitioning of the tree which could result to biomass loss in the form of sawdust, 15 cm was used instead. For trees with $DBH < 15$ cm, fresh weight of the whole stem, branches, twigs and leaves were determined by direct weighing. For trees with $DBH > 15$ cm, stem diameter was measured every two meters length (Ketterings et al, 2001). This measurement was used for stem volume and dry weight estimation. Such a section length provides more precise estimation of volume compared to the four section division done by Araujo et al (1999). Moreover, it is standard procedure in forestry. Fresh weight of leaves, twigs, and branches were also measured.

Wood and leaf samples were collected from each sample trees. Importance sampling is the best method to subsample the tree; however, it was not possible to do it since no computing device was available. Wood subsamples were then selected arbitrarily from the stem: one each in the lower, middle and upper portion. Three wood samples were also collected from each of the large branches, small branches, and twigs factions (Ketterings et al., 2001). Three leaf samples, of about 100 grams each, were also collected for each tree sample. The wood and leaf samples were stored in a sealed plastic bag to retain moisture prior to measurement of fresh weight done on the evening of collection date. The number of subsamples collected in each faction was necessary to account for the variation of moisture content at the different factions.

The collected samples were analyzed in Watershed Management Technology Center in Surakarta, Indonesia. For volume determination, wood samples were saturated with water, and then the volume was measured by water displacement. The wood and leaf samples were also oven-dried at 105^0 C until constant weight (Ketterings et al. 2001, Overman et al, 1994)

2.4.3. Volume and dry weight estimation

Stump and stem faction were measured for volume. Stump volume was calculated using volume formula of a cylinder ($Vol = \frac{\pi D^2 l}{4}$), where D is the diameter and l is the height of the stump. The stump volume was converted into dry weight using the formula (Jarayaman, 1999):

$$DW_f = FV_f * \frac{DW_s}{FV_s} \quad (5)$$

where:

DW_f = dry weight of the stump

FV_f = fresh volume of stump

DW_s = dry weight of the subsample of the stem

FV_s = fresh volume of the subsample of the stem

The volume of each stem section was calculated using Smalian's formula (de Gier, 2003; Jarayaman, 1999). The total stem volume was computed as the sum of the calculated stem section volume.

$$Vol = \frac{\pi}{8}(D^2 + d^2) * l \quad (6)$$

where:

Vol = volume of the stem section

l = length of the stem section

D = diameter of the larger end of the stem section

d= diameter of the smaller end of the stem section

The stem volume was converted into dry weight using the same principle of formula (5) above. This time DW_f and FV_f refers to the dry weight and fresh volume of the stem.

The fresh weight of other factions were converted into dry weight by using the ratio of subsample dry weight and subsample fresh weight, as indicated in the formula below (Jarayaman,1999),

$$DW_f = FW_f * \frac{DW_s}{FW_s} \quad (7)$$

where:

$DW_f =$ dry weight of the faction

$FW_f =$ fresh weight of the faction

$DW_s =$ dry weight of the subsample of the faction

$FW_s =$ fresh weight of the subsample of the faction

The sample tree dry weight is the sum of the dry weight of its factions. The computed sample tree dry weights were used in modelling the relationship of above-ground biomass and tree variables.

2.5. Data analysis

2.5.1. Biomass equation

Five models were considered in determining the equation that best describes the relationship of biomass and tree variables (Table 2.1). These are power function with multiplicative error term; polynomial model, combined variable, square-root transformed, and power function with additive error term. The models selected were found in previous studies to fit strongly with the allometry form of above-ground biomass and tree variables (in this case *DBH* and height) (Brown, 1997; Cunia, 1986a; de Gier, 2003; Ketterings et al., 2001; Overman et al., 1994). Complicated models involving many variables were not considered in this study since additional variables do not significantly improve the fit of the model, but only create problem with multicollinearity and reduce applicability of biomass equation (Overman, 1994).

Four of the models used only *DBH* as explanatory variable while combined variable (Model 3), as the name implies, used a combination of *DBH* and tree height. The first model is linearized by taking the logarithm of the model and parameters were estimated by weighted linear regression. Model 2, 3 and 4 are also linear models, so the parameters were estimated by weighted linear regression. Model 5 is intrinsically non-linear, thus estimated by numerical analysis or non-linear estimation procedure using Gauss-Newton algorithm. The initial values of the parameters for non-linear estimation were taken from the de-transformed parameter estimate of the log-

transformed model (Model 1 in Table 2.1) (Parresol, 2001b). The use of weights is necessary to address the problem of heteroscedasticity (non-constant residual variance) (de Gier, 2003; Parresol, 2001a). The different weights were obtained by iteratively finding the optimal weight that minimizes Furnival's Index. The resulting weights are those that maximize the likelihood of the observed samples (Furnival, 1961). This approach was also used by Saint-Andre et al (2005) on their study of Eucalyptus hybrid in Congo.

Table 2.1. Biomass equation models

Model No.*	Model	Weights
1	$DW = a(DBH)^b * \varepsilon$ $ln(DW) = ln(a) + b*ln(DBH) + ln(\varepsilon)$	$1/DBH^{0.2}$
2	$DW = a + b(DBH)^2 + c(DBH)^3$	$1/DBH^{4.8}$
3	$DW = a + b(D^2H)$	$1/(D^2H)^{2.2}$
4	$sqrt(DW) = a + b(DBH)$	$1/DBH^{2.4}$
5	$DW = a(DBH)^b + \varepsilon$	$1/DBH^5$

DW = above-ground biomass dry weight of tree. *DBH* = diameter at breast height, measured 1.3 m above-ground. $D^2H = (DBH)^2$ *tree height

* 1 (Overman et al., 1994; Brown, 1997; Ketterings et al., 2001); 2 (Cunia, 1986; Brown, 1997); 3, 4 (FAO, 1999); 5 (Overman et al., 1994)

2.5.2. Comparison of models

The different models were compared to determine which one has better fit compared to the others. R^2 (coefficient of determination) has long been used to compare models. However, for models with different set of variables, R^2 gives misleading result (Parresol, 1999). The use of root mean square error (R*MSE*) to compare models is also not logical because some models considered were using transformed variables. As for Model 1, the *RMSE* computed described the fit of the transformed variable, but not the original one. Furnival (1961) introduced a fit index that can be used to compare models of different variables or weights based on the maximum likelihood concept. The advantage of this index is that it can reflect the size of the residuals and possible departures from linearity, normality, and homoscedasticity (Furnival, 1961). Furnival's Index is one of the recommended statistics to compare different models (Jarayaman, 1999; Parresol, 1999). It was used by Garber and Maguire (2005); Montagu et al. (2005); and Teshome and Petty (2000).

Furnival's Index of fit is computed as follows

$$I = \frac{1}{Geomean[f'(Y)]} * RMSE \tag{8}$$

where $f'(Y)$ is the first derivative of the dependent variable with respect to biomass, and *Geomean* denotes taking the geometric mean.

Since the objective of the study is to compare the fit of the models being considered, it is imperative to look whether one model consistently has better fit for a different geographical environment. The modelling procedure described in Section 2.4.1 was therefore also employed to data collected in the Northeastern Forest District in the Netherlands (see de Gier, 1989). These samples consisted of trees from natural woodlands and shrub lands. For these data, only the tree woody biomass is collected, with subsamples determined using randomized branch sampling and then importance sampling (Valentine et al, 1984). The method was found highly accurate, according to Mabowe (2006). Furnival's Index was also calculated for the different models developed from the Netherlands' biomass data.

2.5.3. Integration of biomass estimate errors

As mentioned in Section 1.2, the error in the forest inventory biomass estimate has two components. First, is the error associated with the first phase sampling. When the same sampling procedure is applied repeatedly to the same forest area, different sets of sampling unit (plots) is obtained, thus, resulting in different sets of estimates. The second error is associated with the sample of the second phase or the error of the biomass regression. The size of the second error component is affected by many factors, including the inherent variation of the tree biomass about the regression line and sample size (Cunia, 1986b; 1986c). The normal procedure of simply applying the regression equation to each tree of the sample plots to obtain plot biomass, and using these estimate to obtain the forest landscape biomass estimate results in quantifying the uncertainty due to the first phase sampling only, but not accounting for the error associated with the samples used in the regression equation (Cunia, 1986b; 1986c). To estimate forest landscape biomass taking into consideration the two sources of errors, a procedure outlined by Cunia (1986b) was used. Unfortunately, the procedure is limited to biomass regression function estimated by untransformed weighted least squares linear regression, and can therefore be used for Models 2 and Model 3 but not for Model 1, Model 4 and Model 5 (see Table 2.1).

The procedure involved calculating a new estimator $\hat{w}$ which is an unbiased estimator of μ, calculated as

$$\hat{w} = b_0 z_0 + b_1 z_1 + \ldots + b_m z_m = [b]'[z] \tag{9}$$

where b is a coefficients vector of the polynomial regression equation and z is a vector calculated from the sample plot data. The variance of w is estimated as

$$s_{ww} = s_{ww}^{(1)} + s_{ww}^{(2)} \tag{10}$$

where $s_{ww}^{(1)} = [b]'[s_{zz}][b]$ variance associated with the first phase sampling

$s_{ww}^{(2)} = [z]'[s_{bb}][z]$ variance associated with the regression equation

$[s_{zz}]$ and $[s_{bb}]$ are the covariance matrices of z and b, respectively.

Because of the relatively small number of sample plots in some RKLs, the number of strata was reduced to three. RKL1 and RKL3 were logged in succession, thus combined as one stratum. RKL4 and RKL5 were also combined into one stratum, while RKL 6 and RKL 7 made up the third stratum. The new grouping still follows the logic of successive harvesting as conceived from the start. The quantification of error was computed based on this new stratification.

2.6. Image processing

2.6.1. Geometric, radiometric, and atmospheric correction

Image data captured by Landsat 7 ETM+ on May 31, 2003 was used in this study. The image was already geometrically corrected and was free from distortions related to sensor. However, initial examination of the image indicated that it had a slight south-westerly shift as compared to the ground control points (GCP) measured by GPS. A first-order polynomial transformation was used to register the image and then re-sampled using nearest neighbour method. This approach has the advantage of being simple, efficient and preserving the original values (Campbell, 2002; Foody et al., 2003).

Radiometric correction was done to convert DN values into at-sensor reflectance value, then to surface reflectance value. The conversion followed the equation provided in Landsat 7 Science Data User's Handbook (NASA, 2006). For convenience, the formula is also found in Appendix 6. The parameter values were obtained from the metadata accompanying the image data.

Atmospheric correction using radiative transfer model was done to remove the effect of scattering, absorption and other atmospheric degradation (see Vermote et al., 1997). It was carried out using the ATCOR module implemented in ERDAS IMAGINE 8.7 environment. ATCOR works by performing successive steps; first, is masking of haze, cloud, water and clear pixels; second is haze removal and de-shadowing; third is masking of reference pixels and calculation of their visibility; fourth is calculating path radiance; and lastly, is retrieving water vapour and reflectance spectrum values (Richter, 2006).

2.6.2. Vegetation indices and band ratios

Several studies were conducted to correlate above-ground biomass of tropical forest to different vegetation indices and band ratios (Foody et al., 2003; Lu et al., 2004; Rhaman et al., 2005).Band ratios tend to have higher correlation with above-ground biomass compared to the complex vegetation indices developed (e.g. NDVI, SAVI, MSAVI) (Lu et al., 2004). Complex band ratios investigated by Foody et al. (2003) also showed high correlation with above-ground biomass. Lu et al. (2004) found that vegetation indices and band ratios involving TM3 have low correlation with above-ground biomass for the Brazilian forest; however, these were having good relation with forest in Malaysia. The vegetation indices and band ratios investigated in this study are those that were previously found to have high correlation with tropical forest above-ground biomass (Foody et al., 2003; Lu et al., 2004).

Interestingly, a shortwave infrared modification of Simple Ratio (TM4/TM3), called Reduced Simple Ratio (RSR), was found to be more sensitive to changes in forest parameters, particularly LAI in boreal forest (Brown et al., 2000; Stenberg et al., 2004). The modification addresses the effect of background reflectance. So far, it has not been tested whether is has improved sensitivity to biomass in the tropics. Thus, in this study, sensitivity of RSR to tropical forest biomass was also tested. Table 2.2 summarized the vegetation index and band ratios being investigated.

Table 2.2. Vegetation index and band ratios under investigation.

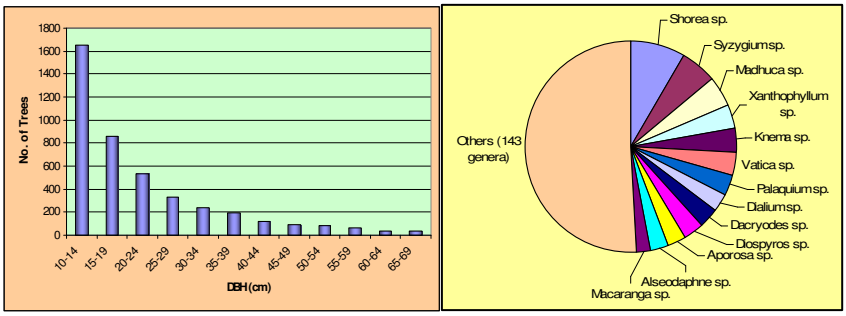
Abbr.	Description	Equation	Reference
RSR	Reduced Simple Ratio	$\frac{\rho_{swir(5)\max} - \rho_{swir(5)}}{\rho_{swir(5)\max} - \rho_{swir(5)\min}} * \frac{\rho_{nir}}{\rho_{red}}$	Brown et al., 2000; Stenberg et al., 2004
ND54	Normalized Vegetation Index	$\frac{\rho_{swir(5)} - \rho_{nir}}{\rho_{swir(5)} + \rho_{nir}}$	Foody et al., 2003; Lu et al., 2004
ND73	Normalized Vegetation Index	$\frac{\rho_{swir(7)} - \rho_{red}}{\rho_{swir(7)} + \rho_{red}}$	Foody et al., 2003;
Ratio 54	Simple Ratio	$\rho_{swir(5)} / \rho_{nir}$	Lu et al., 2004
Ratio 73	Simple Ratio	$\rho_{swir(7)} / \rho_{red}$	Foody et al., 2003
Ratio 271	Complex Ratio	$\frac{\rho_{green} - (\rho_{swir(7)} + \rho_{blue})}{\rho_{green} + (\rho_{swir(7)} + \rho_{blue})}$	Foody et al., 2003
Ratio 327	Complex Ratio	$\frac{\rho_{red} - (\rho_{green} + \rho_{swir(7)})}{\rho_{red} + (\rho_{green} + \rho_{swir(7)})}$	Foody et al., 2003
Ratio 245	Complex Ratio	$(\rho_{green} * \rho_{nir}) / \rho_{swir(5)}$	Foody et al., 2003

To reduce mislocation error (error of GPS), the mean radiance in each band was calculated from a 3 x 3 window centered on the plot (Foody et al., 2001). These were used in the calculation of the vegetation indices and band ratios. The plot biomass data was calculated using the best unbiased biomass equation investigated in Section 2.5.1. Calculation of vegetation indices and band ratios was performed using ArcGIS 9.1 model builder module.

3. Results

3.1. First- and second-phase samples

In the first phase, a total of 143 circular plots of 500 m^2 area each were measured between 2003 and 2006. The plots were located in six out of seven RKLs. There are 12 plots in RKL1, 31 plots in RKL3, 16 plots in RKL4, 29 plots in RKL5, 35 plots in RKL6, and 20 plots in RKL7. Within these plots, 4248 trees having *DBH* ≥ 10 cm were measured. Majority of the trees are small in *DBH* size, with 38.8 % between 10 cm to 15 cm *DBH* and 20.2% between 15cm to 20 cm (Table 3.1a). Larger trees constitute smaller percentage of tree composition, with trees as big as 50 cm to 70 cm *DBH* constituting only 5.22% of the total number being measured. The inverted "J" distribution of tree *DBH* size is expected in any natural forest type. It takes many smaller trees, considering high mortality of this class, to successfully replace the bigger ones in time.



(a) *(b)*

Figure 3.1. Distribution of trees by *DBH* class *(a)* and genera composition (*b*)

The 4248 trees measured comprise 156 genera wherein half of the trees belong to 13 most common genera (Figure 3.2b). *Shorea sp*. was found to be the most dominant in the area, comprising 8.2%. *Syzygium sp., Madhuca sp., Xanthophyllum sp., Knema sp., and Vatica sp.,* were also found in the plots enumerated, comprising 5.76%, 4.66% , 3.67%, 3.58%, and 3.39%, respectively, of the total trees enumerated.

In the second phase, 40 sample trees with diameter ranging from 6 cm to 68.9 cm were measured. The sample trees consisted of 28 genera. The distribution of the tree sample *DBH* size is based on the 5 cm class starting at 5 cm up to 70 cm. A considerable number of sample trees were obtained for smaller *DBH* classes, but less on trees bigger than 50 cm *DBH* (Figure 3.2). In the study area, it has become quite difficult to locate trees of harvestable size (*DBH* ≥ 50 cm or more).

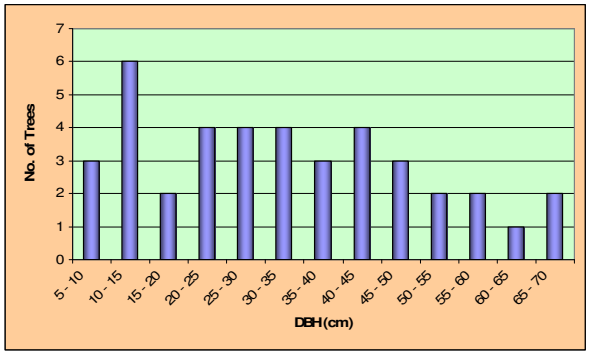


Figure 3.2. Distribution of sample trees by *DBH* class

3.2. Preliminary analysis of second-phase sample trees

The data collected from the sample trees (second phase) were analyzed to develop biomass equation that can be used to estimate tree-based biomass. Initial investigation of the standardized residuals for the 40 sample trees data showed one observation to be a potential outlier. The field log of the measurement was double checked for possible errors in computation or recording. However, the calculated dry weight for the potential outlier was right. A formal analysis using Bonferroni outlier test for different models was performed in R. Result shows that the suspected outlier observation was indeed an outlier only under combined variable model ($max|rstudent| = 3.85189$, *Bonferroni* $p = 0.01799$). For consistency of analysis, the outlier observation was dropped from the succeeding analyses of all models.

Two approaches were used in estimating dry weight; one is by direct weighing as used in trees of *DBH*<15 cm, and the other one by measuring the stem volume as used in trees of *DBH*>15 cm. It is possible that the two approaches may result to different dry weight estimate if performed on the same sample tree. Therefore, analysis of covariance was performed to test whether the two approaches had an effect on the measured dry weight. Table 3.1 (see Appendix 1) indicate that for

different linear models considered, the method of measurement does not have an effect on the measured sample tree biomass.

Table 3.1. Analysis of covariance on the effect of measurement approach to measured sample tree biomass

Model	DF(Error)	F Stat	P-value
$Ln(DW)= Ln(a) + b*Ln(DBH)$	37	0.212	0.648
$DW= a+b(DBH)^2+c(DBH)^3$	36	0.155	0.696
$DW=a + b(DBH^2H)$	37	0.067	0.798
$sqrt(DW) = a + b(DBH)$	37	1.651	0.207

** ANCOVA was not done for model 5 since it is not a linear model*

3.3. Model fitting and parameter estimation

Weighted linear regression was performed for Model 1 to Model 4, while a non-linear least squares estimation using Gauss-Newton algorithm was performed for Model 5. The different weights were obtained by iteratively finding the optimal weight that minimizes Furnival's Index (*I*). These are the weights which maximize the likelihood of the observed samples (Furnival, 1961). The weights obtained were identical to when it is estimated using SPSS software. This is because both procedures use maximum likelihood as criterion.

The results of the weighted linear regression performed on Models 1 to 4 and non-linear least squares estimation applied to Model 5 showed that there is strong relationship between the tree variables used (*DBH* and D^2H) and above-ground biomass (Table 3.2). Analysis of variance result is provided in Appendix 2. In Model 1, where the independent and dependent variable are log-transform of *DBH* and above-ground biomass (as dry matter weight), ln(*DBH*) explained 98.4% of the variability of ln(*DW*) ($DW=exp[-1.2495 + 2.3109(DBH)], p<0.0001$). It should be noted that the computed R^2 for Model 1 refers to the transformed variable. Stepwise analysis of third degree polynomial model showed that *DBH* is not significantly different from zero ($F_{stat}=0.819, df_e=36, n=39, p=0.3718$), hence the polynomial model used only DBH^2 and DBH^3 as predictor variables. Result of fitting the reduced 3rd degree polynomial model to the data showed that the model provides a good fit with 95.06% of the variability of biomass being explained ($DW= -2.6729 + 0.5446(DBH)^2 + 0.0092(DBH)^3, p<0.0001$). Model 3, using combined variable D^2H, where *D* is *DBH* and H is tree height, also showed a strong relationship, explaining as much as 94.48% of the variability of biomass ($DW=6.9664 + 0.0326(D^2H), p<0.0001$). The fourth model, which uses

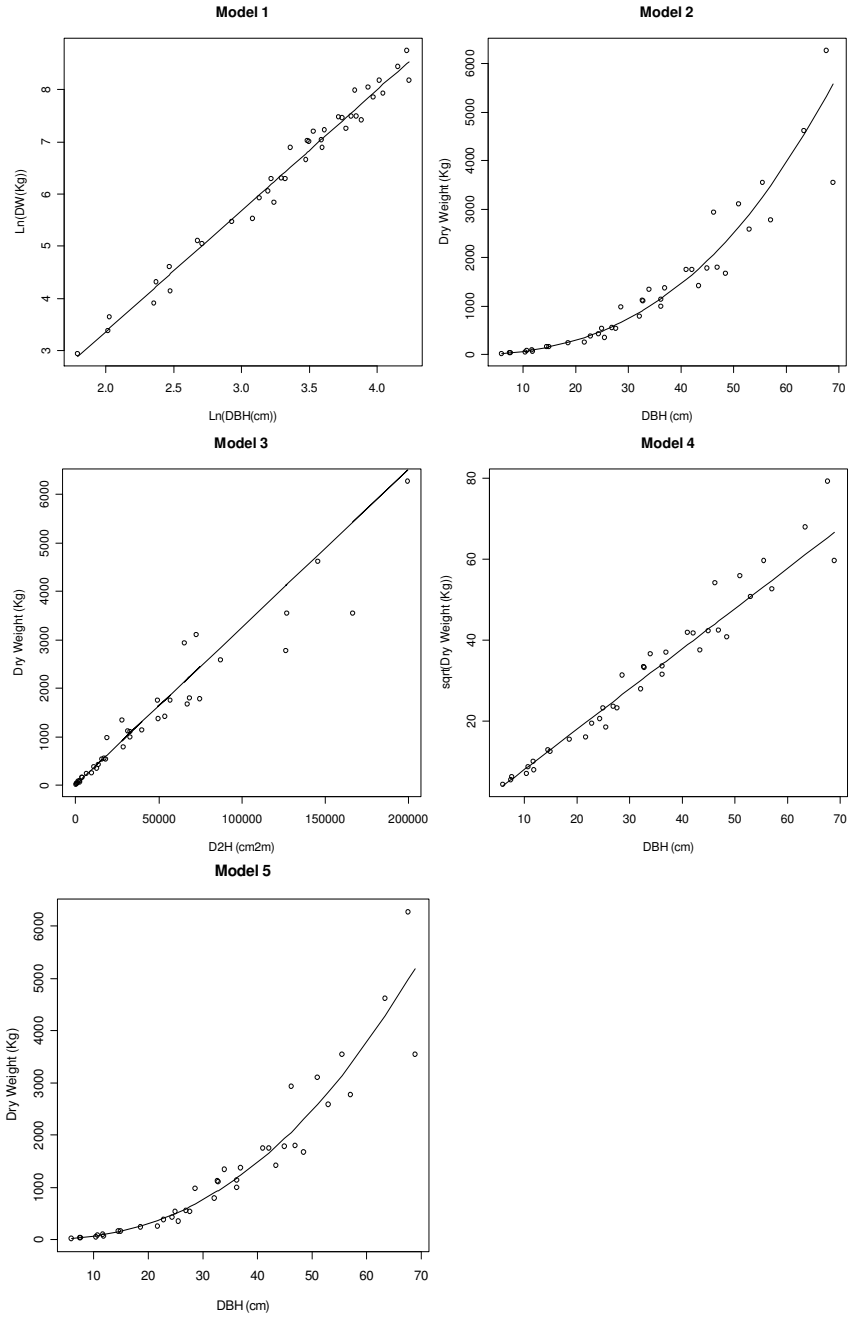


Figure 3.3. Curve fitting of five different models.

square-root transformation of dry weight (*DW*), likewise gives a strong linear relationship between the dependent variable $(\sqrt{DW})$ and *DBH*. *DBH* explained 97.45% of the variability of the square-root transformed biomass ($\sqrt{DW}$ = *-2.0383 + 0.9951 (DBH), p<0.0001*). Non-linear estimation result indicates that Model 5 explains 90.94% of the variability of biomass ($DW = 0.2902(DBH)^{2..3131}$).

Table 3.2. Parameter estimates and significance of the five models.

Model	Parameter	Value	*t*-stat	*p*-value
$ln(DW)= ln(a) + b*ln(DBH) + ln(\varepsilon)$	*a*	-1.2495	-7.720	<.0001
	b	2.3109	47.210	<.0001
$DW= a + b(DBH)^2 + c(DBH)^3+\varepsilon$	*a*	-2.6729	-0.610	0.5484
	b	0.5446	6.700	<.0001
	c	0.0092	4.140	0.0002
$DW =a + b(D^2H)+\varepsilon$	*a*	6.9664	3.930	0.0004
	b	0.0326	25.160	<.0001
$sqrt(DW) = a + b(DBH)+\varepsilon$	*a*	-2.0383	-5.350	<.0001
	b	0.9951	37.580	<.0001
$DW=a(DBH)^b + \varepsilon$	*a**	0.2902	6.700	<.0001
	*b**	2.3131	50.058	<.0001

* approximated t-values

After the model parameter estimates were obtained, the next task was to determine which model fits best to the observations. The coefficient of determination (R^2) and *RMSE* provides the fit of the model under the state of the variables being used. In this study, the different models used different weights and employed transformations to the variables prior to least-squares analysis. In such condition, R^2 and *RMSE* are not appropriate in comparing the different models (Furnival, 1961, Parresol, 1999). The next section considers the fit statistics that is appropriate to compare models employing different variables, weights and transformation.

3.4. Model comparison and validation issues

In order to determine which of the five models is best to estimate above-ground biomass, Furnival's Index (*I*) and coefficient of variation (*CV*) were computed. The fit statistics computed are based on predicted values, detransformed and bias-corrected if necessary, as suggested by Parresol (1999). While all five models exhibited good fit to the data, results showed that power function models (Model 1

and Model 5) exhibited much better fit than the other model forms, as reflected by the differences in their Furnival's Index (*I*) and coefficient of variation (*CV*). Moreover, power function model with multiplicative error term (Model 1 of the form $DW=a(DBH)^b\varepsilon$), estimated by weighted log-transformed least-squares procedure, shows better fit compared to the other models (*I*=127.665, *CV*=32.77%). It has the minimum *I* and *CV*. Power function with additive error term (Model 5) has a fit which is comparable to Model 1 (*I*=127.907, *CV*=32.796%). The computed statistics are summarized in the Table 3.3

Table 3.3. Comparison of different biomass equation models (Kalimantan data)

Model	*I*	*CV%*	*RMSE*
(1) $ln(DW)= ln(a) + b*ln(DBH) + ln(\varepsilon)$	127.665	32.770	0.1479
(2) $DW= a+b(DBH)^2+c(DBH)^3+\varepsilon$	130.972	34.799	0.0451
(3) $DW=a + b(D^2H)+\varepsilon$	134.726	35.948	0.0027
(4) $sqrt(DW) = a + b(DBH)+\varepsilon$	137.617	35.699	0.0521
(5) $DW=a(DBH)^b +\varepsilon$	127.907	32.796	0.0316

* Predicted values of Model 1 and Model 4 are biased and were corrected when the fit statistics were computed. Bias for model 1 is 2.52%. Bias for model 4 is 0.5% at *DBH*=6 cm and reduces to 0.002% as *DBH* reaches 68.9 cm.

**Furnival's Index (*I*) was calculated using equation 8 in Section 2.5.2.

The same models and estimation approaches were applied to above-ground woody biomass data in Netherlands (De Gier, 1989) to determine if power function models will still stand best compared to other models. The predictor variables for polynomial model were also determined using stepwise selection, as performed in the Kalimantan data. Outliers detected using Bonferroni test for outlier were excluded from the analysis. On the Dutch dataset, a consistent tree subsampling method was used on all trees (DeGier, 1989; DeGier, 2003) to obtain independent estimates of Dry Weight, Fresh Weight and Volume of sample trees. This method was later validated in Botswana (Mabowe, 2006) and showed a high accuracy.

The computed fit statistics reveal that Model 1 (power function model with multiplicative error term) seems to fit the data better than the other models considered (*I*=3.396, *CV*=69.445%). Comparison of the results obtained from the two data sets show that power function models exhibits better description of the relationship of above-ground biomass and *DBH*. However, the result does not strongly indicate whether power function with multiplicative error (Model 1) significantly performs better than power function model with additive error term

(Model 5). For the Dutch data set, 3rd degree polynomial model is a good alternative to log-transformed model.

Table 3.4. Comparison of different biomass equation models (Dutch Data)

Model	*I*	*CV%*	*RMSE*
(1) $ln(DW)= ln(a) + b*ln(DBH) + ln(\varepsilon)$	3.396	69.445	0.2372
(2) $DW= a+b(DBH)^2+c(DBH)^3+\varepsilon$	3.529	74.389	0.0168
(3) $DW=a + b(D^2H)+\varepsilon$	3.920	69.238	0.0134
(4) $sqrt(DW) = a + b(DBH)+\varepsilon$	3.688	95.769	0.0300
(5) $DW=a(DBH)^b +\varepsilon$	3.551	68.558	0.0169

* Predicted values of model 1 and 4 are biased and were corrected when the fit statistics were computed. Bias for Model 1 is 5.77%. Bias for Model 2 is 26.24% at *DBH*=2 cm and reduces to 0.01% as *DBH* reaches 56.6 cm.

**Furnival's Index (*I*) was calculated using the equation 8 in Methods chapter.

Model validation is as important as modelling itself. The time spent during the fieldwork did not permit collection of additional sample trees for this purpose. One possibility was to use data collected by Ketterings et al. (2001), however, analysis of covariance for different models (Table 3.5) suggests that their data, taken from Sepunggur, Sumatra, Indonesia, does not represent the forest of Kalimantan ($F_{sta\ t}$=86.704, DF_{error} = 66, p = <0.0001). Independent data is needed to validate the constructed biomass equation in Kalimantan.

Table 3.5. Comparison of biomass data collected from Kalimantan and Sepunggur, Indonesia

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	186.935(a)	2	93.467	1152.665	.000
Intercept	8.525	1	8.525	105.136	.000
lnDBH	144.539	1	144.539	1782.497	.000
Area	7.031	1	7.031	86.704	.000
Error	5.352	66	0.081		
Total	2466.716	69			
Corrected Total	192.286	68			

Dependent Variable: lnDW

a R Squared = 0.972 (Adjusted R Squared = 0.971)

3.5. Integration of biomass estimate errors

Two sources of uncertainty in the estimation of forest above-ground biomass were considered in the study: error due to selection of sample plots in the fist-phase and selection of sample trees in the second-phase. To quantify these errors, an approach developed by Cunia (1986b, 1986c), as explained in Section 2.5.3 of Methods, was used.

Variability of biomass per hectare estimate within strata was found to be high, with one stratum having variance greater than the overall variance ($Var_{strata\ 3}$ = 12161.8589 $tons^2/ha^2$, $Var_{combined}$ =11148.1030 $tons^2/ha^2$). A gain in precision was computed to judge whether RKL stratification was effective in increasing the precision of biomass estimate (Cochran, 1963). Results show that the relative efficiency of stratified random sampling over simple random sampling is 1.069 (see Appendix 5), indicating a very small gain in the precision achieved by stratification. Therefore, the quantification of error of biomass estimate was calculated based on the simple random sampling design as discussed by Cunia (1986b).

Error quantification result (Table 3.6) shows that, on the average, there is 328.0 ± 29.7 tons (95% confidence interval (CI)) of above-ground biomass per hectare of forest. This gives the estimate of total biomass within the six RKLs investigated to be 14 587 502 ± 1 321 712.8 tons (95% CI). The total variance of the estimated mean biomass per hectare amounts to 226 $tons^2$, of which, 77.96 $tons^2$ (34.5%) is attributed to sampling in the first phase and 148.06 $tons^2$ (65.5%) is due to regression error. Without quantifying the uncertainty due to regression error, the 95% confidence interval of estimate of mean above-ground biomass per hectare is 328.0 ± 17.96 tons/ha (95% CI) and for total above-ground biomass is 14 587 502 ± 776 234.7 tons (95% CI). This translates to underestimation of the precision of estimate by 41. 27%.

Table 3.6. Error components of the estimated mean above-ground biomass.

	Combined Errors	First phase only
Mean	328.0 tons/ha	328.0 tons/ha
Total Variance (mean)	226.0 $tons^2/ha^2$	77.96 $tons^2/ha^2$
Variance (mean) due to first-phase samples	77.96 $tons^2/ha^2$	77.96 $tons^2/ha^2$
Variance (mean) due to regression	148.06 $tons^2/ha^2$	
Sampling error	15.034 tons	8.829 tons

Table 3.7. 95% CI of mean biomass (tons/ha) and total biomass estimate (tons)

Estimates	Combined Errors	First phase only
Mean biomass	328.0	328
95% CI Lower limit	298.3	310.6
95% CI Upper limit	357.7	345.5
Total biomass	14 587 502.0	14 587 502.0
95% CI Lower limit	13 265 789.1	13 811 267.3
95% CI Upper limit	15 909 214.8	15 363 736.7

3.6. Landsat ETM+ image-based biomass assessment

The vegetation indices and band ratios (Table 2.2) were computed using the different spectral data of Landsat ETM+. Linear least-squares regression was performed between plot biomass (response variable) and the vegetation indices or band ratios (explanatory variables) to determine whether there is linearly relation between them. Vegetation index or band ratio having good correlation with above-ground biomass can be used to estimate total above-ground biomass as described in Section 2.2. The Table 3.8 summarizes the linear relation of above-ground biomass and different vegetation index and band ratios investigated.

Table 3.8. Correlation between VI/Band ratios and above-ground biomass

VI and Band Ratio	*r*	*t* stat	*p*-value
RSR	-0.0852	-1.015	0.312
ND54	0.0644	0.767	0.441
ND73	-0.0657	-0.782	0.436
Ratio54	-0.1266	-1.516	0.132
Ratio73	-0.7056	-0.835	0.402
Ratio271	0.1070	1.277	0.204
Ratio327	0.0375	0.446	0.657
Ratio245	0.0228	0.271	0.786

The statistical analysis indicates that vegetation indices and band ratios investigated display very poor linear relationship with above-ground forest biomass. The variability of biomass being explained by the spectral data is very low. The slope of the fit line for the different explanatory variables was

not significantly different from zero (p-values > 0.05). With these results, predictive model to estimate above-ground biomass using vegetation index or band ratios being investigated can not be established.

4. Discussion

In the previous chapter, five biomass equations: a power function model with multiplicative error, a polynomial model, a so-called combined variable model, a square-root transformed model and a power function model with additive error, were constructed using *DBH* or D^2H as explanatory variable. The five models show strong fit to the above-ground biomass data collected from the forest of Kalimantan, Indonesia. The power function models were found to have relatively better fit compared to other models investigated. The result also indicated that in quantifying the forest inventory biomass and its associated uncertainty, one must account for both the uncertainty associated with sampling in the first phase and the regression error in the second phase. Predictive modelling of above-ground biomass and spectral data under investigation did not show significant linear relationship.

4.1. Relationship of biomass and tree variable

The observed goodness-of fit of the models investigated was in agreement to previous works on the relationship between above-ground biomass and *DBH* or combined variable D^2H (Arevalo et al., 2007; Crow, 1978; Cunia, 1986a; de Gier, 2003; Ketterings et al., 2001; Overman, 1994). Of all the models being investigated, power function models, (Model 1 and Model 5) shows a slightly better fit than polynomial, combined variable and square-root transformed models.

Studies have shown that power function with multiplicative error term (Model 1) estimates biomass with considerable goodness-of-fit (Aboal et al., 2005; Crow, 1978; Ketterings et al., 2001; Overman, 1994). However, it has also been known that prediction in this approach is biased (Miller, 1984; Smith, 1993; Sprugel, 1983; Wiant and Harner, 1979). The bias stems from the transformation used to linearize a curvilinear relationship. It is usually small, about 10% and the procedure to correct it is straight forward (Miller, 1984; Sprugel, 1983; Smith, 1993). It is implied that for more precise estimation of above-ground biomass, bias of the prediction must be corrected. The mail limitation of this model is that uncertainty of the prediction in original units can not be established from transformed models because the

covariance matrix derived from this model refers to the transformed and not to the original variable (de Gier, 2003).

Like Model 1, square-root transformed model (Model 4) also suffers from the same problems found in Model 1. Prediction values are biased, but a low-bias estimator is obtained by adding $\hat{\sigma}^2$ (Miller, 1984). Uncertainty of the estimates can not be established too since the covariance matrix refers to the square-root of the dependent variable $(\sqrt{DW})$. The plot of observed and predicted biomass (Figure 4.1) shows that there is mostly overestimation at higher biomass indicating that the model is not appropriate for the relation exhibited by the data. But looking at its R^2, one would tend to judge that this model is best compared to polynomial model. This result shows that the use of R^2 as basis on comparing models can be misleading. This is also the concern expressed by Parresol (1999).

Polynomial model is a good alternative to power function model. Even though the relation of biomass and *DBH* is curvilinear, result of this study has shown that polynomial model can fit well while maintaining linear combination of variables. Unlike transformed models, the polynomial model gives unbiased estimate of the model variables (parameters) and to the predicted biomass.

Previous applications of polynomial models to biomass equation often employ 2nd degree only. It is interesting to note that weighted 3rd degree polynomial regression, with variables chosen by stepwise selection, in this case selected only DBH^2 and DBH^3 as significant explanatory variables, in parallel to the findings of de Gier (2003). There is no detailed study that explains this result, however, the inclusion of DBH^3 into the model increased the percentage of explanation and rendered *DBH* term not significant. This is an indication that 3rd degree polynomial should be explored when one constructs biomass equation of the polynomial form.

In the Kalimantan data, power function with additive error shows slightly better fit compared to the polynomial model. However, in the Dutch data, the polynomial model fits slightly better to the measured biomass. This result suggests that the allometry between biomass and DBH is not constant for different forest ecosystem. This implies that when one wishes to construct a biomass equation for a new area of interest, these two models be considered for fitting.

Polynomial curve has the possibility to reach negative minimum values, or the minimum predicted biomass does not correspond to the minimum *DBH* (de Gier, 1999). This means that polynomial curve gives negative biomass estimate, or at *DBH* below the point of curve minimum, biomass is increasing. These two scenarios are ecologically impossible. In this study, the above scenarios were not observed. This is due to inclusion of sufficient number of sample trees with smaller DBH. Furthermore, the weighting used reduced the influenced of bigger trees to the regression model in comparison with the influence of smaller trees. The study of de Gier (1999; 2003) employing weighted polynomial model combined with stepwise selection of regression variables also resulted to an ecologically sound polynomial curve fit.

The non-linear estimation approach to obviously curvilinear relation such as biomass studies is promising. The agreement of biomass estimates by Model 5 to that of Model 1 is illustrated in Figure 4.2. Model 5 has consistently higher biomass estimate compared to Model 1, but the difference was only 56 kg for the biggest tree sample. The same pattern is also observed with the Dutch data, but in here the maximum difference was only 20 kg. This result is in parallel with the findings of Jansson (1985) in comparing predicted sediment load in a Swedish river using power function with multiplicative error term and the power function with additive error term. The former model has lower predicted sediment load compared to that predicted by the latter. This means the fit line of Model 5 is above the fit line of Model 1. Accordingly, the residuals for Model 5 is lower compared to residuals of Model 1 for observations above the fit line, and conversely, the residuals for Model 5 is higher compared to residuals of Model 1 for observations below the fit line. Although bias correction is applied, it only reduced the extent of the bias, not totally eliminate it. Smith (1993) said that there are cases where bias correction factor can actually overcompensate or undercompensate the bias. There is still no solid understanding yet how often this occurs and under what conditions (Smith, 1993).

The result indicates that non-linear estimation provides a good estimation which is at par with the fit of the log-transformed approach. It does not require the data to be transformed; hence, transformation bias is not a problem. With the availability of computers, the parameters of power function, as the case of Model 5, can be easily estimated. However, promising as it can be, the use of non-linear estimation is not without hindrances. Two particular challenges are deciding on the starting values of the parameters and increasing the chance that the solution is a global minimum. Since the curvilinear relation of biomass and *DBH* has long been studied and found

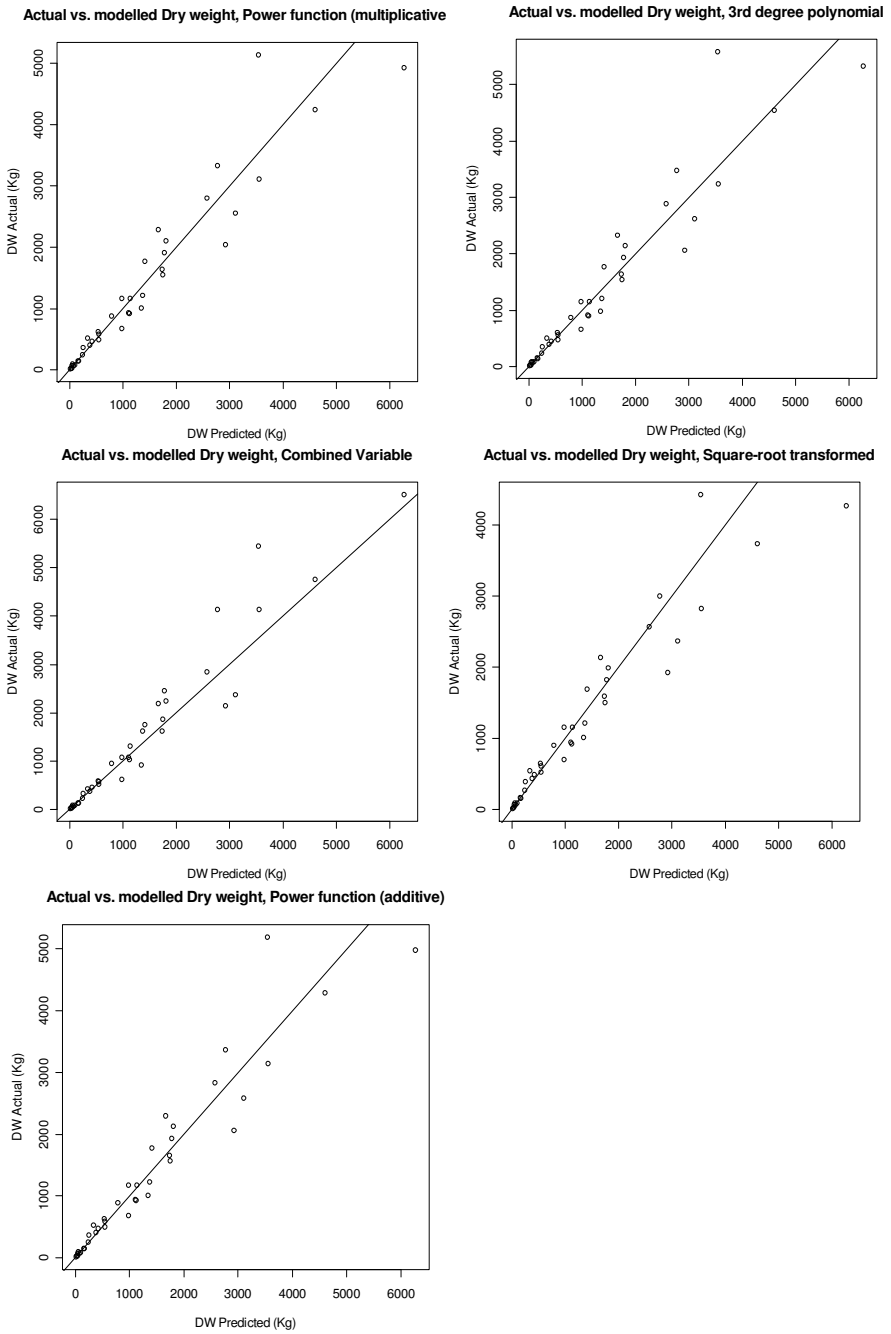


Figure 4.1. Plot of actual and predicted biomass using the five models.

adequate for prediction, using this knowledge provides some insight on setting the parameters where the solution obtained is the one that minimizes residual sum of squares (Parresol, 2001a).

Typically, biomass equation behaves erratically when used to estimate biomass of trees whose DBH is well beyond the range of sample tree size used to develop it. This is illustrated with the observation of Aboal et al. (2005) that more error is encountered when extrapolating biomass for larger tree DBH. So when trees are much larger than those used to construct the biomass equation, the tree biomass should not be extrapolated using that equation.

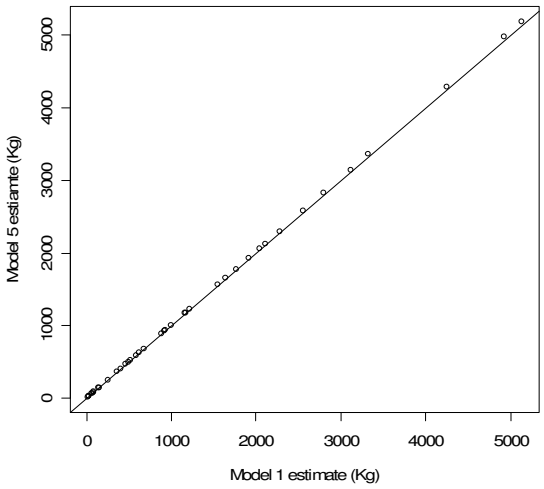


Figure 4.2. Comparison of tree-based biomass estimate using Model 1 and Model 5 (power function models)

4.2. Field measurement limitations

There were some problems encountered during the fieldwork. The first phase sample plots were determined by stratified random sampling. But in the field, difficulty to access the deeper part of the forest and the limited time allotted for fieldwork limits the strict adherence to sampling plan. Furthermore, management policy does not allow cutting of sample trees for the second phase inside the concession area, instead, the trees were selected from locations just outside the boundary. This put some setback on the representativeness of the sample trees to the concession area even though ocular comparison of the two areas suggests that the conditions are similar. De Gier (2003) argued that even though purposive sampling to represent

different tree sizes is advisable, there should still be randomness in the location of the sample trees selected. But true randomness can not be ascertained in the study area because of the above mentioned restrictions.

The number of sample trees used to develop the biomass equation is relatively small (n=39 trees) due to limited time. During the destructive measurement, the conventional method was employed due to technical limitation. This method has some limitations in contrast to the new method recommended by de Gier (2003). The weighing scale is also limited in capacity that large trees have to be cut into pieces. In the process, some pieces of woody biomass were lost. The subsamples collected for laboratory analysis were not selected based on some probability principle, but rather on arbitrary locations (for example, lower, middle and upper portion of the stem). This procedure introduces some degree of bias into the biomass estimate (Valentine et al, 1984; de Gier 2003). Lastly, conversion of volume or fresh weight into dry weight involves a ratio estimator (the ratios explained in Section 2.3.3. of Methods). It is known that ratio estimators are biased (Cochran, 1963). All these introduce errors into the measured weight of the sample tree biomass (de Gier, 2003).

4.3. Comparison of best fit model with existing biomass equations

The power function models (Model 1 and 5), were compared with the biomass equation of Brown (1997) and Ketterings et al. (2001). Brown's biomass equation is *DW=exp [-2.134+2.530*ln (DBH)]*, and is applicable to tropical moist forest. It is developed from sample trees collected in Brazil, Cambodia and Indonesia. Ketterings' (2001) biomass equation was developed using sample trees from Sumatra. It is a modification of the power function where the parameters are broken down into components to account for geographical variability. It is of the form $B = r\rho(DBH)^{2+c}$ where r is a constant over wide geographical area, ρ is the average wood density for the site, and c is a parameter estimated from the relationship of tree height and DBH ($H=kD^c$). The value c was computed to be 0.502, the mean density (ρ) is 0.625, and r is 0.11. Biomass estimates using Brown's equation shows considerable agreement with the developed power function models, however, biomass estimates using the equation of Ketterings et al. (2001) was far off the general trend of the biomass data collected in Kalimantan (Labanan area) (Figure 4.3).

Two possible reasons explain why Ketterings' et al. (2001) equation deviated so much from the equation developed in Kalimantan. First is due to geographical differences of the two study areas. Analysis of covariance shows that biomass data of from Sumatra, Indonesia does not represent the forest of Kalimantan (Table 3.5). For the same *DBH* size, the above-ground biomass of trees in Sepunggur area is lower compared to the above-ground biomass collected in Kalimantan. Even though the locations are relatively close, being in the same country, there is indication that site specificity plays a role in the differences of above-ground biomass of trees, resulting to difference in the curvature of the relationship. This is also similar to the findings of de Gier (2003) on the comparison of biomass equation from four different countries. The biomass equation from Burkina Faso and Ethiopia, both semi-arid African countries, are very much different, while the biomass equation between Tunisia and Netherlands almost coincide with each other. Second, the tree species collected in Sepunggur, Sumatra were mostly different from the tree species measured in Kalimantan. Different tree species have different wood density, thus, dry matter content will vary even if the trees are of the same size (Ketterings et al., 2001). Furthermore, even when their biomass equation was calibrated using the data in Kalimantan, the resulting equation was still far off the best fit model in Kalimantan. This suggests that the calibration they proposed has not solved entirely the transferability problem of biomass equations. This implies that it may well be better to develop a new biomass equation based from sample trees taken from the area of interest.

Brown's (1997) equation for tropical moist forest fits quite well with the Kalimantan data. A closer look of the fit line from Brown's (1997) equation reveals that, at *DBH*<60, biomass is underestimated by 7 kg to 136 kg (Figure 4.2). Probably the good agreement between Brown's equation and the new biomass equation is attributed to the large number and wider range of tree *DBH* being used. Furthermore, some of the trees used to develop this equation were coming from Indonesia. Depending on the degree of precision that one wants for the estimate, Brown's (1997) equation can be used in Kalimantan. However, uncertainty of the prediction using transformed models can not be established because the covariance matrix derived from this model refers to the transformed and not to the original variable (de Gier, 2003). In addition, a critical assumption that the tree population from which Brown's equation was developed is very similar with the forest in Kalimantan has to be made. The result clearly indicates that even if previously constructed biomass equation seems to be applicable to the new area of interest, validating it is necessary to avoid bias of unknown magnitude. Validation often requires a good number of

trees (at least 25), that instead of validating previously published biomass equation, one may decide to construct a new equation as this is even better than the former other option.

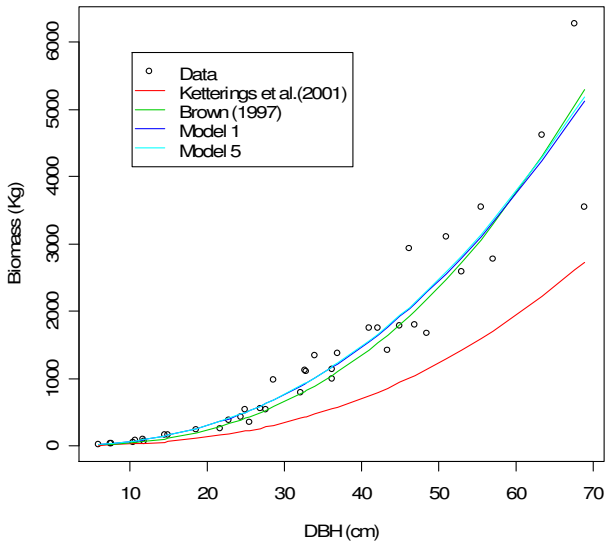


Figure 4.3 Fit of biomass equation using Ketterings et al. (2001), Brown (1997) and the constructed power function models.

4.4. Integration of biomass estimate errors

Even though power function model is the most probable relation exhibited by above-ground biomass and *DBH*, there is still knowledge gap as to how the uncertainty propagates to forest inventory estimate precision under a given model form. The work of Cunia (1986b; 1986c) is limited to untransformed weighted linear least squares, but can not be used on the two power function models considered in this study. Therefore, the polynomial model was used to quantify the precision of forest above-ground biomass estimate. The polynomial model exhibited a good fit when compared to the others, except the power function models.

A gain in precision was computed to see whether the stratification used during the data collection significantly increased the precision of the estimate. The result showed that using RKLs as stratification variable did not increase the precision of the estimate (see Appendix 4). This means that biomass did not vary much across

RKLs. Theoretically, RKLs which were selectively logged long ago should have more biomass variability than those recently logged. However, over the years, RKLs not scheduled for selective harvesting were affected by unplanned or illegal logging operations (Casson and Obidzinski, 2002). This has probably made the RKLs more or less homogeneous in terms of biomass variability. Thus the estimation of forest biomass was carried out using simple random sampling procedure.

The regression error contributed significantly to the overall precision of the mean above-ground biomass per hectare. The result shows that 65.5% of the total variation is attributed to this source alone. This agrees with the findings of Cunia (1986b; 1986c) using biomass data of 353 trees from the US. The findings imply that in quantifying forest landscape biomass estimate using regression function, one need to assess the contribution of regression error to the overall precision of estimate. Ignoring this source of error can have enormous consequence on the precision of the quantified biomass estimate. As shown in this study, the underestimation of the precision of estimated biomass was 41.27%. The precise quantification of uncertainties in biomass estimates is of great relevance to the objectives of UNFCCC and the Kyoto Protocol.

Precision of tree-based biomass estimate using biomass equation is directly proportional to the size of the tree. This is because measurement of biomass involves many steps (measurement of *DBH*, fresh weight, volume) which become increasingly difficult as trees get bigger. The difficulty increases the magnitude of error at each step (Cunia, 1986b; de Gier, 2003). Unfortunately, measurement errors were not decomposed in this study. Another source of the large uncertainty of estimate due to regression error is the fact that a relatively small number of trees were used to develop the regression equation. Thus, the repeated use of the developed regression equation to measure biomass of each tree in the inventory accrues uncertainty to significant amount as quantified here.

4.5. Lansat ETM+ image-based biomass assessment

4.5.1. Relationship of above-ground biomass and spectral data

One objective of this study is to determine what vegetation index or band ratio shows good linear relation with above-ground biomass. The vegetation index and band ratios used were short-listed from many possible vegetation indices and band ratios based from significant findings of previous studies. Contrary to the findings of

Foody et al (2003), Lu (2004) and Brown (2001), results indicate that there is no sufficient evidence to conclude that a linear relation exist between above-ground biomass and RSR or band ratios. Thus, in this study, above-ground biomass mapping using spectral data could not be established. The scatter plot below provides quick impression of the independence of vegetation indices / band ratios to above-ground biomass.

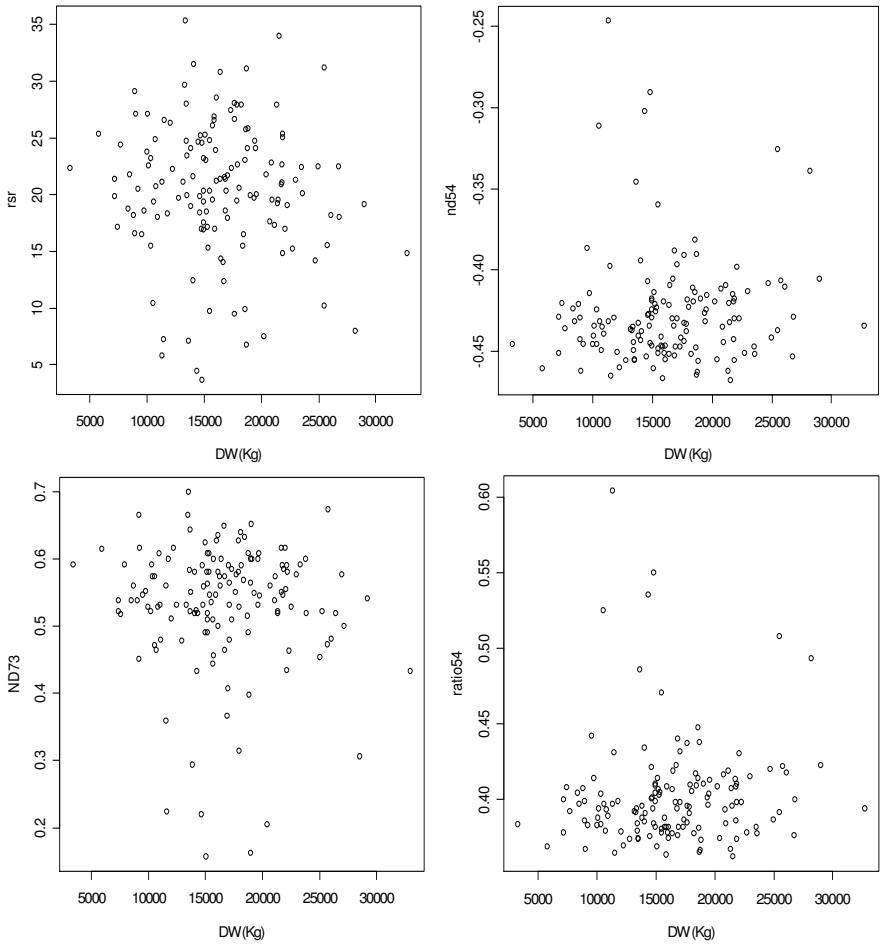


Figure 4.4. Scatterplot of above-ground biomass and vegetation index/band ratios

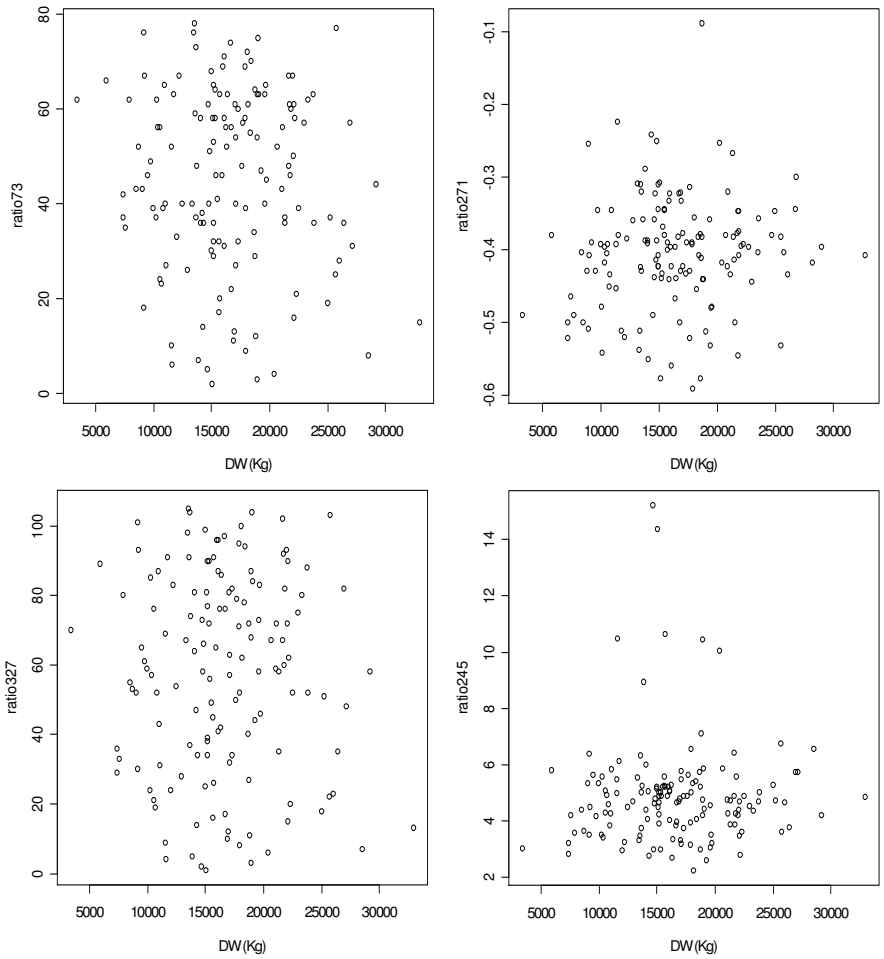


Figure 4.4. (Continuation)

The observed low correlation is possibly due to the forest composition of the area. The reflectance characteristic of vegetation is dependent on several factors. Among them is the orientation and structure of leaf canopy (Kerle et al., 2004). The scatter plot of RSR has no particular pattern. The same is true with ND54 and Ratio54 tested by Lu et al. (2004) in the Brazilian Amazon basin. These were found to have good correlation with biomass in their study area but not in the case of Kalimantan. ND73, Ratio73 and Ratio327 were found to have substantial correlation with the forest of Malaysia Foody et al. (2004), however the result of this study did not agree

to their findings. The scatter plot of Ratio73 and Ratio327 does not reveal any pattern. Comparison on the composition, condition, structure and health of the two forests is needed to reveal what causes this contradiction. However, ND73 seems to be at saturation condition as indicated by the horizontal distribution of ND73 values across the biomass range. This is the same condition commonly observed with the more complex vegetation indices, such as NDVI (Okuda, 2005; Huete et al, 1997), SAVI, MSAVI, and ARVI (Lu et al, 2004). When saturation occurs, any further increase in biomass does not affect the values of vegetation index or band ratio values.

There are several possible reasons why the tested vegetation indices and band ratios have low correlation with biomass. First, optical remote sensors can only 'see' the forest canopy and can not detect how much biomass is found under the canopy. In all cases, the stem biomass that is hidden from the sensor comprises majority of the above-ground biomass. Montagu et al. (2005) estimated the amount to be around 40% to 93%. Second, reflectance is affected by leaf physiochemical properties, like structure (Bousquet et al., 2005), chlorophyll content (Zarco-Tejada et al., 2000) and water content (Danson and Bowyer, 2004). For example, reflectance in the NIR and SWIR decreases due to absorption of photons as leaf water content increases (Danson and Bowyer, 2004). These characteristics are specific to groups of forest trees (species). Somehow, the variation on the observed reflectance is partly explained by the phenological characteristics of the trees being sensed and these characteristics, thus explaining the disagreement of previous results and of this study.

A problem typically observed in the tropical forest when using medium resolution sensor like Landsat ETM+ is "mixed pixel" condition (Asner, 1998). The combined reflectance observed is not only due to the amount of vegetation present, but also from other factors such as senescence of vegetation, soil or shadow (Davidson and Cssilag, 2001).The relation between above-ground biomass and vegetation indices or band ratios becomes poor because of this effect. Thus, it is imperative to efficiently classify the cover type and use it as additional information to explain the variability of spectral values as suggested by Rahman et al. (2005). However, such classification may not be effectively achieved by Landsat ETM+ data. In the next section, the use of alternative imaging technology is considered.

Lastly, the use of a 3 x 3 filter to reduce mislocation error might have affected the vegetation indices or band ratios computed. When the averaging is done, a new the

new value is defined by the spectral data of the center pixel and the eight neighbouring pixels. The result is a form of smoothing which either increases or dampens the centre pixel depending on its neighbour's spectral value. The change in the vegetation index or band ratio value of the pixel is independent of the actual biomass contained in the forest area represented by that pixel.

4.5.2. Biomass estimation using alternative imaging technology

One may realize that above-ground forest biomass is directly related to the number of trees present in the area, the tree size and height. If all these characteristics can be captured by the sensor, chances are higher relationship between biomass and spectral data can be achieved. But, medium spatial resolution imagery data, such as Landsat ETM+ used in this study, may not be sufficient to capture these characteristics (Okuda et al., 2004; Suganuma et al., 2006). Alternative imaging technology such as high spatial resolution imagery (Quickbird or Ikonos) can be used instead to better capture the fine spatial distribution of trees in the forest stand (Aplin, 2004). In addition, better forest classification and canopy characterization can be achieved from this type of sensor. Further studies on how to capture the information from high spatial resolution imagery that is sensitive to biomass becomes very essential. The cost of acquiring such images is high, but it should not limit making use of its potential considering the importance of the forest.

Another type of sensor that can be used to capture textural characteristic of the forest stand is RADAR, such as Synthetic Aperture Radar (SAR). Hussin et al. (1991), Kuplich et al. (2003), Luckman et al. (1998), and Santos et al. (2003) demonstrated that the use of backscatter (a measure of canopy texture) from SAR improves biomass estimation accuracy. SAR can also be used to estimate forest height which is highly correlated with above-ground biomass (Mette, 2002). Additional benefit from RADAR sensors is that it is not affected by cloud cover normally present in highly vegetated areas. One limitation though is that backscatter tends to saturate as biomass becomes large (above 60 tons/ha) (Luckman, 1998). As found in this study, biomass per hectare in Kalimantan is well beyond the 60 tons per hectare level where backscatter starts to saturate. Thus further studies are essential to improve the sensitivity of backscatter to densely vegetated forests.

Light Detection and Ranging (LiDAR) technology has recently been proven to be effective in extracting biomass information (Hyde et al, 2006; Hyde et al, 2007, Patenaude et al., 2004). This type of sensor emits light pulses and measures the time

elapse for the emitted pulses to be reflected back. The result is high resolution horizontal and accurate vertical information (Lim et al, 2003). Hyde et al. (2006) indicates that LiDAR alone can best estimate canopy height and biomass information, and the addition of ETM+ data further improve these estimates. The potential of this technology to biomass assessment is enormous.

5. Conclusion

The pressures brought by climate change have elevated biomass assessment instrumental to measure the forest's potential as carbon storage and source. Much attention is given to precisely measure how much biomass there is in the forest. Approaches in biomass assessment involve predictive modelling, thus, improving the quality of ground data and precision of models is very important.

Which model form – power, polynomial, combined variable and square root transformed variable – gives the most precise biomass estimate?

- Power function model was found to be the best in describing the relation of tree biomass and DBH. Furthermore, power function model with additive error term proved to be a good alternative to the log-transformed power function model with multiplicative error.
- Weighted polynomial model with explanatory variable determined by stepwise selection is also a good alternative to the log-transformed power function model. The weighting and stepwise selection employed is very important to circumvent the problem of heteroscedasticity and ecologically incoherent curve behaviour at lower DBH.

How much in the above-ground biomass estimate uncertainty is attributed to sampling error in the first phase and regression error in the second phase?

- The first-phase and second-phase samples contribute 34.5% and 65.5% of the variability of the biomass estimate. Ignoring the regression error underestimated the precision of biomass estimate by 41.27%. Therefore, it is recommended that the two sources of errors must be accounted in future biomass assessment activities.
- The result of this study provides baseline information on the carbon source potential of the Labanan concession area in East Kalimantan, Indonesia.

What vegetation index/ band ratio best relate to above-ground biomass, and what is the resulting forest biomass estimate and its uncertainty?

- Assessing above-ground biomass using vegetation indices and band ratios derived from Landsat ETM+ image proved to be very difficult. The very low linear relation between the vegetation indices and band ratios investigated indicates that they are not sufficient to effectively predict forest biomass. Thus, above-ground biomass distribution map can not be produced.

Finally, the biomass equation developed for this study can be used to assess above-ground biomass in the forest of Kalimantan, Indonesia. Institutions like the local government of Berau district, the national government of Indonesia, and other national or international agencies who are interested in knowing the standing forest resource and carbon stock in this region will particularly benefit from the result of this study.

6. Recommendation

1. Biomass assessment

- The biomass equation developed for this study can be used to assess aboveground biomass in the forest of Kalimantan, Indonesia, especially in areas where tree cutting is not allowed. However, model validation must be done. There are several methods of assessing tree-based biomass, hence can be used to verify the constructed biomass equation.
- The method of quantifying the precision of biomass estimate used in this study is recommended to be used in future biomass assessment studies of tropical forests. For the forest in Kalimantan, additional sample trees are needed to increase the precision of forest biomass estimate.
- The method of quantifying the precision of biomass estimate is limited to linear models. Further research is recommended to extend this to non-linear models.

2. Relationship of biomass and spectral data

- The use of ancillary information such as forest type and/or textural data to improve the relationship of spectral data and biomass should be investigated.
- The use of alternative imaging technology (SAR, LiDAR, or high resolution imagery such as Quickbird and IKONOS) be considered and methods to better capture the horizontal (spatial) and vertical (height) characteristics of the forest should be further studied.

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8. Appendix

8.1. Appendix 1

Table 8.1 Comparison of biomass estimated using direct weighing (DBH<15) and using volume estimate (DBH>15) for power function model

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	86.574(a)	2	43.287	986.040	.000
Intercept	.923	1	.923	21.020	.000
LnDBH	24.490	1	24.490	557.854	.000
Measurement	.009	1	.009	.212	.648
Error	1.580	36	.044		
Total	1699.805	39			
Corrected Total	88.154	38			

Dependent Variable: LnDW

a R Squared = .982 (Adjusted R Squared = .981)

Table 8.2 Comparison of biomass estimated using direct weighing (DBH<15) and using volume estimate (DBH>15) for polynomial model

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	1.409(a)	3	.470	225.429	.000
Intercept	.001	1	.001	.251	.619
D2	.070	1	.070	33.801	.000
D3	.032	1	.032	15.405	.000
Measurement	.000	1	.000	.155	.696
Error	.073	35	.002		
Total	1.929	39			
Corrected Total	1.482	38			

Dependent Variable: DW

a R Squared = .951 (Adjusted R Squared = .947)

b Weighted Least Squares Regression - Weighted by w_DBH4.8

Table 8.3 Comparison of biomass estimated using direct weighing (DBH<15) and using volume estimate (DBH>15) for combined variable model

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	.005(a)	2	.002	308.577	.000
Intercept	1.25E-007	1	1.25E-007	.017	.896
D2H	.003	1	.003	344.029	.000
Measurement	4.87E-007	1	4.87E-007	.067	.798
Error	.000	36	7.30E-006		
Total	.008	39			
Corrected Total	.005	38			

Dependent Variable: DW

a R Squared = .945 (Adjusted R Squared = .942)

b Weighted Least Squares Regression - Weighted by w_D2H2.2

Table 8.4 Comparison of biomass estimated using direct weighing (DBH<15) and using volume estimate (DBH>15) for square-root transformed model

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	3.836(a)	2	1.918	719.330	.000
Intercept	.027	1	.027	10.134	.003
DBH	1.167	1	1.167	437.821	.000
Measurement	.004	1	.004	1.651	.207
Error	.096	36	.003		
Total	8.497	39			
Corrected Total	3.932	38			

Dependent Variable: sqrtDW

a R Squared = .976 (Adjusted R Squared = .974)

b Weighted Least Squares Regression - Weighted by w_DBH2.4

8.2. Appendix 2

8.2.1. Model 1: Power function with multiplicative error term

$$Ln(B)= Ln(a) + b*Ln(DBH) + Ln(\varepsilon)$$

Analysis of Variance

Source	DF	Sum of	Mean	F Ratio

		Squares	Square	
Model	1	48.74978	48.7498	2228.679
Error	37	0.809332	0.0219	Prob > F
C. Total	38	49.55912		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-1.24951	0.161769	-7.72	<.0001
LnDBH	2.310915	0.048951	47.21	<.0001

RSquare 0.983669 RMSE 0.147898

8.2.2. Model 2: Polynomial model

B= a+b(DBH)2+c(DBH)3+ε

Stepwise selection of predictor variables

SSE	DFE	MSE	R^2	R^2 Adj	Cp	AIC
0.073237	36	0.002034	0.9506	0.9478	2.8186	-238.827

Entered	Parameter	Estimate	DF	SS	F Ratio	Prob>F
X	Intercept	-2.67291	1	0	0	1
	DBH	0	1	0.001674	0.819	0.3718
X	DBH^2	0.54457	1	0.091416	44.936	<0.0001
X	DBH^3	0.009154	1	0.03483	17.121	0.0002

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	2	1.40854	0.70427	346.1884
Error	36	0.073237	0.002034	Prob > F
C. Total	38	1.481777		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2.67292	4.411443	-0.61	0.5484
DBH*DBH	0.54457	0.081237	6.7	<.0001
DBH*DBH*DBH	0.009154	0.002212	4.14	0.0002

RSquare 0.950575 RMSE 0.045104

8.2.3. Model 3: Combined variable model

$B=a + b(D^2H)+\varepsilon$

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	0.004505	0.004505	632.8345
Error	37	0.000263	7.12E-06	Prob > F
C. Total	38	0.004768		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	6.966411	1.774786	3.93	0.0004
D2H	0.032589	0.001295	25.16	<.0001

RSquare 0.944762 RMSE 0.002668

8.2.4. Model 4: Square-root transformed model

$sqrt(B) = a + b(DBH)+\varepsilon$

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Ratio
Model	1	3.831622	3.83162	1412.165
Error	37	0.100392	0.00271	Prob > F
C. Total	38	3.932014		<.0001

Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
Intercept	-2.03826	0.381243	-5.35	<.0001
DBH	0.995086	0.02648	37.58	<.0001

RSquare 0.974468 RMSE 0.052089

8.2.5. Model 5: Power function with additive error term

$B=a(DBH)^b+\varepsilon$

Solution

SSE	DFE	MSE	RMSE
0.036938237	37	0.000998	0.031596

Parameter	Estimate	ApproxStdErr	Approx t
a	0.290238	0.043317	6.700395
b	2.313121	0.046208	50.05843

Excluded Data

Count	SSE	MSE	RMSE
1	0.019208	0.019208	0.138593

Parameter	Estimate	Low	High
a	0.290238	0.03034	0.55014
b	2.313121	2.03587	2.59037

8.3. Appendix 3

8.3.1. Model comparison (computational formula)

$$FI = 1-(RSS/TSS)$$

where $TSS=\sum_{i=1}^{n}(Y_i-\overline{Y})^2$ and $RSS=\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2$

$$S_e=\sqrt{\frac{\sum_{i=1}^{n}(Y_i-\hat{Y}_i)^2}{n-p}}$$, p is the number of model parameters

$$CV=\left(\frac{S_e}{\overline{Y}}\right)*100$$

$$I=[f'(Y)]-'*RMSE$$

where $[f'(Y)]-'$ is the inverse of the geometric mean computed from the derivative of Y with respect to biomass.

$$\bar{S}(\%) = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|Y_i - \hat{Y}_i\right|}{\hat{Y}_i}$$

$$P_e = \left[\frac{(196)^2}{\chi^2{}_{(n-p)}}\sum_{i=1}^{n}\left(\frac{\hat{Y}_i}{Y_i} - 1\right)^2\right]^{\frac{1}{2}}$$

where the α=0.05 value of $\chi^2{}_{(v)}$ is approximated by

$$\chi^2{}_{(v)} = 0.853 + v + 1.645(2v-1)^{1/2}$$

8.3.2. Model comparison (Summary)

Table 6.1 Fit statistics for Kalimantan biomass data

Model*	*I*	*RMSE*	*FI*	*Se*	*CV*	$\bar{S}(\%)$	*Pe*
1	127.665	0.148	0.910	439.559	32.770	17.507	34.167
2	130.972	0.0451	0.9008	466.773	34.799	16.401	37.897
3	134.726	0.0027	0.8912	482.184	35.948	16.336	36.914
4	137.617	0.0521	0.8927	478.842	35.699	18.285	39.428
5	127.907	0.0316	0.9094	439.906	32.796	16.784	36.947

* 1 Power function with multiplicative error model solved by log-transformation, 2 Third-degree polynomial, 3 Combined variable, 4 Square-root transformed model, 5 Power function with additive error estimated using non-linear least squares estimation

** Predicted values of model 1 and 4 are biased and were corrected when the fit statistics were computed. Bias for model 1 is 2.125%. Bias for model 4 is 0.0175% at DBH=6 cm to <0.0001% as DBH reaches 68.9 cm.

Table 6.2 Fit Statistics for Dutch biomass data

Model*	*I*	*RMSE*	*FI*	*Se*	*CV*	$\bar{S}(\%)$	*Pe*
1	3.396	0.237	0.514	37.098	69.445	25.332	54.552
2	3.528	0.017	0.442	39.739	74.389	23.061	63.289
3	3.920	0.013	0.517	36.988	69.238	24.196	61.906
4	3.688	0.030	0.076	51.160	95.769	26.584	62.127
5	3.551	0.017	0.526	36.624	68.558	23.510	62.397

* 1 Power function with multiplicative error model solved by log-transformation, 2 Third-degree polynomial, 3 Combined variable, 4 Square-root transformed model, 5 Power function with additive error estimated using non-linear least squares estimation

** Predicted values of model 1 and 4 are biased and were corrected when the fit statistics were computed. Bias for model 1 is 4.5%. Bias for model 4 is 0.0016% at DBH=6 cm to <0.0001% as DBH reaches 68.9 cm.

8.4. Appendix 4

8.4.1. Relative efficiency of stratified random sampling over simple random sampling

Stratum	N_h	n_h	$\bar{y}_h$	s_h^2
1	13186.4	43	326.6273	239.834367
2	15033.7	45	322.6908	247.561744
3	16252.8	55	333.4400	221.124707
Total	44472.9	143		

Stratum	W_h	$W_h s_h^2$	$W_h s_h^2 / n_h$	$W^2_h s_h^2 / n_h$
1	0.296504	71.111888	1.65376484	0.490348161
2	0.338042	83.686222	1.85969383	0.628654283
3	0.365454	80.810913	1.46928932	0.536957686
Total	1	235.60902	4.98274799	1.655960131

Stratum	$W_h \bar{y}_h$	$W_h \bar{y}_h^2$
1	96.8463543	31632.66321
2	109.082985	35200.07567
3	121.856988	40631.99401
Total	327.786327	107464.7329

$$v_{st} = \sum \frac{W^2_h s_h^2}{n_h} - \sum \frac{W_h s_h^2}{N} = 1.655960131 - \frac{235.60902}{44472.9} = 1.650662$$

$$v_{srs} = \frac{N-n}{nN}\left[\sum W_h s_h^2 - \sum \frac{W_h s_h^2}{n_h} + \sum \frac{W^2_h s_h^2}{n_h} + \sum \frac{W_h \bar{y}_h^2}{N} - \left(\sum W_h \bar{y}_h\right)^2\right]$$

$$v_{srs} = \frac{44472.9-143}{143 * 44472.9}\left[235.609 - 4.9827 + 1.65596 + 107464.7329 - (327.786)^2\right]$$

$$v_{srs} = 1.764511$$

Relative Efficiency (RE) = $\frac{v_{srs}}{v_{st}}$ = 1.06897

8.5. Appendix 5

Integration of Error

Polynomial Model:

$$[b]' = [-2.67292 \quad 0.54457 \quad 0.009154]$$

Covariance matrix $[s_{bb}]$ of b:

$$[s_{bb}] = \begin{bmatrix} 19.460827121 & -0.2972493612 & 0.006922303 \\ -0.297249361 & 0.0065995050 & -0.0001644272 \\ 0.006922303 & -0.0001644272 & 4.894137\text{x}10^{6} \end{bmatrix}$$

Plot Variables

$$s_0 = n/a; \quad s_1 = \sum_{i=1}^{n} d^2/a; \qquad s_2 = \sum_{i=1}^{n} d^3/a$$

$$z_0 = \sum_{i=1}^{n} s_0/n; \qquad z_1 = \sum_{i=1}^{n} s_1/n; \qquad z_2 = \sum_{i=1}^{n} s_2/n$$

$$[z]' = [5.941259x10^2 \quad 3.717245\text{x}10^5 \quad 1.389220\text{x}10^7]$$

Covariance matrix s_z of z is calculated as

$$[s_{zz}] = \begin{bmatrix} s_{z_0z_0} & s_{z_0z_1} & s_{z_0z_2} \\ s_{z_1z_1} & s_{z_1z_1} & s_{z_1z_2} \\ s_{z_2z_1} & s_{z_2z_1} & s_{z_2z_2} \end{bmatrix}$$

where $s_{z_iz_j} = \sum (s_{hi} - \bar{s}_i)(s_{hj} - \bar{s}_j)/n_p(n_p - 1)$

$$[s_{zz}] = \begin{bmatrix} 155.2972 & 5.335838\text{x}10^4 & 1276787 \\ 53358.3812 & 7.923381x10^7 & 3779925245 \\ 1276787.2259 & 3.779925\text{x}10^9 & 202799268927 \end{bmatrix}$$

The estimated mean biomass per hectare is:

$$w = b_0 z_0 + b_1 z_1 + b_2 z_2 = [b]'[z]$$
$$w = 328.0088 \text{ tons/ha}$$

The variance S_{ww} of estimator w is calculated as:

$$s_{ww} = s_{ww}^{(1)} + s_{ww}^{(2)}$$

where

$$s_{ww}^{(1)} = [b]'[s_{zz}][b] \qquad \text{(sampling plots)}$$
$$s_{ww}^{(2)} = [z]'[s_{bb}][z] \qquad \text{(regression error)}$$

$$s_{ww} = 77958763 + 148064443 = 226023205$$

Underestimation of the precision of estimate

$$= \frac{100 * \left[\sqrt{s_{ww}} - \sqrt{s_{ww}^{(1)}}\right]}{\sqrt{s_{ww}}} = \frac{100 * \left[\sqrt{226023205} - \sqrt{77958763}\right]}{\sqrt{226023205}}$$

= 41.27 %

8.6. Appendix 6

Image pre-processing

Radiometric correction is computed using the formula (NASA, 2004):

$$L_\lambda = L_{\min\lambda} + \left[\frac{L_{\max\lambda} - L_{\min\lambda}}{DN_{\max} - DN_{\min}}\right] * (DN - DN_{\min})$$

where:

$L_\lambda =$ at- sensor radiance in watt/(m^2 steradian μm)

$L_{max\ \lambda}$ = spectral radiance scale to DN_{max} in watt/(m^2 steradian μm)

$L_{min\ \lambda}$ = spectral radiance scale to DN_{min} in watt/(m^2 steradian μm)

DN_{max} = maximum DN value

DN_{min} = minimum DN value

DN = pixel value

At surface reflectance of the object is computed using the formula: (NASA, 2004).

$$\rho = \frac{\pi L_\lambda d^2}{E_o \cos \Theta}$$

where:

ρ = at object reflectance

$L_\lambda =$ at-sensor radiance in watt/(m^2 steradian μm)

d = Earth-sun zenith distance in astronomical units

Θ = Solar zenith angle in degree

E_o = Solar irradiance at mean Earth-sun distance in watt/m^2 μm

8.7. Appendix 7

Kalimantan sample tree above-ground biomass data

No	Genus	Local Name	DBH (cm)	H (m)	DW (Kg)
1	Madhuca sp.	Nyatuh	6.0	11.1	19.09
2	Alseodaphne sp.	Medang	7.5	12.2	29.36
3	Alseodaphne sp.	Medang	7.6	16.2	38.38
4	Calophyllum Sp	Bintangor	10.5	13.0	50.01
5	Garcinia sp.	Manggis	10.7	14.0	75.42
6	Vatica sp.	Resak	11.8	17.2	100.67
7	Knema sp.	Darah-darah	11.9	17.4	63.48
8	Syzygium sp.	Jambu-Jambu	14.5	18.0	165.01
9	Xanthophyllum sp.	Lemak	15.0	17.7	154.99
10	Syzygium sp.	Jambu-Jambu	15.2	19.8	282.06
11	Dacryodes sp.	Asam-asam	18.7	19.4	239.77
12	Diospyrus sp	Arang-arang	21.8	20.2	254.18

No	Genus	Local Name	DBH (cm)	H (m)	DW (kg)
13	Madhuca sp.	Nyatuh	22.9	21.2	376.65
14	Knema sp.	Darah-darah	24.4	23.0	424.63
15	Dacryodes sp.	Asam-asam	25.0	25.3	541.88
16	Knema Sp.	Dara-dara	25.5	20.0	344.64
17	Allantospermum sp.	Kayu tulang	26.9	23.9	551.95
18	Alseodaphne sp.	Medang	27.7	23.6	536.64
19	Allantospermum sp.	Kayu tulang	28.7	22.9	978.62
20	Lophopetalum sp.	Kayu minyak	32.2	27.7	780.83
21	Baccaurea sp.	Jentik	32.7	29.5	1118.71
22	Dyophyllum	Kerek	32.9	30.5	1101.95
23	Dyophyllum	Kerek	34.0	24.0	1342.46
24	Mezzetia sp.	Mempisang	36.2	30.5	1131.19
25	Syzygium sp	Jambu-Jambu	36.3	25.0	989.09
26	Scaphium sp.	Semangkok	37.0	36.3	1368.72
27	Calophyllum sp.	Bintangor	41.0	33.8	1755.29
28	Drypetes sp.	Mentulang	42.1	27.9	1743.91
29	Shorea sp.	Meranti kuning	43.4	28.5	1411.90
30	Scaphium sp.	Semangkok	45	37.0	1785.34
31	Dialium sp	Karanji	46.2	30.6	2929.11
32	Bouea sp.	Merapoh	46.9	31.1	1801.30
33	Lithocarpus sp.	Pasang	48.5	28.5	1663.49
34	Stemonurus sp	Katok	51.0	27.9	3107.12
35	Parishia sp.	Rengas susu	53.0	31.0	2583.27
36	Archidendron sp	Jengkol	55.5	41.2	3551.82
37	Heretera sp.	Teraling	57.1	38.8	2773.13
38	Canarium sp.	Asam-asam	63.5	36.1	4611.33
39	koompassia sp.	Impas	67.7	43.5	6270.05
40	Mangifera sp.	Palong	68.9	35.1	3546.68

8.8. Appendix 8

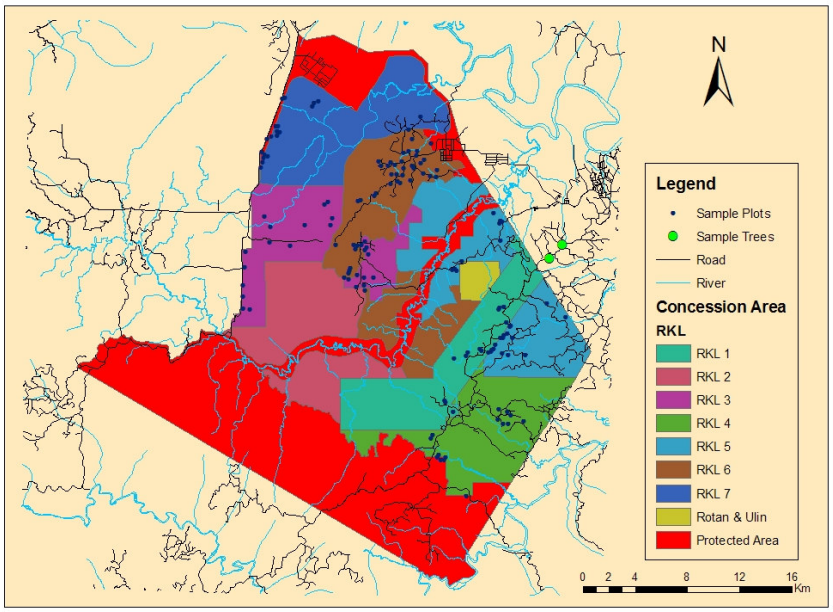

Figure 8.1. Map showing the study area and RKL classification.